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Restructuring and layoffs in the Industry 4.0 era: the role of exposure to advanced manufacturing technologies

Fabio Lamperti[1,*] Katiuscia Lavoratori[2] and Davide Castellani[3]

[1]Department of Economic Policy, Università Cattolica del Sacro Cuore, Via Lodovico Necchi, 5, 20123 Milano, Italy. e-mail: fabio.lamperti@unicatt.it, [2]Sapienza University of Rome, Department of Computer, Control and Management Engineering, V. Ariosto, 25, 00185 Roma, Italy e-mail: katiuscia.lavoratori@uniroma1.it and [3]Henley Business School, University of Reading, Whiteknights, RG6 6UD Reading, United Kingdom, e-mail: davide.castellani@henley.ac.uk

*Main author for correspondence

This study examines how Industry 4.0 advanced manufacturing technologies (AMTs) influence restructuring decisions. Analyzing data from European manufacturing firms (2013–2020), we find that greater AMT exposure correlates with a lower overall likelihood of restructuring. When restructuring occurs, AMTs reduce closure probabilities while increasing downsizing likelihood and minimizing layoffs. AMT exposure is measured through industry-level adoption and firm-level capital intensity. This study emphasizes the need to consider both the benefits and disruptions of automation in shaping strategies.

JEL Classification: D22, D24, J23, O33

1. Introduction

The current debate on new digital technologies has devoted much attention to understanding the mechanisms through which the diffusion of new forms of automation triggers the displacement of jobs where tasks can now be performed by capital (Acemoglu and Autor, 2011; Frey and Osborne, 2017; Acemoglu and Restrepo, 2018, 2019, 2020). Such conversation stands at the crossroads between the long-standing literature delving into the multifaceted relationships between innovation, adoption of new technologies, and the related employment effects (Freeman *et al.*, 1982; Freeman and Soete, 1994; Vivarelli, 1995; Pianta, 2005) and that on the crucial role played by techno-economic paradigms and trajectories (Dosi, 1982, 1988; Dosi *et al.*, 2022) in defining patterns of industrial dynamics, competitiveness, and firms' survival (Malerba and Orsenigo, 1997; Breschi *et al.*, 2000).

The new digital technologies of Industry 4.0 (Fourth Industrial Revolution or I4.0) have triggered a profound transformation of industries and firms, changing the way businesses operate and are organized (Porter and Heppelmann, 2014, 2015; Dalenogare *et al.*, 2018; Müller *et al.*, 2018; Benassi *et al.*, 2022), both at a local level and on an international scale (Alcácer *et al.*, 2016; Laplume *et al.*, 2016; Strange and Zucchella, 2017; Hannibal and Knight, 2018). New digital technologies, which emerged over recent decades, have the potential to permeate and reshape many aspects of economic and social activities; depending on the context of application, they may disrupt (substitute) existing activities (tasks) or complement existing ones (Ciarli *et al.*, 2021).

The pervasiveness of such transformation, stemming from the interdependence between innovation, skills, and new digital (automation) technologies, increasingly pushes firms to reorganize their productive operations (Sinha and Noble, 2008; Dalenogare *et al*., 2018; Frank *et al*., 2019; Marcucci *et al*., 2021). In turn, this reorganization can affect the competitiveness of the firm, its growth trajectories, and employment decisions. Hence, new digital technologies and the associated benefits (e.g., productivity gains)[1] may increase firms' chances of survival and prevent plant closures, as well as appear as a beacon of hope for workers.

Organizational restructuring typically follows a strategic decision to increase profitability and reach the 'right' size to maximize a firm's market value and to face increasing competition, or simply to survive. While it can take various forms, it often leads to significant layoffs of employees. Therefore, understanding what drives these decisions is crucial (Cascio, 1993; Coucke *et al*., 2007; Coucke and Sleuwaegen, 2008). We build on the study by Coucke *et al*. (2007) on the determinants of collective employee layoffs through different modes of restructuring, by directly looking at the opportunities that advanced manufacturing technologies (AMTs) can offer to firms as a unique form of capital.

Therefore, this paper investigates the role played by three AMTs of the I4.0 (Eurofound, 2018; Stornelli *et al*., 2021)—advanced industrial robots (AIRs), additive manufacturing (AM) and the Internet of Things (IoT). We look at the probability of a firm engaging in three types of restructuring events that result in a net dismissal (or relocation) of the whole or parts of business and the related employee layoffs (Coucke *et al*., 2007): (i) the dismissal of a consistent proportion of the workforce (downsizing), (ii) the dismissal of either the entire workforce or a part of it, due to the relocation of activities abroad, with or without the maintenance of ownership (offshoring), and (iii) the cessation of business activities in a plant and/or dismissal of the entire workforce (closure), the most drastic decision.

We devise a conceptual framework describing the firm-level mechanisms through which AMTs could affect restructuring strategies. Due to scarce availability of firm-level data on technology adoption, our hypotheses are tested using a measure of exposure to such technologies. In detail, firm-level exposure to AMTs is constructed as the interaction between industry-level AMT adoption and firm-level capital intensity. Industry-level adoption reflects how prevalent a technology is within an industry, increasing the likelihood that firms within it are exposed to the technology. Meanwhile, firms with a higher capital–labor ratio typically have the financial resources and infrastructure to integrate new technologies. Thus, firms with higher capital intensity, operating in industries with greater AMT adoption, are more likely to adopt AMTs due to greater exposure.

