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COMPUTERIZED MACHINE TOOLS AND THE TRANSFORMATION OF US MANUFACTURING

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ABSTRACT

The diffusion of computerized machine tools in the mid-20th century was a pivotal step in the century-long process of factory automation. We build a novel measure of exposure to computer numerical control (CNC) using initial variation in tool types across industries and differential shifts toward CNC by type. Industries more exposed to CNC from 1970-2010 increased labor productivity and reduced production employment. Workers in more exposed labor markets adjusted by shifting from metal to non-metal manufacturing. Union members were shielded from this job loss, and some workers returned to school to retrain.

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Imagine, if you will, a factory as [a] clean, spacious, and continuously operating [facility]... The production floor is barren of men. Only a few engineers, technicians, and operators walk about on a balcony above, before a great wall of master control panels... All else is automatic.[1]

-Leaver and Brown, "Machines Without Men," 1946.

I. Introduction

Industrialists have long dreamed of a highly-productive and easily managed automatic factory with a production floor "barren of men." During the past century, the manufacturing sector indeed experienced a continuous (but punctuated) process of *automation*, by which new technology enabled tasks previously completed by human labor to be accomplished, in whole or in part, by machine. The latest stage in this process of automation replaces manpower and human skill with computer-assisted machines. Many technologies have contributed to this stage, including "computer numerical control machinery, industrial robots, and artificial intelligence" (Acemoglu and Restrepo 2019, p. 3).

In this paper, we focus on the first of these computer-assisted technologies, computer numerical control (CNC) machine tools, which began to diffuse widely in the 1970s. CNC tools rely on computer programs and sensors rather than human operatives to select and perform the sequence of physical movements needed to produce a metal part. Like other forms of automation, CNC has the potential to enhance labor productivity and to create new tasks for high-skilled technicians who can install, program, and fix complex machines. However, CNC may also have reduced employment of mid-skilled workers who had been responsible for guiding hand-operated machine tools.

Our analysis is based on a novel measure of exposure to CNC technology at the industry-year level, which we can then apply to variation in industrial composition across local labor markets. The measure has two components: (1) baseline variation in installed machine tools across metal manufacturing industries by tool type – such as lathes, mechanical presses, grinding machines and

[1] From Leaver and Brown (1946)'s article "Machines Without Men," published in a supplement on "The Automatic Factory" in Fortune Magazine.

so on (*shares*) and (2) shifts from hand-operated to computerized tools by tool type, as measured by trade data from the world's major exporters of machine tools (*shifts*). Baseline shares are measured in 1958, before the spread of CNC technology, from a plant survey tabulated in the *American Machinist Inventory of Metalworking Equipment*. The shifts at the tool level from hand-operation to CNC reflect varying engineering challenges across tools and differences in industrial policy within major exporters.

By our measure, all metal industries had very low exposure to CNC in the early 1970s. Diffusion of the technology was faster for some tool types than others. By 1990, industries like precision mechanisms that relied more heavily on lathes or aircraft that relied on boring machines increased exposure to CNC tools dramatically (up to 40% of its tool base by value), while industries like motor vehicles were less affected (25% of its tool base). We then apply our measure to local labor markets based on 1970 employment shares by industry. Labor markets with similarly high employment shares in heavy manufacturing, such as Seattle and Detroit, were differentially exposed to CNC due to specialization in different sub-industries (aerospace in Seattle and motor vehicles in Detroit).

Summarizing our results, we find that the diffusion of CNC technology led to rising productivity in manufacturing. In particular, the advent of CNC was associated with growing capital investments, rising labor productivity, and a falling labor share in manufacturing industries more exposed to this new technology. Exposed industries shed workers, particularly on the production floor. Demand for workers with a high school degree or less fell, while demand for college-educated workers increased.

We find that workers were able to partially adapt to the CNC technology shock in three notable ways. First, the CNC shock was limited to metal manufacturing and did not spread (until very recently) into wood or plastics. We see that workers were able to shift from metal manufacturing into less affected industries, in contrast to recent studies of the diffusion of industrial robots (see Acemoglu and Restrepo 2018, 2020). In local labor markets that were more exposed to CNC, the decline in employment in metal manufacturing was wholly compensated by a rise in employment in non-metal manufacturing and in the wholesale and retail trade sector for men.[2] Women

[2] This pattern is consistent with an earlier episode of concentrated automation – telephone operators in the 1920s and 1930s (Feigenbaum and Gross, 2020).

experienced an *increase* in total employment due to the expansion of the non-metal manufacturing sector. Second, unionization rates were reasonably high when the shock began, and workers who belonged to unions were less affected by the shock. The estimated decline in employment was concentrated among non-unionized employees, either because unionized firms adopted the new technology more slowly or because they adjusted their workforce more gradually as new technology arrived. Third, unlike the robot shock, which affected the lowest-skill workers, CNC technology substituted for mid-skill workers. We find that some of these workers were more likely to go back to school after CNC diffusion to earn two- and four-year degrees. Colleges and universities expanded their degree offerings related to CNC technology to accommodate this growing interest.

We trace the effects of CNC automation using a variety of sources. Productivity and employment by industry is measured in the Census of Manufactures. Worker responses in union membership and returning to school are drawn from two supplements to the Current Population Survey. Local labor market outcomes are measured using data from the Census of Population. Evidence on educational programs comes from the Higher Education General Information Survey (HEGIS) and later sources.

Industries with higher exposure to CNC technology and local labor markets concentrated in these industries may have faced other economic shocks over this period. We provide four pieces of evidence against the idea that our results are driven by other potentially correlated factors. First, we do not find pre-trends in outcomes at the industry or labor market level before the diffusion of CNC technology. Second, results do not change when we control for obvious alternative events like rising import competition or trade with Mexico or China. Third, the CNC shock only affects some sub-industries within manufacturing, allowing us to compare labor markets with similar levels of baseline manufacturing employment but differential exposure to CNC. Fourth, our measure of shifts toward CNC technology is based on global exports, rather than adoption of machine tools in the US alone, reducing potential reverse causality due to US-specific demand for automation technologies.

In a task-based model, the predicted effects of automation on the production process can differ according to the specific tasks being replaced, the types of new tasks created, and the broader state of labor market institutions (Acemoglu and Autor 2011, Acemoglu and Restrepo 2020). Therefore, we should not expect that episodes of automation today necessarily have the same effect as automation in the past, and vice versa. Rather, it is important to study each of the key steps in the history of automation to trace out the range of empirical effects of automation technology shocks with different characteristics and under different institutional environments.

Our paper fills an important gap in our understanding of how a century of automation has affected manufacturing productivity and the labor market, filling in a timeline that spans factory electrification in the early 20th century, the adoption of industrial robots in recent decades, and the potential consequences of artificial intelligence in the near future. Scholars have found that electrification substantially raised labor productivity and *increased* total employment (Goldin and Katz, 1998; Gray, 2013; Katz and Margo, 2014; Fiszbein, et al., 2024).[3] More recently, adoption of industrial robots has been associated with *falling* employment in the US, but with null or positive effects on employment in countries like Germany and Japan with stronger unionization and labor market protections (Acemoglu and Restrepo, 2020; Graetz and Michaels, 2018; Dauth, et al., 2021; Adachi, Kawaguchi and Saito, 2020).[4]

We find that CNC-based automation is an intermediate case between the strong employment gains of electrification and the strong dis-employment effect of industrial robots in the US. According to the task-based model, the fact that CNC technology did not generate an increase in total employment suggests the productivity gains of CNC were not sufficient to offset the displacement effects of automation. Yet, the productivity gains of CNC appear to have been larger than those of industrial robots because CNC did not lead to overall dis-employment.

Our study also builds on earlier plant-level analyses of CNC adoption, and a large qualitative literature on this era. Plants that adopt CNC become more efficient (e.g., experience a reduction in run times) and advertise for more skilled operatives (Bartel, Ichniowski and Shaw, 2007). Dunne, et al. (2004) show that investment in computer technology can account for much of the dispersion

[3] Gaggl et al. (2021) and Lewis and Severnini (2020) study the effect of electrification on structural transformation from agriculture to manufacturing and on the agricultural sector in rural areas, respectively.

[4] Related papers compare firms that invest in robot technology (or, more broadly, in "industrial equipment") to competitors who do not. Firms that adopt robots experience rising productivity, output and total employment (Humlum, 2019; Acemoglu, et al. 2020; Koch, et al. 2021; Aghion, et al. 2021). Bessen, et al. (2019, 2020) instead find evidence of displacement, even at the firm level, following automation events in the Netherlands.

in productivity and wages across plants, but Keefe (1991) and Doms, Dunne and Troske (1997) caution that these plants may not shift toward a skilled workforce at a faster pace than their competitors.[5] Our paper expands on these plant-level studies in two ways. First, plant-level analyses provide *relative* comparisons between firms that choose to invest in additional CNC tools to firms that do not. Our work instead offers industry-wide estimates of productivity and employment effects of CNC automation, which also allows us to study how workers adjust to this industry-wide shock. Second, earlier studies are based on adoption data in the late 1980s and 1990s, twenty years after the new technology begins to diffuse. We instead trace out the diffusion of this new technology from its very inception, allowing us to incorporate meaningful pre-trends and to study the first CNC machines.

II. Historical Context

The punctuated history of automation in the manufacturing sector

This section situates the development of computer numerical control machine tools in the longer-run history of factory automation.

Automation has evolved in four main stages. The first step, which was a necessary precursor to all later automation episodes, was the development of *interchangeable parts* in the 19th century (Hounshell 1984). With interchangeability, the production of metal goods could be subdivided into two distinct activities: the production of parts from raw metal stock and the assembly of those parts into finished goods in bulk. Interchangeability eliminated the need for skilled "fitters," who adjusted parts to fit together as they were assembled by hand.

The achievement of true interchangeability depended on the advent of modern machine tools that could cut or bend raw metal in ways that were both precise and replicable. Machine tools such as lathes and drills have been in use since the 18th century but underwent rapid improvement and

[5] The existing papers on CNC consider different parts of the skill distribution. Doms, Dunne and Troske (1997) find that plants adding computer-assisted production do not hire more college graduates. Keefe (1991) documents that machine shops adopting CNC replace skilled occupations like machinists with unskilled occupations like machine tenders. Bartel, Ichniowski and Shaw (2007) show that skill requirements for newly-hired machine operators are higher at firms with CNC, suggesting that there can be some skill upgrading *within* occupation categories.

diffusion after 1860 (Rosenberg, 1963, Holt 1966, Woodbury 1972; Atack, Margo and Rhode, 2019). These machine tools were operated by skilled machinists who translated engineering drawings into precise operations by manipulating the wheels and levers of the machine by hand.

The second step in the history of automation, beginning in metal manufacturing, was the invention of the assembly line, pioneered by the Ford Motor Company in 1908 (Hounshell 1984). Factory electrification, which diffused rapidly between 1910 and 1930, was important to the development of the assembly line because it allowed for the flexible placement of each machine in the order required to maximize efficiency (Devine 1983). Previously, machines were powered by a central drive, which limited flexibility and required porters to move parts around the factory. Electrification thus substituted for human labor and was complementary with more high-skilled tasks needed to install and fix machines (Goldin and Katz, 1998).

Automated machine tools, the subject of this paper, were the third step in this automation process. Before this step, semi-skilled operators were required to control the motions of machine tools. Numerical control – as first developed in the late 1950s and then computerized in the mid-1970s – codifies the movements of skilled operators into a program so that a less-skilled operative can execute them automatically. Numerical control required the invention of both *computer systems* that could execute the programs and *servomechanisms* that translated the programs into precise physical movements of the tools. Both technologies advanced substantially during World War II, the computer primarily for ballistics computations and servomechanisms for the automatic targeting of guns to ships or airplanes detected on radar (Mindell 2004). We describe the invention and diffusion process for CNC tools in the next section.

The fourth step in the automation of metal manufacturing has been the use of industrial robots in the assembly of metal products from components parts. Unlike CNC tools, which replaces the fine motor skills of skilled machinists, robots automate the gross motor skills involved with assembly, as well as with "welding, painting… handling materials and packaging" (Acemoglu and Restrepo 2020, p. 2189). Robots began to diffuse widely in the 1990s and have received significant attention from economists.

The invention and diffusion of CNC machine tools

The first numerically controlled machine tool was invented in the United States in the early 1950s at the MIT Servomechanisms Lab, building on the advances in computing and servomechanisms that emerged during World War II. These early tools, developed under contract with the US Air Force, were used for the machining of helicopter rotor components, which required a level of precision that even skilled machine tool operators of the day could not readily attain (Noble 1986).

The original numerically controlled machine tools built at MIT were too expensive to be commercially viable. The goals of the Air Force, along with the preferences of the scientists involved, resulted in a machine that was extremely precise and of wide capability but also very expensive. While commercialization began in the late 1950s, initial adoption was largely confined to the aircraft industry, where a large share of revenue came from cost-plus contracts with the US government.

The first computer numerical control tools designed for wide commercial applications were developed in Japan in the late 1960s. Japanese tool makers became the dominant producers by the early 1970s, followed by German competitors. Throughout the 1960s, Japanese tool makers – with the support of the Ministry of International Trade and Industry (MITI) – were pursuing lower-cost (and thus less precise) designs that were more suited to Japanese metal manufacturing. American machines used closed-loop feedback mechanisms, in which the location of the cutting edge of a tool was independently measured by sensors. Japanese machines used open-loop systems, which eliminated costly sensors and assumed tools had moved without error. This design was not initially precise enough to use in aircraft manufacture but was suitable for other industries and much cheaper to produce.

In the mid-1970s, microprocessors replaced dedicated hardware modules, a transition marked by the replacement of the term "numerical control" with the alternative "computer numerical control," or CNC. We adopt the term CNC to refer to automated machine tools throughout the paper, even though the earliest periods in our data series are before this transition from NC to CNC. Microprocessors increased the flexibility of CNC tools, lowered production costs directly, and made the addition of more accurate closed-loop controllers cheap. The US machine-tool industry lagged behind Japan's in converting their designs to CNC (Weiandt 1994).

CNC technology was developed for use with metal cutting tools. Although CNC is now employed in the machining of wood and plastic, the diffusion of CNC to these industries lagged several decades behind metal due in large part to inherent difficulties with these materials including their thermal properties and the presence of irregularities (Landschiedt and Kans 2016, Raymond 2019). This lag is also apparent in the number of mentions of the terms "metal," "wood," and "plastic" in the text of CNC-related patents. Further, studies of CNC such as the 1993 Survey of Manufacturing Technology limited themselves to the metalworking industries, suggesting those technologies were not yet important outside of metals.

