Anatomy of Automation: CNC Machines and Industrial Robots in UK Manufacturing, 2005-2023

Aniket Baksy
University of Melbourne

Daniel Chandler
LSE

Peter John Lambert
LSE & University of Warwick

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Abstract

Using a novel proprietary survey of UK manufacturing sites, we study the impact on employment of arguably the two most important industrial automation technologies of the past fifty years: computer numerical control (CNC) machine tools and industrial robots. First, we document the growing prevalence of both technologies across a wide range of industries between 2005 and 2023. Second, we use a local-projection difference-in-difference design to show that plants that adopt these technologies for the first time increase their employment by 6% to 9% compared to non-adopting plants in the same industry. Third, we find that for both technologies, automation is associated with an increase in employment among industry-competitor sites, and a positive overall impact on industry-level employment.

Keywords: Automation, Manufacturing, Employment, Technology Adoption, Robots
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1 Introduction

How does automation affect employment? Recent advances in artificial intelligence have heightened both hopes and fears about the consequences of technological progress for workers and society more broadly. There is widespread concern that new technologies will displace workers, leading not just to temporary disruption, but to a secular decline in labour demand, putting downward pressure on wages and employment. And yet, historically, such displacement effects have typically been accompanied by improvements in productivity and the creation of new products and labour-intensive tasks, driving up the demand for labour (Autor 2015). Which of these channels dominates is fundamentally an empirical question.

In this paper, we examine how the widespread adoption of computer numerical control (CNC) machine tools and industrial robots in the UK economy since 2005 affected employment. CNC machines are programmable tooling devices that cut, drill, or shape materials (typically metals) into precisely defined components. They have been widely available since the 1980s and play a foundational role in modern manufacturing. Industrial robots, by contrast, are programmable machines designed to manipulate objects with considerable spatial flexibility. They typically operate across multiple axes using motors and sensors to guide their movements, and are commonly used for tasks such as assembly, welding, packaging, and material handling. While CNC machines are generally used to transform raw materials into components through precision machining, industrial robots are more often deployed in later stages of production to assemble or move those components. Together, these technologies represent two of the most important and widely used forms of industrial automation in recent decades.

This paper makes three main contributions. First, we introduce novel evidence on the use of these manufacturing technologies from a proprietary survey of manufacturing establishments in the United Kingdom between 2005 and 2023. This dataset, produced by the Mark Allen Group, contains information on plant-level stocks of CNC machine tools and (from 2014) indicators for the use of industrial robots on site. Crucially for our purposes, it also includes site-level information about total employment and, separately, the number of workers by broad occupational groups, including manufacturing workers.

We establish that our dataset is broadly representative of the UK manufacturing sector, closely tracking statistics obtained from the UK's statistical agency, the Office for National Statistics (ONS). We also document an increase in the use of both technologies over the period we study: the share of manufacturing production plants using CNC machines increased from about 46% in 2004 to nearly 56% in 2023, while the share of employees who work in such establishments increased from about 52% to 62%. We find that the share of plants using industrial robots has increased from about 4% in 2014 to 6% in 2023, while the share of employees working in such plants increased from around 15% to more than 25%, indicating that robot adoption has been skewed towards large plants.

Second, we use modern differences-in-differences event study methods to study the impact of CNC machine and industrial robot adoption at the extensive margin on a firm's workforce. In our preferred specification, we find that plants that adopt CNC machines for the first time increase their total employment by about 6% over the subsequent four years, compared to non-adopting plants in the same industry. Plants that adopt industrial robots for the first time also see employment increase by around 8% in the years following adoption. We find that treated plants which experience an "adoption event" exhibit broadly similar pre-treatment trends to those that do not; while the substantial cost and planning involved in adopting such technologies makes it unlikely that our results are being driven by contemporaneous shocks affecting both technology adoption and employment. Unlike much of the literature, we do not find any significant impact on the share of manufacturing workers after adoption events.

For CNC machines, we can also look at the impact of "expansion events", which occur when a plant increases the total number of CNC machines from an already positive number. We find that these events are associated with a larger increase in total plant employment than initial adoption, and a notable reduction in the share of manufacturing workers. This pattern is consistent with a learning-based view of technology adoption, in which experienced firms are better able to take advantage of new technologies, leading both to larger gains in productivity and employment, and a deeper reorganisation of their production processes (e.g. Atkeson and Kehoe 2007).

Third, we explore the dynamics of worker reallocation across companies and industries. We first look at the impact of firm-level automation events on employment among competitors firms within the same industry. We find evidence of positive spillovers, in the sense that adoption in one plant is associated with an expansion of employment among peer firms. In order to capture the overall impact of automation on industry level employment, we adapt our main event-study specification to study industry-level automation events, defined as a relatively large annual change in the share of employees working in companies that use a given technology, compared to all year-on-year changes. Although our results vary depending on the threshold used to define an industry level event, we find positive industry level employment effects in all specifications, with varying degrees of statistical significance. These results suggest that, at least in the UK manufacturing context, the broader effects of automation on employment may be more benign than is often feared.

Related Literature. Our paper contributes to a small but growing empirical literature that uses firm-level data to look at the labour market effects of various modern technologies (for a recent overview see Aghion et al. (2023a) and Restrepo (2024)). The papers in this literature span a range of countries and recent time-periods, and study a variety of technologies, with a particular focus on industrial robots. Most use event-study designs similar to our own, though a handful combine this with a more explicitly causal approach.[1]

As in our study, this literature consistently finds that investment in new technologies is associated with an increase in total employment at focal (adopting) companies (Aghion et al. 2023a).[2] The literature is more divided when it comes to the impact on specific occupational groups. Most studies, including all those looking at industrial robots, find that investment in new technologies is associated with a reduction in employment (and in some cases wages) for "exposed" occupations, typically lower-skilled and/or manufacturing workers (Bessen 2019, Humlum 2021, Acemoglu and Restrepo 2020); but other recent studies find no evidence of differential effects on different skill groups (Curtis et al. 2021, Hirvonen et al. 2023, Aghion et al. 2023c). Our results – that expansion but not adoption events are associated with a decline in the share of manufacturing workers – suggest that the impact of automation technologies on exposed groups of workers may increase as companies accumulate experience with a given technology.

While the studies discussed above examine the effects of technology adoption within firms, a largely separate literature focuses on the impact of automation on employment at the industry or labour market level. This literature has produced mixed results. For example, Acemoglu and Restrepo (2020) find that the addition of one industrial robot per 1,000 workers in U.S. commuting zones reduces the employment-to-population ratio by 0.4 percentage points; whereas Dauth et al. (2021), using a similar approach in Germany, find no adverse effect on regional employment. At the cross-country level, Graetz and Michaels (2018) find no aggregate employment effect of robot adoption across 17 developed economies, while Klenert et al. (2023), using similar methods for 14 European countries, find positive correlations between robot adoption and employment. Other studies, such as Webb (2020), Mann and Püttmann (2023), Kogan et al. (2023), use patent-based measures of exposure to assess occupational risk, but also reach inconsistent conclusions about aggregate employment effects. The only previous study to focus specifically on CNC adoption at the industry

[1] Aghion et al. (2023c) use a shift-share IV design leveraging pre-determined supply linkages and productivity shocks. Hirvonen et al. (2023) use a quasi-experimental design comparing companies that secured access to a government subsidy programme with those that narrowly lost out.

[2] Studies which also have access to information about firm-level sales and productivity find that this increase in employment is associated with rising sales and productivity. Some of these studies also look at the impact on wages, and typically find no significant effect.

level is Boustan et al. (2022), who find that industries more exposed to CNC technologies experienced increases in investment, productivity, and employment, with gains for college-educated workers offsetting losses among less-educated ones.

We see our contributions to this literature as threefold.

First, we are able to exploit direct plant-level measures of two critical automation technologies: CNC machines and industrial robots. Most recent papers with access to firm-level data rely on composite measures of technology such as the total value of manufacturing capital (Aghion et al. 2023b,c) or investment in third party automation services (Bessen et al. 2023). As Aghion et al. (2023c) argue, these broad measures can help give us a sense of the impact of typical investments in manufacturing capital. But the impact of new technologies depends critically on their particular characteristics, and the degree to which they are used to displace workers rather than, say, create new products. A better understanding of the effects of modern technologies on labour markets must study the characteristics and abilities of specific technologies. Moreover, while there is now a fairly large literature looking at the impact of industrial robots, studies of CNC technology are surprisingly rare, given their huge importance for modern manufacturing. To the best of our knowledge, ours is the first paper to use firm-level data on CNC use across a wide range of industries.[3]

A further advantage of our data is that we can isolate adoption events, when a plant starts using a given technology for the first time, and in the case of CNC machines distinguish them from "expansion" events, when plants increase their use of CNC machines from an already positive baseline. Other papers, which typically use price-based measures of technology investment, cannot distinguish investment at the extensive margin – which involves the deployment of a new machine in tasks previously performed by humans, and is the canonical definition of automation, at least within the task framework – from investment at the intensive margin, which seeks to increase the productivity of capital in existing tasks. Our focus on adoption events, then, provides a cleaner empirical analogue to automation. At the same time, being able to compare the effects of adoption and expansion for CNC machines allows us to test the predictions of learning-based models of technological change (Atkeson and Kehoe 2007).[4]

[3]Of the two recent papers focused on CNC machines, Boustan et al. (2022) only have access to industry level data, while Bartel et al. (2007) have access to plant-level data for the US valve manufacturing sector only. Bartel et al. (2007) find that plants adopting CNC tools improve the efficiency of all stages of the production process by reducing setup times, run times, and inspection times; see increases in the skill requirements of machine operators and the adoption of new human resource practices; and shift their business strategies towards more customized products.

[4]Another advantage of measuring technology use directly is that changes in price-based measures may simply reflect shifting prices rather than changes in technology use in a given company. A downside is that we are unable to account for changes in the quality of machines across firms or over time.

Our second key contribution is to provide a unified analysis of the implications of technology adoption at the firm and industry levels. This is clearly not possible for papers using aggregate-level data, while many papers with firm-level data have focused exclusively on firm-level outcomes (Bessen et al. 2023, Dixon et al. 2021, Koch et al. 2021). A number of papers with access to firm-level data have studied the impact of automation at one firm on "competitors" in the same industry and, like us, find negative spillover effects (Acemoglu et al. 2020, Koch et al. 2021, Aghion et al. 2023c). But few have looked at the overall impact on industry or area-level employment. An important exception is Aghion et al. (2023b,c), who use French firm-level data to look at the impact of investments in manufacturing capital on firm, industry and labour market outcomes, finding positive employment effects at all levels. Addressing these different levels of analysis within a single empirical setting is critical for understanding the relationships between firm-level effects, and wider general equilibrium implications.

Our third contribution is simply to provide the first UK-based study of automation in the manufacturing sector using firm-level data. Studying different countries is valuable because, as we discuss in more detail below, the impact of automation depends not simply on the technology in question, but on the wider labour market context. In other words, we cannot simply assume that the broad effects of robot adoption on aggregate employment in (say) the US or Germany will carry over to the UK. As we gather more data points from different countries and labour markets, we can better understand the contexts in which new technologies are likely to lead to positive or adverse effects for different groups.

This paper is structured as follows. Section 2 provides background on CNC machines and industrial robots. Section 3 outlines the task-based conceptual framework that guides our analysis. Section 4 describes our data and benchmarks it against UK administrative data. Section 5 outlines our empirical approach, and section 6 outlines our results. Section 7 studies spillover effects. Section 8 concludes.

2 Background: CNC machines and industrial robots

In this section, we provide background on the history of CNC machines and industrial robots, and their distinctive role in modern manufacturing.

At the most fundamental level, manufacturing is a process by which parts or pieces of raw materials are cut, drilled, bent and shaped into desired shapes to produce components. These components are then assembled to produce manufactured goods. Machine tools are a broad class of machines which fulfil the first step of this process, typically through a subtractive process which removes material from the workpiece until the desired shape is achieved. Their importance for manufacturing is difficult to overstate: they are sometimes described as the "mother" machine, since, as Holland (1989b, 2) memorably put it, "every manufactured product is made by a machine tool or by a machine that was made by a machine tool".

Prior to the development of machine tools, manufacturing was the domain of skilled artisans who performed the entire range of tasks associated with the production of a final good from raw material. The late 18th and 19th century saw a paradigm change, as manufacturing embraced standardisation and specialisation, and production processes were redesigned to focus on producing large numbers of interchangeable components, which were then assembled into final products (National Research Council 1995). As a result, manufacturing jobs were increasingly devoted to repeatedly performing the same task. Critical to the adoption of this system was the availability of special purpose machine tools built specifically for each task (Jaikumar 2005). [5]. These tools were, however, manual in their operation, controlled fully by their operators.

This started to change with the invention of numerical control (NC) machines in the 1950s and 1960s, and their widespread adoption throughout the 1970s[6]. Rapid developments in computing, including the creation of computer-aided design technologies, led to the birth of the first true computer numerical control (CNC) machines, displacing the punched cards used by NC machinery.[7] The first CNC tools designed for wide commercial application were developed in Japan in the late 1960s and their worldwide diffusion accelerated in the 1980s and 1990s[8]. Rapid improvements in both microprocessor technology and Computer-Aided Design (CAD) software in the 1980s transformed the capabilities of these machines and radically simplified the design process, leading to their widespread diffusion. CNC machine tools offer increased precision and repeatability, and significantly reduced the set-up times

[5]Mechanisation yielded massive improvements in productivity, particularly when combined with the managerial and organisational changes that were taking place alongside it. Bright (1958) shows, for example, that lamps produced per operator per day rose from 160 in the 1910s and 20s, to 800 in the 1920s and 30s, and to 2,700 by the 1950s.

[6]In 1966, a report by the US National Commission on Technology, Automation and Economic Progress heralded the invention of NC machine tools as "probably the most significant development in manufacturing since the introduction of the moving assembly line" (Lynn et al. 1966)

[7]The first CNC machine was created at MIT in 1952, as part of a contract with the US Air Force to create high-precision helicopter parts. Ross (1978) describes the development of the Automatically Programmed Tool programming language, which was incorporated into a numerical control system in collaboration with the US Air Force by 1957 and demonstrated publicly in 1959.

[8]As Boustan et al. (2022) show, CNC machinery was adopted more quickly in some industries than others, reflecting the differential pace at which the underlying technology was developed for different tool types and actions, like lathing, drilling and so on.

needed to adjust and prepare a machine between different tasks.

Industrial robots can perform many of the same tasks as CNC machine tools, such as drilling, cutting or bending. But their distinctive feature is their spatial flexibility, and their ability to move and manipulate objects in a variety of ways. Whereas CNC machine tools are mainly used in the production of parts, industrial robots are typically used for welding, sorting, painting and a variety of other tasks needed to assemble parts into final products.[9] The first industrial robots were created in the 1950s, and their use expanded during the 1960s and 1970s, especially in the automotive sector, but it is only since the 1990s that they have started to be used across a much wider range of applications including electronics, food processing, logistics, and precision engineering. As with CNC machines, industrial robots have benefited from advances in computing, as well as the development of sensors and machine vision, and recent developments in artificial intelligence continue to transform their capabilities, allowing increasing precision and flexibility.

