NBER WORKING PAPER SERIES

AUTOMATION AFTER THE ASSEMBLY LINE: COMPUTERIZED MACHINE TOOLS, EMPLOYMENT AND PRODUCTIVITY IN THE UNITED STATES

Leah Platt Boustan
Jiwon Choi
David Clingingsmith

Working Paper 30400
http://www.nber.org/papers/w30400

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
August 2022, Revised October 2022

We benefited from valuable suggestions from seminar audiences at the Census Bureau, Cleveland Fed, Federal Reserve Board, Johns Hopkins, Rochester, UC-Davis, University of St. Andrews and UVA. We thank David Autor, Henry Farber, Teresa Fort, Susan Helper, Robert Margo, Enrico Moretti and Owen Zidar for useful conversations. We are grateful to the Association for Manufacturing Technology for access to their archival material. Camilla Adams, Kaan Cankat, Nicole Gandre and Katie Guyot provided excellent research assistance. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Automation After the Assembly Line: Computerized Machine Tools, Employment and Productivity in the United States
Leah Platt Boustan, Jiwon Choi, and David Clingingsmith
NBER Working Paper No. 30400
August 2022, Revised October 2022
JEL No. J24,N32

ABSTRACT

Since the 1970s, computerized machine tools have been replacing semi-skilled manufacturing workers, contributing to factory automation. We build a novel measure of exposure to computer numerical control (CNC) based on initial variation in tool types across industries and differential shifts toward CNC technology by tool type over time. Industries more exposed to CNC increased capital investment and experienced higher labor productivity. Total employment rose, with gains for college-educated workers and abstract tasks compensating for losses of less-educated workers and routine tasks. Employment gains were strongest for unionized jobs. Workers in exposed industries returned to school and relevant degree programs expanded.

Leah Platt Boustan
Princeton University
Industrial Relations Section
Louis A. Simpson International Bldg.
Princeton, NJ 08544
and NBER
lboustan@princeton.edu

Jiwon Choi
Industrial Relations Section
Louis A. Simpson International Bldg.
Princeton University
Princeton, NJ 08544
jwchoi@princeton.edu

David Clingingsmith
Dept. of Economics
Case Western Reserve University
10900 Euclid Ave.
Cleveland, OH 44106
david.clingingsmith@case.edu

I. Introduction

For the past century, manufacturing has been characterized by a continuous (but punctuated) process of *automation*, whereby new technology enables tasks previously completed by human labor to be accomplished, in whole or in part, with machines. Many technologies have contributed to this transformation – including "computer numerical control machinery, industrial robots, and artificial intelligence" (Acemoglu and Restrepo 2019, p. 3).

In this paper, we document the effect of computer numerical control (CNC) machinery – a primary and relatively unexamined source of automation – on productivity and employment in the manufacturing sector, and on the adjustment of workers and firms to the technological shock. Beginning in the 1970s, CNC machine tools began to diffuse widely. CNC tools rely on computer programs and servomechanisms rather than human operatives to select and perform the tool's physical movements. Like other forms of automation, CNC has the potential to enhance labor productivity, but also to displace low- or mid-skill workers who perform routine tasks. Furthermore, the diffusion of CNC resulted in the creation of new tasks, including the need for high-skilled technicians who could install, program, and fix these complex machines, as well as white-collar workers who could fulfill the customized orders increasingly made possible by this more flexible form of metalworking technology.

Economists have studied the effects of industrial robotics intensively in recent years (see, e.g., Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Adachi, Kawaguchi and Saito, 2020; Dauth, et al., 2021). There are two main reasons why the spread of CNC technology in the US in the 1970s and 1980s may have had different effects on the labor market than the effects of industrial robots today.

First, CNC and robots automate different parts of the production process. CNC displaces semi-skilled operatives in the production of parts by cutting and bending metal, whereas robots automate the lower-skilled assembly of these parts into a final product.[1] Automation of high-wage positions

[1] CNC "often replaced skilled craftspeople" (Doms, Dunne and Troeske 1997, p 260) including "the skilled jobs of setter and set-up operator [and] the semi-skilled job of machine operator" (Keefe 1991, p. 516). By contrast, robots are primarily used "to perform several manual tasks" in the second stage of the process, "such as welding, painting, assembly, handling materials and packaging" (Acemoglu and Restrepo 2020, p. 2189).

can induce stronger productivity effects and thus more positive employment effects than the automation of low-wage positions. Perhaps for this reason, time series evidence suggests that automation at mid-century (1947-1987), in which CNC technology played a central role, may have been "accompanied by the introduction of new tasks… that counterbalanced the adverse labor demand consequences of automation," a phenomenon that is not taking place today (Acemoglu and Restrepo 2019, p. 16).

Second, the labor market institutions were very different when CNC was first adopted by manufacturing firms. In the early 1970s, 45% of workers in the metal industry were covered by a union, compared to around 10% in 2010. Unionized firms may adopt new technology more slowly than their non-union counterparts or may adjust their workforce more gradually as new technology arrives, leading displacement effects to be muted.

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 that were more exposed to CNC experienced an *increase* in total employment, with the growing number of college-educated workers outpacing the decline in high school graduates and high school dropouts. The diffusion of CNC was also associated with growth in occupations associated with abstract or manual tasks and a decline in occupations engaged in routine tasks.

Some of the positive effect of CNC technology on total employment can be attributed to union activity. Indeed, the non-union workforce in exposed manufacturing industries declined, with the largest losses experienced by high school dropouts and additional losses among high school graduate and workers with some college education. By contrast, the union workforce in these industries expanded, fueled by larger gains among college graduates and smaller losses among less-educated workers.

Workers responded to this new technology by returning to school, which may have insulated them to some extent from the shock. Workers who were either current employees or recently employed in exposed industries were more likely to go back to school to earn a two-year or four-year degree. We also provide new evidence that colleges and universities expanded their degree offerings related to CNC technology to accommodate the growing interest. However, we do not find that this shock encouraged firms to move to the South, where worker protections were weaker, or that it affected the size distribution of manufacturing establishments.

Our analysis is based on a novel measure of exposure to CNC technology at the industry-year level. We exploit baseline variation in the use of certain tool types in production across industries as of 1958, before the spread of CNC. Machine tools – including lathes, mechanical presses, grinding machines and so on – shifted from manual to automatic control in different years and to different extents. Our measure is one of the first to use detailed aspects of the production process to understand why certain industries adopt automation technology earlier than others.

The *American Machinist Inventory of Metalworking Equipment* provides detailed information on machine tool use by industry in 1958, before the invention of CNC. Annual trade statistics on the count and value of exports of CNC and non-CNC tools from the three major world exporters – Germany, Japan and Italy – are available until 2009 and allow us to identify differential timing in the diffusion of CNC by tool. Our completed diffusion measure spans 1968 to 2009.

We focus on seven metal manufacturing industries that account for the majority of CNC adoption.[2] By our measure, all sample industries had very low exposure to CNC in the early 1970s, accounting for less than five percent of their tool base. By 1990, industries like aircraft increased exposure to CNC tools dramatically (up to 40% of its tool base by value), while other industries like motor vehicles were less affected (25% of its tool base).

Ideally, we would have annual data on the adoption of CNC technology across industries in the US to estimate the effect of CNC diffusion on economic activity. We would then use our exposure measure, which is driven primarily by varying engineering challenges across tools as well as differences in industrial policy in major world exporters,, as an instrument for adoption. Because data on industry-level CNC tool use does not exist, we use our exposure measure in an “intent to treat” framework, rather than as an instrument.

We provide three pieces of evidence that the falling demand for low- and mid-skilled workers associated with rising exposure to CNC technology was not driven by other potentially correlated factors. First, we do not find a pre-trend in workforce composition in industries that were more or

[2] Similarly, four industries account for around 70% of robot adoption (Acemoglu and Restrepo, 2020).

less exposed to the later CNC shock before the shock takes place (pre-period = 1968-75). Second, we consider – and reject – the possibility that industries with rising exposure to CNC also faced growing import competition for final products due to growing international trade. The timing of CNC diffusion pre-dated major changes in import competition by at least 10 to 15 years. Third, our exposure measure is based on shifts to CNC technology among global exporters, not on shifts within the US machine tool industry. We present evidence that toolmakers in Japan and Germany were not reacting to demand from the United States but instead were shaped by their own domestic manufacturing sectors.

Our paper is most closely related to classic work on the effect of factory electrification on demand for skill in US manufacturing (Goldin and Katz, 1998; Katz and Margo, 2014). We extend this timeline forward beyond factory electrification in the 1910s and 1920s – and the heyday of mass production employment in the 1940s and 1950s – to the automation of the machining process for fabricating metal parts in the 1970s and 1980s. We introduce well-identified variation in the adoption of automated machine tools across industry based on pre-existing differences in tool use. In doing so, our paper joins new work documenting the effect of new specialized (but worker-operated) machine tools in the late 19th century (Atack, Margo and Rhode, 2019) and factory electrification from 1910-40 (Gray, 2013; Fiszbein, et al. 2020).[3] Like these earlier episodes, we find that the diffusion of automated machine tools increased labor productivity and employment. One important contrast is that many of the new jobs resulting from CNC technology were higher-skilled (college graduates), whereas electrification led to de-skilling.

Our findings also contain insights for our understanding of the effects of industrial robots on the contemporary labor market. Adoption of industrial robots has been associated with falling employment at the industry level in the US, but with null or positive effects on employment in Germany and Japan (Acemoglu and Restrepo, 2020; Graetz and Michaels, 2018; Dauth, et al., 2021; Adachi, Kawaguchi and Saito, 2020). Dauth, et al. (2021) suggests that differences in

[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. Feigenbaum and Gross (2020) consider a specific episode of historical automation: the replacement of manual telephone switchboards with automatic exchanges. They find that young women workers were displaced from the telephone industry, but employment more than rebounded in other sectors (e.g., typists and secretaries) and so overall employment did not fall.

unionization rates may play a role in explaining differential effects of robot technology across countries, while Acemoglu and Restrepo (2019) point to higher manufacturing wages in Germany and Japan versus lower wages in the United States. Consistent with these theories, we find that CNC technology, which diffused in the US during a period of high unionization and displaced a relatively high-paid task, is associated with rising employment. Moreover, the positive effect of CNC on total employment was stronger in the union sector than in the non-union sector, suggesting that labor market institutions can mediate the effect of technological change.[4]

Both automated machine tools and industrial robots are specific examples of the transformative role of computers in the factory. As such, our paper joins a large literature on the effect of computerization and skill-biased technical change on the workforce (a few touchstone papers include Autor, Katz and Krueger, 1998 and Autor, Levy, Murnane, 2003). Much of this literature combines white collar computer use with computerization in the factory, or explicitly focuses on workers who perceive themselves as using a computer on the job (which may exclude some manufacturing uses where the role of computers is less transparent). We focus on a narrower but more well-defined use of computing technology and trace out the specific effects on productivity and the workforce.

Finally, our study builds on three earlier quantitative studies of CNC adoption. Unlike our industry-level study, these papers compare establishments or plants that adopt CNC to competitors who do not. Doms, Dunne and Troske (1997) show that plants adding new computer-assisted production practices 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) survey human resource managers and find 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. None of these papers use event-study research designs, and so it is hard to separate the effect of CNC technology from other differences between firms that choose to adopt new technology and those that do not (e.g., these

[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.

firms could be bigger, better managed, more engaged in export, located in different areas, and so on). Furthermore, these studies do not consider the effect of automation on total employment, capital investment or labor productivity.

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 – or the process by which new technologies "enable capital to substitute for labor in a range of tasks" (Acemoglu and Restrepo 2019, p. 3) – 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 diffusion after 1860 (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, particularly 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 of these 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).

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 tools; and the value share of exports of new machine tools made up of CNC (rather than hand-operated tools) by year from the three major machine tool exporters (Japan, Germany, and Italy). 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.

Our empirical analysis captures the most significant players in the world market. Japan overtook the United States to become the largest producer of CNC machine tools 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.

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 cumulative CNC share for exporter *i* by year *t* can be written:

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

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 $X_{i,\tau,k}^{NC}$ are the annual export value of CNC tools of type *k* from exporter *i* in year τ.

We then aggregate across exporters to create the tool-level cumulative CNC share. To do so, we weight the cumulative 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 cumulative 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 cumulative 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:

$$Exposure\_CNC_{j,t} = \sum_k \left(\frac{VT_{k,j,1958}}{\sum_k VT_{k,j,1958}} ShareNC_{k,t} \right) \quad (3)$$

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.

1958 value shares of tool k for industry j: We construct the industry-level measures of tool base used 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.[5]

Figure 1 demonstrates that there is substantial variation in the intensity of tool use across industries. For example, we find that mechanical presses are relatively heavily used in fabricated metal products, boring machines in aircraft, gear cutting machines in farm machinery, and lathes in precision mechanisms. 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. We report tool use for the 14 tool types included in the export series.