Innovation in CNC tools was not driven by US demand

We use trade statistics to measure the evolution of machine tools from hand-operated to computer-operated for the three largest exporters. Japan overtook the United States to become the largest producer of CNC lathes in 1975 and served more than 60% of the world market by 1981 (Renderio 1985). Germany was the second largest producer with around 20% of the market while the United States was left with only 10%. Italy was the fourth largest producer. We exclude US machine tool production in the analysis, which may have been more responsive to demands from domestic manufacturers.

The historical record suggests that both the direction and the speed of innovation by Japanese, German and Italian tool exporters were driven primarily by their own domestic markets.[6] Japan and Germany specialized in different machine tools – Japan in lathes and Germany in boring machines, for example – as suited to their own domestic manufacturing sectors.

Japan's small-to-medium sized manufacturing firms created substantial domestic demand for lathe production in the 1960s (Itohisa 2010). Japan's MITI provided incentives to machine tool makers in the mid-1960s to develop economies of scale in CNC lathes by producing for the domestic market first before promoting exports (Johnson, 1982; Sarathy, 1989). "Exports nevertheless remained of secondary concern to the Japanese industry until it had exploited the domestic market

[6] The US comprised approximately 40% of the export market for Japan, 13% for Germany, and 10% for Italy. Calculations based on statistics reported in the Economic Handbook of the Machine Tool Industry, various years, and UN COMTRADE.

and gained technological leadership in low-cost CNC machine tools" (Collis, 1988). Japan's early expertise in the making of lathes was then persistent as the market shifted to CNC.

Expertise in one machine tool did not translate directly into supremacy in others. Indeed, "to develop a lathe required a different design expertise from that needed to develop a grinding machine or a drill" (Collis, 1998). Twenty-five percent of Japan's lathe exports were CNC in 1975, rising to 95% CNC by 1985. By contrast, only 50% of Japanese boring, drilling and grinding machines were CNC by that year.

While Japan specialized in lathes, Germany instead specialized in boring machines and Italy in milling machines; boring machines were the first to convert to CNC in Germany and milling in Italy. These country-specific patterns are confirmed in the US patent records: lathes dominate early patenting by Japanese firms related to CNC technology, while boring machines dominate patenting by German firms (see Appendix Figure 1).

Inherent differences in the difficulty of automation between tool types can also explain some of the temporal patterns in CNC diffusion. For example, grinding is inherently more difficult to automate than milling, drilling, or turning (Collis, 1988). The later and less complete diffusion of CNC in the grinding tool category is consistent with this greater technical challenge.

III. Construction of CNC exposure measure and data sources

Industry-year exposure to CNC technology

We construct a measure of exposure to CNC technology that varies by year and by industry. Our measure relies on two sources of variation: the share of each tool type (e.g., lathes, boring machines) in an industry's tool base as of 1958, before the diffusion of CNC; and the cumulative value share of exports of new machine tools made up of computer-operated tools up to year t from the three major machine tool exporters (Japan, Germany, and Italy).[7] Our exposure measure to CNC machine tools for industry j is thus the cumulative share of CNC tools in the global market as of year t, weighted by baseline tool use in that industry. Although our measure does not capture

[7] We use the cumulative CNC share, rather than the annual CNC share, to reflect the transition of the total tool stock toward CNC for a given year.

actual growth in the stock of CNC tools, we show below that our measure is correlated with the stock of CNC tools in the limited years in which we can measure this stock.

To construct our measure, we begin at the tool level, measuring the cumulative CNC share of exports for each tool type *k* and exporter *i* from 1971 up to year *t*. The CNC share for exporter *i* by year *t* can be written:

$$Share\_CNC_{i,k,t} = \frac{\sum_{\tau=1971}^{t} X_{i,\tau,k}^{CNC}}{\sum_{\tau=1971}^{t} X_{i,\tau,k}^{Total}} \tag{1}$$

where $X_{i,\tau,k}^{Total}$ are the total annual export value of type *k* machine tools of any mode (hand-operated or CNC) from exporter *i* to the global market in year τ and $X_{i,\tau,k}^{CNC}$ are the annual export value of CNC tools of type *k* from exporter *i* in year τ.[8]

We then aggregate across exporters to create the tool-level CNC share. To do so, we weight the CNC share for took *k* from exporter *i* (equation 1) by exporter *i*'s share of the total export value of tool type *k*, which can be written $\frac{X_{i,k,t}^{Total}}{\sum_{\iota} X_{\iota,k,t}^{Total}}$. The CNC share at the tool-by-year level (weighted across exporters) can be expressed:

$$Share\_CNC_{k,t} = \sum_{i} Share\_CNC_{i,k,t} \frac{X_{i,k,t}^{Total}}{\sum_{\iota} X_{\iota,k,t}^{Total}} \tag{2}$$

Finally, we link the CNC share for tool k (equation 2) to industry *j* by weighing by the 1958 value share of tool *k* among the tool inventory for that industry $\frac{VT_{k,j,1958}}{\sum_{j} VT_{k,j,1958}}$. Equation 3 thus presents our exposure measure to CNC technology at the industry-by-year level:

$$Exposure\_CNC_{j,t} = \sum_{k} \left(\frac{VT_{k,j,1958}}{\sum_{k} VT_{k,j,1958}} Share\_CNC_{k,t} \right) \tag{3}$$

In the remainder of the section, we explain the data sources for constructing each component of this measure and illustrate the resulting patterns of variation.

[8] We assume that CNC and non-CNC tools depreciate at the same rate. This means that the cumulative CNC share is not affected by depreciation.

1958 value shares of tool *k* for industry *j*: We construct the industry-level measures of tool base in equation 3 from the 1958 *American Machinist Inventory of Metalworking Equipment* (AMIME). The AMIME contains information on the value of tool inventories for 28 detailed tool types for each metalworking sub-industry.[9]

Figure 1 demonstrates that there is substantial variation in the intensity of tool use across sub-industries within the metal manufacturing sector. [10] The figure is organized as a heatmap of tool-type usage for the seven metalworking industries in our analysis, ordered by the amount of variation in use of the tool (standard deviation) across the industries. Cells that are shaded orange reflect greater-than-average use of the tool type relative to other metal manufacturing sub-industries, and purple shading reflects less-than-average use. The dark orange shading suggests that certain industries are more heavily reliant on given tools: for example, mechanical presses make up close to 10 percentage points more of the tool base in the fabricated metal industry than in other sub-industries. The same pattern holds for gear cutting machines in the farm machinery industry, lathes in precision mechanisms, and boring machines in aircraft.

Annual CNC shares by tool *k*: We collect the export values for each machine tool type by exporter (Japan, Germany, and Italy) from the *Economic Handbooks of Machine Tool Industry*. The series separately reports tool exports by type as counts and as values for CNC and non-CNC tools. We calculate the cumulative share of tool exports made up of CNC tools from 1971 to the year *t*.[11]

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[9] The 1958 AMIME survey was distributed to the 23,000 metalworking plants with more than 20 employees identified in the 1958 McGraw Hill Census of Manufacturers (MHCM). AMIMIE returns were received from 5,560 plants. The response rate was 24% in terms of plants and about 40% in terms of plant employment. Return rates were calculated for 1,056 industry-by geography-cells. Total employment in each cell was then divided by the total employment in the MHCM census, which gives the share of total employment in each cell covered by the AMIME. Machine counts/values were multiplied by this share to estimate the total number/value of machines of each type in each cell. These estimates were aggregated to the industry level to produce the industry level machine tool type value estimates we use to compute our tool type shares by industry.

[10] The AMIME contains SIC codes for 16 sub-industries. We aggregate these SIC codes into 7 categories using the 1950 census industry codes to merge in the other variables and outcomes used throughout the project. Similarly, four industries account for around 70% of robot adoption (Acemoglu and Restrepo, 2020).

[11] The export data includes 14 major tool types by CNC status from 1971 to 2009. We consolidate these 14 tool types to seven categories to reflect differential reporting patterns by exporter. Our measure captures the majority of variation in tool use reported in the 1958 AMIME: the 14 tools

Figure 2 documents that different tool types shifted toward CNC technology in different years and to different extents. By tool and exporter, we plot the time series of CNC tools as a value share of all machine tool exports (as in equation 1). For Japan (Panel A), lathe exports reach 50% CNC by 1976, a level only reached by milling machines around 1980, boring and drilling machines around 1984, and grinding machines around 1992. For German exports (Panel B), there is a thirty-year lag between the first tool to reach the 50% CNC mark (boring machines, 1980) and the last tool to do so (mechanical presses, 2010). In Italy (Panel C), lathes and boring machines pass the 50% mark in the late 1980s.

Figure 3 plots our industry-level CNC exposure measure (equation 3), which combines the 1958 tool shares by industry from Figure 1 with the annual CNC shifts by tool from Figure 2. CNC tools diffused most rapidly for the aircraft and precision mechanism industries and most slowly for fabricated metal and motor vehicles. Aircraft reached a diffusion level of 38% of its tool base by 1990, whereas motor vehicles did not quite reach this level by the year 2000. The construction of our measure makes it clear why this was so: The aircraft industry was particularly reliant on two types of machines – boring and milling tools – that were early to shift to CNC technology. By contrast, the motor vehicles industry was less likely to use early-adoption tools like lathes and more reliant on late-adoption tools like gear cutting.

Validation of CNC exposure measure

We validate our new measure of CNC exposure by documenting that it is correlated with two intermittently-available measures of adoption of computerized machine tools from the 1970s through the 1990s. We then show that our CNC measure is only weakly correlated with a later stage in automation: exposure to industrial robots in the 1990s and 2000s.

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included in the trade data represent 78% of the value share of the 1958 tool base from the AMIME, which has 28 detailed tool types. To complete the series, we impute the CNC share to be the lowest CNC share for the given exporter in that year for the other 14 tool types included in the 1958 tool base that are not covered in the trade data. We extend each of these series back to 1968 by assuming that each tool had zero CNC share in 1968, 1969 and 1970 before CNC diffusion truly began to coincide with the dates available for our main outcomes.

Figure 4 contains correlations between our CNC exposure measure and two measures of the adoption of CNC machine tools. For adoption of CNC, Figure 4a reports measures of the share of the installed tool base made up of CNC tools. This measure of adoption is available in three years (1973, 1978, and 1983) in the AMIME data.[12] Figure 4 shows a strong correlation ($\rho = 0.74$) between our measure of exposure to CNC and this measure of actual adoption adjusting for year and industry fixed effects.

Figure 4b correlates our CNC exposure measure with a measure of worker exposure to CNC machines from the Survey of Manufacturing Technology (SMT) in 1988 and 1993. The SMT was administered to plants in metal manufacturing industries (SIC = 34-38). Each plant reported total employment, along with indicators for the use of CNC machines and other computer-assisted technologies. We calculate a share of workers employed at plants with CNC machines and then correlate this with our measure ($\rho = 0.54$), again adjusting for year and industry effects.

Although our CNC measure is strongly correlated with actual CNC adoption, it is only weakly correlated with subsequent exposure to industrial robots. Appendix Figure 2 shows scatterplots comparing a commuting zone's exposure to CNC technology (1970-2000) and exposure to robots (1993-2000) taken from Acemoglu and Restrepo (2020). Panel A shows that commuting zones with high exposure to CNC also tended to have high exposure to robots, with a correlation of 0.46. However, a substantial portion of that relationship appears to reflect the overall manufacturing intensity of the commuting zones. Panel B shows the relationship after residualizing both variables on the 1970 commuting zone manufacturing share of employment. The correlation remains positive but is a much weaker 0.19.

Data sources for outcome variables

We use three data sources to measure productivity and employment effects of CNC technology at the industry or local labor market level.

First, we draw on the NBER-CES Manufacturing Industry database for measures of capital investment, labor productivity, the labor share by industry, total employment and employment by

[12] The AMIME included information on CNC adoption in 1989 but the three-digit breakdown necessary to construct was not included in the published report.

category (production, non-production) originally tabulated by the Census of Manufactures (Bartelsman and Gray 1996). The NBER database uses harmonized industry definitions from the original files that are based on SIC and NAICS; we use the "SIC 1987" version. We then map these SIC industry codes to our seven metal manufacturing categories. Labor productivity is measured as log value added per worker, and the labor share is measured as wage bill divided by value added.

Second, we use the CPS Annual Social and Economic Supplement (ASEC) to count employment by industry and education category (less than high school degree, exactly high school degree, some college, and college degree or more). In both the Census of Manufactures and CPS datasets, we consider outcomes from 1968-2007, ending before the onset of the Great Recession.

Third, to map our CNC shocks to local labor markets, we use Census data in 1970 to calculate the baseline share of employment by industry and commuting zone. For each commuting zone, we measure total employment and employment by gender or education group by sector (metal manufacturing, non-metal manufacturing, and other 1-digit industries) in 1970 and 2000.

To measure worker adjustments to the CNC technology shock, we use two CPS supplements. We count workers by industry and union membership from the CPS May supplement (1973-1983) and then from the CPS Outgoing Rotation Groups (1984-2007). We use data on current/last industry of employment and school enrollment from the CPS October Educational supplement (1976-2007). Our sample includes prime-age men who did not already hold a bachelor's degree in the survey year.

IV. CNC adoption and industry-level outcomes

This section documents the relationship between exposure to CNC technology and economic outcomes at the industry level. In particular, we estimate:

$$y_{j,t} = \alpha_j + \gamma_t + \beta Exposure\_CNC_{j,t} + \varepsilon_{j,t} \tag{4}$$

where α_j is a set of seven industry fixed effects and γ_t is a set of year fixed effects. We report estimates of β, which summarize the relationship between changes in exposure to CNC and outcomes like capital expenditure, labor productivity and employment. For some outcomes, we also control for the size of the production and non-production workforce.

Capital expenditures, productivity and labor share*:* We start in Table 1, Panel 1 by considering outcomes from the Census of Manufacturers. Adoption of CNC technology, which requires the purchase and installation of new machine tools, should lead firms to undertake new capital expenditures. Column 1 presents a positive correlation between exposure to CNC and the logarithm of capital expenditures. A 10-percentage point increase in CNC exposure, which is the approximate difference between the aircraft and motor vehicles industry in 1990, corresponds to a 14-log point increase in annual capital expenditures.

Labor productivity should rise with automation as labor is reallocated away from tasks for which it does not have a strong comparative advantage and as the new technology augments labor in the tasks that remain. A 10-percentage point increase in CNC exposure corresponds to a 9-log point increase in labor productivity, measured as wage bill divided by value added (Column 2).