What can we take from this brief history for thinking about the impact of the growing use of CNC machines and industrial robots in modern manufacturing? First, it's clear that both CNC machine tools and industrial robots are "automation" technologies, in the sense that they are designed to replace humans in performing specific tasks. Second, these technologies typically apply to different parts of the production process, and hence may have different implications for employment: as Boustan et al. (2022) argues, CNC machines primarily automate the work of skilled machinists with advanced motor skills, as well as lower skilled machine setters and set-up operators; while industrial robots tend to automate lower skilled jobs requiring gross motor skills connected to assembly, welding, packaging processes. Third, CNC machines are a more mature technology than industrial robots and, as we shall see in our data, are much more widely diffused across the manufacturing sector. This is relevant for thinking about learning effects, since there is likely to be a much greater stock of accumulated experience with CNC machines than for robots.

3 Conceptual Framework

For many years, the dominant approach in the theoretical literature on automation was the canonical *factor-augmenting* framework. In this view, technological progress raises the productivity of a given factor—capital, skilled labour, or unskilled labour—uniformly across

[9] The International Federation of Robotics defines industrial robots as "automatically controlled, reprogrammable multipurpose manipulator, programmable in three or more axes, which can be either fixed in place or fixed to a mobile platform for use in automation applications in an industrial environment".

all tasks.[10] Within this framework, which dates back to Tinbergen (1974), and was developed in detail by Katz and Murphy (1992) and Goldin and Katz (2008), new technologies are generally viewed as benign in their effects on labour markets: they raise productivity, boost labour demand, and leave the labour share of income broadly unchanged, at least under realistic values for key parameters.

But as Acemoglu and Restrepo (2022a) argue, this model lacks descriptive realism. Most technologies do not improve the productivity of a factor across the board. Instead, they tend to enhance performance in specific tasks while leaving others unchanged—or, in the case of automation, replacing workers altogether in some tasks. The factor-augmenting model cannot easily capture this task-specific nature of technological change, nor the displacement of workers that is central to public and scholarly concerns about automation. Nor does it align with a growing body of empirical evidence showing that many new technologies have coincided with declining real wages and employment for exposed workers, as well as a falling labour share overall.

These limitations have led to the development of the *task-based* framework, which forms the theoretical foundation of this study. In this framework, production is understood as a set of tasks that can be performed by either human labour or capital, depending on their relative productivity and cost. Automation refers to the reallocation of specific tasks from human labour to machines. Crucially, this framework allows us to distinguish automation from two other forms of technological progress: the creation of new tasks (which can boost demand for labour) and improvements in the productivity of capital at tasks it already performs (so-called *intensive margin* progress, which does not directly displace workers). While all these forms of technological change can raise productivity, only automation—as defined here—entails a direct displacement of labour.

Automation technologies trigger two competing forces. The first is a *displacement effect*, which reduces demand for workers who previously performed the automated tasks. The second is a *productivity effect*, which makes production more efficient by lowering costs and reallocating tasks, potentially enabling firms to expand output. Whether employment rises or falls depends on the balance of these forces. Importantly, this is not something that theory alone can determine—it is an empirical question.

The task-based framework also makes clear that the impact of automation can differ significantly depending on the level of analysis. At the *firm level*, automation may reduce the number of workers needed for particular tasks but increase overall productivity. If demand for the firm's output is elastic, these productivity gains can lead to firm expansion and

[10] The following discussion draws on Acemoglu and Restrepo (2022a) and Restrepo (2024).

net employment growth. While the impact of automation on total company employment is ambiguous, according to the task-based framework it should lead to a decline in the employment share of "exposed" occupations whose tasks are directly replaced by machines.

At the *industry level*, automation can trigger a range of spillover effects that shape employment dynamics beyond the adopting firm. On the one hand, automation may lead to a reallocation of output toward more efficient producers, leading to job losses in non-adopting firms—what the literature refers to as "business stealing"—especially if industry-level demand is inelastic. If these negative spillovers are strong enough, this could lead to a decline in industry-level employment, even if automation leads to an increase in employment among focal plants. On the other hand, automation may also generate positive spillovers: by lowering prices and expanding overall demand, raising demand for complementary goods and services, or inducing learning and productivity gains through demonstration effects. At the *regional or labour market level*, aggregate employment outcomes reflect not only these firm and industry dynamics but also a wider set of general equilibrium effects including, among other things, how easily displaced workers can transition to new jobs.

These insights help clarify the motivation for this study. First, the task-based framework explains why the impact of automation on employment is theoretically ambiguous and must be resolved through empirical analysis. Second, it highlights that the effects of automation can diverge across firms, industries, and regions, making it essential to track these dynamics at multiple levels of aggregation. And third, it underlines the importance of focusing on specific technologies and distinguishing automation from other forms of technological change. A key advantage of our study is that we are able to track the adoption of two of the most important automation technologies of recent decades. Moreover, we directly observe "adoption" events—the first time a firm introduces a given technology—which provides a clean empirical analogue to the concept of automation at the extensive margin, as opposed to other forms of technological investment.

While the task-based framework offers a powerful conceptual tool for thinking about how automation reshapes the allocation of tasks between labour and capital, it typically abstracts from the dynamic processes through which firms adjust to new technologies.[11] In particular, it overlooks the fact that adopting and integrating automation may itself be a gradual process, involving costly experimentation, reorganization, and learning. Learning-based models, such as those developed by Atkeson and Kehoe (2007), emphasize that initial adoption is only the first step in a lengthy "learning-by-doing" process, during which firms

[11] While the learning dynamics discussed below are not modelled explicitly in the canonical task-based framework, they are not incompatible with it.

accumulate the complementary human and organizational capital needed to fully exploit a new technology. As a result, the benefits of automation may unfold gradually, with later investments yielding larger effects on productivity and employment than initial adoption.[12] As we will argue in Section 6, this provides a compelling account of why "expansion" events – when companies increase their use of CNC machines from an already positive baseline – may yield stronger effects than first-time adoption.

4 Data: The MAG Manufacturing Survey

A central challenge in automation research has been gaining access to firm-level data on technology adoption. In this paper, we have access to such data through the Mark Allen Group (MAG) Manufacturing Survey, a private census of UK manufacturing plants that has been updated continuously for over 30 years, and which we have access to from 2003 to 2023.[13] MAG is a media and information company that, among other things, publishes more than one hundred industry-focused publications across a wide range of sectors. It sells access to its manufacturing survey to clients who use it to target advertising and for sales prospecting by post, phone, and email. This exerts a strong market discipline on data quality, since clients rely on the accuracy of the information for commercial targeting, and errors would quickly be discovered, undermining MAG's reputation.

The MAG survey is conducted through a series of telephone interviews, and seeks to provide a comprehensive picture of manufacturing sites in the UK. As we can see in Figure 1, the MAG data largely mirrors the aggregate decline in total manufacturing employment that is observed in official national statistics over the past twenty years. Table A1 shows that the MAG survey captures around 80% of total annual manufacturing employment on average from 2005 to 2023, with a sharp decline in coverage during the Covid-19 pandemic; while Table A2 shows that most of the gap in coverage comes from missing plants with fewer than 10 employees. Although the raw MAG data is not perfectly representative of the national manufacturing sector, this is not a serious issue since our analysis is focused on within-plant changes in technology and employment.

[12] As Atkeson and Kehoe (2007) show, learning-based models can help explain key facts about previous periods of rapid technological change, including the long lag between technological innovations and improvements in productivity, the slow diffusion of new technologies, and continued investment even in mature technologies, such as CNC machines. In their calibrated models internal innovations among existing users can exceed those at the technology frontier. For a discussion of similar ideas in relation to artificial intelligence see Brynjolfsson et al. (2019).

[13] The survey was created and run by Findlay Media Limited until 2014 when it was acquired by Mark Allen Data Services (MADS), a subsidiary of the Mark Allen Group. For further information about MAG, see https://www.markallengroup.com/

For each surveyed site, the data includes the company name (note that companies can include multiple establishments), whether the company is part of a group, the postcode within which the site is located, detailed industry codes, the total number of employees at a given site, and the number of employees in four key sub-groups: manufacturing production, factory services, engineering design and electronic design. The survey also includes the self-described "primary product" manufactured at the site, as well as information about key supplier relationships, including whether a plant makes its own products and/or performs subcontract work for others, and whether they supply the aerospace, automotive or defence sectors.

The unique feature of this dataset is that it contains rich plant-level information about the use of key technologies. Of particular interest is data on the number of machine tools, broken down into Computer Numerical Controlled (CNC) versus non-CNC machine tools; and a binary variable recording whether a plant makes use of industrial robots.[14] MAG has collected data about CNC machine tools since 2003, while data on industrial robots was added in 2012. However, we only use data on technology use from 2005 and 2014 respectively, since most sites are interviewed at least once every three years, allowing us to construct a reasonably accurate baseline of machine use.[15] In the subsequent analysis we limit our sample to manufacturing production sites, defined as sites that use some kind of mechanical tool. Dropping sites that never report positive tool usage in any period reduces our sample by about 40%. These non-tool using sites are likely to represent a combination of corporate offices, sales rooms, wholesalers and intermediary firms that are connected to manufacturing and hence of interest to MAG's customers, but not relevant to our analysis.[16] We also impute missing values of key employment and tool use variables using a carry-forward imputation.

[14]MAG also collect more detailed information about these technologies, which we do not currently have access to. For example, they gather data about the number of CNC and non-CNC tools used for cutting vs forming, as well as a breakdown of whether a plant uses machine tools for various specific activities including drilling, grinding, milling, bending and/or pressing. They also collect a more detailed breakdown of industrial robots into four categories: Automated Handling or Storage Systems; Assembly/Welding Robots; Painting/Finishing Robots; Collaborated Robots. In recent years, they have started collecting data about the use of 3D Printing Machines and Plastics Machines.

[15]When a new question is introduced, every site is recorded as either having 0 or a positive number of tools. As a result, we cannot directly distinguish plants that have no tools from those that have not yet been sampled since the question was introduced. Since most plants are sampled at least every three years, we only use technology data from the third year after a question has been introduced.

[16]In practice, whether or not we include these sites does not make a significant difference to our results.

4.1 Levels and trends in CNC and industrial robot use

Table 1 provides some descriptive statistics about our dataset, focusing on the manufacturing production sites that are the focus of the subsequent analysis. Our data contains 368,914 site-year observations, covering 26,974 unique sites. Of these sites, just under half use CNC machine tools at some point, while just over 6% use industrial robots. Consistent with the wider literature, we find that plants that use these advanced technologies have more employees than those that do not, though the difference is much larger for industrial robots than for CNC machines: plants that have at least one CNC machine employ 79 people on average, compared to 76 across all plants; whereas plants with robots have 234 employees on average.

Although CNC machine tools were already a relatively mature technology by the early 2000s when our data begins, the past 20 years have seen a continued increase across industries. Figure 2a shows that the share of manufacturing production plants using at least one CNC machine increased from about 47% in 2005 to nearly 56% in 2023, while the share of employees who work in such establishments increased from about 52% to 60%. The share of plants using industrial robots has increased from barely 4% in 2014 to 8% in 2023, while the share of employees working in plants that use industrial robots jumped from around 14% to more than 27% over the same period.

As we can see in Figure 3, these technologies are used more heavily in some parts of manufacturing than others. CNC machines are most prevalent in metal-heavy sectors like mechanical engineering, motor vehicles and metal manufacturing, where a clear majority of workers are employed in plants with at least one CNC machine. Industrial robots are heavily used in many of the same metal-heavy sectors, but also in other sectors where CNC machines play little role. In the "food, drink and tobacco" sector, for example, almost 43% of employees work at sites with industrial robots, compared to just 2.5% for CNC machine tools. These differences likely reflect the different capabilities of these technologies: while CNC machines are designed to cut and shape metal, industrial robots have a much wider range of possible applications. As we can see in Figure 4, most manufacturing sectors have seen an increase in the use of both technologies during this period, albeit at different rates.

Our empirical strategy, which we discuss in the following section, takes advantage of the growing diffusion of these technologies over the past twenty years. Variation in the pace of technology adoption across industries highlights the importance of controlling for industry-level employment trends that might otherwise confound our estimates.

5 Empirical Approach

In this section we describe our empirical strategy for estimating the impact of the growing use of CNC machines and industrial robots on plant-level employment. We exploit the rich panel structure of our dataset using an event-study design, comparing the evolution of employment at focal plants after an "automation event" with a control group of non-automating sites. We do this using the Local Projection Difference-in-Differences (LP-DiD) estimator proposed by Dube et al. (2023), which addresses some of the well-known issues with standard two way fixed effects estimators in settings like ours with staggered treatment timing and heterogeneous treatment effects.

5.1 Automation Events

We study the effect of two distinct types of automation event: **adoption events**, which occur when a firm acquires a given technology for the first time, and **expansion events**, which occur when a firm increases its stock of that technology having already adopted it in an earlier year.

Formally, we define an adoption event using a binary treatment variable $D^{adopt}_{i,t,A} \in \{0,1\}$, which switches from 0 to 1 in the first year that plant i uses automation technology $A \in \{\text{CNC Machines, Industrial Robots}\}$:

$$D^{adopt}_{i,t,A} = \begin{cases} 1 & \text{if technology } A \text{ is used at any date } s \leq t \\ 0 & \text{otherwise} \end{cases}$$

An adoption event is then defined as the first difference of this variable, $\Delta D^{adopt}_{i,t,A}$, indicating the year a plant moves from non-use to use of the technology. As is standard, we model treatment status as absorbing: once adopted, $D^{adopt}_{i,t,A}$ remains 1 in all subsequent periods.

We define expansion events similarly, using a binary variable $D^{expand}_{i,t,A} \in \{0,1\}$, which switches from 0 to 1 in the first year that a plant increases its number of CNC machines, having already adopted the technology in an earlier year:

$$D^{expand}_{i,t,A} = \begin{cases} 1 & \text{if } Tech_{i,s,A} > Tech_{i,s-1,A} > 0 \text{ for any } s \leq t \\ 0 & \text{otherwise} \end{cases}$$

As with adoption events, we model the expansion indicator as absorbing. Since we observe machine counts only for CNC technologies, we are not able to define expansion events for industrial robots.

Adoption and expansion events capture distinct margins of technological change, both of which are central to understanding the labour market effects of automation. Adoption events provide a clean empirical analogue to automation as defined in the task-based framework discussed in Section 3, which conceptualizes automation as a reallocation of tasks from labour to capital. Our definition of adoption—capturing the first time a plant uses a given automation technology—corresponds closely to this notion of a discrete qualitative shift in the allocation of tasks from humans to machines. By contrast, expansion events may reflect either further automation at the extensive margin i.e. the replacement of humans in additional tasks, or intensive margin investments i.e. the scaling up of already automated tasks. While this limits their usefulness for identifying canonical automation effects, expansion events are of independent interest because they provide an opportunity to investigate so-called learning effects, as discussed in Section 3.