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 data includes 14 major tool types by CNC status for at least one exporter and is available 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: the 14 tools included in the trade data represent 78% of the value share of the 1958 tool base. To complete the series, we impute the CNC share to be the lowest CNC share for the given exporter in that year for the 14 tool types that are not in the trade data.

Figure 2 documents that different tool types shifted toward CNC technology at different times and, ultimately, at different rates. We plot the time series of CNC machine tools as a value share of all

[5] 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.

machine tool exports for the three major exporters (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). Comparable Italian export series are reported in Appendix Figure 1. 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.

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 30% of its tool base by 1986, whereas motor vehicles took another decade to reach this level. 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.

Innovation in CNC tools was not driven by US demand

The historical record suggests that both the direction and the speed of innovation by Japanese and German 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 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

[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.

remained of secondary concern to the Japanese industry until it had exploited the domestic market 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 (Collis, 1988).

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 boring machines were the first to convert to CNC in Germany. 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 2).

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.

Data sources for outcome variables

We use two major data sources to measure productivity and employment effects of CNC technology at the industry level, and then supplement these sources with data on other outcomes.

First, we draw on the NBER-CES Manufacturing Industry database to collect measures of capital investment, labor productivity and the labor share originally tabulated by the Census of Manufactures. We map the SIC industry codes used in the database 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.

We also consider the log number of production workers in the industry as an outcome. We do not use the count of "total" employment, which includes non-production workers, because the employment counts in the Census of Manufactures do not include workers in "auxiliary units (e.g., headquarters or support facilities," many of whom may be white collar, higher skilled workers hired as complements to CNC-based production (Bartelsman and Gray 1996).

Second, we use the CPS Annual Social and Economic Supplement (ASEC) to measure total employment and average annual earnings for prime-age men (18-65 years old) by industry and education group starting in 1968. We combine education measures into four standard categories: less than high school degree, high school graduates, some college, and four or more years of college. We also use CPS data on occupations to compute the average abstract, routine, and manual task scores of workers in each industry over time by mapping the occupation-level task scores from Autor, Levy, and Murnane (2003) to the worker-level occupation variables.

Third, we use three CPS supplements to measure worker adjustments to the CNC technology shock. We collect union status from the CPS May supplement (1973-1983) and then from the CPS Outgoing Rotation Groups (1984-2009). We use data on school enrollment from the CPS October Educational supplement. In both cases, we then aggregate up the share of workers who report being covered by a union or being enrolled in school by industry, year, and education group.

Fourth, we measure firm responses to the arrival of the CNC technology in two ways. We compute the share of workers by industry located in the US South from the CPS ASEC sample. Southern states were primarily "right to work" states that were unfriendly to union activity and so we hypothesize that industries exposed to CNC technology might opt to relocate to the South. We use the County Business Patterns (CBP) data to measure changes in the distribution of establishment size by industry over time. The CBP data records the number of establishments by industry and employment size bin located in each county. We measure the share of establishments by industry in each size bin (that is, we do not use the *county* dimension of the CBP data). Larger firms may be more apt to adopt new technology and thus may have been more likely to survive after the diffusion of CNC.

IV. Empirical Strategy

Our empirical analysis examines whether and how the diffusion of CNC technology was associated with industry-level productivity and employment, and how workers in the affected industries adjusted to the automation of the production process (e.g., by investing in further education).

We estimate versions of the following equation with different outcome variables:

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

where α_j is an industry fixed effect, γ_t is a year fixed effect, and $CNC_{j,t}$ is our industry-year level measure of CNC exposure based on pre-existing differences in tool use. The coefficient of interest β is thus identified from changes in exposure to CNC tools within an industry over time, after controlling for pre-existing gaps across industries (α_j) and common annual trends within the metal manufacturing sector (γ_t) .

If we had access to data on *actual* CNC tool use by industry, we would estimate the effect of CNC adoption on economic outcomes by instrumenting the potentially endogenous CNC adoption with our measure of *exposure* to CNC diffusion. Because data on actual CNC use is not collected, we instead run the 'intent to treat' specification in equation 4, estimating the effect of exposure to CNC technology on employment and productivity. Note that we cannot interpret the magnitude of the coefficient of interest β as estimating the effect of changes in tool use directly, but instead as the effect of exposure to automated tools. If exposure to CNC technology does not predict adoption one-for-one, then the 'true' effect of CNC use on economic outcomes – such as one could recover from an IV regression – would be smaller than the 'intent to treat' estimates that we report in the paper.

We consider a series of outcome variables for $y_{j,t}$ including: log of capital expenditures; log of value added; labor share of value; log total employment and employment by education category; log annual earnings by education category; average task ratings of workers in each industry for abstract, routine and manual tasks; and the share of workers enrolled in some higher education by industry over time.

V. The effect of automated machine tools on economic outcomes

Capital expenditures

We start our empirical analysis by considering the relationship between our measure of industry exposure to CNC technology and capital expenditures. We expect that the purchase and installation of automated machine tools would lead firms to undertake new capital expenditures, so this association serves as a validity check of our proxy for CNC adoption.

Figure 4 illustrates the evolution of log capital expenditure by industry exposure level before, during and after the diffusion of CNC technology. For the purposes of this figure, we partition industries into low, medium, or high exposure to CNC (low = motor vehicles and fabricated metals; medium = electronics, farm equipment, general industrial equipment; high = aircraft, precision mechanisms).

Before the diffusion of CNC, the three capital expenditure series move together. The one exception is a short-lived boom in capital investment in the high-exposure industries in the late 1960s, which is concentrated in aircraft, very likely because of military demand during the Vietnam War, and returns to trend by 1972. As CNC spreads through American manufacturing starting in 1974, capital expenditures in high exposure industries rises, and capital investment begins to fan out across industries by CNC exposure level. The three series diverge, particularly from the late 1970s to the mid-1980s, consistent with the shock having a larger positive effect on capital investment in the most exposed industries.

We investigate capital investment in more detail in Table 1 by using variation across all industries (rather than three coarse groupings) and by controlling for production and non-production employment, along with industry and year fixed effects. We continue to find a strong positive correlation between exposure to CNC and the logarithm of capital expenditures (column 1). 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 29% increase in annual capital expenditures.

Productivity and labor share

After validating that our exposure measure is associated with capital expenditures, we turn to the effect of the CNC technology shock on labor productivity and labor share of revenue. The task model of production has clear predictions for each outcome. Labor productivity should rise with automation as labor is reallocated away from tasks for which it does not have a strong comparative advantage. New technology can also be labor-augmenting in the tasks that remain. Likewise, the labor share should fall as firms reallocate tasks from labor to capital (*displacement*) but will rise if a sufficiently large number of new tasks are created (*reinstatement*) (Acemoglu and Restrepo, 2018, 2019).

The logarithm of value-added increases with exposure to CNC, with a 10-percentage point increase in exposure to CNC tools corresponding to an 20% increase in value added (Table 1, column 2). The specification controls for production employment and non-production employment, so we interpret the effect as value added per worker – or labor productivity. Results are similar if we instead directly consider the effect on the logarithm of value added per worker. However, the labor share – measured as wage bill divided by value added – is falling with industry exposure to CNC technology, with a 10-percentage point increase in CNC exposure associated with a 1.6 decline in the share of revenue paid out to labor (Table 1, column 3).

Total employment, and employment by education level

In a task-based model, automation can have positive or negative effects on overall labor demand. On the one hand, a smaller share of the tasks will be allocated to labor as some tasks are automated and shifted to machines. On the other hand, automation can increase productivity, thereby increasing overall employment, and can lead to the creation of new labor-intensive tasks. We estimate the effect of CNC technology on total employment in this section and find that total employment increases with exposure to CNC. The positive effect of CNC on college-educated workers is large enough to offset the negative effect on high school graduates and high school dropouts.

We begin by considering pre-trends in the educational distribution of the manufacturing workforce before the diffusion of CNC technology. Figure 5 depicts the share of workers with exactly a high school degree, the largest educational employment sub-category before the spread of CNC, representing around 40% of the workforce. As above, we divide industries by low, medium and high exposure to CNC. Before the introduction of CNC tools, the share of workers with exactly a high school degree was qualitatively similar in all sub-industries (around 40%) and was trending up slightly in all industry groups from 1968-1975. After the diffusion of CNC, the share of workers with exactly a high school degree continued to rise in sub-industries with low exposure to CNC (up to 50%), held steady in sub-industries with medium exposure, and fell in sub-industries with high exposure (down to 35%). Appendix Figure 3 includes similar graphs for the other three education categories.

Table 2 reports estimates of the relationship between CNC diffusion and employment, both for total employment and employment by education category. We start in column 1 with the reported number of production workers from the Census of Manufactures. As exposure to CNC tools increases in an industry, the number of production workers declines, with a 10-percentage point increase in CNC exposure – roughly the difference between the motor vehicle and aircraft industries – associated with an 7% decline in production workers.

The remainder of the table (columns 2-6) turns to data from the Current Population Survey, which allows us to count all workers in an industry and to separate workers by education level. Overall, we find that a 10-percentage point increase in CNC exposure is associated with a 25% rise in employment. Employment gains are concentrated among college graduates (86% rise). High school graduates and high school dropouts by contrast experience a 7% and 8% decline respectively. The point estimate for workers with some college education shows a 5% decline but the estimate is not statistically significantly different from zero.

If the falling employment of high school graduates and high school dropouts reflects lower labor demand for this educational group by metal manufacturers (as opposed to coincident declines in labor supply), we would expect it to be associated with lower wages for these groups in those industries as well. Table 3 confirms that this is the case. When CNC diffuses to an industry, the annual earnings of high school dropouts employed there fall by a sizeable amount – a 10 percentage point increase in CNC exposure is associated with a 6% drop in the earnings of high school dropouts – and the earnings of high school graduates decline somewhat (although not significantly so).

Task composition of the workforce

Over the past fifty years, labor tasks in the manufacturing sector have become less routine and more focused on abstract and critical reasoning. Automation is one possible explanation: as the sociologist Daniel Bell put it, from the worker's perspective, automation "destroy[s] physically repetitive and onerous tasks, replacing them with more highly conceptual and socially connected activity… [that require more] training, preparation, and learning" (cited in Keefe, 1991 p. 503). We find that the diffusion of CNC in an industry is associated with a decline in occupations associated with routine tasks and a rise in both abstract- and manual-intensive occupations, much like in the broader computerization literature (Autor, Katz and Kearney, 2006).

For context, Appendix Figure 4 illustrates changes in the average task content of occupations by manufacturing sub-industry from 1968-2009. We document that the presence of routine tasks has been declining throughout metal manufacturing, and the corresponding density of abstract tasks have been rising. There has been little change in the use of manual tasks. On a scale of 0-10, the average routine-task content of occupations in metal manufacturing declined by 0.5-1.0, while the average abstract-task content increased by a similar degree.[7]

Table 4 documents that the diffusion of CNC in an industry is associated with a decline in routine tasks and a corresponding increase in abstract and manual work. A 10-percentage point increase in CNC exposure is associated with 0.17 increase in average abstract task ratings, which can account for roughly 20% of the rise in the abstract content of manufacturing employment over this period.

Robustness of main employment effects

Overall, we find that diffusion of computerized machine tools increased the demand for college-educated workers and abstract tasks, while lowering the demand for high school graduates or dropouts and routine work. Before turning to workers' responses to this technological shock, we

[7] Note that occupations can require both routine and abstract work and that the three task measures are not constrained to sum to a fixed number, and so the increase in abstract tasks alongside the decline in routine work is not a mechanical effect.

first document the robustness of our core employment results to a variety of specifications and alternate controls.

Table 5 presents our core employment results for a variety of specifications. The first row reproduces the baseline results from Table 2. Each observation in this unweighted regression is an industry-by-year cell, with varying numbers of underlying workers contributing to the cell. Results are nearly unchanged when we consider two weighting schemes, either by annual industry employment or by initial employment (rows 2 and 3).

Rows 4 and 5 add groups of industry-year controls. Row 4 includes two demographic measures of workers in each industry: the share of workers who are white and the share who are young (18-35 years old). The same patterns of strong employment gains for college graduates and employment losses for high school graduates and high school dropouts hold, with an increase in total employment still present but significant at the 10% level.

Row 5 considers the possibility that industries exposed to the CNC shock were also facing import competition for their final products in the same period. We use the measure of annual import penetration by industry described in Campbell and Lusher (2016), including this variable as a control.[8] Import penetration is defined as the share of imports among domestic demand by industry. Adding this control if anything makes the total employment gains larger by increasing the estimated effect of CNC on the employment of college-educated workers.