In a task-based model, automation can have either positive or negative effects on overall labor demand. Automation will lead some tasks to be shifted away from labor to capital (the *displacement* effect), while some new tasks – like programming or installing machinery – may be created that can only be done by labor (the *reinstatement* effect) (Acemoglu and Restrepo 2019). An automation-induced increase in *productivity* can also increase labor demand, with the net effect on employment of these three forces theoretically indeterminate. If displacement is stronger than reinstatement and productivity, the labor share will fall. We find a 1.6-point decline in the share of revenue paid out to labor for a 10-percentage point increase in CNC exposure (Column 3).

Total employment and employment by education level: We next turn to the relationship between CNC exposure and employment. Columns 4-6 (Panel 1) show results for the logarithm of total employment, production employment, and non-production employment, respectively. A 10-percentage point increase in CNC exposure is associated with a 6-log point decline in total employment (not significant) and a 12-log point decline in production workers.

Panel 2 of Table 1 reports a series of employment outcomes by education category calculated from the Current Population Survey. A 10-percentage point increase in CNC exposure is associated with a 15-23 log point decline in employment for both high school dropouts and high school graduates, partially counterbalanced by a 17-log point increase in employment for college graduates. CNC technology appears to displace lower-skilled workers who were more likely to work on the production floor, and to create new tasks filled by higher-skilled workers, who likely worked as programmers, engineers, or in white collar positions.

Graphical summary: We summarize the main industry results using time series in Appendix Figure 3. For graphical exposition, we partition the industries into two groups – high and low exposure to CNC – and document initial overlap in the capital expenditures and labor productivity of these two industry groups that start to diverge after the diffusion of CNC in the late 1970s (Panels A and B). The one exception is a short-lived spike in capital expenditures for high shock industries from 1966-1970, driven by the aircraft industry during the Vietnam War.

High exposure industries start with a higher labor share of value in 1960 and converge to the lower labor share of lower exposure industries over the next decades. This convergence is particularly rapid following CNC diffusion in the 1970s (Panel C). Panel D does not show an obvious time-series relationship between exposure to CNC diffusion and total employment. Total employment falls in high shock industries around 1970 (before the diffusion of CNC, and any apparent effects on capital or productivity), rises in the 1970s, before falling again after 1990.

V. CNC exposure at the local labor market level

Workers in local labor markets with clusters of high CNC-diffusion manufacturing industries were more exposed to the CNC automation shock after 1970 than workers in other areas. By examining differences across 722 commuting zones, we develop a more continuous measure of CNC exposure that allows for substantially more variation than at the industry level alone. Furthermore, by considering the effect of this automation shock on local labor markets, we uncover a key margin of worker adjustment: switching between the affected industries (metal manufacturing) and other sectors.

Measuring CNC exposure at the local labor market level

We measure exposure to the CNC shock at the commuting zone-level by weighting CNC exposure in industry *j* and year *t* (*t* = 1970 or 2000) by the initial share of employment in industry *j* in labor market m. We calculate exposure in local market *m* in year *t* as:

$$Exposure\_CNC_{m,t} = \sum_j \left(\frac{EMP_{m,j,1970}}{EMP_{m,1970}} Exposure\_CNC_{j,t}\right) \quad (5)$$

where $EMP_{m,j,1970}$ is a count of workers employed in industry *j* in 1970 and $EMP_{m,1970}$ is a count of all workers in labor market *m* in 1970. $Exposure\_CNC_{j,t}$ is defined as above at the industry-by-year level, with the added assumption that CNC exposure is zero in any non-metal manufacturing industry.

Our local labor market analysis focuses on long differences between 1970 and 2000 using decadal census data for these years. We end the analysis in 2000 to avoid confounds from the Great Recession. By 2000, exposure to CNC tools varied from 0.2% to 14.5% across commuting zones. Much of this cross-market variation is driven by the size of the metal manufacturing sector, but the residual of local CNC exposure after controlling for the 1970 metal manufacturing share of employment still has a sizeable range (2 percentage points).

Figure 5 maps the geographic variation in our CNC exposure measure between 1970 and 2000. Panel A presents the unconditional exposure measure at the commuting zone level. CNC exposure is highest in the Rust Belt, in coastal Washington and California, and in scattered other centers such as the aircraft producing region of Eastern Kansas. CNC exposure is lowest in the Plains states and the rural West.

Panel B shows residuals of CNC exposure from a regression on nine census division indicators. By focusing within division, it is apparent that there is substantial variation in CNC exposure *within* regions – for example, CNC exposure is stronger in Ohio than in Michigan. Panel C maps residuals of CNC exposure from a regression on initial (1970) manufacturing share. Commuting zones with second industrial revolution industries along the Great Lakes have higher exposure relative to former textile regions in New England and the Mid-Atlantic, or other light-industry areas in the Carolinas and Georgia. Panel D depicts residuals of CNC exposure on both census division and initial manufacturing share to coincide with the variation used in the regression analysis below.

CNC exposure and labor market characteristics

We consider the relationship between eventual CNC exposure (in 2000) and initial local labor market characteristics (in 1970) in Appendix Table 1. By construction, exposure to CNC technology by 2000 is highly correlated with initial manufacturing share – and especially the initial metal manufacturing share – of local employment in 1970 (Panel 1). Initial metal manufacturing share of the workforce rises monotonically by quartile of CNC exposure from 2 percent in the first quartile to 17 percent in the fourth quartile. CNC exposure is strongly related to initial metal manufacturing (coeff. = 0.075, s.e. = 0.001) but is unrelated to initial non-metal manufacturing share (coeff. = -0.006, s.e. = 0.005).

Panel 2 contains a set of additional demographic and economic characteristics of local areas. CNC exposure is positively correlated with log population, share white and share high school graduate in a commuting zone in 1970, but is unrelated to share female, share over 65 or share college graduate. We try controlling for this set of local labor market attributes as of 1970 in some specifications, along with controls for census division and baseline employment shares at the 1-digit industry level. Ultimately, these controls have little effect on the coefficient of interest.

CNC exposure and employment patterns

Our regression analysis estimates the relationship between changes in various employment-population ratios (Δy_m) from 1970 to 2000 and changes in market-level exposure to CNC technology over this period at the commuting zone level (m).

$$\Delta y_m = \alpha_d + \beta \Delta Exposure\_CNC_m + X'\Gamma + \varepsilon_m \tag{6}$$

We start by considering this relationship for employment in metal manufacturing (the exposed set of industries), and then we investigate employment in other sectors. In some specifications, we control for census division fixed effects α_d as well as initial demographic characteristics and initial employment shares by 1-digit industry in the vector X.[13] In this case, we identify β by comparing commuting zones with the same initial share of manufacturing employment but a different initial composition of employment *within* the manufacturing (e.g., a higher share of aircraft employment and a lower share of motor vehicle employment). We also weight each commuting zone by its 1970 population and report Conley standard errors to account for potential spatial correlation in the data.

Figure 6 presents the relationship between changes in CNC exposure and changes in the employment-to-population overall and within the manufacturing sector at the commuting zone level. We use our preferred specification controlling for Census division, initial demographics and initial employment shares here, but report alternative specifications and robustness for this relationship in Table 3 below.

Workers in commuting zones with higher exposure to CNC technology are less likely to be employed in the affected sector (metal manufacturing) by year 2000 (Panel A). Consider the effect of a one standard deviation difference in CNC exposure at the commuting zone level (3-percentage point increase). An increase in CNC exposure of this size is associated with a 3.2-point decline in the share of the population employed in metal manufacturing (=-1.068 x 3.0). The average commuting zone experienced a 4.7-point decline in the metal employment share. By this estimate, around two-thirds of this decline be explained by CNC automation. This estimate is comparable to the effect of switchboard automation on telephone operators (Feigenbaum and Gross 2020).

Despite the large decline in employment in metal manufacturing, employment in the manufacturing sector as a whole is little affected by CNC exposure, suggesting that workers were able to switch from the metal to the non-metal sector. The decline in total manufacturing employment with exposure to CNC in Panel B is only 0.35 points (=-0.117 x 3.0). The effect of CNC exposure on the overall employment-to-population ratio is small, positive and not significant (Panel C).

We investigate shifts in employment away from metal manufacturing further in Figure 7, which considers the relationship between changes in CNC exposure and changes in employment by

[13] Demographic controls include the set of variables in Appendix Table 1: log population, education shares (high school dropout, high school graduate, some college, and college graduate or above), race/ethnicity shares (White, Black, Asian, Hispanic), share female, and share over 65.

industry and gender from 1970 to 2000. As above, we find that the employment-to-population ratio in metal manufacturing falls with CNC exposure, both overall (light bars) and separately for men and for women. Yet, CNC exposure is associated with *increases* in employment-to-population in non-metal manufacturing and trade (for men). Taken together, the effect of total employment-to-population is negative and not significant for men and is positive (but small) for women. This pattern suggests that workers in exposed labor markets were able to shift from employment in metal manufacturing to other unexposed sectors.

IV. Other modes of worker adjustment: Unions and returns to school

Workers were able to respond to the concentrated automation shock in metal manufacturing by switching to other manufacturing sectors. This section considers other approaches that workers used to adjust to the CNC shock. In particular, we assess whether unions offered some protection from employment losses, and whether workers responded to the heightened relative demand for tasks associated with more-educated workers by returning to college.

Worker response through union protections: Workers in the union sector may be less affected by the CNC shock, either because unions slowed down firm adoption of this new technology, or because unions bargained with firms to share a portion of the technology rents in the form of job protections. In the early 1970s, as CNC began to diffuse, 45% of workers in the metal industry were members of a union, compared to a unionization rate of only around 10% during the spread of robots in 2010 (Appendix Figure 4).

Table 2, Panel 1 reports the relationship between CNC exposure and total employment in the union sector and non-union sector based on counts of workers by industry and union membership in the CPS. We find that employment losses after the diffusion of CNC technology is concentrated among non-union jobs, which decline by 16-log points for a 10-percentage point rise in CNC exposure. There is no relationship between CNC exposure and employment in the union sector.

Although we cannot determine whether the union sector was cushioned from this automation shock by slowing technology adoption versus rent sharing, we suspect that unions were able to protect workers against employment losses by bargaining for job protections. Following the landmark "Treaty of Detroit" between the United Auto Workers and General Motors in 1950, industrial unions in the United States upheld a shared norm to support technical change in exchange for employment protections and other benefits (Levy 2021, p. 472-475; Reuther, 1963; Barnard, 1983; Brown, 1997). For example, when General Motors planned to upgrade its Linden, New Jersey plant for the use of computer numerical controlled machine tools in 1984, the union negotiated buyouts and job guarantees but did not oppose the retooling effort (Milkman 1997).

Educational attainment and returning to school: CNC technology is associated with a decline in employment for workers without a college degree. Beyond union membership, another possible action that workers in exposed industries may have taken to insulate themselves from the CNC shock was to go back to school to improve their skills. Table 2, Panel 2 reports estimates of equation (4) using the share of workers in an industry who have returned to school as the outcome.[14]

We find that workers are more likely to re-enroll in higher education as CNC technology diffused through their industry. A 10-percentage point increase in CNC exposure is associated with a 2.5 percentage point increase in total enrollment (column 1), which is primarily due to increases in full-time enrollment in four-year degree programs (columns 2-5). The average enrollment in higher education in this sample is around 5%.

To support this finding, Figure 8 graphs a time series of completed college degrees and certificates related to computerized machine tools from 1967 to the present. The series is based on administrative data from Higher Education General Information Survey (HEGIS, 1967-84) and IPEDS (Integrated Post-Secondary Information Data System (1986-present). We classified a subset of degrees as related to CNC technology – including programs like Machinist/Machine Tool Technologist and Industrial/Manufacturing Engineering (full list in footnote).[15]

[14] Recall that the October CPS sample used in this analysis contains men whose current or most recent employment is in metal manufacturing and who did not have a college degree.

[15] Programs coded as CNC-related: programs coded as CNC programs: Automation Engineer Technology/Technician; Computer Numerically Controlled (CNC) Machinist Technology/CNC Machinist; Electromechanical Engineering; Electromechanical Tech./Technician; Industrial/ Manufacturing Engineering; Industrial/Manufacturing Tech./Technician; Machinist/Machine Technologist/Assistant; Mechatronics, Robotics, and Automation Engineering; Robotics Tech./Technician.

CNC-related degree programs grew rapidly in two bursts: first, from 1970 to 1980 and then from 2010 and 2020. The first period corresponds to the advent of CNC machine tools, and the second period corresponds to the spread of industrial robots. General degree completions follow a different pattern, growing steadily from 1985 to 2010. Appendix Figure 5 reports time series in degree completion by degree type (certificates, associate degrees and bachelor's degrees).

VII. Robustness of local labor market- and industry-level results

Robustness of local labor market results

Table 3 explores the robustness of our preferred local labor market specification to a variety of alternatives. We start in Panel 1 with a version of equation (6) that contains no commuting zone level controls (column 1). In this case, a one-point increase in CNC exposure reduces metal manufacturing employment as a share of population by -0.952 points. Column 2 adds controls for census division and initial demographics. The coefficient falls by around 10% to -0.840. Column 3 represents our preferred specification, which adds controls for initial employment shares by 1-digit industry. Here, we find our preferred coefficient of -1.068, which was also reported in Figure 6, Panel A. By controlling for initial share of employment in the manufacturing sector, this coefficient is identified from differences in exposure to CNC *within* the manufacturing sector. Our main results are weighted by commuting zone population. The coefficient is little changed if we instead report unweighted estimates (column 4).

Panel 2 considers a set of regressions that add controls for potentially correlated economic shocks. Columns 5 and 6 add measures of exposure to import competition from China and from Mexico following the NAFTA agreement (Autor, Dorn and Hanson, 2013; Choi, et al. 2024). Results are qualitatively unchanged given the substantially different industry mix exposed to CNC technology versus trade with developing countries (metal manufacturing versus textiles and plastics). Column 7 adds a broader control for import penetration taken from Schott (2008) and weighted to the local labor market level. Again, the results are unchanged. Column 8 divides our control for 1970 manufacturing share of employment into two categories: 1970 share of employment in metal and non-metal manufacturing. Controlling for share of employment in metal manufacturing absorbs much of the variation in CNC exposure across labor markets, but the results remain and are, if anything, even larger in magnitude.