Our dataset includes a substantial number of both types of events. As shown in Table A3, we observe 4,355 CNC adoption events, 1,826 robot adoption events and 8,240 CNC expansion events.

5.2 The Local Projection Difference-in-Differences estimator

Since different plants experience automation events at different points in time, our setting is characterized by staggered treatment timing. Moreover, treatment effects are likely to vary with the number of periods since a treatment event (the "horizon") as plants adjust their production processes, organizational behaviour and employment. We also expect heterogeneity in treatment effects across plants even over the same horizon, reflecting unobserved time-varying factors such as the quality of managerial practices and introduction of new products by downstream or upstream producers.

There is now a large literature on the challenges of estimating event-studies in such a context, and in particular the problems associated with the standard Two Way Fixed Effects (TWFE) framework. These estimators can produce misleading results because they include all available non-treated units in the control group, meaning previously treated units whose outcomes may still be affected by prior treatment are included as controls for currently treated ones. If the effect of treatment grows or shrinks over time, this can distort the comparisons. For example, treated units might appear to do worse than the control group simply because the 'controls' are already benefiting from the treatment. These 'forbidden comparisons' can lead not just to biased estimates, but to ones that have the wrong sign entirely.[17]

While several estimators have been proposed to address these issues, we use the Local Projection Difference-in-Differences (LP-DiD) estimator developed by Dube et al. (2023). As the name suggests, this estimator uses the local projection approach to estimating dynamic treatment effects, which relies on estimating separate regressions for each time horizon relative to treatment. At the same time, it modifies this approach to avoid forbidden comparisons, requiring that the units included in the control group are either never-treated units or have been treated sufficiently far in the past that their current outcomes are no longer influenced by the treatment. LP-DiD has a number of advantages compared to other similar

[17] For a detailed discussion of these issues and potential solutions see de Chaisemartin and D'Haultfœuille (2024, 2022), Roth et al. (2023). A variety of alternative estimators that do not suffer from these difficulties have been proposed, and in Section 6 we show that our core results are robust to four key alternatives.

estimators: it is computationally efficient and fast to implement; its identification assumptions are transparent and easy to understand; and it is highly flexible, making it easy to vary weighting schemes, choose alternative pre-treatment base periods, and pool treatment effects across different horizons. As Dube et al. (2023) emphasize, many other recent DiD estimators can be replicated as special cases of LP-DiD by adjusting these parameters.

Our preferred specification involves estimating the following regression:

$$y_{i,s,t+h} - \overline{y}_{i,s,t-4:t-1} = \beta_h \, \Delta D_{i,t,A} + \theta_{s,t} + \gamma \, \Delta y_{i,s,t-1} + e^h_{i,s,t}, \quad \forall \, h \in \{-4, -3, \ldots, 4\} \tag{1}$$

while restricting the sample to observations that are either:

$$\begin{cases} \text{newly treated} & \Delta D_{it} = 1, \\ \text{clean control i.e. not yet treated at } t+h & D_{i,t+h} = 0 \end{cases}$$

In the above, $y_{i,s,t+h}$ is total employment for plant i in industry s, h years after the treatment period t, and $\overline{y}_{i,s,t-4:t-1}$ is the average outcome over the pre-treatment periods $t-4$ to $t-1$. $\Delta D_{i,t,A}$ captures a generic automation "event", defined as a change in the underlying treatment indicator from $t-1$ to t (as above, where needed, we distinguish adoption and expansion events more explicitly as $D^{\text{adopt}}_{i,t,A}$ and $D^{\text{expand}}_{i,t,A}$). Our coefficient of interest is β_h which measures the treatment effect h periods after the treatment, and we study a time horizon from four years prior to four years after a given event. Although we estimate a variety of specifications to test the robustness of our results, in our main specification we include year-by-industry fixed effects $\theta_{s,t}$ as well as a lag of the differenced outcome variable $\Delta y_{i,s,t-1}$. As discussed below, these help mitigate a number of possible threats to identification, and to strengthen the plausibility of giving a causal interpretation to our results.

With these controls in place, we can interpret our β^h coefficients as the estimated difference in outcomes between plants that experience an automation event and those that do not, relative to pre-treatment trends and other plants in the same year and industry.

5.3 Identification

As with all difference-in-differences estimators, there are two critical identification assumptions

1. **Conditional parallel trends:** Absent treatment, outcomes for treated and control units would have followed similar trends, conditional on covariates.

2. **Conditional no anticipation:** Units do not change their employment behaviour in

anticipation of treatment.

Under these assumptions, the β_h coefficient from equation (1) consistently estimates a weighted average across all treated cohorts of the Average Treatment Effect on the Treated h periods after an automation event. If these conditions hold, we would expect our estimated pre-treatment coefficients to be flat and close to zero. While this is not a sufficient condition for identification, it provides a useful first check on the plausibility of the assumptions.

There are several possible threats to identification, which we seek to mitigate. The fundamental concern is that companies which adopt new technologies might, for a variety of reasons, already be on a faster growth trajectory, thus invalidating the key parallel trends assumption.[18]

It is possible, for example, that companies which adopt CNC machines or industrial robots are disproportionately concentrated in industries that are on more rapid growth trajectories. We include a full set of industry-year fixed effects in our main specification to account not just for secular industry-level trends that may be correlated with technology adoption, but for time-varying industry-level shocks, like a sudden spike in global demand for cars, that might simultaneously raise the probability of technology adoption and affect plant employment.

Even within a given industry, technology adopters might differ in unobserved ways that also affect their employment trajectory. They might, for example, have more capable or better informed managers who are simultaneously more likely to invest in new technology and pursue a range of other strategies that drive faster employment growth. Alternatively, firms in faster growing market segments may be more likely to both expand their employment and adopt new technologies, simply to keep up with rising demand. These concerns help to motivate our inclusion of a lag of the differenced outcome variable, which allows us to account for *firm-level* differences in pre-treatment trajectories that might otherwise bias our results (we effectively partial out these dynamics to better isolate the causal effect of treatment). Dube et al. (2023) recommend this approach in contexts like ours where the outcome variable is likely to be subject to momentum or drift, following a well-established tradition in panel data models.

As we shall see, conditional on these controls, we find that treated and control units exhibit broadly parallel pre-treatment trends. But even if pre-trends appear similar, bias may still arise if treatment coincides with unobserved shocks. For instance, it is possible that a spike in demand leads companies to immediately install new machines; or that new

[18] See, for example, Acemoglu et al. (2023), who find that US companies that adopt new technologies including AI and robotics were already larger and growing faster than other similar companies that did not; and Bessen et al. (2023), who documents that Dutch companies that experience an automation event have a higher average growth rate than those which do not.

managers arrive in a plant and instantly install new technologies, while also overhauling other workplace practices that affect employment levels. However, such contemporaneous shocks are unlikely to explain our results, because decisions to install CNC machines and industrial robots typically involve substantial planning, capital investment approval processes, and installation lead times that can span multiple quarters or even years.[19]

While our discussion so far has focused on threats to the parallel trends assumption, we also consider the possibility of bias arising from anticipatory adjustments to employment prior to treatment. As we have just commented, automation events are likely to be the result of planning over multiple years, which raises the possibility that plants might hire new or different kinds of workers in anticipation of the arrival of new technologies, leading to biased results. Such anticipation effects would also be mitigated by including a lag of the differenced outcome variable, and even without including this lag, we do not find evidence of significant anticipation effects.

In the absence of a valid instrument or other (quasi-)experimental estimation strategy, we cannot justify a strictly causal interpretation of our results, and identifying such a strategy is an important priority for future research. Even so, it is worth noting that Aghion et al. (2023c, 19-20), who combine an event-study design similar to our own with a shift-share IV strategy leveraging pre-determined supply linkages and productivity shocks, find that OLS-based estimates remain positive but of smaller magnitude. In other words, their results suggest that if anything, a strategy such as ours might under-estimate the positive effects of automation at the firm level. In any case, while we cannot rule out all sources of endogeneity, the absence of differential pre-trends in most specifications, the careful use of industry-time controls, and the inclusion of firm-level dynamics should all help to strengthen the plausibility of a causal interpretation.

6 Firm-level results

Figure 5 presents our event-study estimates of plant-level employment around automation events. For CNC adoption, treated plants experience an immediate 5% increase in total employment relative to controls, growing modestly to around 6% four years after adoption. Industrial robot adopters show a similar pattern: a 5% jump in employment in the year of

[19]The high cost of the organizational changes required to implement a successful adoption of ICT are emphasized in Brynjolfsson and Hitt (2000); we expect that the changes required to implement a new machine tooling system are similar. For industrial robots, Humlum (2021) estimates that the total cost (equipment and non-equipment) of robot adoption for the typical firm can be up to 25% of the firm's sales, with the equipment component estimated at around 13%.

treatment that rises to roughly 8% after four years. In other words, for both technologies, firm-level productivity effects appear to dominate displacement effects, leading to a positive overall impact on employment. Importantly, our event studies support the two critical identification assumptions: treated and control firms exhibit broadly parallel pre-treatment trends, conditional on our industry and lagged dependent variable controls; and there is no evidence of significant anticipation effects.

Figure 5 also displays the results for CNC expansion events, which occur when a plant increases the total number of CNC machines from an already positive number. Although there is modest evidence of a positive pre-treatment trend, CNC expansion events are associated with an even larger increase in total plant employment of about 6% in the year following an expansion event, rising to 9% after four years. In contrast to adoption events, the increase in employment following an expansion event does not plateau after four years, indicating that such events may not only increase the level of employment, relative to controls, but also shift firms onto a different growth trend.

Although the positive difference between expansion and adoption events is modest, it is consistent with the idea that plants undergo a learning process after adopting new technologies Atkeson and Kehoe (2007). As discussed in Section 3, in learning-based models it takes time for firms to accumulate the human, organizational, and process-specific capital needed to make the most of a given technology, and to undertake the complex work of re-shaping production processes and cultivating new supplier and customer relationships. Once a plant has climbed the steepest section of this learning curve, further investments — such as adding more CNC machines — may deliver disproportionately larger returns, since the firm already knows how to integrate new capacity into its routines and can redeploy it immediately into higher-value tasks.

6.1 Alternative specifications and robustness

Figure 6 compares our baseline technology adoption results from the previous section to four alternative specifications of the LP-DiD estimator. As explained in Section 5, our primary concern is to control for employment-related factors that are correlated with treatment (technology adoption), and hence satisfy the conditional parallel trends assumption.

To recap, our baseline specification includes year by industry fixed effects, as well as a lag of the differenced outcome variable. The latter mechanically flattens the estimated pre-treatment coefficients in $t-1$ and $t-2$. To see how these controls affect our results we look first at the simplest reasonable specification with year fixed effects only (in green). In contrast to our baseline, we find that treated units have a slightly positive pre-treatment employment trend; and that this pre-trend is more pronounced for sites that adopt CNC machines than industrial robots. Nevertheless, we continue to observe a clear jump in employment compared to untreated units in the year of treatment, followed by a gradual further increase over the subsequent four years.

In our third specification (in purple) we add a full set of year by four-digit industry controls, to allow for the possibility that technology adoption is correlated with broader industry-level employment trends, but once again omit the lag of the differenced outcome variable. Compared to our specification with year fixed effects only, this further reduces the observed pre-treatment trends for CNC adopters (though not for robots), suggesting that treated units are slightly more likely to be in faster-growing industries; and for both CNC and robots we continue to observe a substantial and sustained jump in employment after treatment, compared to untreated units. In order to demonstrate that our results are not being driven by the lag of the differenced outcome variable, in Table A we report the four year pooled post-treatment coefficient with no lag and with one, two and three lags. Varying the number of lags makes little difference to our results.

Our fourth specification (in blue) adopts a slightly different approach: instead of using the lag of the differenced outcome variable to control for differential trends immediately prior to treatment, we control for linear plant-specific time trends in employment across the whole span of our data.[20] In this specification, the modified parallel trends assumption is that, after removing site-specific trends, treated and control units would have been parallel in deviations from those trends; and we can interpret the estimated LP-DiD coefficients as the average effect of treatment relative to each plant's own linear employment trend. In practice, pre-treatment coefficients in this model are largely flat and close to zero; while the estimated treatment effects continue to be significant, albeit slightly smaller in magnitude than in our baseline model, and (thanks to the addition of many extra parameters) less precise.

Finally, we include a specification (in red) that repeats our baseline specification, but restricts the control group to "future adopters", in other words plants that eventually experience an adoption event for the technology in question. We do this by dropping "never-treated" units from our sample. This approach is inspired by Bessen et al. (2023), who argues that sites which adopt advanced technologies are likely to differ in unobserved ways from sites that never adopt. They may, for example, have better informed management, or be in faster growing sectors. By comparing adopters with future adopters, rather than with never

[20]This is accomplished by explicitly adding a unit fixed effect to the standard LP-DiD specification. As the authors of the relevant command explain, since unit fixed effects are already filtered out by the differencing of the outcome in LP-DiD, "adding unit fixed effects to the LP-DiD specification is equivalent to including unit-specific linear time trends". See http://fmwww.bc.edu/repec/bocode/l/lpdid.sthlp

adopters, this specification exploits the *timing* rather than the incidence of adoption events, and is more likely to compare like with like. The downside is that the size of control group is significantly reduced. Again, this specification supports our headline findings: we find no evidence of differential pre-treatment trends between current and future adopters; and we find that automation events are associated with a statistically significant and sustained increase in employment, albeit slightly lower than in our baseline.

In addition to these alternative specifications, we conduct a placebo test using our baseline specification. Specifically, we conduct fifty separate trials in which we randomly assign technology adoption events across the complete sample, preserving the temporal distribution of events throughout. In contrast to the alternative specifications above — which test the robustness of the conditional parallel-trends assumption by varying our controls — this exercise performs a simple randomization-inference check: the aim is to confirm that our results capture a genuine treatment effect rather than a mechanical artifact of the LP-DiD estimator or a chance fluctuation in the data. We report our results in Figure 7. On the right is the estimated impact of technology adoption after four years, as reported in Figure 5, where the standard error is depicted as normally distributed in blue shading. On the left (in green shading), we report the distribution of the four-year post-treatment coefficient across our fifty placebo trials. Our results are reassuring: for both CNC machines and robots, the distribution of placebo coefficients is centred around zero, and barely overlaps with the estimates from our baseline specification.

To complete our robustness tests, in Table B1 we show the pooled post-treatment coefficient obtained from estimating our core specification using four alternative estimators put forward in the recent literature on difference-in-difference estimation in the context of staggered treatments and heterogeneous treatment effects. While different estimators yield slightly different point estimates, the results are remarkably similar across these specifications. Finally in A we show that the significance of our core results is also robust to a range of alternative clustering strategies.

6.2 Employment-mix following Installation of Automation Technology

One of the key predictions of the task-based framework is that automation will reduce the share of employment among workers whose tasks are displaced. Our data single out employment of "manufacturing workers", who are most likely to be exposed to automation as a result of the installation of CNC machines and industrial robots.