It is not surprising to see that adding controls for trade conditions does not change the results because the import penetration measure is not highly correlated with our industry-level CNC shock. In Appendix Figure 5, we plot the import penetration measure by industry over time. First, industries with the highest import penetration (motor vehicles and electronics) are not the industries with the highest exposure to CNC machine tools. Second, the steepest rise in import penetration starts in the 1990s, which is after the main period in which CNC machine tools diffused to the industries.

Row 6 considers an additional control group, a composite of non-metal manufacturing industries including food processing, textiles, chemicals and other materials, under the assumption that non-metal manufacturing did not adopt CNC tools. In this specification, observations for non-metal

[8] Data for the measure is drawn from Schott (2008).

manufacturing industries will control for annual trends in skill composition within the manufacturing sector more broadly. We continue to find that sub-industries experiencing CNC diffusion shed high school graduate and high school dropouts from their workforce and increase the employment of college graduates. However, when compared to non-metal manufacturing, the growth in the employment of college graduates is not large enough to compensate for the loss in high school graduates and dropouts, and so the overall effect on employment is zero (but does not turn negative).

VI. Worker and firm adjustments to CNC technology

Less-educated workers and workers on the production floor experienced declining employment opportunities in metal manufacturing following the diffusion of computerized machine tools in the 1970s and 1980s. This group of workers could take two main actions to respond to this employment shock. First, workers could join unions, which negotiated for job protections as factories were retooled. Second, workers could opt to re-enroll in school, either full- or part-time, to earn a degree in one of the new programs like industrial machining or robotics offered at colleges and universities.

Unionization

Since the landmark "Treaty of Detroit" between the United Auto Workers and General Motors in 1950, industrial unions in the United States have abided by a shared norm not to oppose technical change in exchange for a guarantee of employment protections and other benefits from firms (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).

Given this institutional arrangement, we would expect unionized employees to be somewhat more shielded from the displacement effects of CNC technology than non-unionized workers. Overall, the unionization rate declined in manufacturing during this period, from around 45% of the workforce in 1973 to around 10% in 2009 (see Appendix Figure 6), but the decline in unionization may be slower in sub-industries that were retooling for CNC technology.

We test this hypothesis in Table 6 by splitting each industry-year observation into two cells: one containing workers who report being members of or covered by a union and one for non-union workers in the same industry-year. We then stack these industry-year-union status cells and re-estimate the effect of CNC technology on employment, allowing the effect of automation to differ for union and non-union workers. In particular, we estimate:

$$y_{j,t,u} = \alpha_{ju} + \gamma_{tu} + \beta_1 CNC_{jtu} + \beta_2 CNC * Union_{\,jtu} + \varepsilon_{jtu} \quad (5)$$

where α_{ju} controls for fixed differences between union- and non-union workers by industry *j* and γ_{tu} allows the effect of union status to evolve over time. These double interactions absorb the main effects of industry, year and union status. The double interaction of industry *x* year is used to identify the main effect of exposure to CNC at the industry-year level (CNC_{jtu}), and the triple interaction of industry *x* year *x* union status is used to identify any differential effect of CNC exposure for unionized workers ($CNC * Union_{\,jtu}$).

The results are striking: total employment *falls* with the introduction of CNC technology among non-unionized workers, driven by larger declines in employment for high school graduates and dropouts, but also small declines for workers with some college education. By contrast, total employment *rises* for unionized workers. Unionized workers faced some declines in employment among high school graduates and dropouts but also enjoyed gains in employment among workers with a college degree.

The patterns we document in Table 6 could arise from worker or firm actions. First, unionized firms may have been less responsive to the CNC shock – either less likely to adopt CNC technology in the first place or less likely to cut employees after adopting the new technology. Alternatively, these patterns could arise if some workers left non-union positions and switched in unionized jobs to take advantage of union protections, either by switching firms or by organizing at their existing firm . In either case, the data suggest that unions offer some protection from the dis-employment effects of automation.

Educational attainment and returning to school

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. We begin investigating this possibility by documenting that colleges and universities introduced new degree programs (or expanded existing programs) to offer training in the new skills needed in metal manufacturing after the diffusion of CNC technology. Then we investigate whether workers currently or recently employed in industries exposed to CNC were more likely to report re-enrolling in school.

Although most college degrees are not directly related to work with computerized machine tools, there is a subset (e.g., Machinist/Machine Tool Technologist and Industrial/Manufacturing Engineering) long tied to metal manufacturing, as well as new programs like Robotics Technician that were started in this period. We compile a time series on degrees related to CNC technology from 1967 onward using administrative data on degree completion collected from colleges and universities by Higher Education General Information Survey (HEGIS, 1967-84) and IPEDS (Integrated Post-Secondary Information Data System (1986-present). In particular, we classified all certificate programs and associate and bachelor's degrees into those we deemed relevant to automated machine tools (as listed in the footnote) and those that were not.[9]

Figure 6 documents that general degree completions (those not related to CNC) grew steadily, particularly from 1985 to 2010, reaching 4 million annual degree completions by the end of the series. By contrast, CNC-related degree programs show a more punctuated pattern, with very rapid growth between 1970 and 1980, a levelling off with stable completion rates between 1980 and 2010, and then a second burst of strong growth between 2010 and 2020. The first period of growth in CNC-related degree completion corresponds to the diffusion of CNC machine tools, and the second period of growth corresponds to the spread of industrial robots. Appendix Figure 7 report time series in degree completion by degree type (certificates, associate degrees and bachelor's degrees).

[9] 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.

Alongside the expansion of CNC-related educational opportunities, we find that some existing workers in metal manufacturing industries re-enrolled in two- or four-year college degrees as CNC technology arrived in their industry. The CPS October supplement includes information about current educational enrollment and about current/last industry of employment. We restrict our sample to prime-age men who do not already hold a bachelor's degree and whose current or most recent employment (within the past five years) was in a metal manufacturing industry. This data thus includes both current employees in a metal manufacturing industry and workers who are currently unemployed or out of the labor force but whose last employer was in the metal manufacturing industry. The sample is for 1976 through 2009. The average enrollment in higher education in this sample is close to 5%.

Table 7 shows 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 2.4 percentage point increase in total enrollment (column 1), which is derived primarily from increases in full-time enrollment in four-year degree programs (columns 2-5).

We conclude that less-educated workers take active steps to try to protect themselves against job loss associated with CNC-based automation. However, the pace of returning to school is not high enough to compensate for the loss of employment for less-educated workers. For example, a 10-percentage point increase in CNC exposure is associated with a 7% decline in the employment of men with a high school degree. So, if an industry employed 100 high school graduates, 7 would no longer be employed but only 2 would return to school.

Firm adjustments to CNC technology

Firms may also take active steps to adjust to the arrival of new automation technology. If firms want to have the flexibility to hire and fire workers without negotiating with unions, they could relocate their economic activity to the US South, which has a long history of "right-to-work" legislation that complicates union organizing (Kim, 2021). Furthermore, recent work on the adoption of industrial robots have found a robust pattern whereby larger firms are more likely to invest in new automation technology (Humlum, 2019; Acemoglu, et al. 2020; Koch, et al. 2021).

Thus, we might expect that industries exposed to CNC would be increasingly made up by larger firms, as smaller firms are rendered uncompetitive.

We test both of these hypotheses in Table 8 and do not find evidence in support of either. According to CPS data, workers in industries exposed to CNC technology are no more likely than other workers to live in the US South (column 1). We then turn to the County Business Patterns data, which contains aggregate counts of establishments by industry and employment size (in bins). We report the shares of establishments in various size bins from under 20 to over 500 (columns 2-6). Yet, we find no associations between exposure to CNC technology and firm size.

VII. Conclusions

Compared to the past, the modern factory floor is filled with machines and empty of people. In a modern factory, observers would find computerized machine tools producing complex parts based on instructions encoded in computer programs, conveyors moving parts from station to station, and robots assembling 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 – and to date overlooked – step in the long evolutionary process of factory automation: the advent and diffusion of automated machine tools. Automation began with the development of interchangeable parts in the late 19th century, which eliminated the need for skilled 'fitters,' and continued with the assembly line of the 1910s and 1920s, which economized on the use of porters to move parts around a factory. Electric power enabled more efficient organization on the factory floor and is associated with rising labor productivity and employment, primarily of lower-skilled operatives (Gray, 2013; Fiszbein, et al. 2020). Automated machine tools began to diffuse widely in the 1970s. At mid-century, machine tools required a semi-skilled machinist to perform operations to specification by hand. 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 and employment gains, with new employment driven by college graduates. Workers in exposed industries also responded to this technology shock by returning to school, perhaps to qualify for such higher-skilled work. Our measure of exposure to CNC tools is based on initial differences in tool use across industries interacted with variation in the timing and extent of the shift to CNC technology across tools over time.

In the century-long process of factory automation, the association of industrial robots with employment *losses* stands out as an exception (Acemoglu and Restrepo, 2018, 2020). For the first time, the displacement effects of automation, as some tasks shift from workers to machines, appear to be stronger than the productivity effects, which can increase labor demand for all tasks, and the reinstatement effects of new, often high-skilled, labor-intensive tasks.

In countries or settings with stronger worker protections, the spread of industrial robots is not associated with falling employment, and can even lead employment to rise (Adachi, Kawaguchi and Saito, 2020; Dauth, et al., 2021). Similarly, we document fewer employment losses for low-skilled workers and stronger overall employment growth in the union sector following the spread of CNC technology in the US.

At least since the initial development of automated machine tools, scholars have speculated that worker protections would constrain the adoption of productivity-enhancing automation (Killingsworth 1963). Future work could explore how firms in settings with stronger worker protections respond to automation shocks. For example, are unionized firms in the United States slower to adopt automation technologies, or do they adopt technology 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.

References

Acemoglu, Daron, Claire Lelarge, and Pascual Restrepo (2020) "Competing with robots: Firm-level evidence from France." *AEA Papers and Proceedings*, vol. 110, pp. 383-88.

Acemoglu, Daron, and Pascual Restrepo (2018) "The race between man and machine: Implications of technology for growth, factor shares, and employment." *American Economic Review* 108, no. 6: 1488-1542.

Acemoglu, Daron, and Pascual Restrepo (2019) "Automation and new tasks: How technology displaces and reinstates labor." *Journal of Economic Perspectives* 33, no. 2: 3-30.

Acemoglu, Daron, and Pascual Restrepo (2020) "Robots and jobs: Evidence from US labor markets." *Journal of Political Economy* 128, no. 6: 2188-2244.

Adachi, Daisuke, Daiji Kawaguchi, and Yukiko Saito (2020) "Robots and Employment: Evidence from Japan, 1978-2017." *Discussion papers* 20051, Research Institute of Economy, Trade and Industry (RIETI).

Aghion, Philippe, Céline Antonin, Simon Bunel, and Xavier Jaravel (2020) "What are the Labor and Product Market Effects of Automation? New Evidence from France." Working Paper.

Atack, Jeremy, Robert A. Margo, and Paul W. Rhode (2019) "'Automation' of Manufacturing in the Late Nineteenth Century: The Hand and Machine Labor Study." *Journal of Economic Perspectives* 33, no. 2: 51–70.

Autor, David, H., Lawrence F. Katz, and Melissa S. Kearney (2006) "The polarization of the US labor market." *American Economic Review* 96, no. 2: 189-194.

Autor, David H., Frank Levy, and Richard J. Murnane (2003) "The skill content of recent technological change: An empirical exploration." *Quarterly Journal of Economics* 118, no. 4: 1279-1333.

Autor, David H., Lawrence F. Katz, and Alan B. Krueger (1998) "Computing inequality: have computers changed the labor market?" *Quarterly Journal of Economics* 113, no. 4: 1169-1213.

Bartel, Ann, Casey Ichniowski, and Kathryn Shaw (2007) "How does information technology affect productivity? Plant-level comparisons of product innovation, process improvement, and worker skills." *Quarterly Journal of Economics* 122, no. 4: 1721-1758.

Barnard, John (1983) *Walter Reuther and the Rise of the Auto Workers*. New York: Little, Brown, and Co.

Bartelsman, Eric J. and Wayne Gray (1996) The NBER Manufacturing Productivity Database. NBER Technical Working Paper 205.

Bell, Daniel (1976) *The Coming of Post-Industrial Society*. New York: Basic Books.

Bessen, James, Maarten Goos, Anna Salomons, and Wiljan van den Berge (2019) "Automatic reaction: What happens to workers at firms that automate?" *Boston Univ. School of Law, Law and Economics Research Paper.*

Bessen, James, Maarten Goos, Anna Salomons, and Wiljan van den Berge (2020) "Firm-level automation: Evidence from the Netherlands." *AEA Papers and Proceedings*, vol. 110, pp. 389-93.

Brown, Michael K. (1997) "Bargaining for social rights: Unions and the reemergence of welfare capitalism, 1945-1952." *Political Science Quarterly* 112, no. 4: 645-674.