Column 9 includes a control for pre-trends in employment growth in metal manufacturing by commuting zone from 1950 to 1970. Areas that were more exposed to CNC automation after 1970 also had more rapidly growing manufacturing employment in the previous decades (see Appendix Figure 6), perhaps because the most exposed industries were younger and more rapidly expanding (e.g., aircraft, precision mechanisms). Thus, it is possible that the declining employment captured in our main analysis is simply reflecting regression to the mean. Yet, controlling for the change in metal manufacturing employment-to-population from 1950-1970 does not affect our estimate.

Robustness for industry-level results

Appendix Tables 2-4 assess the robustness of our industry-level results to different specification choices (compared to Tables 1 and 2). The following patterns are robust to all variants: CNC is associated with rising productivity (log value added per worker), falling production employment, and rising rates of returning to school. Furthermore, in all specifications we find that CNC is associated with greater declines in employment for less-educated workers than for more-educated workers, and for non-unionized workers than for unionized workers. Exposure to CNC technology has a similar positive relationship with capital expenditures in all specifications, but the results are not always statistically precise.

In each robustness table, we consider five alternatives to the main specification: weighting by industry-year cell count, adding controls for demographics of the workforce at the industry-year level (as measured in CPS data), adding a control for import penetration at the industry-year level, dropping the highest exposure industry (precision mechanisms) and dropping the lowest exposure industry (motor vehicles, which is also the industry with the highest baseline union share). The association between CNC exposure and the labor share disappears when controlling for demographics or import penetration. The falling employment of high school graduates is present but not significant when excluding motor vehicles, and the rising employment of college graduates disappears when excluding precision mechanisms. Yet, in relative terms, CNC continues to be associated with stronger employment declines for less-educated workers in this specification.

VII. Conclusions

Compared to the past, the modern factory floor is filled with machines and empty of people. Computerized machine tools produce complex parts based on instructions encoded in computer programs, conveyors move parts from station to station, and robots assemble the parts into finished products. Jobs in the factory increasingly require a sophisticated understanding of the programming of machines and often a college degree.

This paper studies one important step in the long process of factory automation: the advent and diffusion of automated machine tools. At mid-century, machine tools required a semi-skilled machinist to perform operations to specification by hand. Automated machine tools began to diffuse widely in the 1970s. New CNC tools replaced these routine operations with detailed computer programs overseen by skilled workers.

We find that metal manufacturing industries that were more exposed to CNC tools experienced rising labor productivity with little decline in total employment at either the industry or local labor market level. Labor demand shifted from low- and mid-skill workers to college graduates. Workers in exposed industries responded to this technology shock in three ways: by shifting to other industries, particularly to less-exposed parts of the manufacturing sector, by returning to school, perhaps to qualify for higher-skilled work, and by taking advantage of some protections of union status if members of a union. This combination of productivity gains, displacement from core tasks, and limited overall dis-employment place CNC between the large automation gains in the early 20th century though factory electrification and the more minimal gains associated with industrial robots today.

Future work could explore how firms in settings with stronger worker protections respond to automation shocks. For example, were unionized firms slower to adopt automation technologies, or did they adopt technology at similar rates while offering job protection to their existing workforce, thus sharing more of the gains from new technology with workers? Do firms react to new technology by shifting production from union to non-union establishments? A firm-level analysis of the diffusion of automation technologies could shed light on these questions and help guide the adjustment process in the future.

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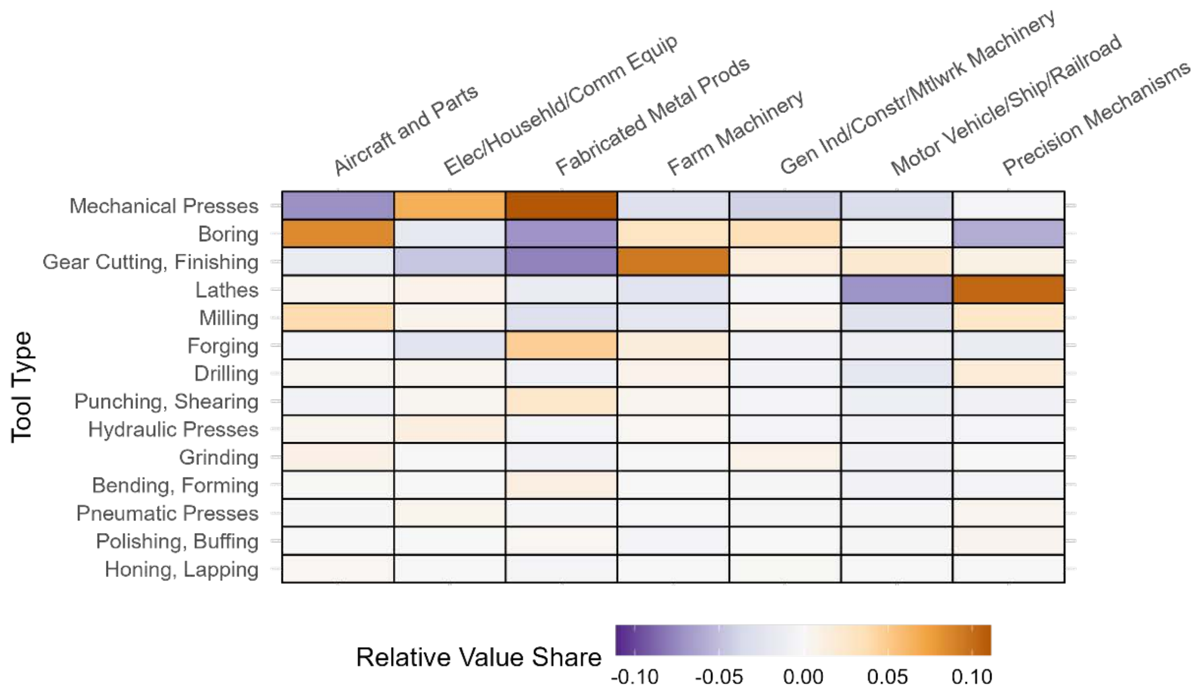
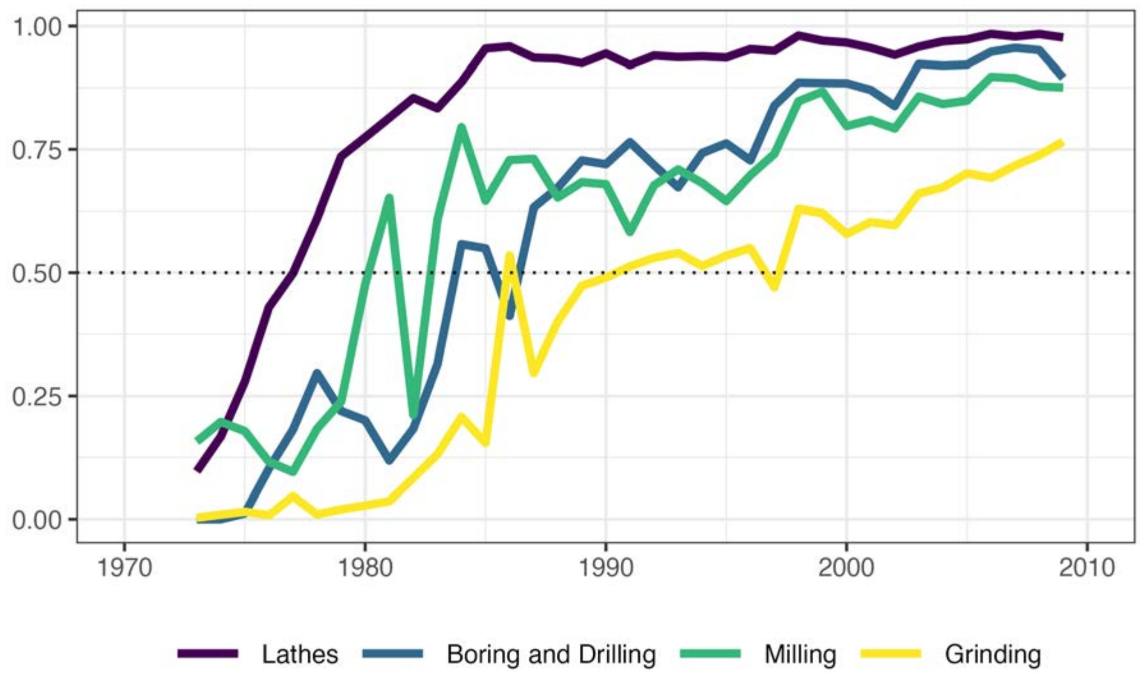
Figure 1: Relative Value Share of Installed Tools by Seven Metal Manufacturing Industries in 1958



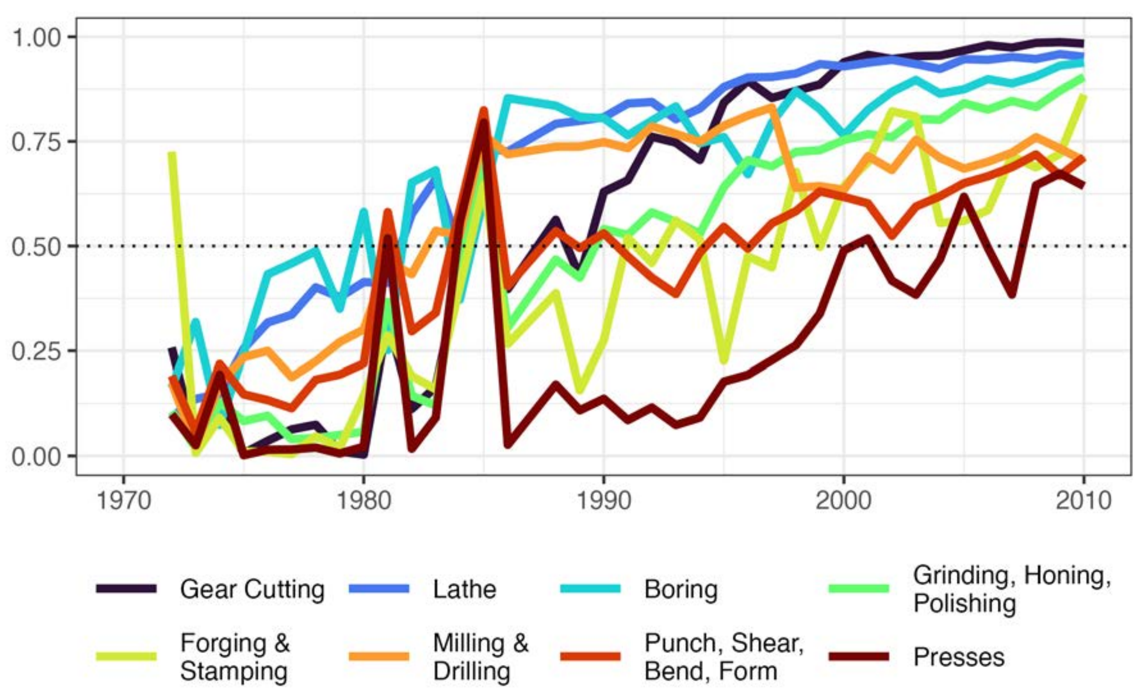
Notes: Cells in the figure show the relative value share of for each type of machine tool by industry. Orange indicates that an industry is more intensive in that tool type than the average industry, while purple indicates it is less intensive than the average. To compute the relative value share, we first compute the value share of installed tool types for each of the seven metal manufacturing industries. We then subtract the mean across industries for each tool type. Data on tool value come from the 1958 *American Machinist Inventory of Metalworking Equipment.*

Figure 2: CNC Share by Machine Tool Type

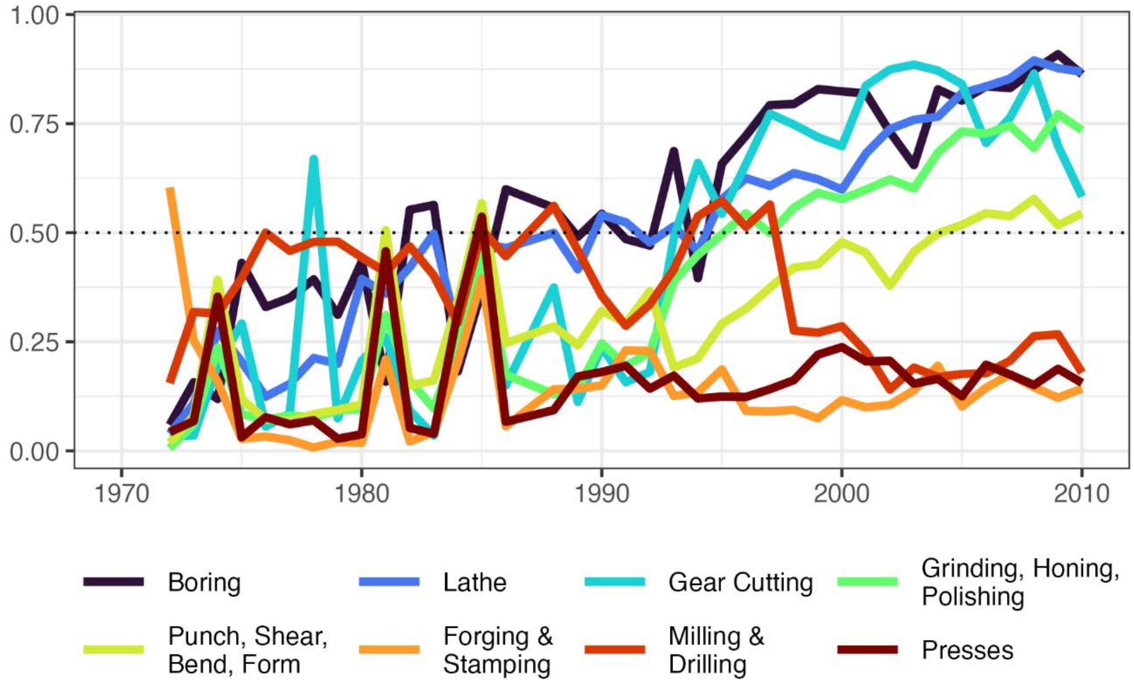
Panel A: Japan



Panel B: Germany

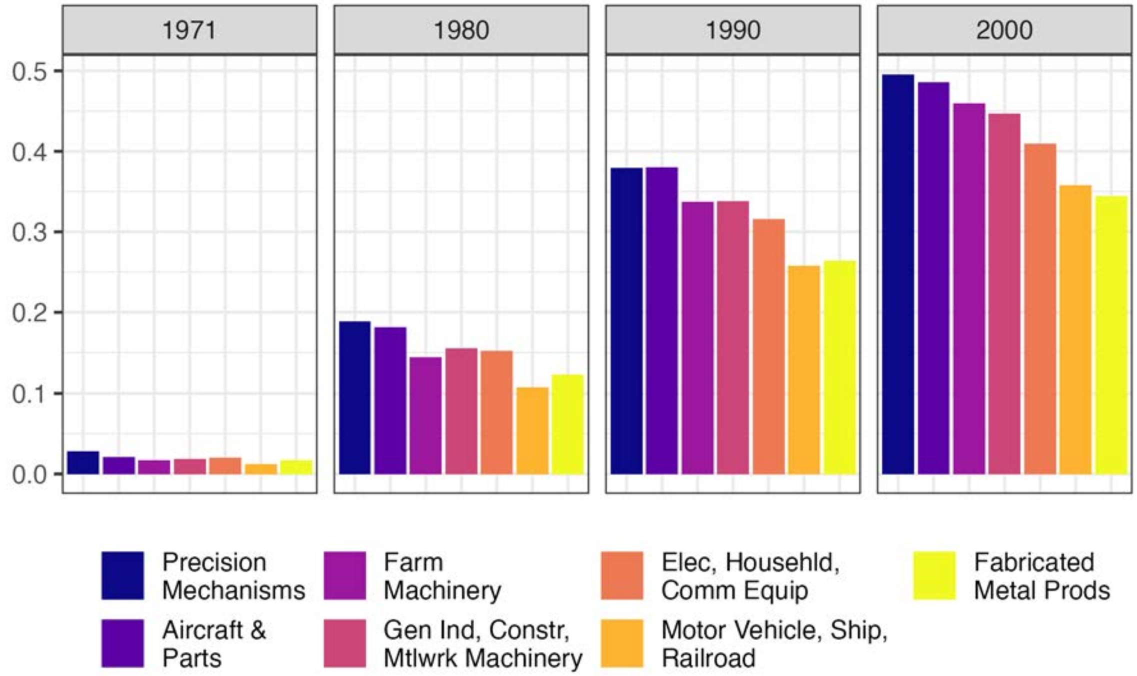


Panel C: Italy



Notes: This figure presents the annual CNC shares of exports by machine tool type for Japan, Germany, and Italy The data come from volumes of the *Economic Handbook of the Machine Tool Industry* as described in section III.