In Figure 8 we report the results of our baseline LP-DiD specification, but replacing the outcome variable with the share of manufacturing workers.[21] Our results looking at adoption events do not support the prediction of the task model. For CNC machines, there is no discernible effect of automation events on the share of manufacturing employees. For industrial robots there is some evidence of a slight decline, but this follows a significant negative pre-trend, and in any case the individual post-treatment coefficients are not significantly different from zero at the 5% level.

However, we find that CNC expansion events are associated with a large and statistically significant reduction in the share of manufacturing workers of around 8 percentage points after six years. This is further suggestive evidence that the distinction between adoption and expansion events is economically significant. These results are also consistent with the idea that plants which adopt new technologies undergo a learning process. On this view, it takes time for firms to work out how to reorganise their production processes in ways that make the most of a given new technology. If this is the case, we would expect first adopters to use technologies in ways that are more easily adapted to existing work processes, and more likely to complement existing workers. However, as firms accumulate more know-how about a new technology, they are likely to see opportunities to redesign processes in more fundamental ways that might automate away existing tasks. Investigating this mechanism further, both theoretically and empirically, is an important question we leave for future research.

[21] We calculate the share of manufacturing workers as the ratio of manufacturing workers to all workers in the manufacturing, engineering, and design roles.

7 Industry-level results

As we saw in our discussion of the task-based framework in Section 3, even if automation events are associated with an increase in employment at focal plants, this need not translate into an increase in industry-level employment. This depends on how automation at focal plants also affects the employment of their competitors. On the one hand, it's possible that as automating firms become more productive, we see a reallocation of production away from less productive firms. A number of empirical papers have documented evidence of such "business stealing" effects, where automating companies expand at the expense of their competitors (Aghion et al. 2023c, Acemoglu et al. 2020, Koch et al. 2021). If this is the case, the eventual impact at the industry level will still depend on whether the expansion among automating firms outweighs the contraction of their competitors. While both Acemoglu et al. (2020) and Aghion et al. (2023c) find evidence of business stealing, they find opposite overall effects on industry employment. On the other hand, automation can also lead to positive spillover effects on competitor firms. If demand is elastic, lower prices as a result of automation may expand total output in the industry, for example, especially if capacity constraints or market frictions limit the dominance of automating companies. In addition, automation may increase demand for complementary inputs or services, some of which may be supplied by other firms in the same sector, or trigger broader productivity improvements through demonstration and diffusion effects.

In this section, we first test for evidence of business stealing, before looking directly at the impact of automation on industry level employment.

7.1 Impact on competitor plants

In order to look at whether automating firms steal business from their competitors, we first need to define who those competitors are. The best proxy for this in our data is whether two sites share a given industry code, which is a reasonably strong indicator that they are producing similar products and competing in the same market segments. We then follow the strategy proposed by Aghion et al. (2023c), who replace each firm's own employment outcome in their event study specification with the employment of its competitors. Specifically, we adapt our firm-level LP-DiD specification by replacing the outcome variable for each plant-year observation with the total employment among other firms in the same six-digit SIC code:[22]

[22]Our data provider extends the existing four-digit 1987 SIC classifications, adding a handful of additional categories. For example, they split '3169: Finished metal products not elsewhere specified' into sub categories including: '316901: Locks, Hinges, Curtain Rails', '316902: Needles and Pins', '316903: Base

$$Y_{i,t,s}^{-i} = \sum_{\substack{j \neq i \\ s_j = s}} y_{j,t} \tag{2}$$

This specification captures how the employment of a treated firm's competitors evolves in response to automation events. Specifically, the estimated LP-DiD coefficients compare the change in competitors' employment for treated firms h years after treatment to the change in competitors employment' for untreated firms over other h-year periods in our dataset. If there is business stealing, we would expect competitors' employment to decline in the periods following a treatment event compared to the trajectory at untreated firms over similar time horizons. Conversely, if there are positive spillover effects, we would expect automation at one firm to lead to an increase in employment among its peers, relative to other firms and periods.

As we can see in Figure 9, we find evidence of positive spillover effects rather than business stealing. For CNC machines, automation at a focal plant is associated with a statistically significant increase in competitors' employment of around 3% after four years. This is true for both adoption and expansion events. The direction of travel appears to be the same for competitors of plants that adopt industrial robots, though the magnitude of the effect is smaller and not statistically significantly different.

A natural concern with these results is that they are simply capturing positive industry-level trends that are common to treated companies and their competitors in a given industry. So, for example, we might worry that companies that automate are more likely to be in faster growing industries, and that as a result employment among their peers is likely to grow faster than that of peers in other industries. We mitigate this concern directly by continuing to include industry and year fixed effects, and a lag of the differenced outcome variable. More importantly, if this was driving our results, it would show up in a positive pre-treatment trend among treated units, something we do not observe.[23]

metal fittings'. Unless otherwise specified, when using industry controls we leverage the full richness of this 6-digit classification.

[23]Another potential concern is that the outcome variable for untreated units in this specification, namely total employment among all other firms in their industry, will include the employment of treated units in that industry. Since treated firms generally see a (relative) increase in employment after automation events, this will mechanically increase employment among their peer group. If anything, however, this would lead us to understate positive spillovers, since it would mechanically increase the outcome variable for untreated units when one of their peers is treated. To examine this concern we have also looked at specifications using total employment among never treated peer companies in the same industry, and find qualitatively similar results.

7.2 Industry-level automation events

We now turn to look more directly at the implications of automation for industry employment, taking into account both the impact on focal firms and on their competitors. Following Aghion et al. (2023c), we adapt our LP-DiD design once again, but this time embracing a fully industry-level specification: studying the impact of industry-level automation events on total industry employment. Intuitively, we study what happens in an industry after a significant increase in the penetration of a given automation technology, taking into account the full set of direct, indirect and general equilibrium effects.

We define an industry-level automation event as a year in which we see a large increase in the share of employees working for companies that use a given technology, relative to all positive annual increases in this measure. Specifically, we first measure all positive annual changes in the share of employees working at plants using a given technology in each industry, and then define an industry automation event as an increase in this share above a given percentile threshold in the distribution of all positive year-on-year changes.[24] Focusing on the share of employees working at firms that use a given technology, rather than simply the share of companies using that technology, means the influence of a given firm's adoption is weighted by its size. For example, an automation investment at a large multi-site employer will have a much larger effect on industry employment dynamics than adoption by a small fringe firm. Unlike at the firm-level, where adoption and expansion provide natural binary thresholds for defining events, the definition of an automation event at the industry level using thresholds is inherently somewhat arbitrary. As such, we display our results for three thresholds: the top half, the top third, and the top quartile of positive year-on-year changes in the share of employees working at companies that use a given technology.

To examine the impact of automation on industry-level employment, we adapt our firm-level LP-DiD specification to the industry level. Specifically, we estimate:

$$y_{s,t+h} - \overline{y}_{s,t-4:t-1} = \beta_h \, \Delta D_{s,t,A} + \theta_t + \gamma \, \Delta y_{s,t-1} + e^h_{s,t}, \quad \forall \, h \in \{-4, -3, \ldots, 4\} \tag{3}$$

while restricting the sample to observations that are either:

$$\begin{cases} \text{newly treated} & \Delta D_{s,t} = 1, \\ \text{clean control i.e. not yet treated at } t+h & D_{s,t+h} = 0 \end{cases}$$

[24]For comparison, Aghion et al. (2023c) define industry-level investment events as an above-median annual change in the balance sheet value of industry equipment.

In this specification, $y_{s,t+h}$ denotes total employment in industry s, h years after the baseline year t; $\overline{y}_{s,t-4:t-1}$ is the average of the outcome in the four years prior to treatment; $\Delta D_{s,t,A}$ is an indicator for an automation "event" in year t, defined as a large increase in the share of employees working at technology-using plants in industry s; θ_t captures year fixed effects, controlling for economy-wide shocks that might be correlated with automation events; and $\Delta y_{s,t-1}$ is the lagged first-difference of the outcome variable.[25] The coefficient of interest is β_h, which captures the dynamic effect of automation on industry-level employment h years after the event.

This industry-level LP-DiD approach allows us to trace out the evolution of employment following major increases in automation intensity, comparing industries that experience an automation event to those that remain untreated over a comparable time horizon. Of course, it's possible, for example, that strong demand growth in a given industry drives both large automation events and an increase in employment growth relative to other industries. As before, the absence of significant pre-treatment trends is a necessary but not sufficient condition for satisfying the critical parallel trends and no anticipation conditions.

Our results are displayed in Figure 10. The first thing to note is that we do not observe significant pre-trends. Turning to our post-treatment coefficients, in most specifications the impact of automation events on industry-level employment is positive, and we can largely rule out negative employment effects. This is consistent with our finding that firm-level automation events increase employment at both focal firms, and at competitor firms within a given industry. Looking in more detail at the results for CNC machines, we find that the estimated effects vary substantially from one event threshold to the next. The largest and only statistically significant effect is based on a threshold set at the median of positive changes in the share of employees at CNC-using companies. When we focus on the top third or top quarter of changes, we get small positive but not significant effects. At first sight, it might seem surprising that more extreme automation events (those in the top quartile rather than the top half) appear to have a smaller impact on total industry employment. But it's important to remember that changes in these event thresholds affect the composition both of the treatment and control groups: when we shift to top-quartile events, industries that experience changes above the median but below the top-quartile, and which likely grow as a result, become part of the control group. This attenuates the estimated treatment effect, since industries in the revised control group are also likely to experience moderate automation-related growth.

[25] Although we no longer include industry level controls, note that because LP-DiD uses differenced outcome variables it implicitly controls for industry fixed effects.

Turning to our results for industrial robots, we find more consistent results across the three thresholds, with a gradual but clearly positive effect emerging four years after a major industry level automation event. As before, we estimate the largest effect when using the median threshold, while our estimates using the top third and quartile thresholds are smaller and similar to one another.

As a final step in the industry-level analysis, we look at the impact of the same set of industry-level automation events on the industry-level share of manufacturing employees[26] As we saw in Section 3, one of the stronger predictions of the task-based framework is that automation will reduce the employment share of the most exposed workers at both the firm and industry level. In practice, as we discussed in the Introduction, other empirical studies have reached mixed conclusions on this question. Our results contribute to this mixed picture. When it comes to industry-level CNC events, Figure 10 shows limited evidence of any clear pattern: we find a slight but not significant increase in the manufacturing share immediately after an automation event, which fades out by year four. For industrial robots, we find a gradual but statistically significant reduction in the share of manufacturing workers after four years, across all three event threshold specifications, reversing an apparently positive pre-treatment trend.

8 Conclusion

This paper provides new evidence on one of the most pressing questions in labour economics: how does automation affect employment? Using a novel dataset tracking the adoption of CNC machine tools and industrial robots across UK manufacturing plants from 2005-2023, we find that automation events are associated with positive employment effects, both at automating plants and the wider industry level.

Our key finding is that automation technologies increase employment at adopting firms by approximately 6 to 8% in the four following adoption. This result is robust across different specifications and estimation strategies, and holds for both CNC machines and industrial robots. In other words, productivity effects clearly dominate displacement effects at the firm level, consistent with theories emphasizing automation's role in expanding output and creating complementary tasks. At the industry level, we find evidence of positive spillover effects rather than business stealing, with automation events at focal firms associated with

[26] Similar to our plant-level approach, we define the share of manufacturing workers by dividing each industry's number of manufacturing workers by the count of all workers in manufacturing, engineering, and design roles.

employment growth among competitors. Industry-wide automation events generally show positive or neutral effects on total employment.

While initial technology adoption shows little impact on the share of manufacturing workers, CNC expansion events are associated with a significant reduction in the manufacturing employment share of around 8 percentage points. This pattern is consistent with learning-based theories of technology adoption, suggesting that firms initially use automation in ways that complement existing workers but gradually reorganize production processes in more transformative ways as they accumulate experience with the technology.

Our findings are broadly consistent with other studies using firm-level data on technology, and suggest that fears of widespread job displacement from automation may be overstated. Looking forward, several important questions remain. While our findings at the firm and industry levels are predominantly positive, a complete assessment of automation's labour market impact requires examining general equilibrium effects at the labour market and national levels. Workers displaced from non-adopting firms or industries may face adjustment costs and transitions that are not captured in our plant and industry-level analysis. The mechanisms driving positive spillover effects between firms also deserve further investigation.

Finally, while our results provide valuable insights into the employment effects of CNC machines and industrial robots—two foundational automation technologies—caution is warranted in extrapolating these findings to newer technologies, such as artificial intelligence. The task-based framework suggests that different technologies may have fundamentally different employment consequences depending on their specific capabilities and the nature of the tasks they automate. As automation technologies continue to evolve, understanding how the employment effects vary across different types of technological change will be crucial for anticipating future labour market dynamics.