Campbell, Douglas L., and Lester Lusher (2016) "Trade Shocks, Taxes and Inequality." Centre for Economic and Financial Research at New Economic School Working Paper.

Collis, David J. (1988) "The Machine Tool Industry and Industrial Policy, 1955-82" in *Trade Policies for International Competitiveness.* Eds. Spence and Hazard. Pensacola, FL: Ballinger Publishing Co.

Dauth, Wolfgang, Sebastian Findeisen, Jens Suedekum, and Nicole Woessner (2021) "The adjustment of labor markets to robots." *Journal of the European Economic Association* 19, no. 6: 3104-3153.

Devine, Warren D (1983) "From shafts to wires: Historical perspective on electrification." *The Journal of Economic History* 43, no. 2: 347-372.

Doms, Mark, Timothy Dunne, and Kenneth Troske (1997) "Workers, Wages, and Technology." *The Quarterly Journal of Economics* 112, no. 1: 253-290.

Feigenbaum, James, and Daniel P. Gross (2020) "Automation and the Future of Young Workers: Evidence from Telephone Operation in the Early 20th Century." NBER Working Paper w28061.

Fiszbein, Martin, Jeanne Lafortune, Ethan G. Lewis, José Tessada (2020). "Powering Up Productivity: The Effects of Electrification on U.S. Manufacturing." NBER Working Paper No. w28076.

Gaggla, Paul, Rowena Gray, Ioana Marinescu, and Miguel Morine (2021). "Does electricity drive structural transformation? Evidence from the United States." *Labour Economics* 68.

Goldin, Claudia, and Lawrence F. Katz (1998) "The origins of technology-skill complementarity." *The Quarterly Journal of Economics* 113, no. 3: 693-732.

Graetz, Georg, and Guy Michaels (2018) "Robots at work." *Review of Economics and Statistics* 100, no. 5: 753-768.

Gray, Rowena (2013) "Taking technology to task: The skill content of technological change in early twentieth century United States." *Explorations in Economic History* 50, no. 3: 351-367.

Holt, L.T.C. (1966) *A Short History of Machine Tools*. Cambridge, MA: MIT Press.

Hounshell, David A. (1984) *From the American System to Mass Production: The Development of Manufacturing Technology in the United States.* Baltimore, MD: Johns Hopkins University Press.

Hounshell, David A. (2000) "Automation, Transfer Machinery, and Mass Production in the U.S. Automobile Industry in the Post–World War II Era." *Enterprise and Society* 1, no. 1.

Humlum, Anders. "Robot adoption and labor market dynamics." Working Paper, *Princeton University.*

Katz, Lawrence F., and Robert A. Margo (2014) "Technical change and the relative demand for skilled labor: The united states in historical perspective." In *Human Capital in History: The American Record*, pp. 15-57. University of Chicago Press.

Keefe, Jeffrey H (1991) "Numerically controlled machine tools and worker skills." *ILR Review* 44, no. 3: 503-519.

Killingsworth, Charles C. (1962) "Industrial Relations and Automation." *The Annals of the American Academy of Political and Social Science* 340: 69–80.

Kim, Eunbi (2021) "The impact of right-to-work legislation on foreign manufacturing employment in the United States." *International Journal of Urban Sciences*: 1-18.

Koch, Michael, Ilya Manuylov, and Marcel Smolka (2021) "Robots and firms." *Economic Journal* 131, no. 638: 2553-2584.

Itohisa, Matasao (2010) "Fanuc's Competitive Advantage and the Revolt of Machine Tool Builders: A Look at Fanuc's User and Its User's Customer Relationships from a Historical Perspective (1950s–1980s)" *Manufacturing Management Research Center Discussion Paper* No. 534.

Johnson, Chalmers (1982) *MITI and the Japanese Miracle: The Growth of Industrial Policy, 1925-1975.* Redwood City, CA: Stanford University Press.

Lafortune, Jeanne, Ethan Lewis, José Tessada (2019) "People and Machines: A Look at the Evolving Relationship between Capital and Skill in Manufacturing, 1860–1930, Using Immigration Shocks." *Review of Economics and Statistics* 101, no. 1: 30–43.

Levy, Jonathan (2021) *Ages of American Capitalism: A History of the United States*. New York: Random House.

Lewis, Joshua and Edson Severnini (2020). “Short- and long-run impacts of rural electrification: Evidence from the historical rollout of the U.S. power grid.” *Journal of Development Economics* 143.

Milkman, Ruth (1997) *Farewell to the Factory: Auto Workers in the Late Twentieth Century*. Berkeley, CA: University of California Press.

Mindell, David A. (2004) *Between Human and Machine: Feedback, Control, and Computing before Cybernetics*. Baltimore, MD: Johns Hopkins University Press.

Noble, David F. (1986) *Forces of Production: A Social History of Industrial Automation.* New York, NY: Oxford University Press.

Piore, Michael J. (1968) “The Impact of the Labor Market Upon the Design and Selection of Productive Techniques Within the Manufacturing Plant.” *Quarterly Journal of Economics* 82, no. 4.

Rendiero, Joao (1985) “How the Japanese Came to Dominate the Machine Tool Industry.” *Long Range Planning.* 18(3), pp 62-67.

Reuther, Walter P. (1962) “Policies for Automation: A Labor Viewpoint.” *The Annals of the American Academy of Political and Social Science* 340: 100–109.

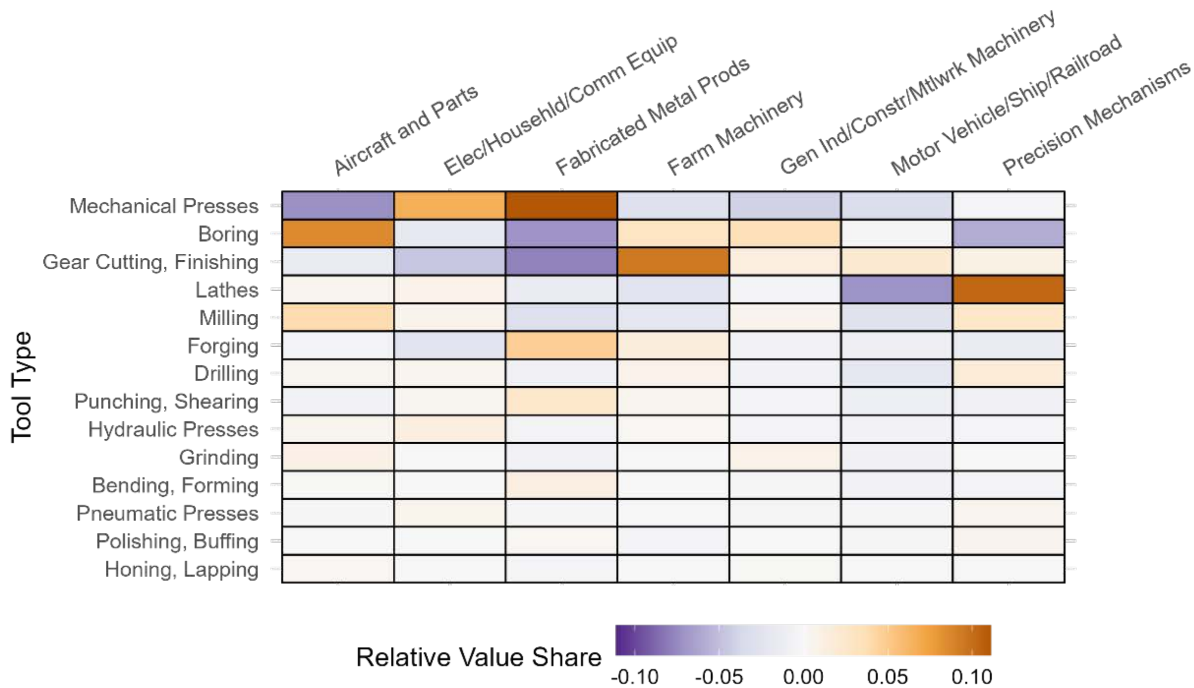
Sarathy, Ravi (1989) “The Interplay of Industrial Policy and International Strategy: Japan's Machine Tool Industry.” *California Management Review*. 31(3), 132-160.

Schott, Peter K. (2008) “The Relative Sophistication of Chinese Exports” *Economic Policy* 23(53), 5–49.

Wieandt, Axel (1994) “Innovation and the Creation, Development and Destruction of Markets in the World Machine Tool Industry.” *Small Business Economics* 6, 421-437.

Woodbury, Robert S. (1972) *Studies in the History of Machine Tools.* Cambridge, MA: M.I.T. Press.

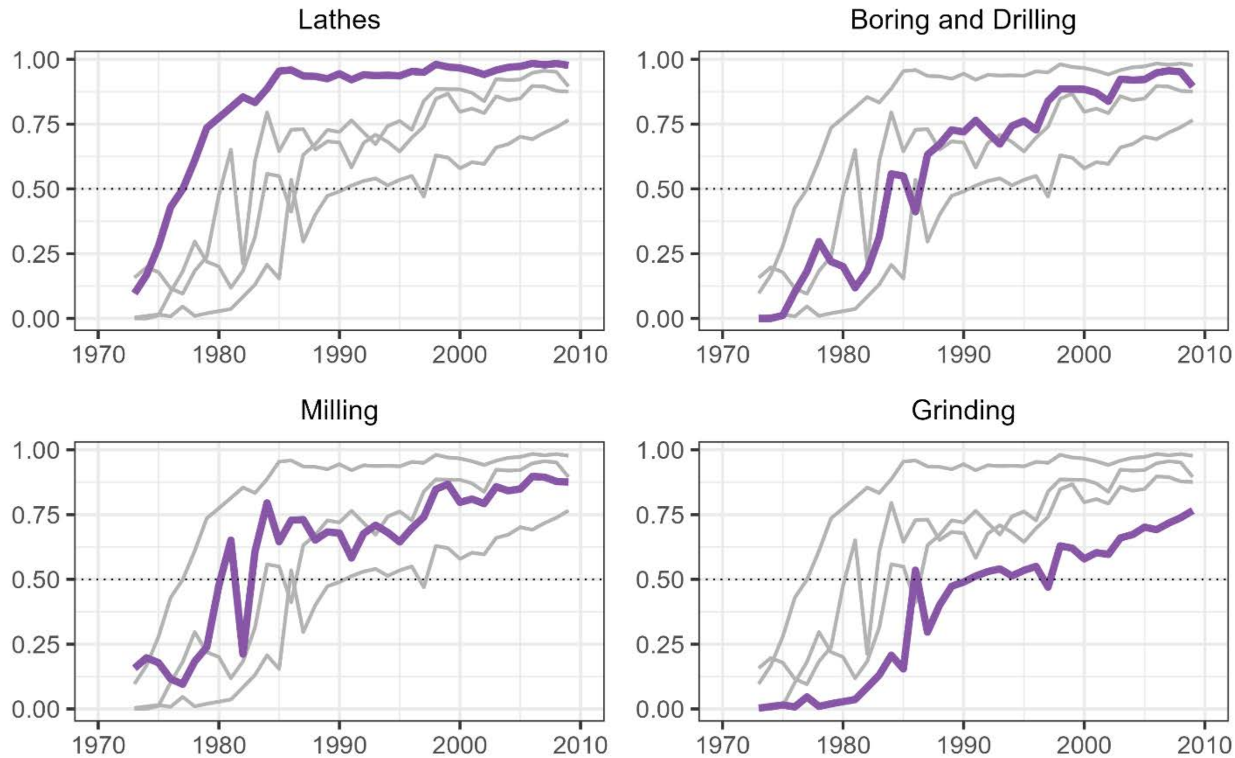
Figure 1: Relative Value Share of Installed Tools by Seven Metal Manufacturing Industries in 1958