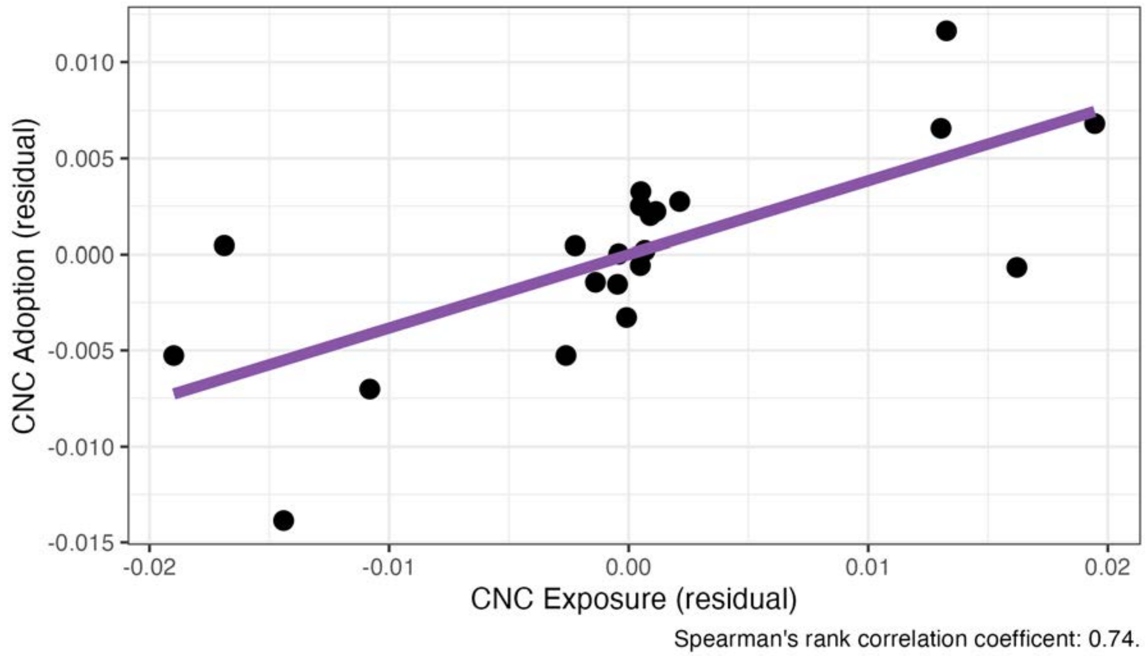
Figure 3: Cumulative CNC Share by Metal Manufacturing Industries



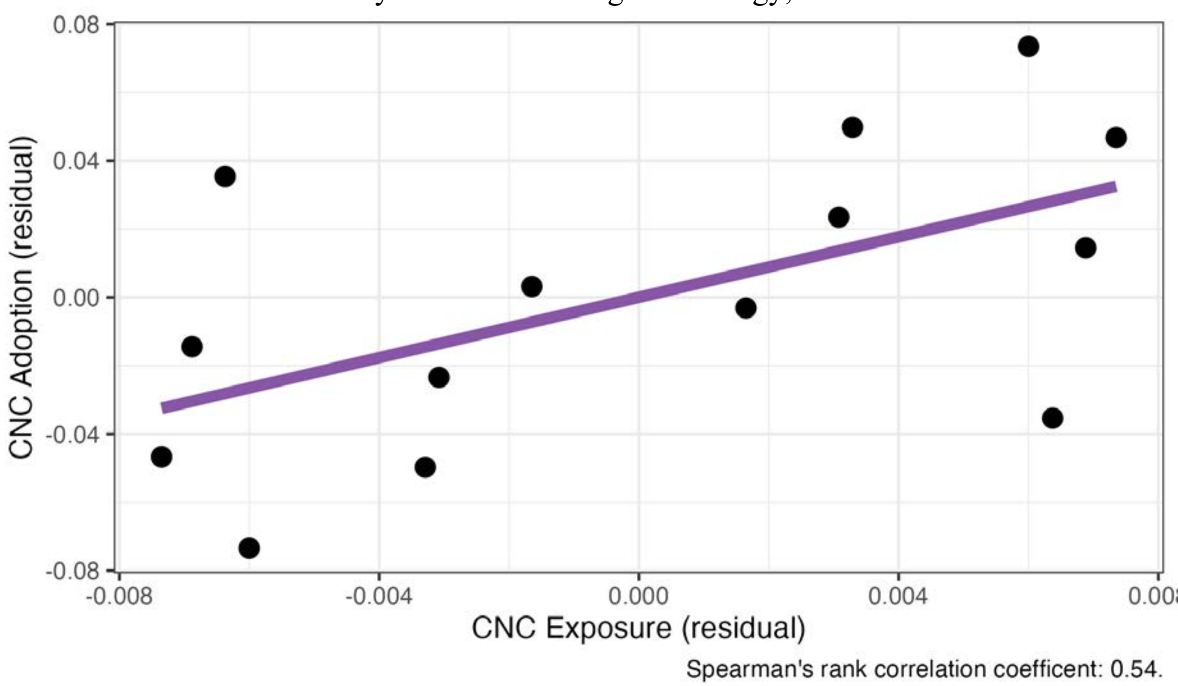
Notes: Cumulative CNC shares for the seven metal manufacturing are computed from the initial tool distribution by industry and the CNC share of exports by tool as described in section III. Dotted lines indicate the year in which the cumulative share passed 30%. Data underlying the figure come from the 1958 *American Machinist Inventory of Metalworking Equipment* and volumes of the *Economic Handbook of the Machine Tool Industry.*

Figure 4: CNC Adoption and CNC Exposure

Panel A: American Machinist Inventory of Metalworking Equipment, 1973, 1978, 1983

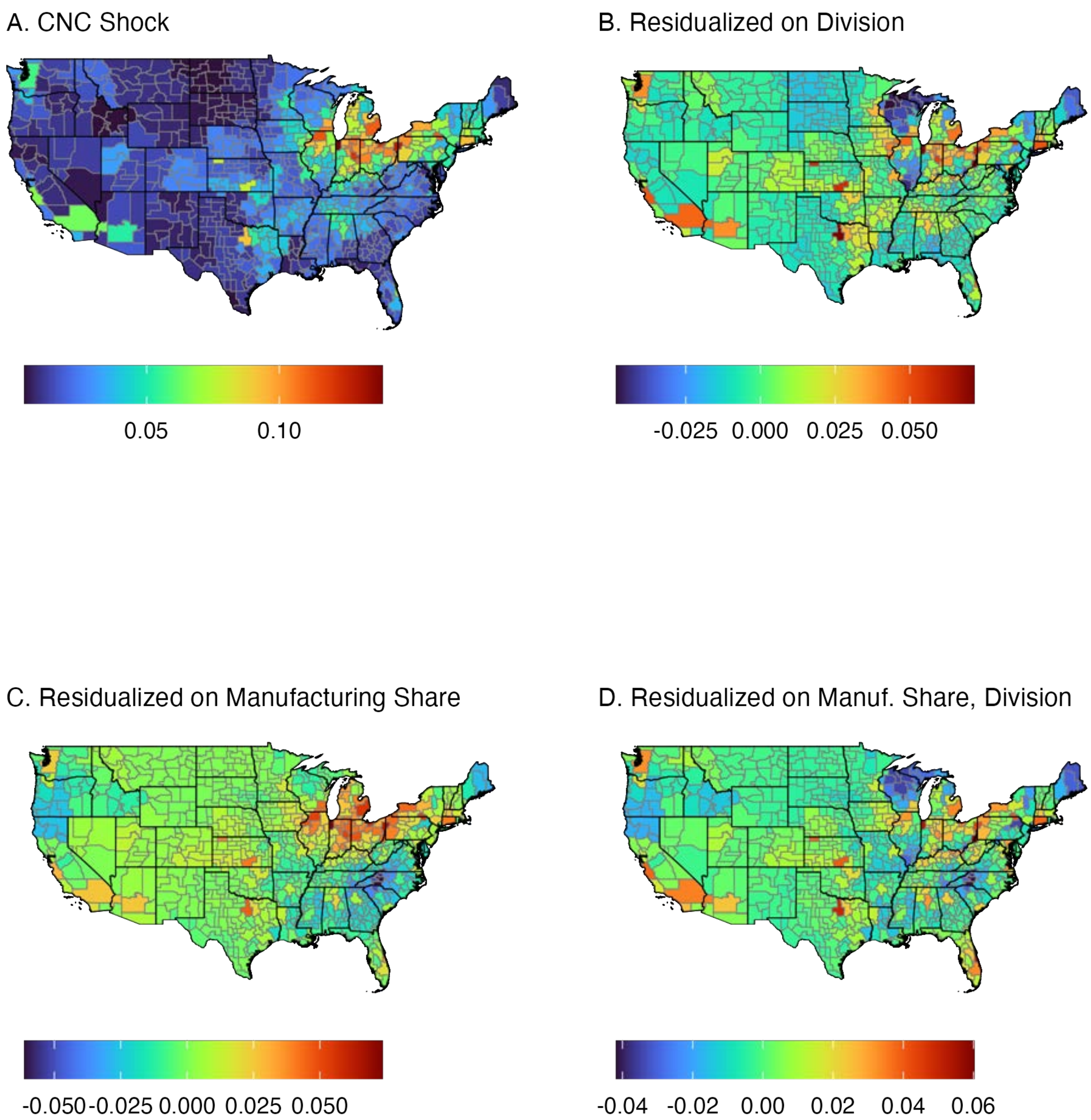


Panel B: Survey of Manufacturing Technology, 1988 and 1993



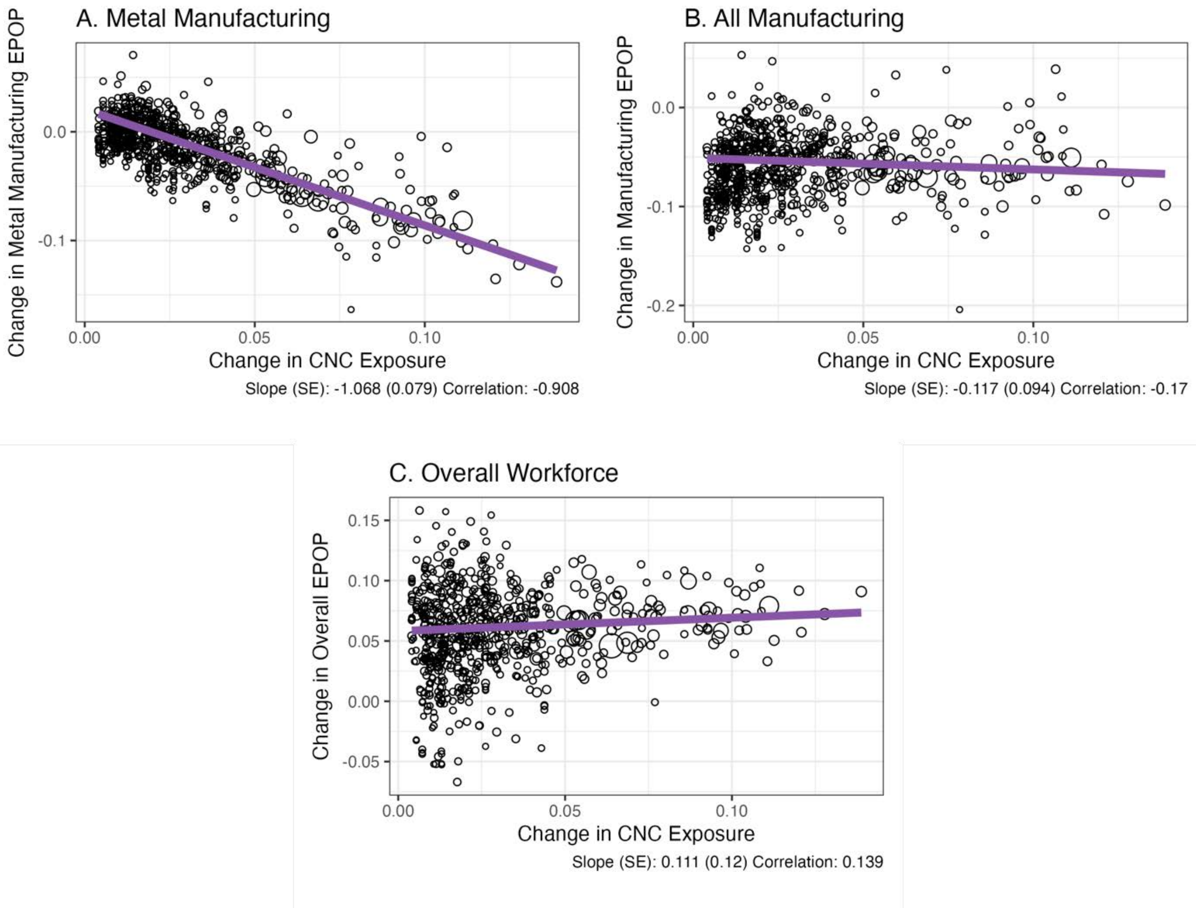
Notes: Plots show residuals from regressing our CNC exposure measure and CNC adoption measure on industry and year fixed effects. Adoption is measured by the share of installed machine tools in an industry and year that are CNC machines in panel A and by the share of plants in an industry and year that use CNC machines in panel B..