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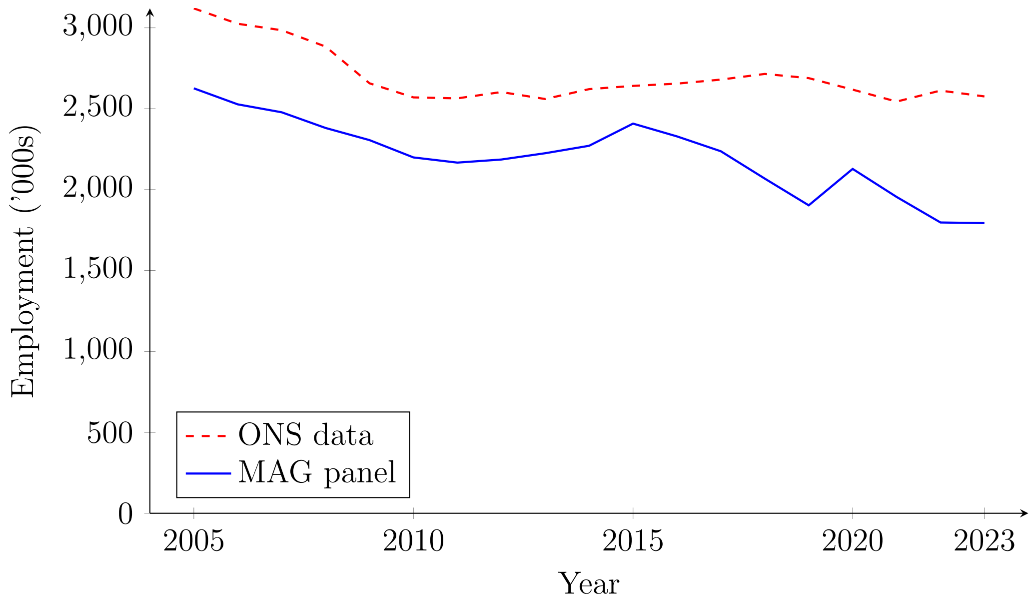
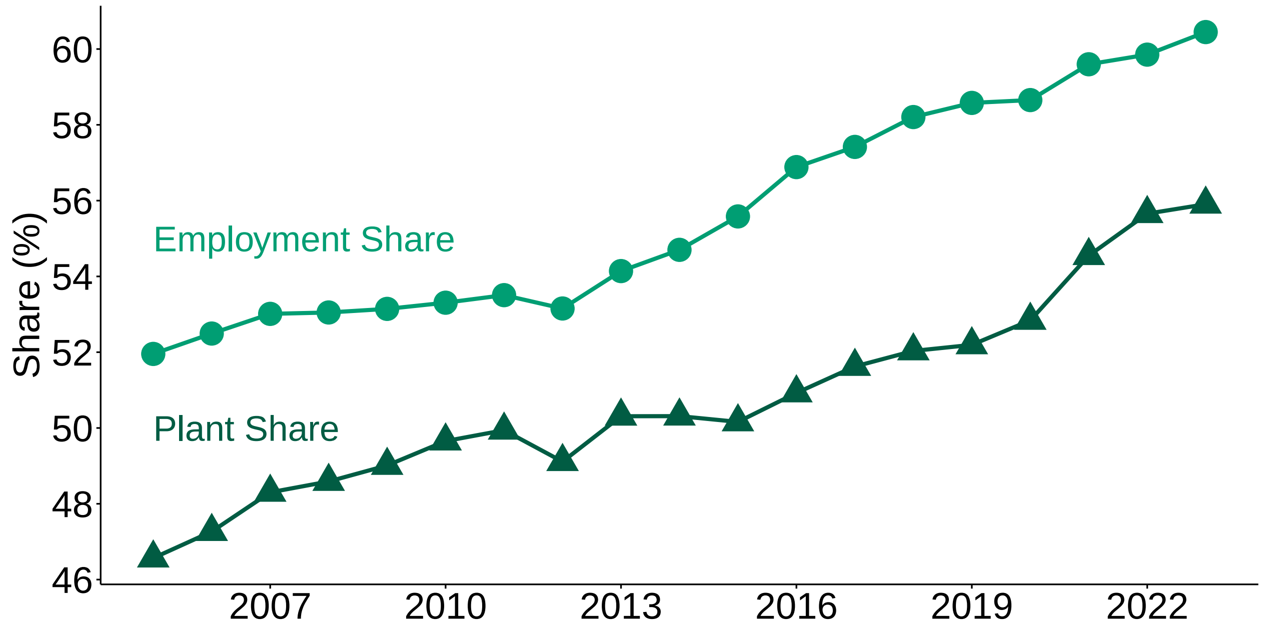
Figure 1: Employment trends in MAG vs ONS



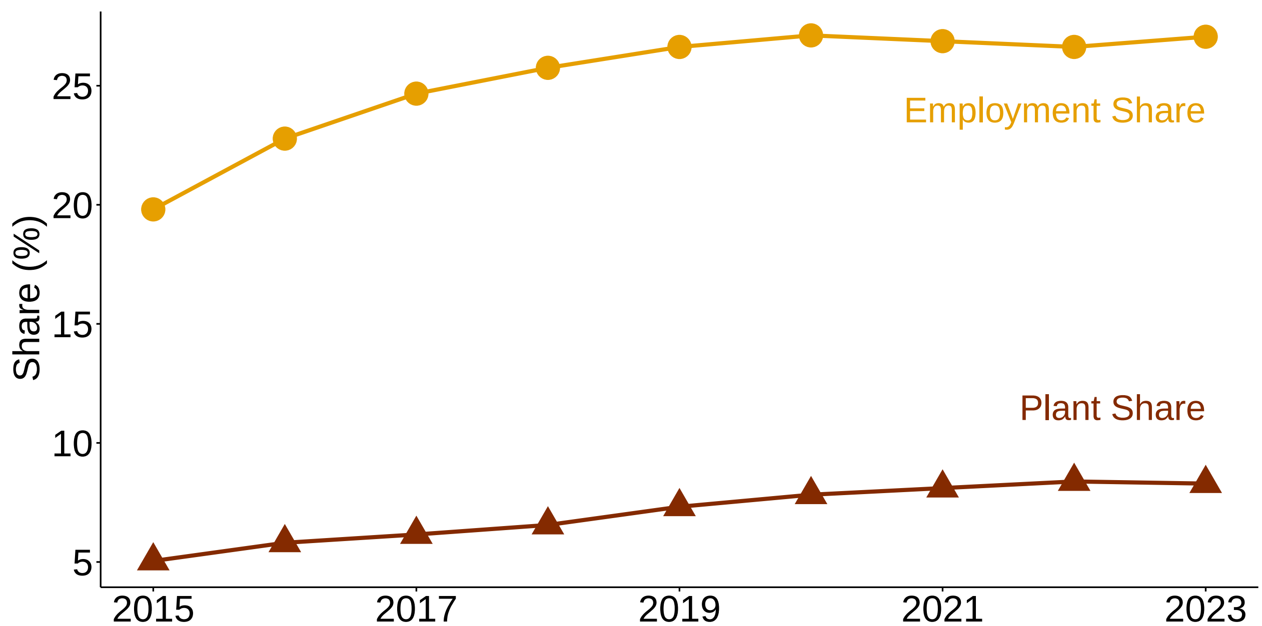
Notes: this table compares total employment (in '000s) in the MAG survey with official data from the quarterly Labour Force Survey, produced by the Office for National Statistics. As per Table A1, the MAG survey captures 80% of total ONS manufacturing employment on average.

Figure 2: Automation Technology Diffusion in UK Manufacturing

(a) CNC Machine Tools, 2004-2023



(b) Industrial Robots, 2014-2023

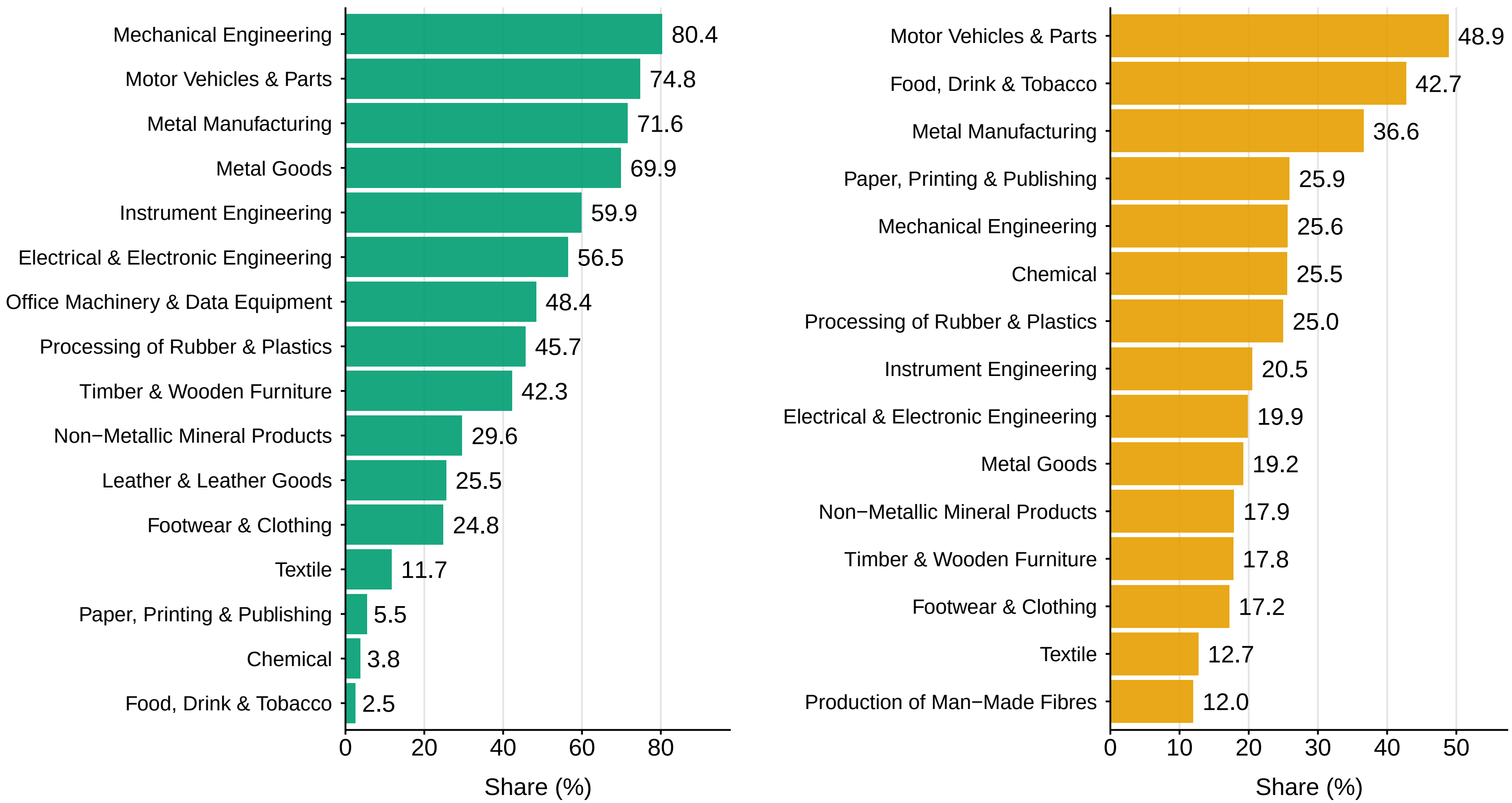


Notes: "Plant Share" is the share of plants with at least one CNC machine or industrial robot, based on the MAG survey. "Employment Share" is the share of employees at such plants. The sample is limited to "manufacturing production" plants in the MAG survey, as defined in the text. Reliable information about robot use is only available from 2015.

Figure 3: Share of Workers at Plants with Automation Technology in 2023, by Industry

(a) CNC Machine Tools

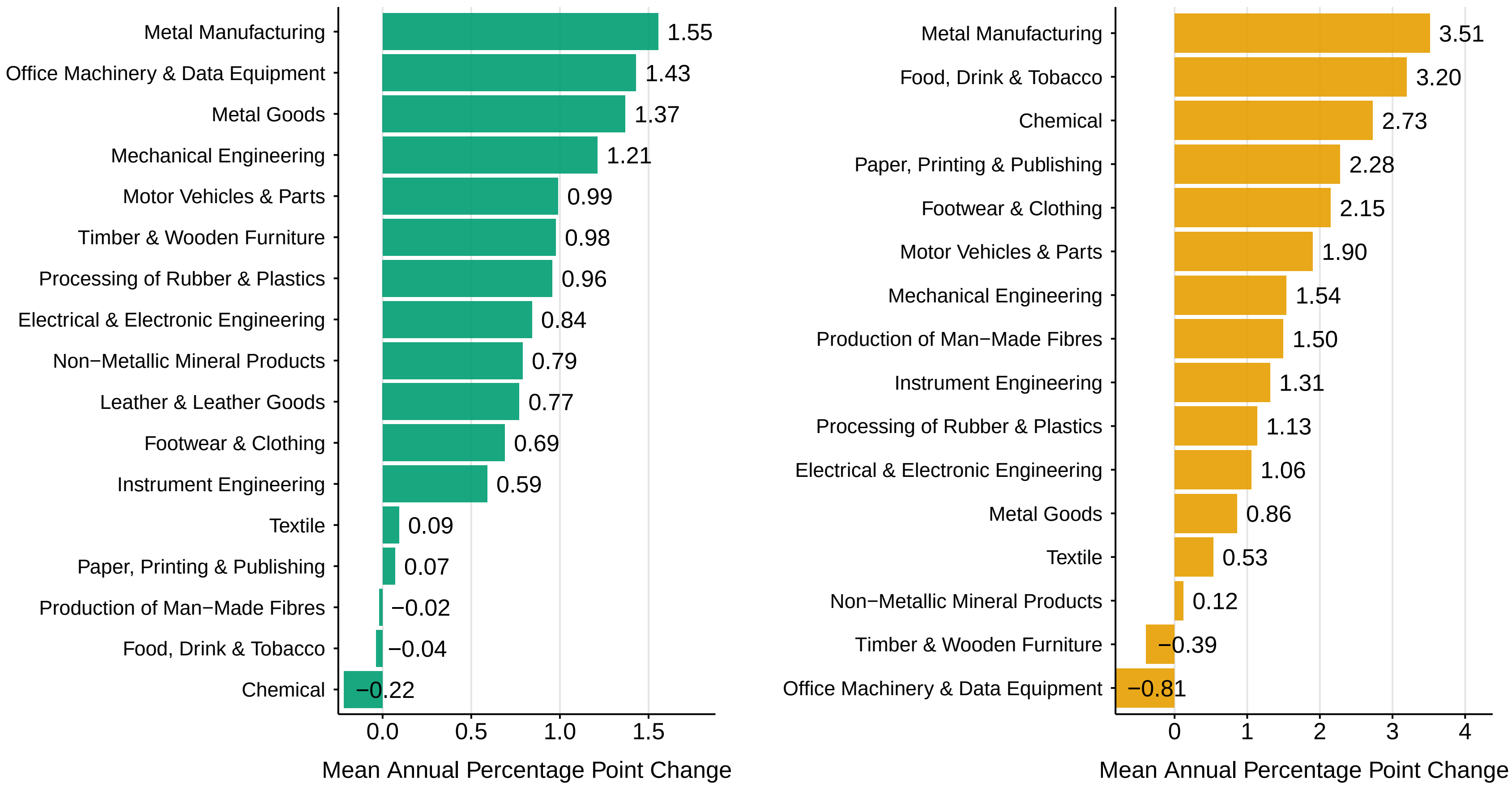
(b) Industrial Robots



Notes: share of employment in plants with at least one CNC machine or industrial robot. Shows top-20 manufacturing industry divisions (2-digit SIC codes). The sample is limited to "manufacturing production" plants in the MAG survey, as defined in the text.