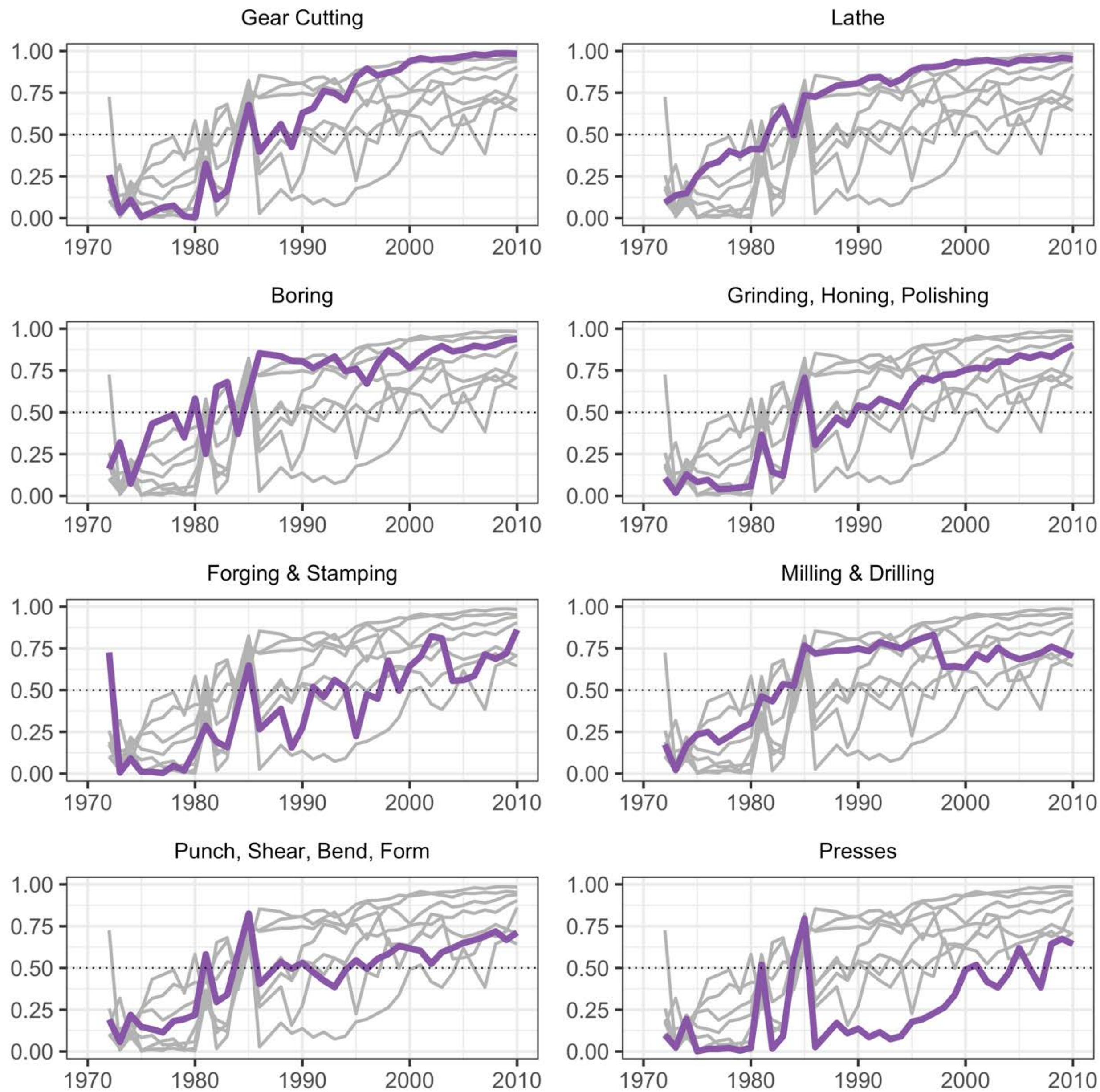
Notes: Cells in the figure show the relative value share of for each type of machine tool by industry. Orange indicates that an industry is more intensive in that tool type than the average industry, while purple indicates it is less intensive than the average. To compute the relative value share, we 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

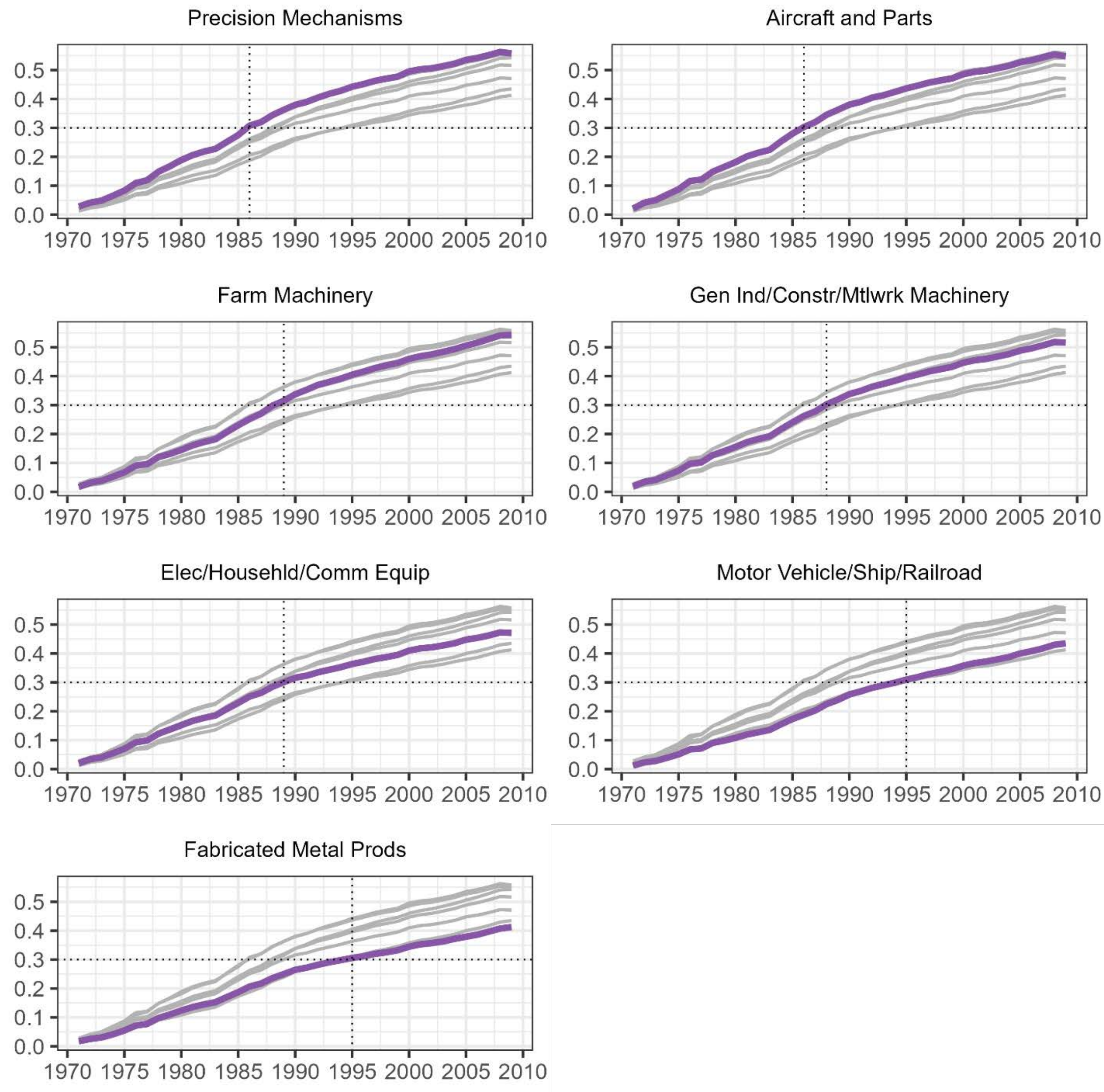


Panel B: Germany



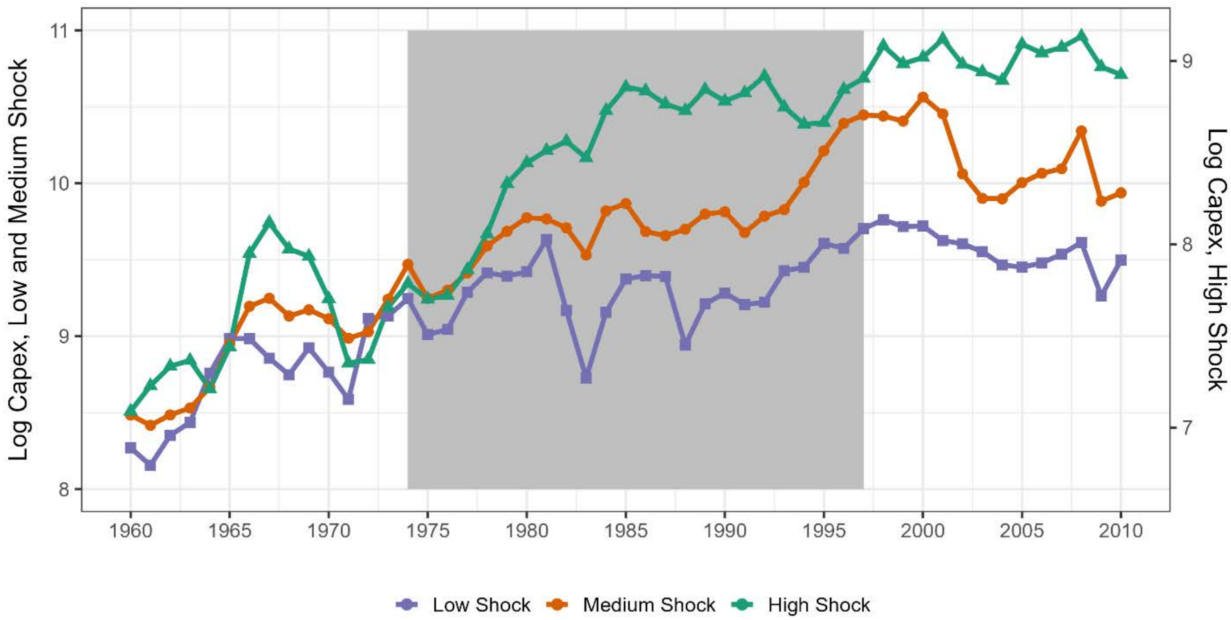
Notes: This figure presents the annual CNC shares of exports by machine tool types for both Japan and Germany. See Appendix Figure 1 for Italy. The data come from volumes of the *Economic Handbook of the Machine Tool Industry* as described in section III.

Figure 3: Cumulative CNC Share by Metal Manufacturing Industries



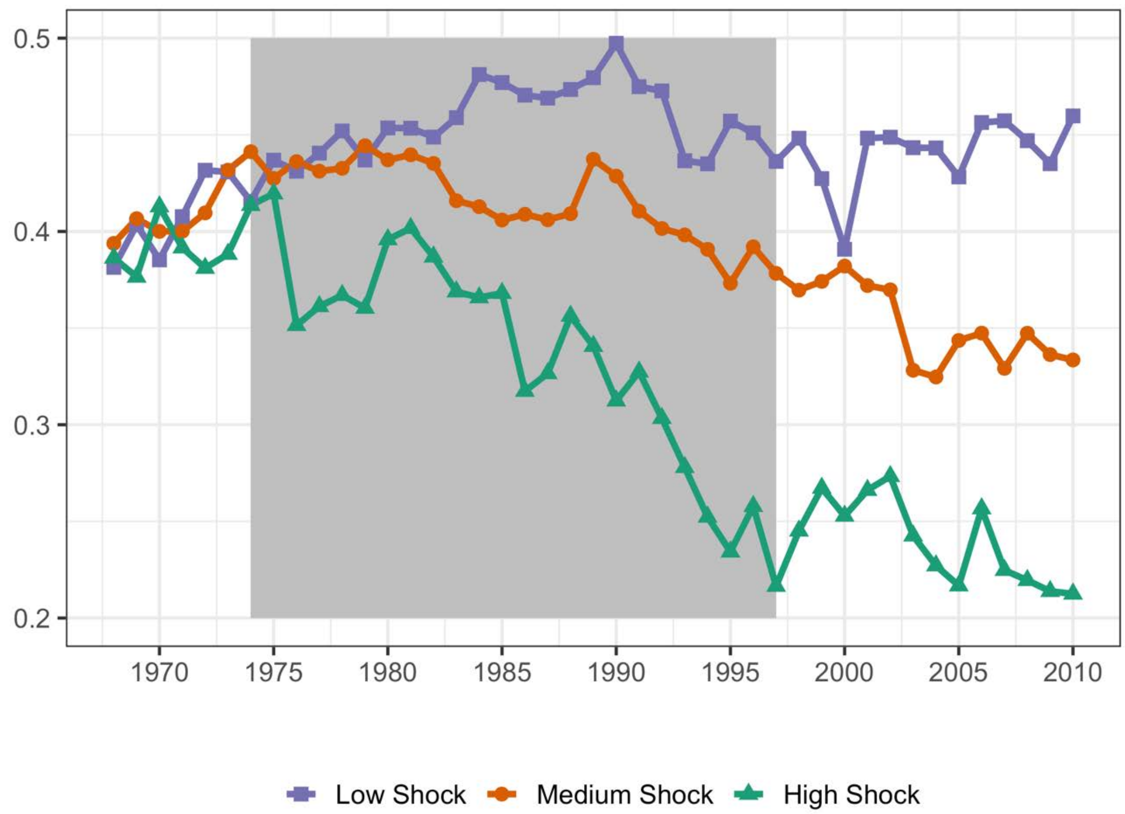
Notes: Cumulative CNC shares for the seven metal manufacturing are computed from the initial tool distribution by industry and the CNC share of exports by tool as described in section III. Dotted lines indicate the year in which the cumulative share passed 30%. Data underlying the figure come from the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