Figure 5: CNC Shock for Commuting Zones



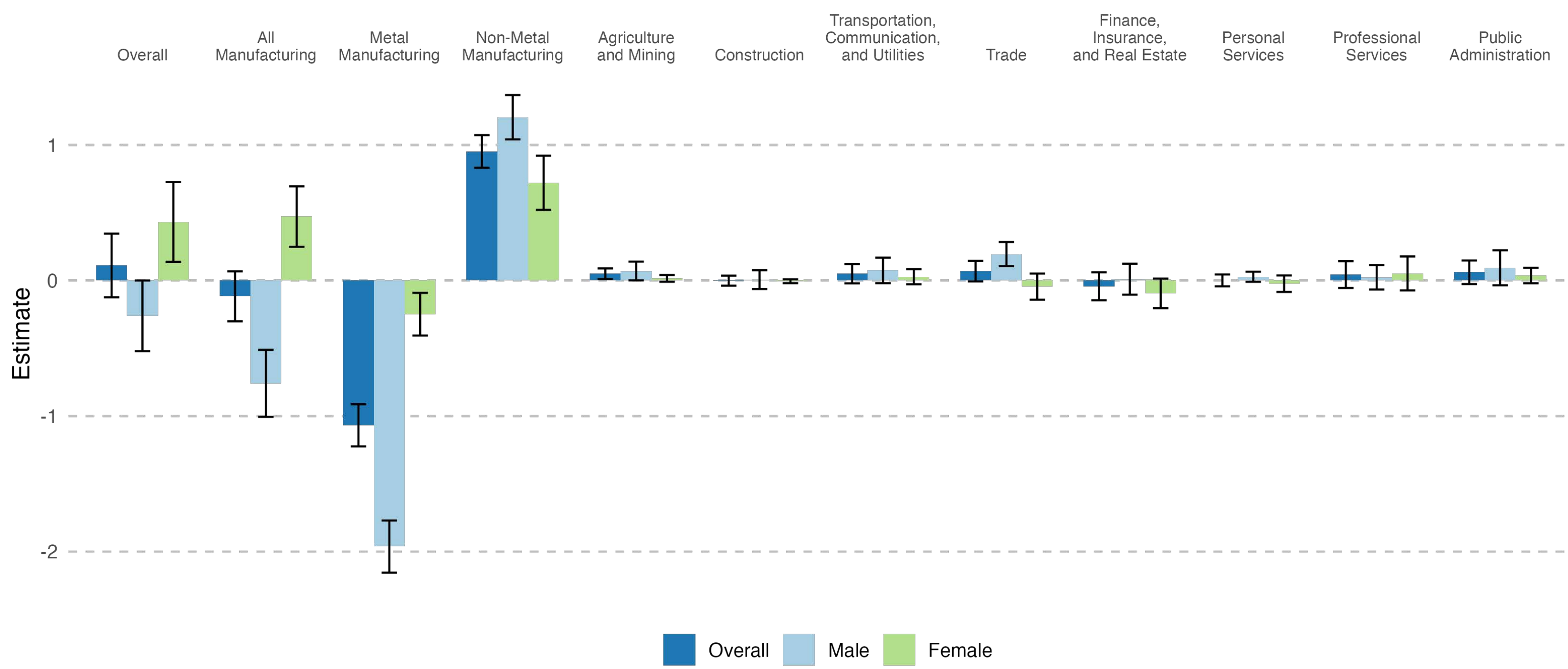
Notes: Maps show our CNC exposure measure for each of the 722 commuting zones. The top left map shows the CNC exposure measure itself while the others show residuals from a regression of the measure on the variables indicated.

Figure 6: Changes in CNC Exposure and CZ Employment-Population Ratios



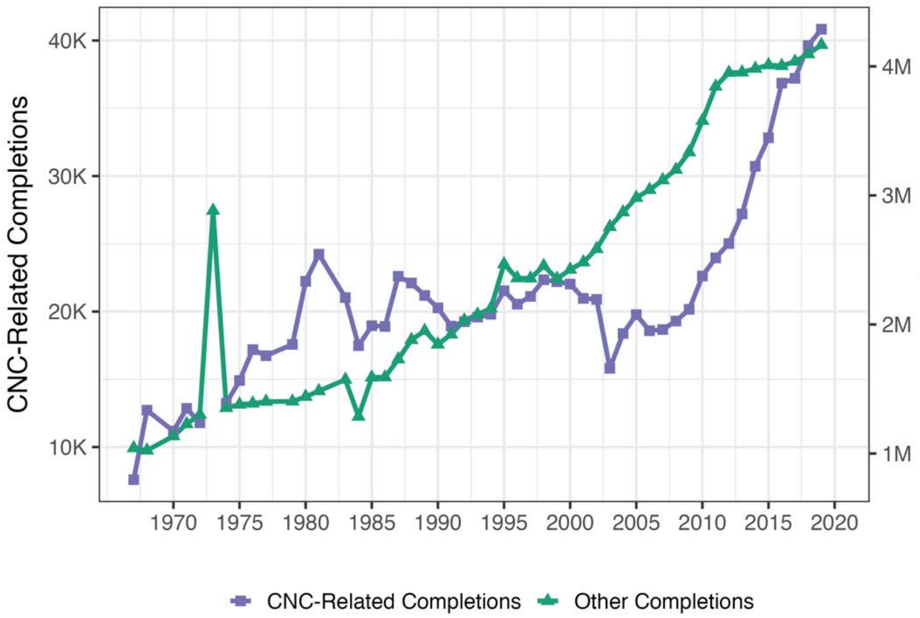
Notes: Plots partial out controls from our preferred specification (controls for census division, initial values of population, manufacturing employment, the share of females, the share of the population over 65 years old, the shares of the population with a high school, college, and advanced degree, the shares of White, Black, Hispanic, and Asian individuals) following Figure 6 in Acemoglu and Restrepo (2020). Weighted by 1970 population. Conley (1999) standard errors with 100km cutoff.

Figure 7: Effects of Changes in CNC Exposure on Employment-Population Ratios



Notes: Estimates of the effects of change in CNC exposure on changes in employment outcomes by industry and gender using preferred specification (controls for census division, initial commuting zone demographic characteristics, and initial manufacturing employment). Weighted by 1970 population. Conley (1999) standard errors with 100km cutoff.

Figure 8: CNC-Related Degree and Program Completions



Notes: The figure shows the number of completed degrees and program in US higher educational institutions. Degrees and programs are categorized by whether their subject matter is related to CNC. Data come from the *HEGIS* and *IPEDS* databases as described in section VI.

Table 1: The effect of CNC exposure on industry-level economic outcomes

Panel 1: Outcomes from the Census of Manufactures	log(Capital Exp.)	log(Value Added)	Labor Share	log(Total Emp)	log(Prod. Emp)	log(Nonprod. Emp)
	(1)	(2)	(3)	(4)	(5)	(6)
CNC Exposure	1.3576*	0.8916***	-0.1616**	-0.6383	-1.2019***	-0.5114
	(0.7433)	(0.2743)	(0.0771)	(0.4100)	(0.3815)	(0.4556)
Observations	280	280	280	280	280	280
Industry FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Emp. controls	X	X				
Dep. var mean	7.8139	10.6721	0.4144	6.5796	6.1623	5.4373

Panel 2: Outcomes from the Current Population Survey	log(HS Dropouts)	log(HS Grads)	log(Some Coll.)	log(Coll. Grads)
	(1)	(2)	(3)	(4)
CNC Exposure	-2.3408***	-1.4872**	-0.8084	1.6703*
	(0.7245)	(0.5935)	(0.6286)	(0.8717)
Observations	280	280	280	280
Industry FE	X	X	X	X
Year FE	X	X	X	X
Dep. var mean	4.1022	5.1240	4.4929	4.3902

Note: In Panel 1, outcome variables are log of annual capital expenditure, log of value-added, labor share (payroll per value added), log of total employment, log of production employment, and log of non-production employment in each metal manufacturing industry. Columns (1) and (2) of Panel 1 include the log of production employment and log of non-production employment (production employment subtracted from the total employment) as control variables. The variables are constructed from the NBER-CES Manufacturing Industry database (1968-2007). In Panel 2, outcome variables on columns (1) to (4) are log of employment by education group in each metal manufacturing industry, computed from the CPS ASEC sample (1968-2007). We restrict our CPS ASEC sample to prime-age (18-64) men who reported to be employed. All specifications include industry and year fixed effects. Standard errors are robust.

*** = significant at 1%, ** = significant at 5%, * = significant at 10%

Table 2: The effect of CNC exposure on worker adjustments

Panel 1: Employment by Union Membership	log(Non-union)	log(Union)			
	(1)	(2)			
CNC Exposure	-1.6135**	0.0138			
	(0.6298)	(0.8401)			
Observations	231	231			
Industry FE	X	X			
Year FE	X	X			
Dep. var mean	6.3553	5.1461			
Panel 2: College Enrollment	All enrollment	2-yr, full-time	2-yr, part-time	4-yr, full-time	4-yr, part-time
	(1)	(2)	(3)	(4)	(5)
CNC Exposure	0.2502**	0.0439	0.0554	0.1267***	-0.0494
	(0.0970)	(0.0296)	(0.0468)	(0.0436)	(0.0556)
Observations	224	224	224	224	224
Industry FE	X	X	X	X	X
Year FE	X	X	X	X	X
Dep. var mean	0.0539	0.0047	0.0167	0.0120	0.0170

Note: Columns (1) and (2) in Panel 1 have log of non-union and union workforce in each metal manufacturing industry as outcome variables, computed from the CPS May Supplement sample (1973-1983) and the CPS Outgoing Rotation Groups (1984-2007). Column (1) in Panel 2 has the annual share of enrollment for workers in each metal manufacturing industry as the outcome, and columns (2) to (5) have the annual share of two-year or four-year college enrollment as the outcomes. The outcome variables in Panel 2 are constructed from the CPS October Supplement sample (1976-2009). In Panel 2, we restrict our sample to prime-age men who do not hold bachelor's degree and whose current or last employment were in the metal manufacturing industry. All specifications include industry and year fixed effects. Standard errors are robust.

*** = significant at 1%, ** = significant at 5%, * = significant at 10%

Table 3: The effect of changes in CNC exposure on changes in metal manufacturing employment relative to population within local labor markets, 1970-2000

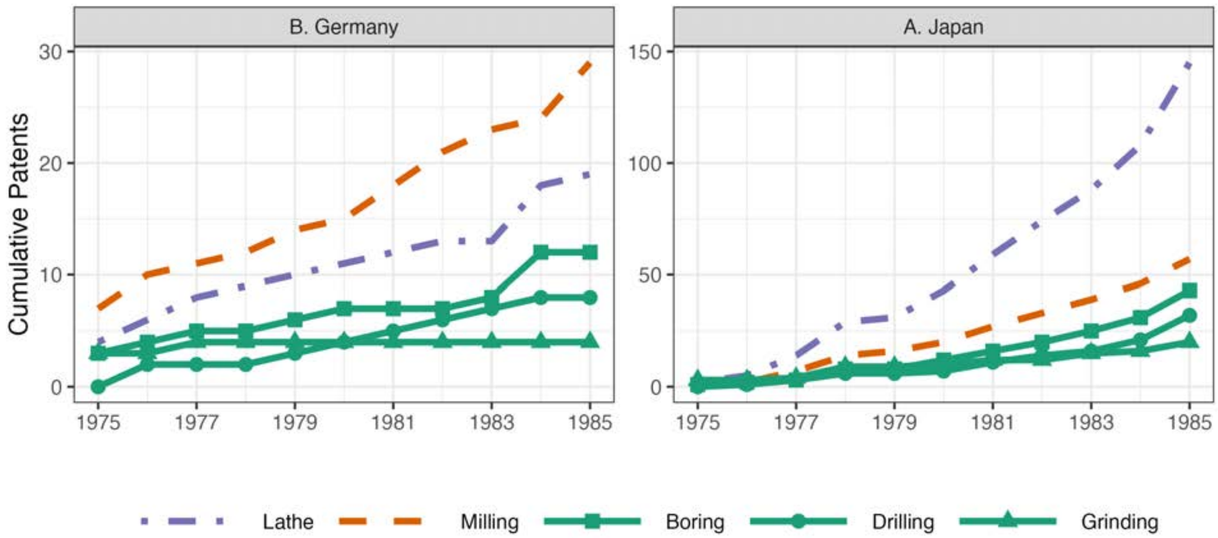
Panel 1: Main Results	Weighted by Population			Unweighted
	(1)	(2)	(3)	(4)
Change in CNC Exposure	-0.952***	-0.840***	-1.068***	-1.119***
	(0.063)	(0.084)	(0.079)	(0.079)
Census divisions		X	X	X
Demographics		X	X	X
Industry shares			X	X
Observations	722	722	722	722
Mean 70-00 Change in Metal MFG EPOP	-0.0301	-0.0301	-0.0301	-0.0031
Mean '70 Metal MFG EPOP Level	0.0526	0.0526	0.0526	0.0452
Mean 70-00 Change in CNC Exposure	0.0476	0.0476	0.0476	0.0283

Panel 2: Additional Controls and SEs	China Shock	NAFTA Shock	Import Penetration	Metal/Non-Metal Shares	Control for Pre-Trends	State Clustered SEs
	(5)	(6)	(7)	(8)	(9)	(10)
Change in CNC Exposure	-1.061***	-1.039***	-1.031***	-2.491***	-1.085***	-1.068***
	(0.080)	(0.079)	(0.338)	(0.695)	(0.082)	(0.080)
Observations	722	722	722	722	722	722
Mean 70-00 Change in Metal MFG EPOP	-0.0301	-0.0301	-0.0301	-0.0301	-0.0301	-0.0301
Mean '70 Metal MFG EPOP Level	0.0526	0.0526	0.0526	0.0526	0.0526	0.0526
Mean 70-00 Change in CNC Exposure	0.0476	0.0476	0.0476	0.0476	0.0476	0.0476

Note: Analysis is at the commuting zone (CZ) level with microdata from the 1970 ACS Metro Form 1 and Form 2 one percent sample and the 2000 ACS five percent sample. The outcome variable is the long difference 1970-2000 change in metal manufacturing employment relative to population, within a commuting zone. CNC exposure at the local labor market level is calculated by weighting CNC exposure in industry j and year t by the initial share of employment in industry j in labor market m. All but column (4) are weighted by 1970 population. Column (1) includes no controls, while column (2) includes controls for Census Division and demographic controls (age, age squared, nonwhite indicator, indicators for educational attainment, and sex). Column (3) add controls for 10-digit industry shares. Thereafter, we take column (3) as our preferred specification, adding the column headers as controls in each of columns (5-9). Column (10) clusters standard errors at the state level. Columns (5-7) control for other shocks. Column (8) splits the manufacturing share control into separate metal manufacturing and non-metal manufacturing controls. Column (9) controls for the 1950-1970 change in metal manufacturing employment relative to population. All controls utilize 1970 data unless otherwise noted. The final two table rows show the mean change in the dependent variable, the mean change in the independent variable, and the mean level of the dependent variable in the base period, conditional on the sample restrictions/weighting in that column. Standard errors are spatially clustered, with a 100km cutoff.