Figure 4: Annualized Change in Share of Workers at Plants with Automation Technology, by Industry

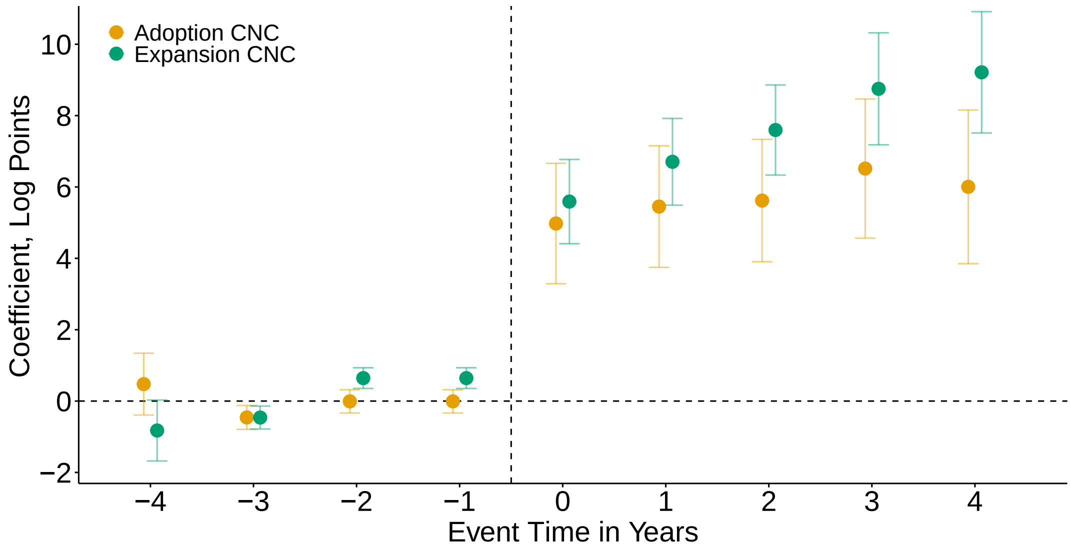
(a) CNC Machine Tools (2006-2023) **(b)** Industrial Robots (2014-2023)



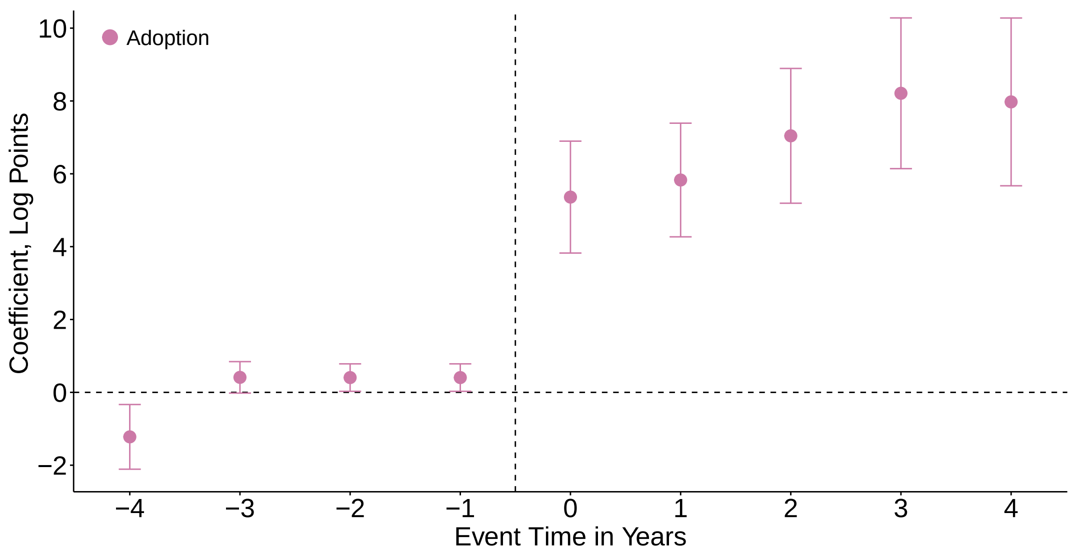
Notes: annualised change in the share of employment in plants with at least one CNC machine or industrial robot. Shows top-20 manufacturing industry divisions (2-digit SIC codes). The sample is limited to "manufacturing production" plants in the MAG survey, as defined in the text.

Figure 5: Plant-level Event Study, Total Employment

(a) CNC Machine Adoption



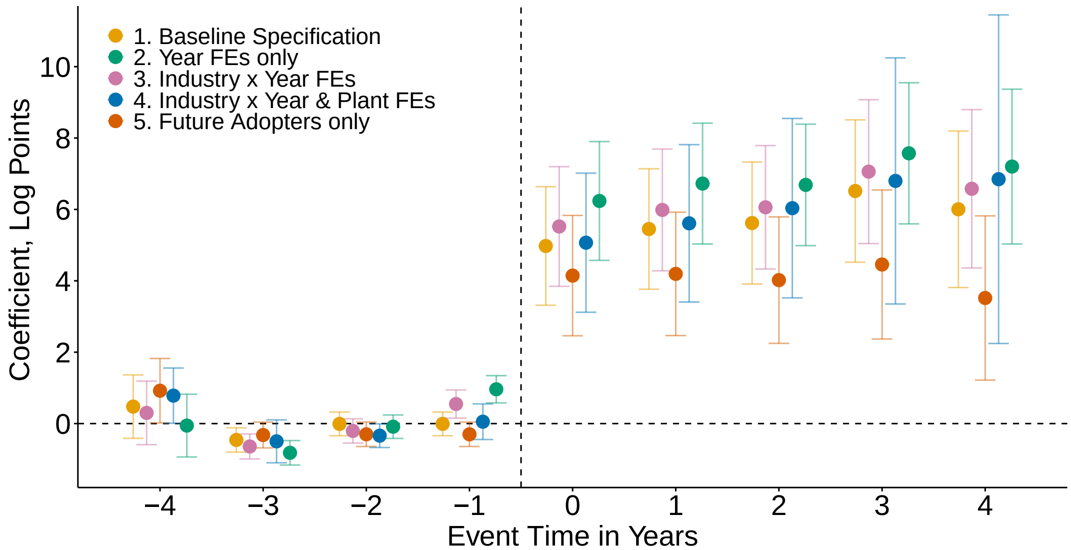
(b) Industrial Robot Adoption



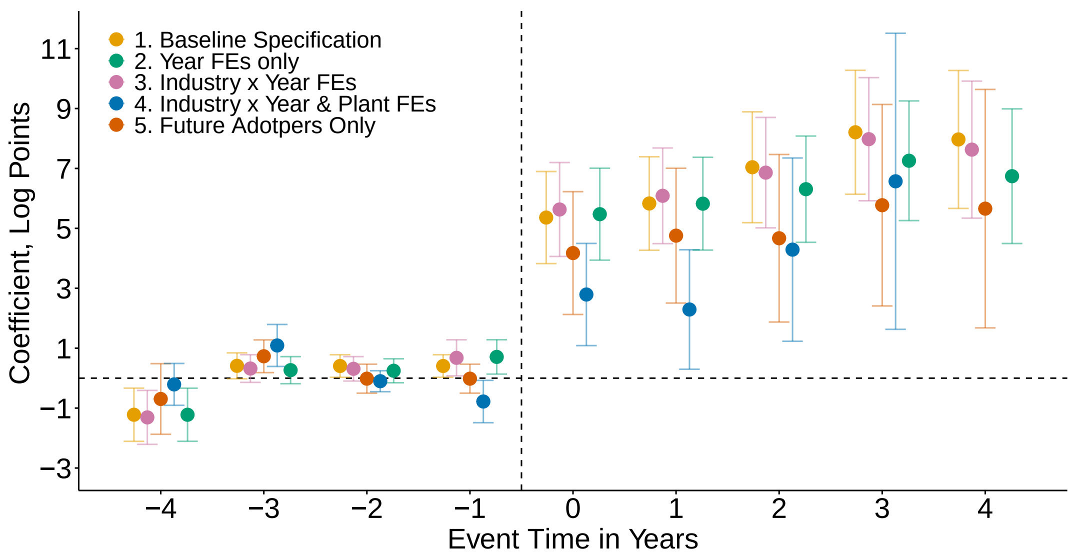
Notes: These figures show LP-DiD estimates of employment effects following automation events, as defined in the text. Panel (a) uses $N = 368,914$ observations from 2005-2023, with 4,355 adoption events and 8,240 expansion events. The post-treatment pooled coefficient is 5.058*** (adoption) and 6.821*** (expansion). Panel (b) examines industrial robot adoption using $N = 229,731$ observations from 2010-2023, of which $1,826$ experienced an adoption event. The post-treatment pooled coefficient is 6.98***. Both designs use detailed Industry Codes $\times$ Year fixed effects and a lag of the differenced outcome variable in period $t-1$ as controls, as per equation 1, with standard errors clustered at the plant-level. Vertical bars represent 95% confidence intervals.

Figure 6: Alternative Plant-level Event Study Specifications

(a) CNC Machine Adoption



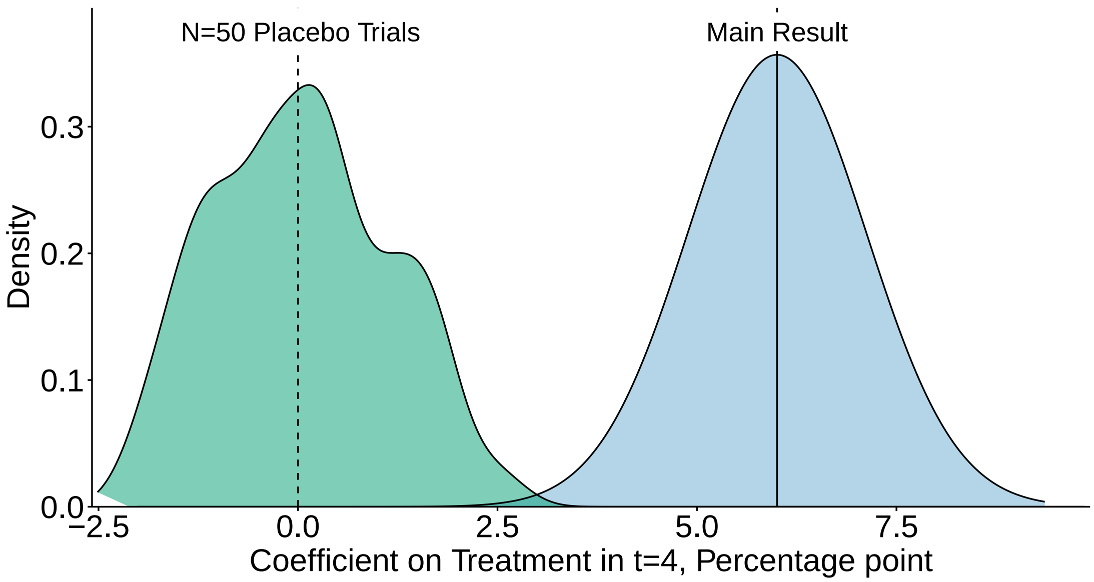
(b) Industrial Robot Adoption



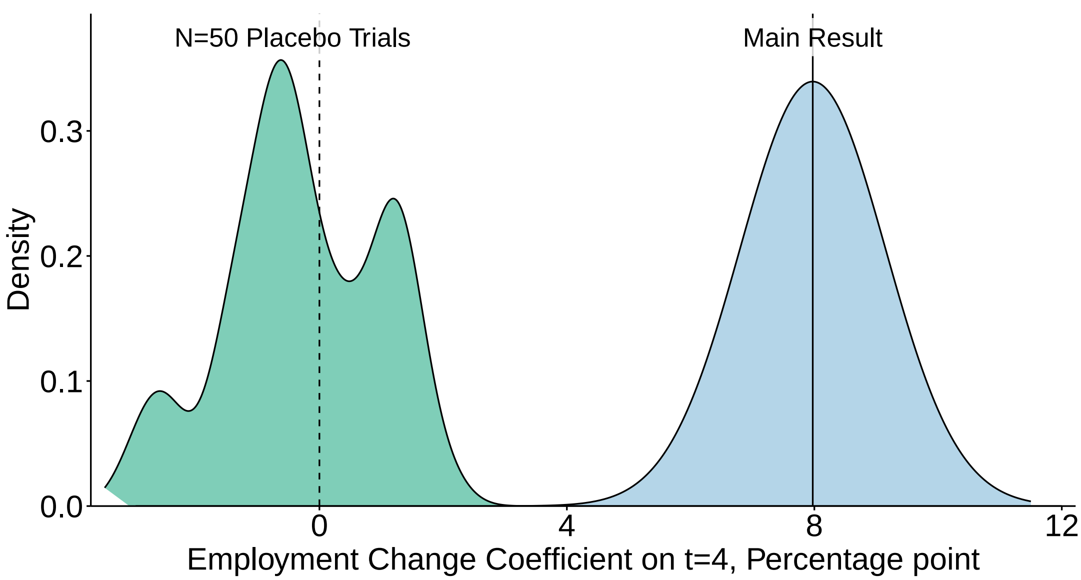
Notes: These figures compare five alternative LP-DiD specifications, as described in the text. The baseline specification is that from Figure (5), which includes Industry by Year fixed effects and a lag of the differenced outcome variable. Specification 2. includes Year fixed effects only; 3. includes Industry by Year fixed effects only; 4. includes Industry by Year fixed effects plus a linear site-specific trend; and 5. runs the baseline specification on the subsample of units who experience an adoption event at some stage i.e. it removes never-treated units from the control group, leaving only 'future treated' ones.

Figure 7: Placebo Test of Baseline Event-study Results

(a) CNC Machine Adoption

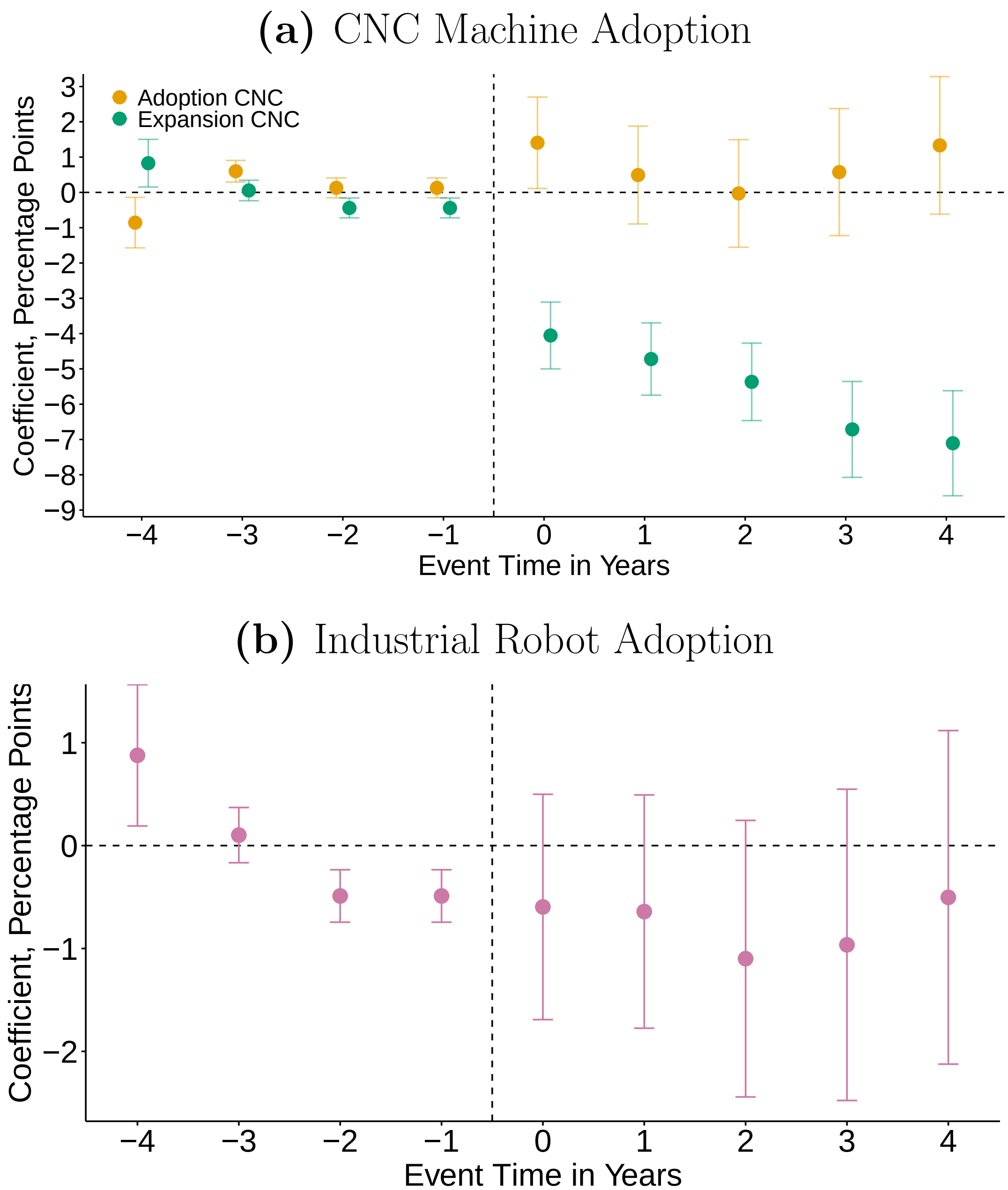


(b) Industrial Robot Adoption



Notes: This figure reports the coefficient estimate from $t = 4$ found in Figure (5), where the standard error is depicted as normally distributed in blue shading. Additionally, the left-most distribution in both panels shows a kernel-density plot of the same coefficient estimate from $N = 50$ placebo trials, where technology adoption events are randomised across the complete sample, preserving the temporal distribution throughout. The mean/median of the placebo-treatment coefficient estimates in panel (a) are 0.04/0.03 and in panel (b) are −0.28/0.43.