Figure 4: Capital Expenditures by CNC Shock Intensity



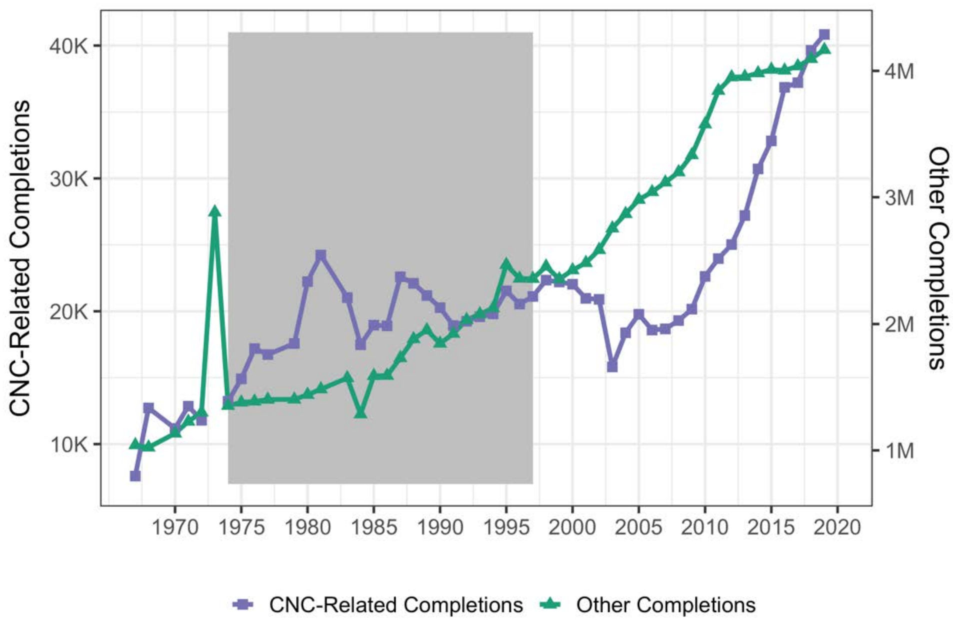
Notes: The figure shows the average annual capital expenditures in metal manufacturing. Metal industries are partitioned into groups according to the intensity of the CNC shock they experience. Low shock industries are motor vehicles and fabricated metals; Medium shock industries are electronics, farm equipment, and general industrial equipment. High shock industries are aircraft and precision mechanisms. The figure is constructed using the *NBER-CES Manufacturing Industry* database. The shock was most intense from 1974 to 1997, as shown by the gray box.

Figure 5: High-School Share of Employment by CNC Shock Intensity



Notes: The figure shows the average share of workers employed in metal manufacturing who have a high school degree. Metal industries are partitioned into groups according to the intensity of the CNC shock they experience. Low shock industries are motor vehicles and fabricated metals; Medium shock industries are electronics, farm equipment, and general industrial equipment. High shock industries are aircraft and precision mechanisms. The data comes from the *CPS Annual Social and Economic Supplement.* The CNC shock was most intense from 1974 to 1997, as shown by the gray box.

Figure 6: 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. The gray box shows the period 1974-1997 during which the CNC shock was most intense.

Table 1: The effect of CNC exposure on capital expenditure, value added, and labor share

	log(Capital Exp.)	log(Value Added)	Labor Share
	(1)	(2)	(3)
CNC Exposure	1.3526*	1.0920***	-0.1702**
	(0.7086)	(0.2727)	(0.0745)
Industry FE	X	X	X
Year FE	X	X	X
With emp. controls	X	X	
Dep. var mean	7.8482	10.7077	0.4098
N	294	294	294

Note: Outcome variables are log of annual capital expenditure, log of value added, and labor share (log of payroll per value added) in each metal manufacturing industry. Columns (1) and (2) include log of production employment and log of non-production employment (production employment subtracted from the total employment) as control variables. The outcome variables are constructed from NBER-CES Manufacturing Industry database (1968-2009). 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 employment

Data source:	NBER-CES	CPS ASEC				
	log(Prod. Emp)	log(Total Emp)	log(Less-than-HS)	log(HS Grad)	log(Some-Coll)	log(4+ Yrs Coll)
	(1)	(2)	(3)	(4)	(5)	(6)
CNC Exposure	-1.0823***	1.2557**	-1.7875***	-1.2638**	-0.6245	2.2612**
	(0.3740)	(0.5006)	(0.6863)	(0.5574)	(0.6172)	(0.8736)
Industry FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Dep. var mean	6.1471	6.1051	4.1017	5.1356	4.5220	4.4236
N	294	294	294	294	294	294

Note: Outcome variables are log of production workers computed from NBER-CES Manufacturing Industry database (1968-2009) and log of employment by education group in each metal manufacturing industry x year computed from the CPS ASEC sample (1968-2009). 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 3: The effect of CNC exposure on average annual earnings by education group

	Less than HS	HS Grad	Some Coll	4+ Yrs Coll
	(1)	(2)	(3)	(4)
CNC Exposure	-0.9433**	-0.1122	0.1058	0.2503
	(0.4229)	(0.1759)	(0.2611)	(0.2639)
Industry FE	X	X	X	X
Year FE	X	X	X	X
Dep. var mean	10.5214	10.7594	10.9182	11.3341
N	294	294	294	294

Note: Outcome variables are log of average annual earnings by education group in each metal manufacturing industry and year, computed from the CPS ASEC sample (1968-2009). We restrict our sample to prime-age (18-64) men who reported to be employed. Each reported annual wage and salary income is converted to a dollar measure in 2012. The average annual earnings are computed by taking the average of all workers' annual earnings in each industry and year by skill group. All specifications include industry and year fixed effects. Standard errors are robust.
*** = significant at 1%, ** = significant at 5%, * = significant at 10%

Table 4: The effect of CNC exposure on average task composition

	Manual	Routine	Abstract
	(1)	(2)	(3)
CNC Exposure	0.9875***	-0.7889*	1.6481***
	(0.1858)	(0.4530)	(0.5466)
Industry FE	X	X	X
Year FE	X	X	X
Dep. var mean	1.1030	5.3587	3.4109
N	294	294	294

Note: Outcome variables are average manual, routine, and abstract task scores in each metal manufacturing industry x year, computed from the CPS ASEC sample (1968-2009). We restrict our sample to prime-age (18-64) men who reported to be employed. Each worker in the sample with occupation code is mapped to a set of manual, routine, and abstract task scores following Autor, Levy, and Murnane (2003). We use task score crosswalks using the 1990 occupation codes (occ1990dd). Then, the average of task scores are computed by taking the average of all workers' task scores in each metal manufacturing industry and year. All specifications include industry and year fixed effects. Standard errors are robust.
*** = significant at 1%, ** = significant at 5%, * = significant at 10%

Table 5: Robustness analysis: The effect of CNC exposure on level of employment by education group

Data source:	NBER-CES	CPS ASEC				
	log(Prod. Emp) (1)	log(Total Emp) (2)	log(Less-than-HS) (3)	log(HS Grad) (4)	log(Some-Coll) (5)	log(4+ Yrs Coll) (6)
Panel 1: OLS						
CNC Exposure	-1.0823***	1.2557**	-1.7875***	-1.2638**	-0.6245	2.2612**
	(0.3740)	(0.5006)	(0.6863)	(0.5574)	(0.6172)	(0.8736)
Dep. var mean	6.1471	6.1051	4.1017	5.1356	4.5220	4.4236
Panel 2: Weighted by annual (total) industry employment						
CNC Exposure	-1.1112***	1.2438**	-1.4369**	-1.4731***	-0.6618	2.3455***
	(0.3664)	(0.4849)	(0.5650)	(0.5348)	(0.5824)	(0.8758)
Dep. var mean	6.1471	6.1051	4.1157	5.1356	4.5220	4.4236
Panel 3: Weighted by initial industry size in 1968						
CNC Exposure	-1.0940***	1.1782**	-1.7582***	-1.4162**	-0.6822	2.0926**
	(0.3672)	(0.4832)	(0.6511)	(0.5457)	(0.5961)	(0.8865)
Dep. var mean	6.1471	6.1051	4.1017	5.1356	4.5220	4.4236
Panel 4: Demographic controls included						
CNC Exposure	-1.0289***	0.8880*	-1.9204***	-1.0301*	-0.3483	2.1073**
	(0.3304)	(0.4884)	(0.6532)	(0.5325)	(0.6345)	(0.8725)
Dep. var mean	6.1471	6.1051	4.1017	5.1356	4.5220	4.4236
Panel 5: Import penentration control included						
CNC Exposure	-1.2679***	1.4036**	-2.3832**	-1.0125	-0.2704	3.3987***
	(0.4320)	(0.6382)	(0.9699)	(0.6459)	(0.7613)	(0.9912)
Dep. var mean	6.1629	6.0793	4.0636	5.1235	4.5232	4.4191
Panel 6: Non-metal manufacturing included as a control group						
CNC Exposure	-0.1239	-0.0420	-1.4948***	-0.8879***	-0.2523**	0.3354**
	(0.0832)	(0.1245)	(0.1446)	(0.1220)	(0.1265)	(0.1477)
Dep. var mean	6.4939	6.3735	4.4367	5.4133	4.7657	4.6759

Note: Outcome variables are log of production workers computed from NBER-CES Manufacturing Industry database (1968-2009) and log of employment by education group in each metal manufacturing industry x year computed from the CPS ASEC sample (1968-2009). 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. Panel 1 is identical to table 2. Panels 2 to 5 are versions of table 2 analysis with different weighting schemes and control variables. Panel 2 is a version of table 2 analysis where each industry-year cell is weighted by the annual industry employment. Panel 3 weights each industry-year cell by the initial industry size in 1968. Panel 4 includes annual demographic characteristics of each industry workforce, share of white workers and share of young workers of age 18 to 35, as control variables. Panel 5 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). Panel 6 includes a non-metal manufacturing group as a control group. N=294, except for panel 5 with N=238 and panel 6 with N=336. Standard errors are robust.
*** = significant at 1%, ** = significant at 5%, * = significant at 10%

Table 6: The effect of CNC exposure on the size of workforce by education and union status

	log(Total Emp)	log(Less-than-HS)	log(HS Grad)	log(Some-Coll)	log(4+ Yrs Coll)
	(1)	(2)	(3)	(4)	(5)
CNC Exposure	-1.2664**	-3.8066***	-3.4201***	-2.5846***	0.2237
	(0.6061)	(0.8016)	(0.7148)	(0.8486)	(0.7817)
CNC Exposure x Union	1.6724	2.6652*	1.5757	2.6258	1.9854
	(1.0285)	(1.4254)	(1.1497)	(1.5961)	(2.2363)
Industry FE	X	X	X	X	X
Union FE	X	X	X	X	X
Year FE	X	X	X	X	X
Union x industry FE	X	X	X	X	X
Union x year FE	X	X	X	X	X
Dep. var mean	5.7573	3.6712	4.8875	4.2342	3.7258
N	490	482	490	490	475

Note: Outcome variables are log of employment by education group in each metal manufacturing industry x year computed from the CPS May Supplement (1973-1983) and CPS Outgoing Rotation Groups (1984-2009) sample. We restrict our sample to prime-age (18-64) men who reported to be employed. The table is analogous to table 2, but it splits the sample in each industry and year (and education group) into a sample with union membership and another without union membership. The log of employment is then regressed to the CNC exposure measure and the exposure measure interacted with an indicator for union membership. All specifications include industry and year fixed effects. Standard errors are robust. *** = significant at 1%, ** = significant at 5%, * = significant at 10%

Table 7: The effect of CNC exposure on the two- and four-year 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	0.2346**	0.0455	0.0555	0.1110***	-0.0459
	(0.0904)	(0.0292)	(0.0434)	(0.0403)	(0.0531)
Industry FE	X	X	X	X	X
Year FE	X	X	X	X	X
Dep. var mean	0.0531	0.0048	0.0163	0.0120	0.0165
N	238	238	238	238	238