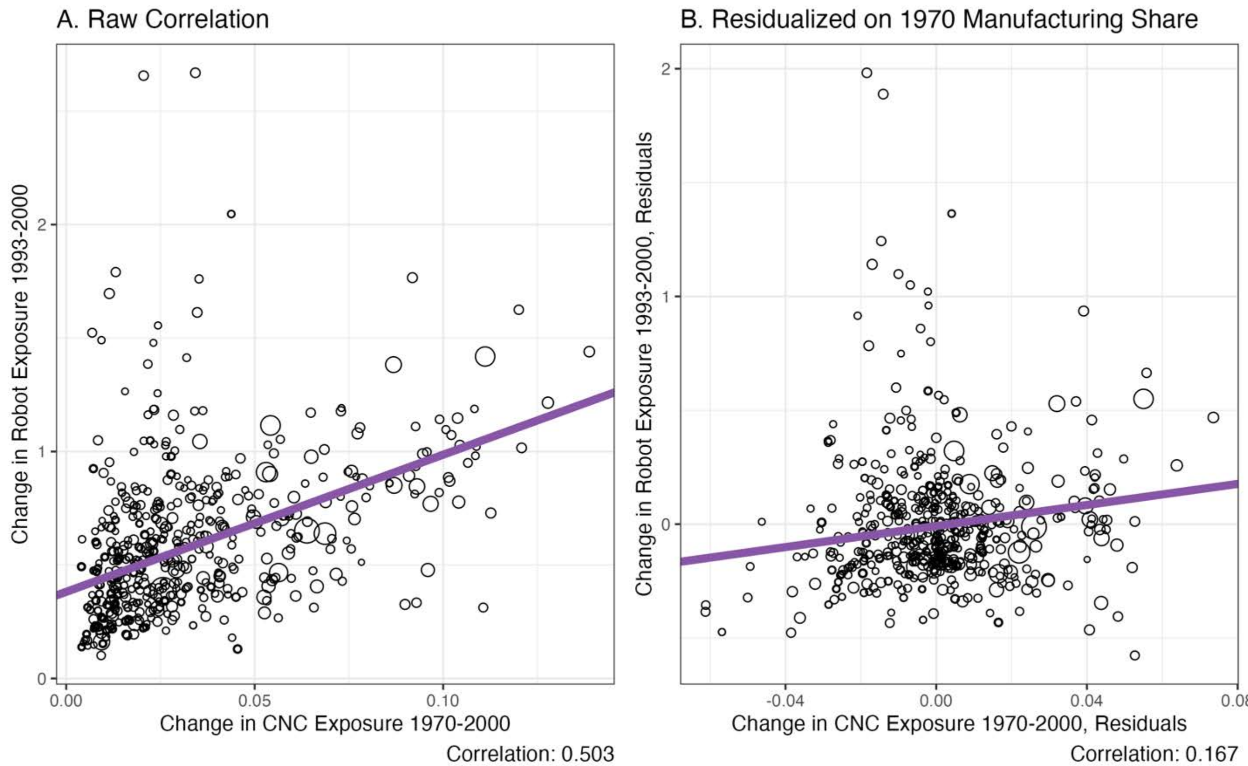
*** = significant at 1%, ** = significant at 5%, * = significant at 10%

Appendix Figure 1: CNC-Related Patent Counts by Tool and Country



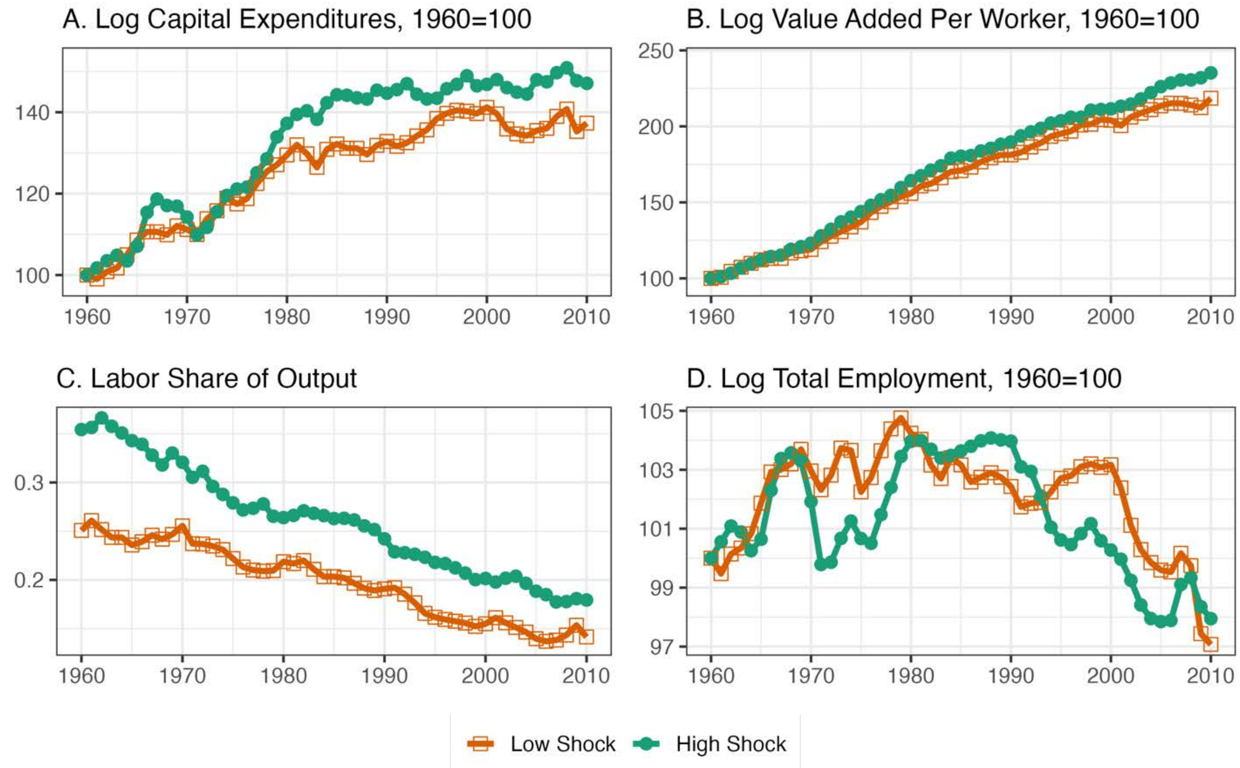
Notes: We began with a list of all US utility patents created for Kogan et al (2017) to scrape the digitized text from Google Patent. It is common for innovations created outside the United States to be patented in the US. Data from Lai et al (2011) provides the country of the grantee for each patent. We link Cooperative Patent Classification codes to the US patents. The patent subclass G05B contains classifications related to CNC. In particular, the subgroup G05B 19/18 covers "numerical control [NC], i.e., automatically operating machines, in particular machine tools..." We searched the patent text in our dataset to identify NC-related patents that are associated with five tool types: lathes, milling machines, drilling machines, boring machines, and grinding machines. We used the functions of the machines as the search terms. Our final figure examines patenting by Germany and Japan between 1975 and 1985. For those countries and period, there were 2,467 patents in G05B. The five tool types were mentioned in 52% of the patents.

Appendix Figure 2: Changes in CNC Exposure and Robot Exposure by Commuting Zone



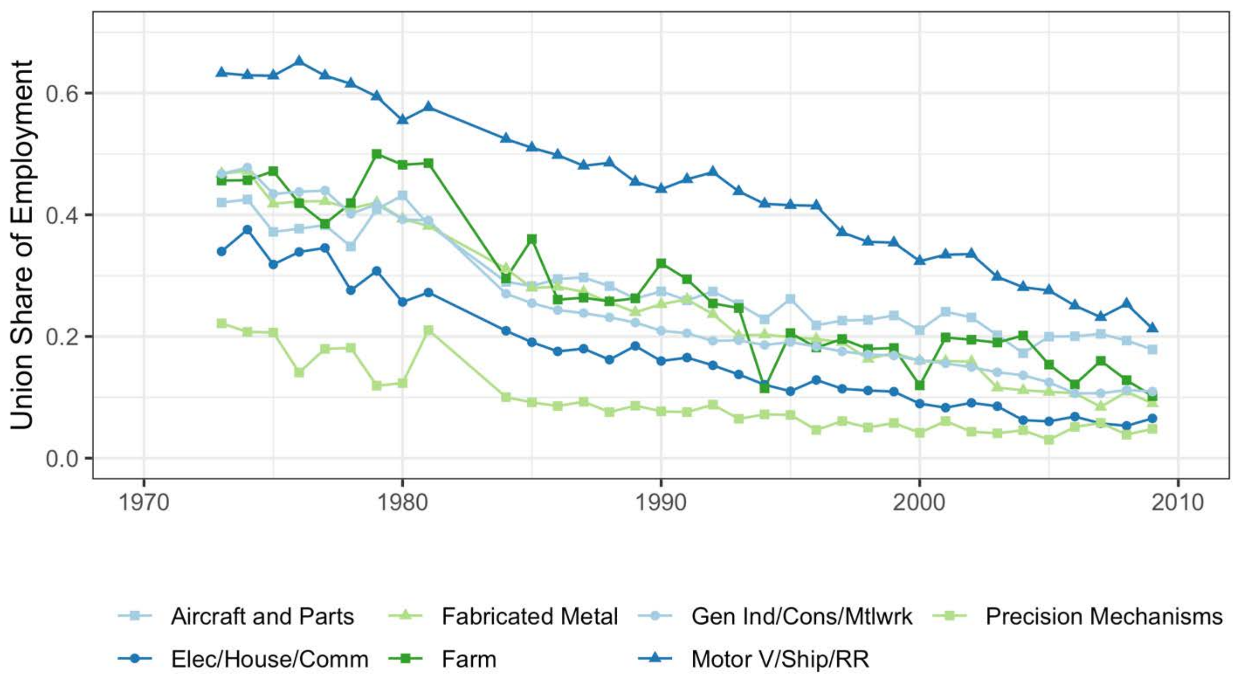
Notes: The left panel shows the change in raw CNC and robot exposure measures while the right panel shows residuals from regressing the variables on the 1970 commuting zone manufacturing share. Weighted by 1970 commuting zone population.

Appendix Figure 3: Core Economic Outcomes by CNC Shock Intensity Category



Notes: Core economic outcomes come from the *NBER-CES Manufacturing Industry* database. Metal industries are partitioned into two groups according to the intensity of the CNC shock they experience. Low shock industries are motor vehicles and fabricated metals; electronics, and general industrial equipment. High shock industries are farm equipment, aircraft and parts, and precision mechanisms.

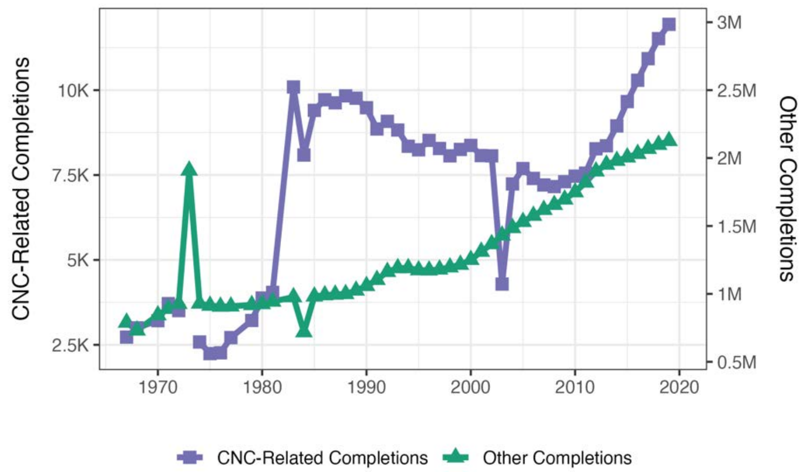
Appendix Figure 4: Union Share by Seven Metal Manufacturing Industries



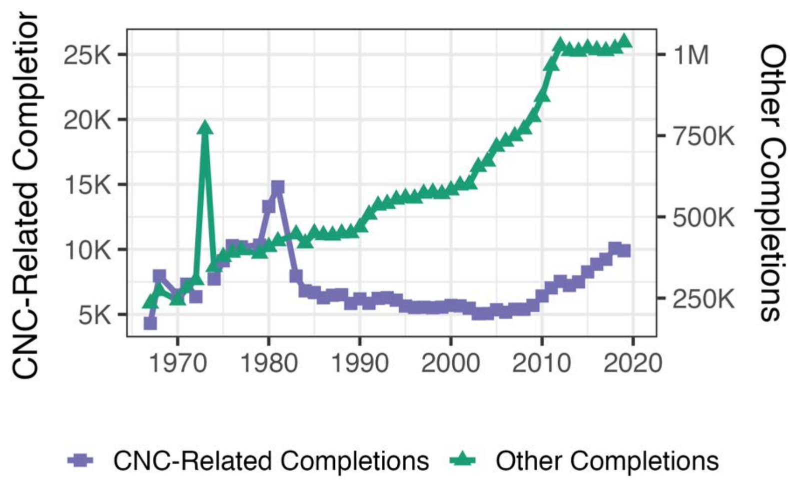
Notes: Average share of workers in each of the seven metal manufacturing industries belonging to a union. The share is computed from the CPS May Supplement (1973-1983) and CPS Outgoing Rotation Groups (1984-2009) sample.