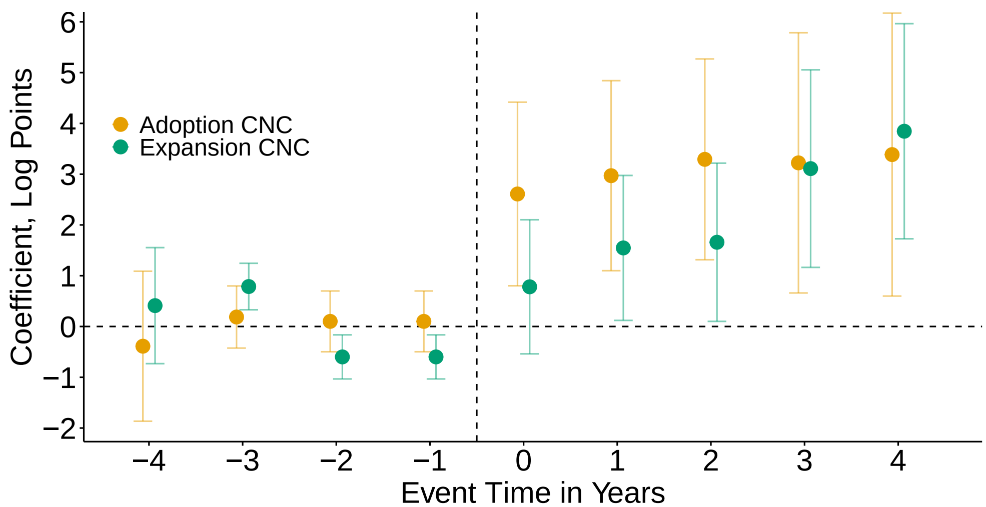
Figure 8: Plant-level Event Study, Share of Manufacturing Employment



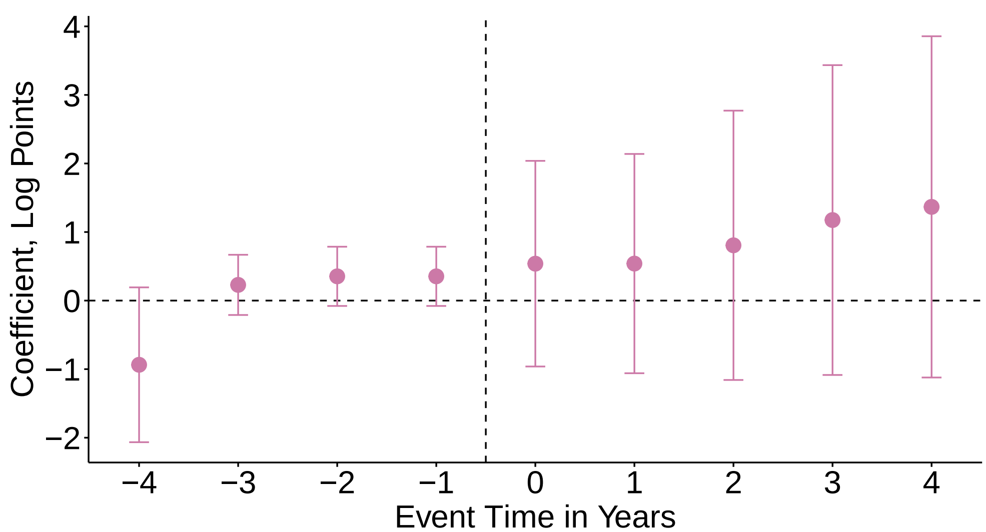
Note: These figures show LP-DiD estimates of employment-composition effects following automation events, as defined in the text. The outcome variable is the share of manufacturing workers to higher skilled designers/engineers. Panel (a) uses $N = 368,914$ observations from 2005-2023, with 4,355 'adoption' events and 8,240 expansion events. The post-treatment pooled coefficient is 1.541* (adoption) and −5.854*** (expansion). Panel (b) examines industrial robot adoption using $N = 229,731$ observations from 2010-2023, of which $1,826$ experienced an adoption event. The post-treatment pooled coefficient is −0.611. Both designs use detailed industry codes × Year fixed effects and a lag of the differenced outcome variable in period $t-1$ as controls, as per equation 1, with standard errors clustered at the plant-level. Vertical bars represent 95% confidence intervals.

Figure 9: Spillover Effects of Automation Events on Industry-Competitor Employment

(a) CNC Machine Adoption



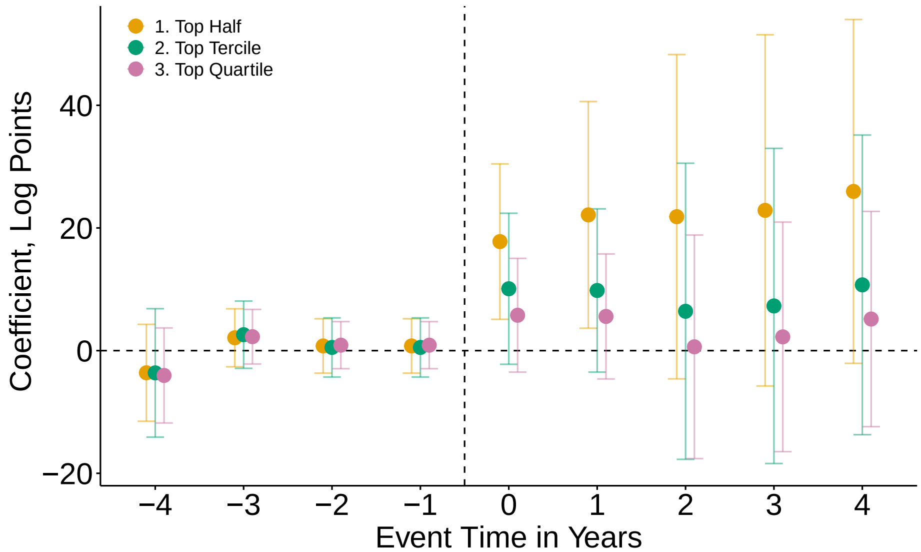
(b) Industrial Robot Adoption



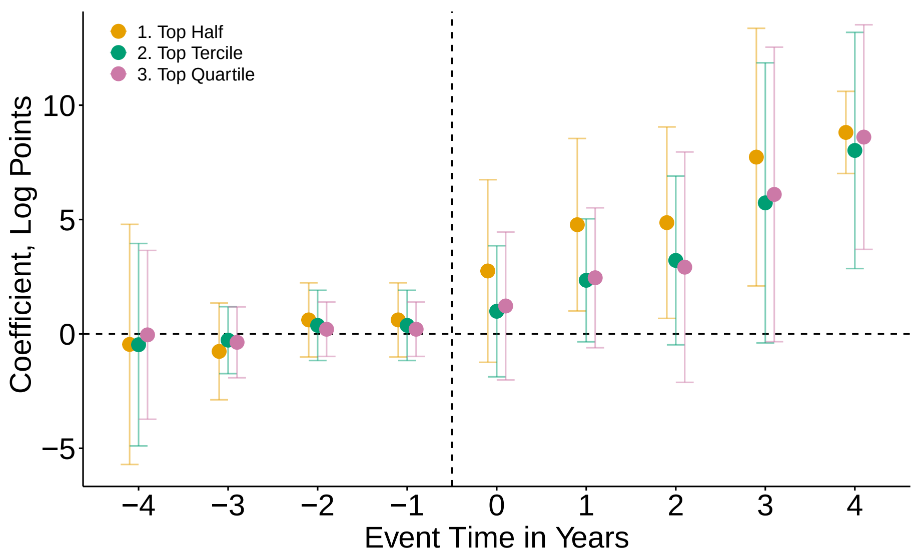
Notes: These figures show LP-DiD estimates of the effect of focal plant automation events on industry-competitor employment, as described in the text. The outcome is the leave-out sum of employment among other sites in a given industry and year, defined in Equation 2. Panel (a) uses $N = 368,914$ observations from 2005-2023, with 4,355 adoption events and 8,240 expansion events. The post-treatment pooled coefficient is 3.315^{***} (adoption) and 2.416^{***} (expansion). Panel (b) examines industrial robot adoption using $N = 229,731$ observations from 2010-2023, of which $1,826$ experienced an adoption event. The post-treatment pooled coefficient is 0.636. Both designs use 6-digit Industry Codes $\times$ Year fixed effects and a lag of the differenced outcome variable, as per equation 1, with standard errors clustered at the plant-level. Vertical bars represent 95% confidence intervals.

Figure 10: Industry-level Event Studies, Total Employment

(a) CNC Machine Adoption



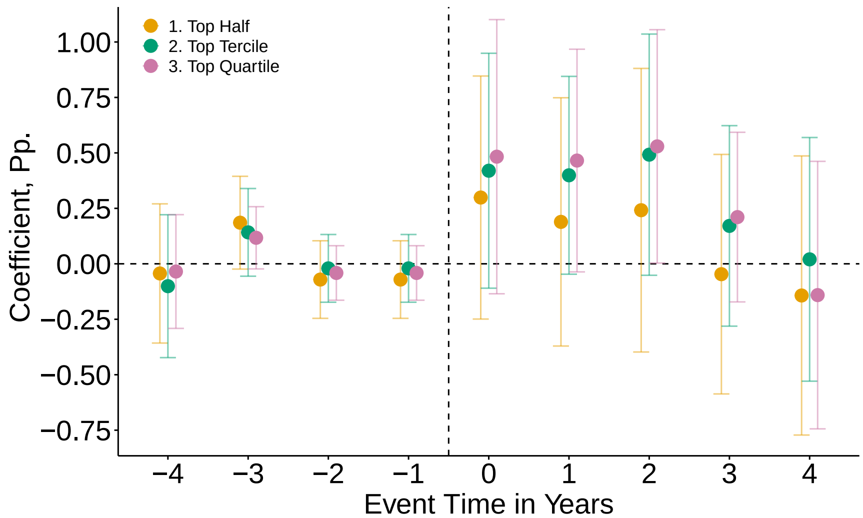
(b) Industrial Robot Adoption



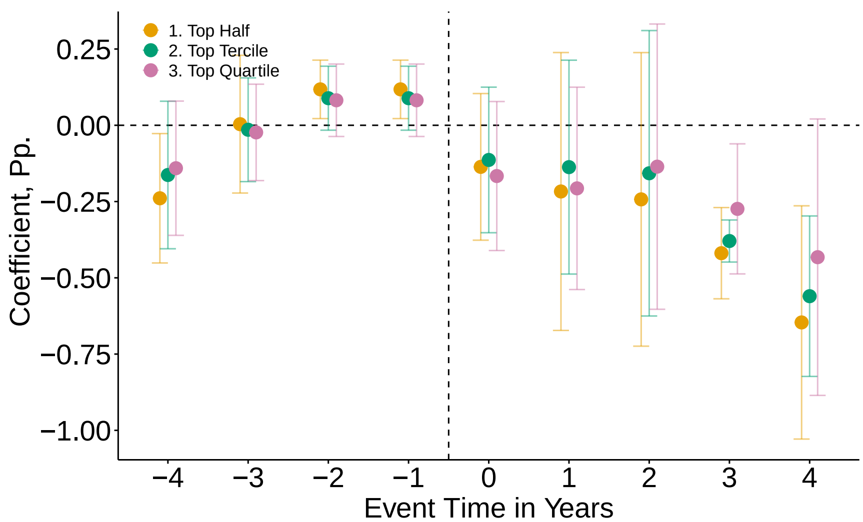
Notes: These figures show LP-DiD estimates of the effect of industry-level automation events on total industry employment, as described in the text. Industry is defined using detailed SIC codes provided by MAG. Events are defined as an increase in the industry share of employees working in firms with a given technology above a given percentile threshold in the distribution of all positive year-on-year changes. We use three thresholds: the top half, top third and top quarter of positive year on year changes. These correspond to an increase of 5%, 11%, 17%, respectively for CNC penetration, and 18%, 52%, and 90% for robots. All designs include year fixed effects and a lag of the differenced outcome variable, as per equation 3, with standard errors clustered at the industry level. Vertical bars represent 95% confidence intervals.

Figure 11: Industry-level Event Studies, Share of Manufacturing Employment

(a) CNC Machine Adoption



(b) Industrial Robot Adoption



Notes: These figures show LP-DiD estimates of the effect of industry-level automation events on the industry share of manufacturing employment. Industry is defined using detailed SIC codes provided by MAG. Events are defined as an increase in the industry share of employees working in firms with a given technology above a given percentile threshold in the distribution of all positive year-on-year changes. We use three thresholds: the top half, top third and top quarter of positive year on year changes. These correspond to an increase of 5%, 11%, 17%, respectively for CNC penetration, and 18%, 52%, and 90% for robots. All designs include year fixed effects and a lag of the differenced outcome variable, as per equation 3, with standard errors clustered at the industry level. Vertical bars represent 95% confidence intervals.