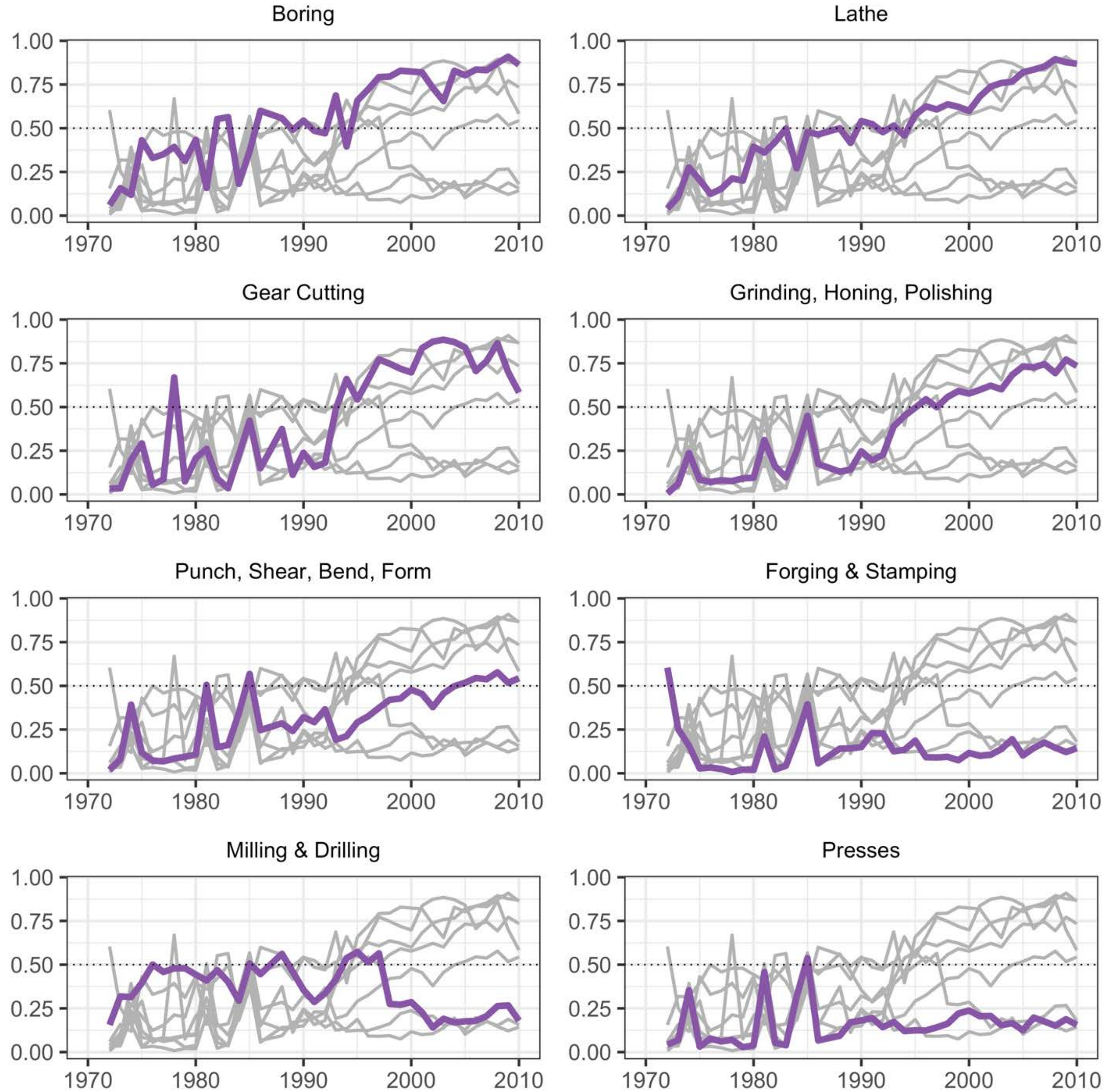
Note: Outcome variables are the annual share of two-year or four-year college enrollment among each metal manufacturing industry workforce constructed from the CPS October Supplement sample (1976-2009). We restrict our sample to prime-age men who do not hold bachelor's degree and whose current or last employment were in 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 8: The effect of CNC exposure on firm location and size

Data source:	CPS ASEC	CBP				
	Share South	Under 20	Under 50	Over 100	Over 250	Over 500
	(1)	(2)	(3)	(4)	(5)	(6)
CNC Exposure	0.1060	0.0319	0.0120	0.0409	0.0145	-0.0070
	(0.0908)	(0.0783)	(0.0672)	(0.0523)	(0.0369)	(0.0286)
Industry FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Dep. var mean	0.2037	0.5978	0.7663	0.1445	0.0669	0.0333
N	294	245	245	245	245	245

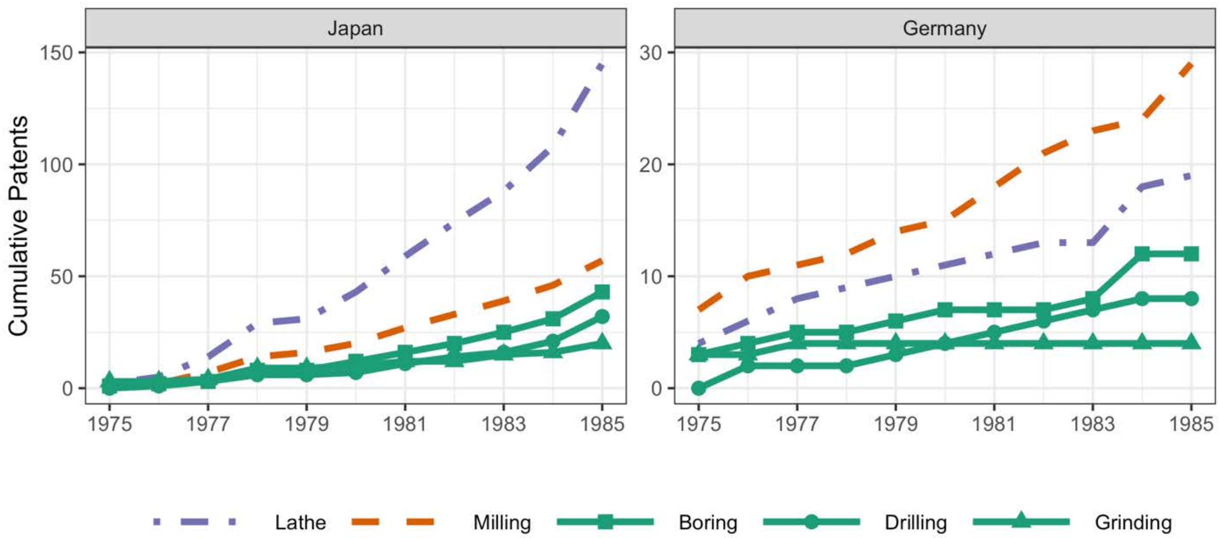
Note: Outcome variables are annual share of workforce located in the Southern states by each metal manufacturing industry computed from the CPS ASEC samples (1968-2009) on column 1 and annual shares of firms in each firm size bin from the County Business Patterns (1968-2009) on columns 2-6. All specifications include industry and year fixed effects. Standard errors are robust. *** = significant at 1%, ** = significant at 5%, * = significant at 10%

Appendix Figure 1: CNC Share by Machine Tool Type for Italy



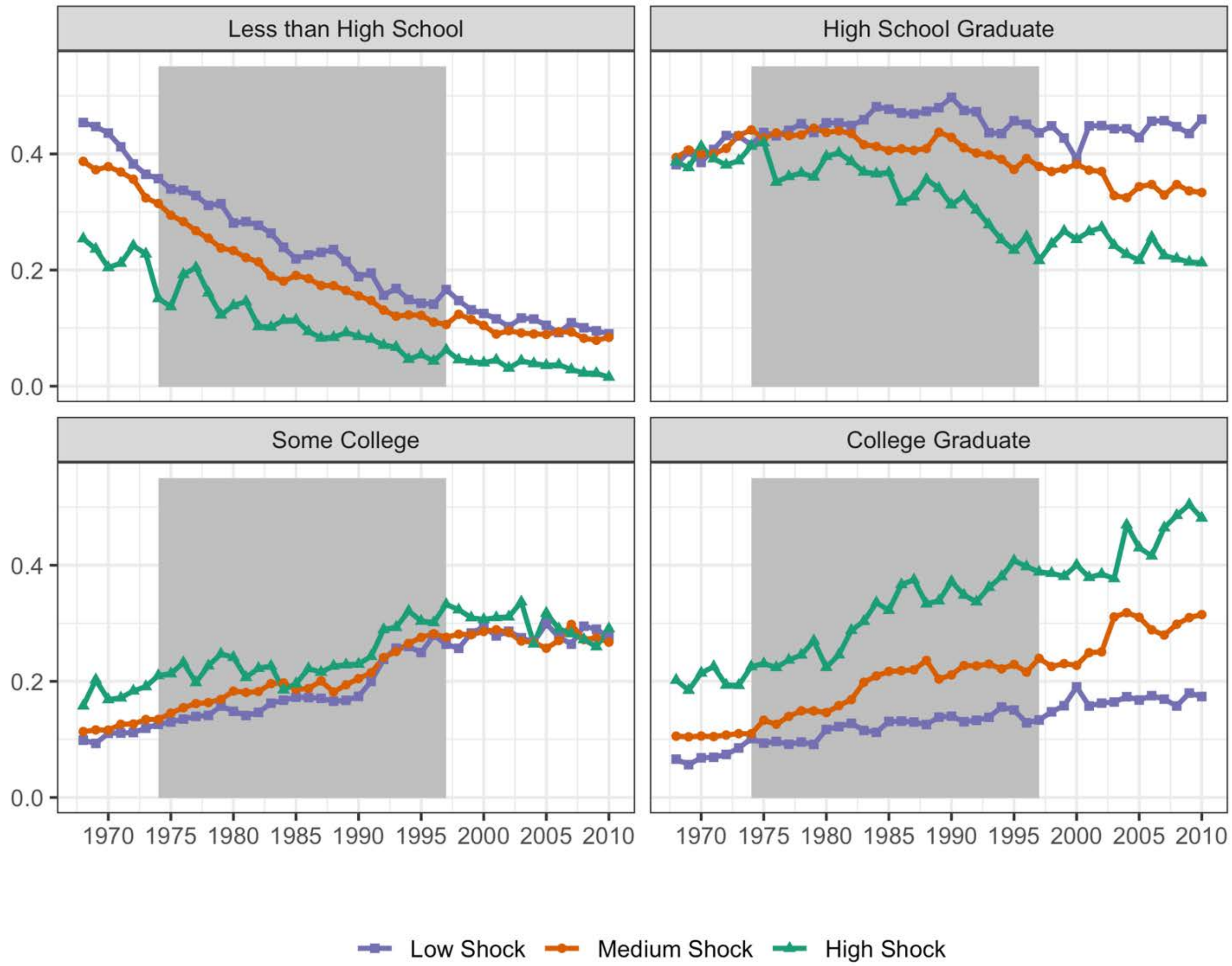
Notes: This figure presents the annual CNC shares of exports by tool type for Italy. See Figure 1 in the paper for Japan and Germany. The data come from volumes of the *Economic Handbook of the Machine Tool Industry* as described in section III.

Appendix Figure 2: CNC-Related Patent Counts by Tool and Country



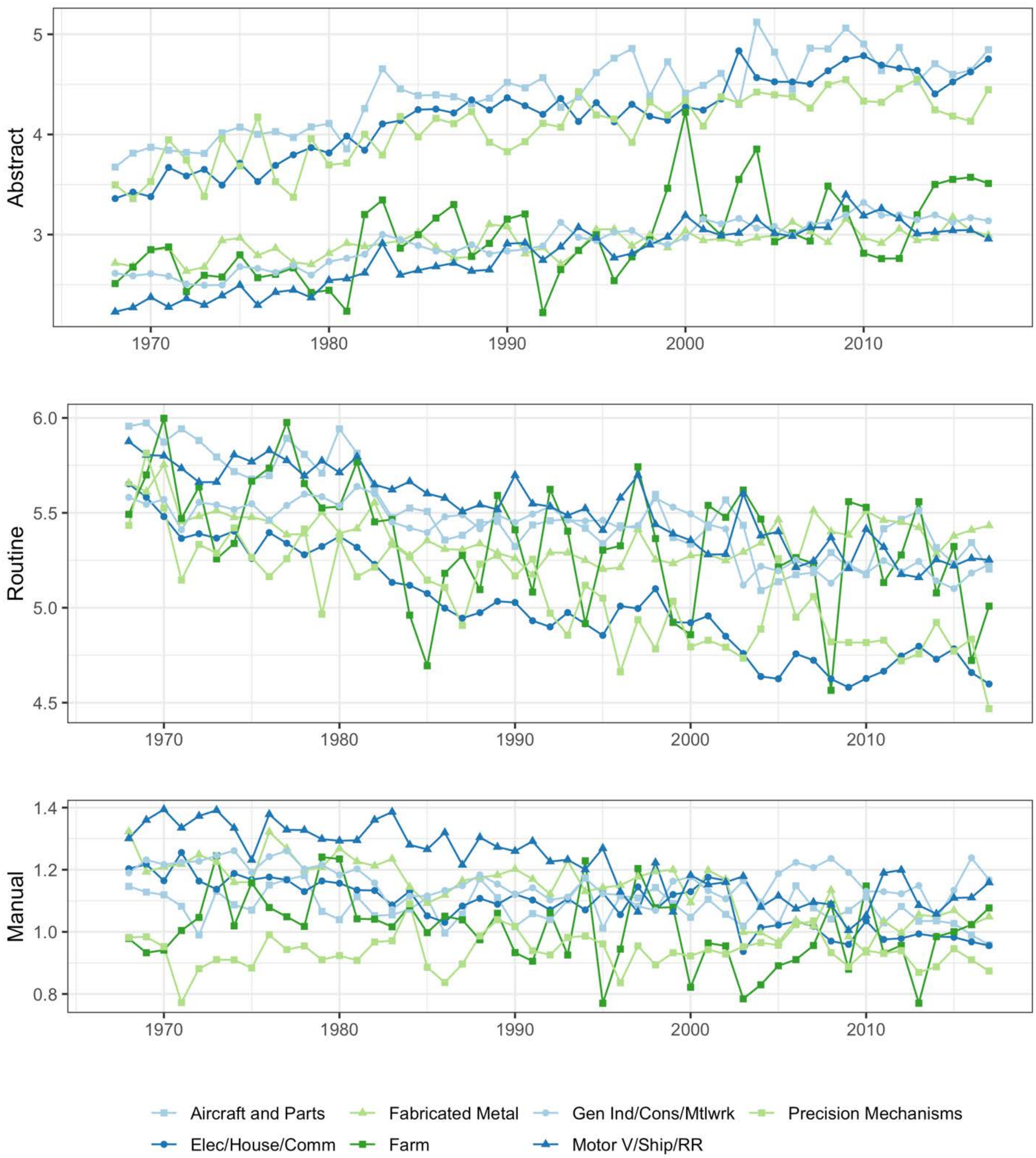
Notes: We began with a list of all US utility patents created for Kogan et al (2017) to scrape the digitized text from Google Patent. It is common for innovations created outside the United States to be patented in the US. Data from Lai et al (2011) provides the country of the grantee for each patent. 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 3: Education Group Shares of Employment by CNC Shock Intensity