Appendix Figure 5: CNC-Related Degree and Program Completions by Degree Type

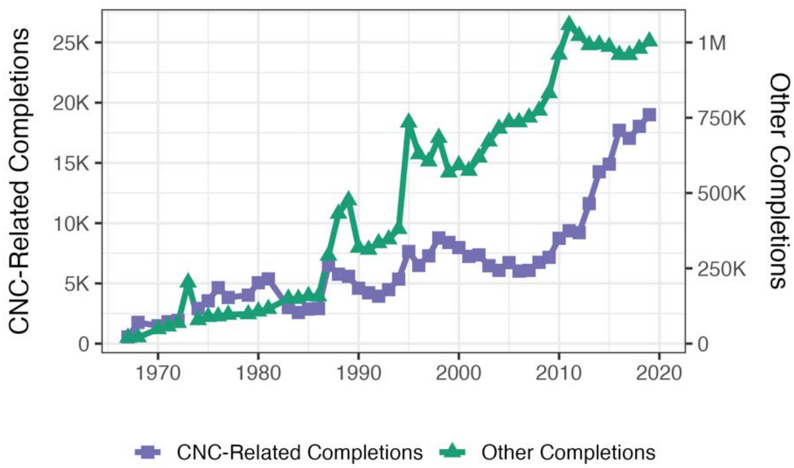
Panel A: Bachelor's Degrees



Panel B: Associate Degrees

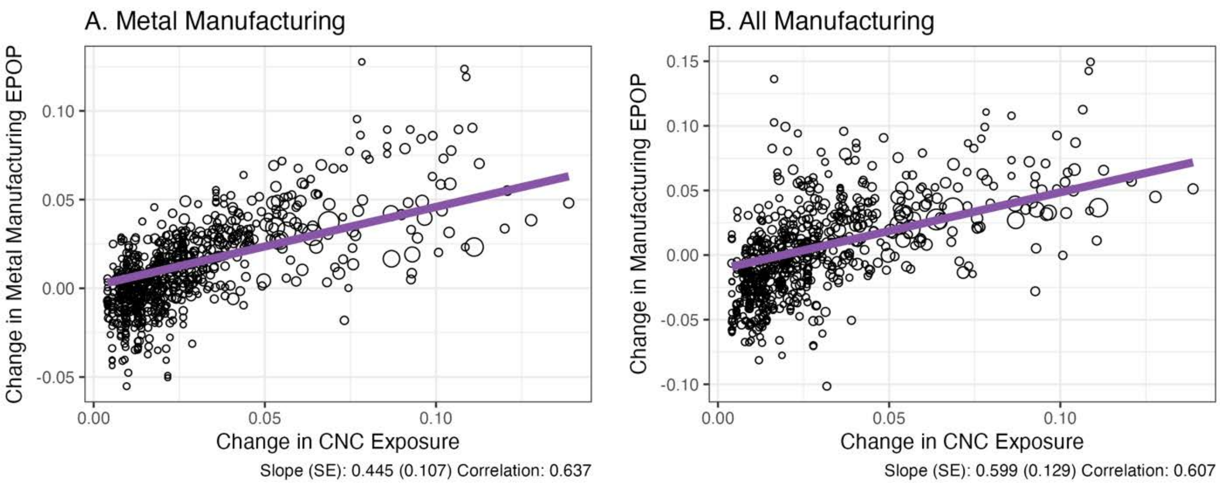


Panel C: Certificate Programs



Notes: The figure shows the number of completed degrees and programs in US higher educational institutions by type of degree or program. Degrees and programs are categorized by whether their subject matter is related to CNC. Data come from the *HEGIS* and *IPEDS* databases as described in section VI.

Appendix Figure 6: Changes in CNC Exposure 1970-2000 and Pre-Period CZ Employment-Population Ratios 1950-1970



Notes: The horizontal axes show the change in CZ CNC exposure from 1970-1990, while the vertical axes show the change in CZ employment-population ratios from 1950 to 1970. Plots partial out controls from our preferred specification (controls for census division, initial values of population, the share of females, the share of the population over 65 years old, the shares of the population with a high school, college, and advanced degree, the shares of White, Black, Hispanic, and Asian individuals, and employment shares in 11 industry categories) following Figure 6 in Acemoglu and Restrepo (2020). Weighted by 1970 population. Conley (1999) standard errors with 100km cutoff.

Appendix Table 1: Means of 1970 commuting zone characteristics by exposure to CNC

		By Quartiles of Exposure to CNC				
	All Commuting Zones	First Quartile	Second Quartile	Third Quartile	Top Quartile	Balance Tests
	(1)	(2)	(3)	(4)	(5)	(6)
Panel 1: Industries						
Manufacturing Employment Share in 1970	0.25	0.11	0.18	0.22	0.30	0.069
						(0.004)
Metal Manufacturing Employment Share in 1970	0.12	0.02	0.04	0.07	0.17	0.075
						(0.001)
Non-Metal Manufacturing Employment Share in 1970	0.13	0.08	0.14	0.15	0.13	–0.006
						(0.005)
Panel 2: Demographics						
1970 Log Population	13.80	12.61	12.31	13.77	14.28	0.543
						(0.163)
Share White in 1970	0.88	0.86	0.84	0.85	0.90	0.023
						(0.008)
Share Black in 1970	0.11	0.12	0.15	0.14	0.09	–0.020
						(0.008)
Share Hispanic in 1970	0.04	0.09	0.05	0.05	0.03	–0.016
						(0.006)
Share Asian in 1970	0.01	0.01	0.00	0.01	0.00	–0.001
						(0.001)
Share HS Grad in 1970	0.52	0.53	0.47	0.50	0.54	0.017
						(0.006)
Share College in 1970	0.11	0.12	0.09	0.11	0.11	–0.002
						(0.003)
Share Grad School in 1970	0.05	0.05	0.04	0.05	0.05	–0.000
						(0.002)
Share Female in 1970	0.51	0.51	0.51	0.52	0.52	0.001
						(0.001)
Share Over 65 in 1970	0.09	0.08	0.11	0.10	0.09	–0.003
						(0.002)

Note: Analysis is at the commuting zone (CZ) level with microdata from the 1970 ACS Metro Form 1 and Form 2 one percent sample. Panel 1 shows baseline industry shares at the commuting zone (CZ) level in 1970, while Panel 2 shows demographic characteristics in 1970. Columns (1) through (5) outline variable means, while column (6) shows balance tests from Borusyak, Hull, and Jaravel (2022). The numbers in this column report the coefficient of a population-weighted regression of a standardized CNC exposure measure on the 1970 characteristic in that row. Column (1) has no sample restrictions, while columns (2) through (5) split the sample by quartiles of exposure to CNC.

Appendix Table 2: The robustness of the effect of CNC exposure on industry-level economic outcomes from Census of Manufactures

	log(Capital Exp.) (1)	log(Value Added) (2)	Labor Share (3)	log(Total Emp) (4)	log(Prod. Emp) (5)	log(Nonprod. Emp) (6)
Panel 1: Baseline specification						
CNC Exposure	1.3576*	0.8916***	-0.1616**	-0.6383	-1.2019***	-0.5114
	(0.7433)	(0.2743)	(0.0771)	(0.4100)	(0.3815)	(0.4556)
Observations	280	280	280	280	280	280
Panel 2: Weighted by annual (total) industry employment						
CNC Exposure	1.2160	0.9339***	-0.1668**	-0.5550	-1.1862***	-0.3318
	(0.7448)	(0.2772)	(0.0765)	(0.4047)	(0.3771)	(0.4481)
Observations	280	280	280	280	280	280
Panel 3: Demographic controls included						
CNC Exposure	1.0428	0.6237**	-0.0644	-0.6482*	-1.0854***	-0.7135*
	(0.7293)	(0.2520)	(0.0729)	(0.3546)	(0.3365)	(0.3907)
Observations	280	280	280	280	280	280
Panel 4: Import penentration control included						
CNC Exposure	2.5229***	0.7009**	0.0382	-0.6193	-1.2679***	-0.4187
	(0.7782)	(0.2920)	(0.0933)	(0.4813)	(0.4320)	(0.5397)
Observations	238	238	238	238	238	238
Panel 5: Excluding Precision Mechanism Industry						
CNC Exposure	2.6938***	0.6695**	-0.2539***	-2.0667***	-2.3100***	-2.2302***
	(0.9484)	(0.3377)	(0.0911)	(0.3916)	(0.3858)	(0.4251)
Observations	240	240	240	240	240	240
Panel 6: Excluding Motor Vehicle Industry						
CNC Exposure	2.8871***	1.6422***	-0.3286***	-0.9543**	-1.3590***	-1.1691**
	(0.6589)	(0.2333)	(0.0742)	(0.4544)	(0.4357)	(0.4918)
Observations	240	240	240	240	240	240
Industry FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Employment controls	X	X				
Dependent variable mean (Panel 1)	7.8139	10.6721	0.4144	6.5796	6.1623	5.4373

Note: Panel 1 of the table contains the estimates from Row 1 of Table 1. Panel 2 is the analog of Panel 1, where each industry-year-level cell is weighted by its total employment count. Panel 3 includes demographic controls computed from CPS ASEC, including the share of white workers and the share of young workers aged 18 to 35 among the industry workforce. Panel 4 includes import penetration measure as a control variable. The import penetration definition is drawn from Campbell and Lusher (2019), and we construct the measure using the US import data from Schott (2008). Panels 5 and 6 exclude the industry with the highest and lowest CNC exposure, Precision Mechanism and Motor Vehicle industry, respectively. Standard errors are robust.

*** = significant at 1%, ** = significant at 5%, * = significant at 10%

Appendix Table 3: The robustness of the effect of CNC exposure on industry-level economic outcomes from Current Population Survey

	log(HS Dropouts) (1)	log(HS Grads) (2)	log(Some Coll.) (3)	log(Coll. Grads) (4)
Panel 1: Baseline specification				
CNC Exposure	-2.3408***	-1.4872**	-0.8084	1.6703*
	(0.7245)	(0.5935)	(0.6286)	(0.8717)
Observations	280	280	280	280
Panel 2: Weighted by annual (total) industry employment				
CNC Exposure	-2.1811***	-1.4777**	-0.6784	1.8382**
	(0.6950)	(0.5855)	(0.6074)	(0.8734)
Observations	280	280	280	280
Panel 3: Demographic controls included				
CNC Exposure	-2.6725***	-1.2774**	-0.5468	1.5058*
	(0.6938)	(0.5732)	(0.6599)	(0.8724)
Observations	280	280	280	280
Panel 4: Import penentration control included				
CNC Exposure	-2.7122***	-1.2014*	-0.3679	3.3382***
	(0.9890)	(0.6622)	(0.7694)	(0.9980)
Observations	238	238	238	238
Panel 5: Excluding Precision Mechanism Industry				
CNC Exposure	-4.0638***	-3.2647***	-2.1937***	-0.0257
	(0.8270)	(0.6063)	(0.7195)	(0.9968)
Observations	240	240	240	240
Panel 6: Excluding Motor Vehicle Industry				
CNC Exposure	-2.9349***	-0.9189	0.4374	4.7111***
	(0.8066)	(0.7442)	(0.7293)	(0.7142)
Observations	240	240	240	240
Industry FE	X	X	X	X
Year FE	X	X	X	X
Dependent variable mean (Panel 1)	4.1022	5.1240	4.4929	4.3902

Note: Panel 1 of the table contains the estimates from Table 1 Panel 2. Panel 2 is the analog of Panel 1, where each industry-year-level cell is weighted by its total employment count. Panel 3 includes demographic controls computed from CPS ASEC, including the share of white workers and young workers aged 18 to 35 among the industry workforce. Panel 4 includes import penetration measure as a control variable. The import penetration definition is drawn from Campbell and Lusher (2019), and we construct the measure using the US import data from Schott (2008). Panels 5 and 6 exclude the industry with the highest and lowest CNC exposure, Precision Mechanism and Motor Vehicle industry, respectively. Standard errors are robust.

*** = significant at 1%, ** = significant at 5%, * = significant at 10%

Appendix Table 4: The robustness of the effect of CNC exposure on worker adjustments

	log(Non-union) (1)	log(Union) (2)	All enrollment (3)
Panel 1: Baseline specification			
CNC Exposure	-1.6135**	0.0138	0.2502**
	(0.6298)	(0.8401)	(0.0970)
Observations	231	231	224
Panel 2: Weighted by annual (total) industry employment			
CNC Exposure	-1.4706**	0.1488	0.2056**
	(0.6161)	(0.8094)	(0.0859)
Observations	231	231	224
Panel 3: Demographic controls included			
CNC Exposure	-1.6532***	-0.0158	0.2591***
	(0.6100)	(0.8650)	(0.0983)
Observations	231	231	224
Panel 4: Import penentration control included			
CNC Exposure	-1.4565**	-0.5235	0.1682**
	(0.6260)	(0.8299)	(0.0756)
Observations	217	217	210
Panel 5: Excluding Precision Mechanism Industry			
CNC Exposure	-3.5760***	-1.0895	0.3498***
	(0.5652)	(1.0131)	(0.1111)
Observations	198	198	192
Panel 6: Excluding Motor Vehicle Industry			
CNC Exposure	-0.6316	2.2390***	0.2383**
	(0.6846)	(0.8365)	(0.1037)
Observations	198	198	192
Industry FE	X	X	X
Year FE	X	X	X
Dependent variable mean (Panel 1)	6.3553	5.1461	0.0539

Note: Columns (1) and (2) of Panel 1 contain the estimate from Columns (1) and (2) of Table 2, Panel 1. Columns (3) of Panel 1 contains the estimate from Column (1) of Table 2, Panel 2. Panel 2 is the analog of Panel 1, where each industry-year-level cell is weighted by its total employment count. Panel 3 includes demographic controls computed from CPS ASEC, including the share of white workers and the share of young workers aged 18 to 35 among the industry workforce. Panel 4 includes import penetration measure as a control variable. The import penetration definition is drawn from Campbell and Lusher (2019), and we construct the measure using the US import data from Schott (2008). Panels 5 and 6 exclude the industry with the highest and lowest CNC exposure, Precision Mechanism and Motor Vehicle industry, respectively. Standard errors are robust.

*** = significant at 1%, ** = significant at 5%, * = significant at 10%