Table 1: Descriptive Statistics of UK Manufacturing Plant Survey

	Selected Years			All Years by Technology Use		
Variable	2005	2014	2023	All	CNC Users	Robot Users
Sample Size						
Number of Observations	20,087	17,923	13,133	368,914	229,697	38,079
Number of Sites	20,087	17,923	13,133	26,974	15,341	1,996
Number of Firms	19,549	17,516	12,934	26,180	14,970	1,947
Employment						
Mean	81.1	69.9	76.9	75.7	79	236.7
Total	1,629,658	1,253,437	1,010,213	27,913,290	18,147,636	9,013,907
p5	2	2	3	2	3	6
p25	7	7	8	7	8	30
Median	20	20	20	20	20	82
p75	60	50	55	55	55	230
p95	330	269	300	300	300	828
Technology Use						
Employment with CNC (%)	52	54.7	60.4	54	83	66.4
Employment with Robots (%)	-	14	27.1	22.8	26.5	63.1
Plants with CNC (%)	46.6	50.3	55.9	49.3	79.1	61
Plants with Robots (%)	-	3.9	8.3	6.2	7.2	51.4
Total Machine Tools	348,574	254,847	189,055	5,683,642	4,773,935	1,138,851
Total CNC Machine Tools	83,684	80,976	69,525	1,652,840	1,652,840	424,355
Tools per Worker	0.2	0.2	0.2	0.2	0.3	0.1
CNC Tools per Worker	0.1	0.1	0.1	0.1	0.1	0

Notes: This table presents summary statistics for ‘manufacturing production’ plants in the MAG survey, as defined in the text. Reliable information about robot use is only available from 2015. ‘CNC Users’ are sites that have ever used CNC machines, ‘Robot Users’ are sites that have ever used robots.

Online Appendix: Data

This section summarizes and validates the Mark Allen Group (MAG) Manufacturing Survey data used in the analysis, focusing on their representativeness and coverage. The MAG dataset underpins the paper's empirical work, providing plant-level information on employment, production activities, and technology use over nearly two decades. Because it is a commercial census rather than an official register, we benchmark it against administrative sources from the Office for National Statistics (ONS) to assess coverage quality. The following tables show that the MAG data closely track official employment patterns across time and plant sizes.

Table A1 compares aggregate manufacturing employment in the MAG survey with the ONS Labour Force Survey from 2005–2023. MAG captures roughly four-fifths of total UK manufacturing employment on average, with coverage varying between about 70 and 90 percent by year. The two series move closely together, diverging only slightly during the Covid-19 period when survey coverage temporarily dipped. The shortfall mainly reflects very small establishments below MAG's commercial threshold rather than systematic bias among larger plants. Hence, while not a complete census, the data provide a reliable and representative panel for analysing within-plant employment dynamics.

Table A2 compares employment by plant-size category in 2016. Under-coverage arises almost entirely from plants with fewer than 10 workers, which account for a minor share of total employment. For all larger categories, MAG and ONS totals align closely—slightly exceeding ONS values among plants with over 250 employees. This reflects MAG's emphasis on commercially significant production sites more likely to adopt advanced machinery. Overall, the dataset accurately captures the core population of UK manufacturing plants driving aggregate employment and automation investment.

Finally, Table 8 reports annual counts of CNC and robot adoption and expansion events. These reveal a steady, broad-based wave of automation: CNC adoption occurs throughout the sample, while robot adoption becomes visible after 2015 when MAG began recording it systematically. Expansion events—plants adding CNC machines after initial adoption—also rise steadily, suggesting ongoing reinvestment as firms accumulate experience. These patterns form the basis for the event-study analysis and show that automation diffusion in UK manufacturing has been gradual but pervasive.

Table A1: Aggregate Employment in MAG Survey vs ONS

	(1)	(2)	(3)
Year	MAG Panel Data	ONS Data	MAG/ONS (%)
2005	2,626	3,120	84.17
2006	2,527	3,025	83.54
2007	2,478	2,985	83.02
2008	2,381	2,884	82.56
2009	2,306	2,657	86.79
2010	2,199	2,570	85.56
2011	2,167	2,564	84.52
2012	2,186	2,603	83.98
2013	2,225	2,560	86.91
2014	2,271	2,621	86.65
2015	2,408	2,641	91.18
2016	2,329	2,655	87.72
2017	2,237	2,680	83.47
2018	2,068	2,715	76.17
2019	1,903	2,689	70.77
2020	2,128	2,618	81.28
2021	1,955	2,544	76.85
2022	1,797	2,612	68.80
2023	1,793	2,576	69.60
Mean	2,165	2,695	80.33

Notes: This table compares total manufacturing employment in the Mark Allen Group (MAG) Manufacturing Survey with official data from the Office for National Statistics (ONS) Quarterly Labour Force Survey, covering 2005–2023. Employment figures are shown in thousands of workers. The MAG survey captures an average of 80% of total manufacturing employment over this period, with coverage remaining stable prior to the Covid-19 pandemic and declining slightly thereafter. Differences largely reflect under-representation of very small plants and timing differences between the commercial and official surveys. These results confirm that the MAG data closely track official series in both levels and trends, providing a reliable basis for analysing within-plant employment dynamics and automation events.

Table A2: Plant Size Distribution in MAG vs ONS UK Manufacturing Plants, 2016

Size	MAG Emp. ('000s)	ONS Emp. ('000s)	MAG/ONS (%)
1–9	41	238	17.2
10–49	308	461	66.8
50–249	668	606	110.2
250–499	396	248	159.7
500+	892	851	104.9
All	2305	2404	95.9

Notes: This table compares employment by plant-size category in the Mark Allen Group (MAG) Manufacturing Survey with official data from the Office for National Statistics (ONS) Labour Force Survey for 2016. Employment is shown in thousands of workers, grouped into standard size bins based on the number of employees per establishment. The MAG survey closely matches the ONS distribution for medium and large manufacturing plants but under-represents micro-firms with fewer than 10 employees, which account for a small share of total manufacturing employment. Over-representation among plants with more than 250 workers reflects MAG's commercial focus on production-intensive sites and possible differences in the treatment of part-time workers. Overall coverage exceeds 95% of total manufacturing employment, confirming that the MAG data provide a representative picture of the sector's core employment structure.

Table A3: Count of Automation Events, by Year

	Events		
Year	CNC Adoption Events	CNC Expansion Events	Robot Adoption Events
2005	562	705	-
2006	274	479	-
2007	422	742	-
2008	277	810	-
2009	189	442	-
2010	265	534	-
2011	193	691	-
2012	172	466	-
2013	318	561	-
2014	231	477	-
2015	134	327	242
2016	265	397	204
2017	342	511	243
2018	137	214	173
2019	87	153	162
2020	125	194	106
2021	230	347	51
2022	99	144	638
2023	33	46	7
Total	4,355	8,240	1,826

Notes: This table reports the annual number of automation "events" observed in the Mark Allen Group (MAG) Manufacturing Survey between 2005 and 2023. CNC adoption events are defined as the first year in which a plant reports using at least one CNC machine tool; CNC expansion events capture subsequent increases in the number of CNC machines at already-adopting plants; and robot adoption events record the first year in which a plant reports using industrial robots. Data on robot use are available only from 2015 onward, when MAG introduced a dedicated survey module on robotics. The figures highlight the gradual but sustained diffusion of CNC technology throughout the sample period and the more recent wave of industrial robot adoption beginning in the mid-2010s. These event counts form the basis for the local-projection difference-in-differences estimations presented in the main text.

A Online Appendix: Additional Results

This section presents robustness checks and complementary estimates that reinforce the main findings reported in Section 6 of the paper. The additional tables examine whether the estimated employment effects of automation are sensitive to alternative estimation methods, clustering strategies, or the inclusion of lagged outcomes in the local-projection difference-in-differences (LP-DiD) framework. Together, these analyses confirm that the positive employment effects observed after CNC and robot adoption are highly robust to different modelling choices and assumptions.

Table A compares the pooled four-year post-event effects across four leading estimators recently proposed in the difference-in-differences literature: CDLZ, CS, BJS, and CC. The results are remarkably consistent across specifications. For both CNC and robot adoption, as well as CNC expansion events, the estimated employment gains remain between five and eight percent, with no evidence of attenuation when alternative estimators are applied. This reinforces the conclusion that the findings are not an artefact of the baseline estimator, but rather a stable feature of the underlying data.

Table A assesses the sensitivity of standard errors to different clustering levels, including plant, industry, and industry-by-year clustering, as well as heteroskedasticity-robust alternatives. While precision naturally varies with the degree of clustering, the estimated coefficients remain significant and of similar magnitude under all options. This indicates that the results are not driven by over-aggregation or serial correlation within sectors, and that plant-level shocks dominate the variation underlying the event-study estimates.

Finally, Table A evaluates the influence of dynamic controls by re-estimating the baseline specification with zero to three lags of the differenced outcome variable. Allowing for additional lags leaves the estimated treatment effects virtually unchanged, suggesting that serial dependence in employment growth does not bias the core results. These consistency checks strengthen the interpretation that the observed post-adoption rise in employment reflects genuine productivity and expansion effects rather than spurious pre-trend correction or unmodelled persistence.

Table B1: Effect of Automation Events on Log Employment: Alternative Estimators

Dependent Variable:	Δ Ln Employment$_t$											
Treatment Definition	CNC Adoption				CNC Expansion				Robot Adoption			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables												
Treatment Effect	5.74***	5.74***	5.06***	5.63***	7.67***	7.68***	6.82***	8.63***	6.95***	6.95***	6.98***	7.05***
	(0.828)	(0.828)	(0.932)	(0.861)	(0.549)	(0.550)	(0.664)	(0.592)	(1.05)	(1.05)	(1.03)	(1.17)
ΔLn Employment$_{t-1}$	-0.037***	-0.037***	0.703***	-0.034***	-0.035***	-0.035***	0.706***	-0.035***	-0.024***	-0.026***	0.718***	-0.022***
	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.006)	(0.007)	(0.009)	(0.005)
Estimator	CDLZ	CS	BJS	CC	CDLZ	CS	BJS	CC	CDLZ	CS	BJS	CC
Fixed-effects												
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SIC1980-year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics												
Observations	159,262	159,262	123,011	147,825	143,218	143,218	108,379	130,261	112,053	67,868	65,284	104,908
R^2	0.050	0.050	0.230	0.053	0.051	0.051	0.232	0.056	0.041	0.047	0.227	0.043

Notes: This table reports the pooled post-treatment effect of automation events on total plant-level employment using four alternative estimators (1) CDLZ is the Stacked Estimator Cengiz et al. (2019); (2) CS uses the approach from Callaway and Sant'Anna (2021) (3) BJS uses the approach from Borusyak et al. (2024); (4) CC applies a Composition Correction to our baseline estimator to ensure stable comparison groups, as outlined in Dube et al. (2023). All specifications include Year by Industry fixed effects. Standard errors are clustered at the plant level. Significance: *** 0.01, ** 0.05, * 0.1.

Table B2: Effect of Automation Events on Log Employment: Sensitivity to Clustering Method

Dependent Variable:	Δ Ln Employment$_t$											
Treatment Definition	CNC Adoption				CNC Expansion				Robot Adoption			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables												
Treatment Effect	5.74***	5.74***	5.74***	5.74***	7.67***	7.67***	7.67***	7.67***	6.95***	6.95***	6.95***	6.95***
	(0.828)	(0.970)	(0.929)	(0.828)	(0.549)	(0.636)	(0.637)	(0.549)	(1.05)	(1.11)	(1.14)	(1.05)
ΔLn Employment$_{t-1}$	-0.037***	-0.037***	-0.037***	-0.037***	-0.035***	-0.035***	-0.035***	-0.035***	-0.024***	-0.024***	-0.024***	-0.024***
	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)	(0.006)	(0.006)
Clustering	Plant	Industry	Ind×Year	Robust	Plant	Industry	Ind×Year	Robust	Plant	Industry	Ind×Year	Robust
Fixed-effects												
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SIC1980-year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics												
Observations	159,262	159,262	159,262	159,262	143,218	143,218	143,218	143,218	112,053	112,053	112,053	112,053
R^2	0.050	0.050	0.050	0.050	0.051	0.051	0.051	0.051	0.041	0.041	0.041	0.041

Notes: This table reports the pooled post-treatment effect of automation events on total plant-level employment under alternative methods for estimating standard errors. Each column uses the baseline Local Projection Difference-in-Differences (LP-DiD) estimator with year-by-industry fixed effects but varies the clustering approach. "Plant" denotes clustering at the establishment level (our baseline). "Industry" clusters by 6-digit SIC industry, "Ind×Year" by industry–year cells, and "Robust" uses heteroskedasticity-robust standard errors only. Models (1)–(4), (5)–(8), and (9)–(12) report results for CNC adoption, CNC expansion, and robot adoption respectively. Coefficient estimates are stable across clustering schemes, confirming that our inference is not driven by within-industry correlation in residuals. Significance: *** 0.01, ** 0.05, * 0.1.

Table B3: Effect of Automation Events on Log Employment: Sensitivity to Number of Outcome Lags

Dependent Variable:	Δ Ln Employment$_t$											
Treatment Definition	CNC Adoption				CNC Expansion				Robot Adoption			
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Variables												
Treatment Effect	5.45***	5.74***	6.16***	5.22***	7.42***	7.67***	6.97***	6.34***	6.94***	6.95***	6.97***	6.65***
	(0.764)	(0.828)	(0.887)	(0.937)	(0.498)	(0.549)	(0.621)	(0.650)	(1.05)	(1.05)	(1.05)	(1.04)
ΔLn Employment$_{t-1}$		-0.037***	-0.040***	-0.038***		-0.035***	-0.037***	-0.039***		-0.024***	-0.020***	-0.021***
		(0.005)	(0.006)	(0.005)		(0.005)	(0.005)	(0.006)		(0.006)	(0.006)	(0.007)
ΔLn Employment$_{t-2}$			-0.038***	-0.041***			-0.042***	-0.046***			-0.024***	-0.017**
			(0.006)	(0.006)			(0.006)	(0.007)			(0.007)	(0.007)
ΔLn Employment$_{t-3}$				-0.043***				-0.052***				-0.026***
				(0.007)				(0.008)				(0.009)
Number of Lags	0	1	2	3	0	1	2	3	0	1	2	3
Fixed-effects												
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SIC1980-year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics												
Observations	178,806	159,262	140,622	123,011	162,605	143,218	125,042	108,379	129,636	112,053	95,202	79,141
R^2	0.049	0.050	0.051	0.051	0.050	0.051	0.052	0.052	0.041	0.041	0.044	0.047

Notes: This table reports the pooled post-treatment effect of automation events on total plant-level employment using our baseline Local Projection Difference-in-Differences (LP-DiD) estimator, varying the number of lags of the differenced outcome variable included on the right-hand side. Models (1)–(4), (5)–(8), and (9)–(12) report results for CNC adoption, CNC expansion, and robot adoption respectively, with 0 to 3 lags of Δ ln(Employment). All designs include year-by-industry fixed effects to account for sectoral shocks. Standard errors are clustered at the plant level. Adding additional lags has little effect on the magnitude or precision of the estimated treatment effects, confirming that serial correlation in employment growth does not drive the core results. Significance: *** 0.01, ** 0.05, * 0.1.