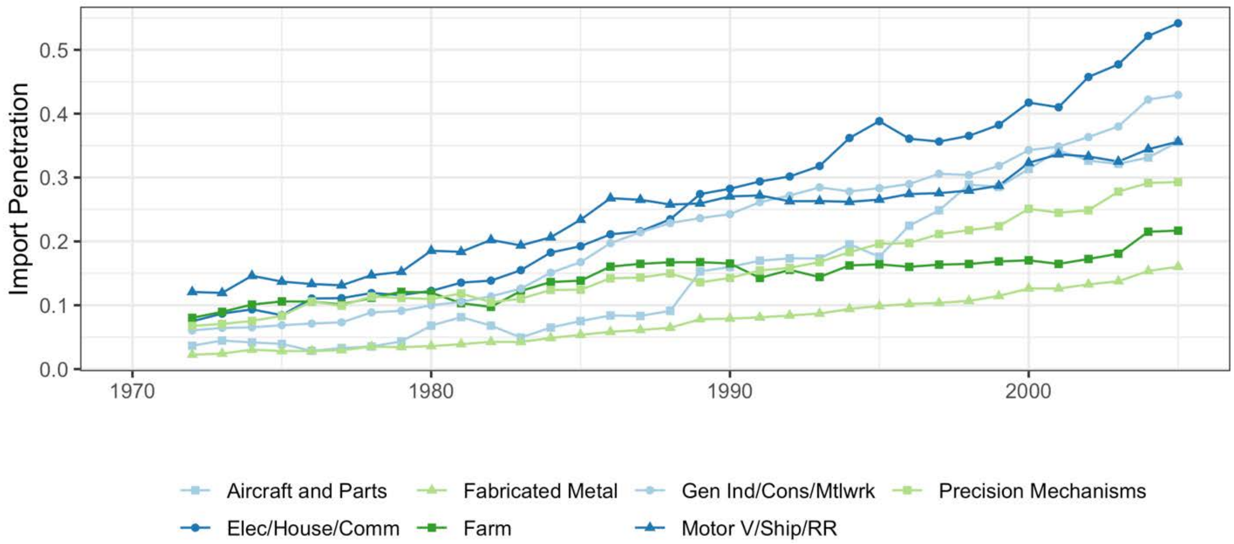
Notes: Industries partitioned into groups according to the intensity of the CNC shock they experience. Low shock industries are motor vehicles and fabricated metals; Medium shock industries are electronics, farm equipment, and general industrial equipment. High shock industries are aircraft and precision mechanisms. The shock was most intense from 1974 to 1997, as shown by the gray box.

Appendix Figure 4: Average Task Scores of Occupations by Seven Metal Manufacturing Industries



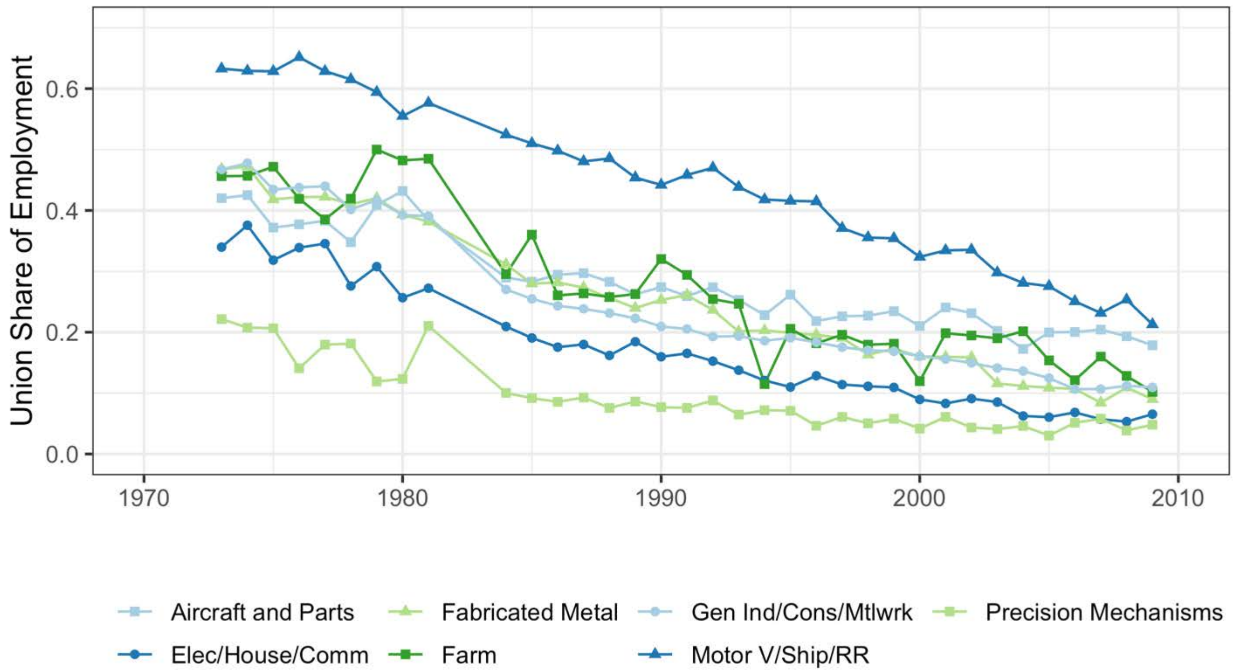
Notes: Task score for occupation are from Autor, Levy, and Murnane (2003). Workers in metal manufacturing in the *CPS Annual Social and Economic Supplement* are assigned the task scores corresponding to their occupations. We then compute averages for each of the seven metal manufacturing industries by year.

Appendix Figure 5: Import Penetration by Seven Metal Manufacturing Industries



Notes: Import penetration computed using trade data from Schott (2008) and the definitions found in Campbell and Lusher (2019). Import penetration is the share of imports in US domestic sales in each industry.

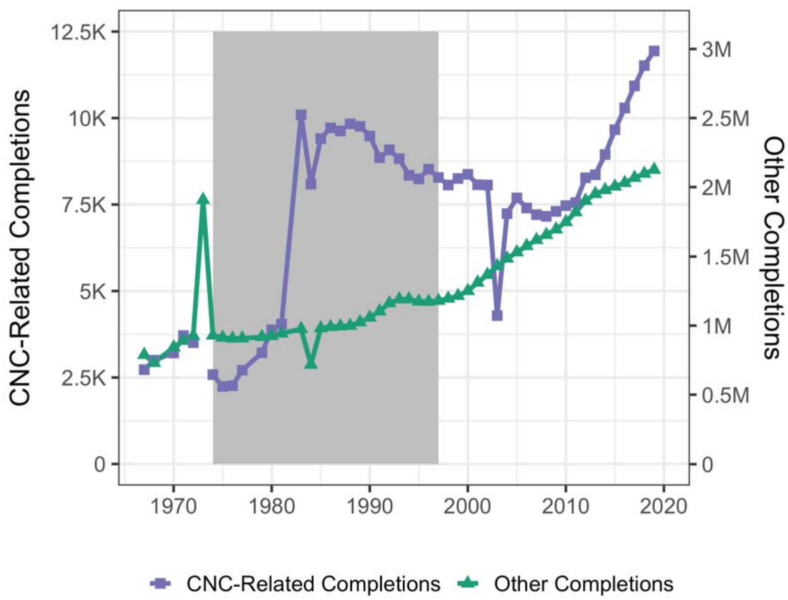
Appendix Figure 6: Union Share by Seven Metal Manufacturing Industries



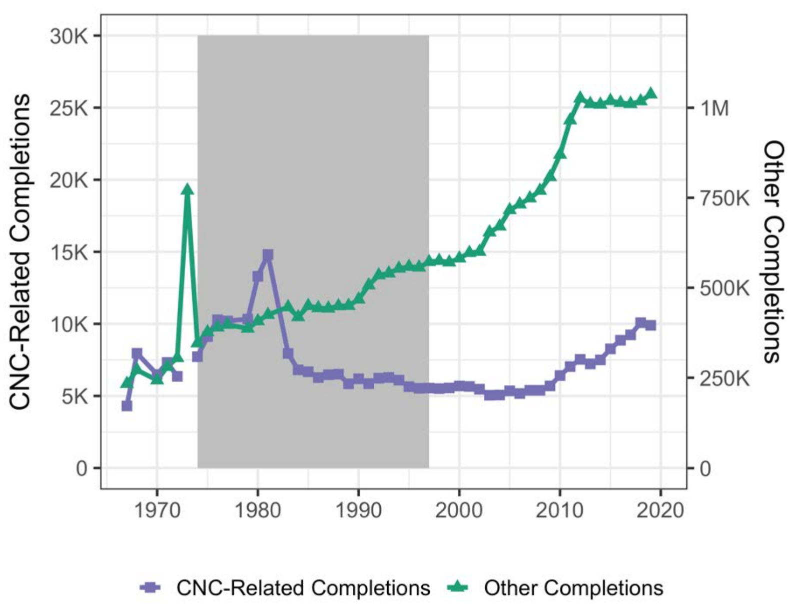
Notes: Average share of workers in each of the seven metal manufacturing industries belonging to a union. The share is computed from the CPS May Supplement (1973-1983) and CPS Outgoing Rotation Groups (1984-2009) sample.

Appendix Figure 7: CNC-Related Degree and Program Completions by Degree Type

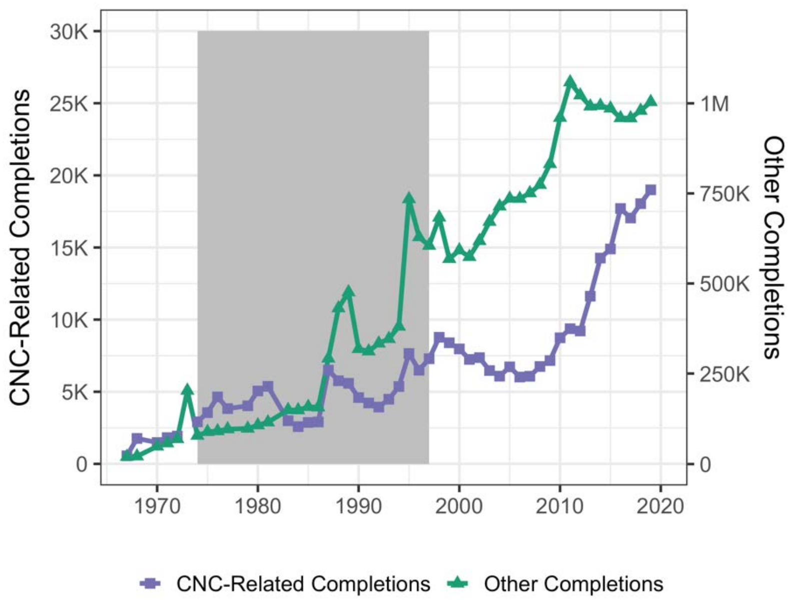
Panel A: Bachelor's Degrees



Panel B: Associate Degrees



Panel C: Certificate Programs



Notes: The figure shows the number of completed degrees and program 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. The gray box shows the period 1974-1997 during which the CNC shock was most intense.