Our analysis adopts a multistage decision approach. We first assess the role of a firm's AMT exposure when it initially faces the decision to restructure or not. Then, when the decision to restructure has been taken, the firm's management encounters a second decision on which of the three restructuring modes to adopt. Further, we assess the impact of AMT exposure on the magnitude of collective layoffs triggered by restructuring decisions. In detail, we first estimate a probit model to understand the determinants of the probability of being involved in a restructuring event, and then a multinomial logit to model the choice of the restructuring mode. We further evaluate the role of AMT on the number of employees laid off. Using data from the European Restructuring Monitor (Eurofound, 2025) and Moody's Orbis Europe databases, we examine a sample of 1,888 manufacturing firms located across 19 European countries and 728 restructuring events over the period 2013–2020. We find robust evidence of a negative association between firm-level AMT exposure and the probability of engaging in any restructuring mode, as compared to non-restructuring firms. Conditional on restructuring, AMT exposure is negatively associated with the probability of closure and positively associated with the probability of continuing business activities through downsizing. We also find no significant evidence that AMTs incentivize firms to offshore as an alternative to terminating business activities. These results hold after a set of robustness checks. Additionally, we analyze the role of AMT exposure at the intensive margin of restructuring choices by looking at the number of employees laid off. Overall, we find that these technologies play a mitigating role as they reduce the magnitude of net layoffs (i.e. total layoffs minus new hirings) and total layoffs that are associated with restructuring strategies. Conversely, AMT exposure has no significant relationship with new hirings. Finally,

[1] Various studies, for instance Acemoglu *et al*. (2020), Acemoglu *et al*. (2023) and Bonfiglioli *et al*. (2024), look at the productivity gains from automation.

we analyze the role of AMT adoption on the entire sample of restructuring and non-restructuring firms at the industry level, further supporting our results on firm-level outcomes.

The central message of this paper is that AMTs are associated with a reduction in the probability of undertaking restructuring events. Furthermore, conditional on undertaking restructuring initiatives, the exposure to I4.0 technologies may act as a counterbalance and create the conditions needed to avoid closure and, ultimately, save jobs. Our findings further reinforce the idea that the impact of automation on employment is complex and multifaceted. Firms' strategic restructuring decisions could be an additional channel of transmission of such effects, which has been overlooked in the literature to date. Effective policy responses should consider both the potential for job displacement and the opportunities for job preservation and economic growth that these technologies may offer.

The remainder of the paper is structured as follows. Section 2 presents the related literature and frames the hypotheses. Section 3 presents the empirical setting, data, and variables, and provides descriptive evidence. Section 4 discusses the results of the empirical analyses, and Section 5 concludes with policy implications.

2. Background literature and hypotheses

2.1 Technical background on AMTs

We focus on a subset of I4.0 technologies (Martinelli *et al*., 2021) which are considered 'game-changing' for their peculiar characteristics (Eurofound, 2018, p. 3). In particular, AMTs embody specific technical characteristics and have the potential to significantly affect the way operations and business activities are conducted across all manufacturing sectors. The industrial applications of AMTs include: AIRs, AM, and the IoT (Stornelli *et al*., 2021). These AMTs share the common characteristic of being embodied technologies, as they require the installation of specialized physical assets (Lamperti *et al*., 2024).

AIRs represent the latest advancement in robotics (as compared to the previous generation of industrial robots from the 1970s). They have high-level dynamic programming features that combine with advanced and interconnected sensors. These features make them suitable for adaptive performance and, as they take up a larger set of tasks, enable a partial substitution of human labor. AIRs further increase the potential for autonomy, accuracy, flexibility and support enhanced forms of human–machine interaction (Eurofound, 2018; Frey and Osborne, 2017; Martinelli *et al*., 2021).

AM techniques—also known as 3D printing—are currently employed in various sectors and services (e.g. in the aerospace and automotive industry, and in medicine and education). AM is a highly flexible and adaptable digital manufacturing process, resulting in reduced material consumption and waste, the production of highly customized goods and components (characterized by advanced technical features and complex geometric designs e.g. hollow shapes), fewer manufacturing and assembly stages, higher cost-effectiveness, and faster prototyping (Weller *et al*., 2015; Martinelli *et al*., 2021). These benefits endow AM adopters with the potential to reduce production and logistics costs in several manufacturing contexts, adopt innovative business models, and serve niche markets by differentiating products without excessive additional costs and organizational complexity (Weller *et al*., 2015; Felice *et al*., 2022).

Finally, the IoT is the adoption of smart sensors, actuators, and several other smart distributed systems (e.g. global positioning system, near-field communication, and radio-frequency identification) that enable the creation of an interconnected infrastructure involving both physical (e.g. factory machines, computers, and manufactured products) and digital components (e.g. management software, monitoring tools, and artificial intelligence). This infrastructure allows the collection of data on efficiency, machine usage, and energy consumption from integrated devices, to enhance the reliability of assets by preventing faults and downtimes through predictive maintenance. Automating production simultaneously lowers costs and improves output quality (Porter and Heppelmann, 2014, 2015). Similarly, this huge integration potential and flow of data leads to the creation of connected and more sustainable networks between firms, suppliers, and customers (Porter and Heppelmann, 2014; Benassi *et al*., 2022).

2.2 AMTs and employment: a dual perspective

The widespread diffusion of automation technologies has generated concerns about the potential threat to employment (recently, Ciarli *et al.*, 2021; Dosi *et al.*, 2021, 2022; for recent surveys, see Calvino and Virgillito, 2018; Montobbio *et al.*, 2024) as automation may displace workers from their traditional tasks and roles, and increase the risk of inequality (Acemoglu and Autor, 2011; Frey and Osborne, 2017; Acemoglu and Restrepo, 2018, 2019, 2020). Conversely, another perspective emphasizes the opportunity for automation to enhance company competitiveness and resilience (Dalenogare *et al.*, 2018; Frank *et al.*, 2019; Marcucci *et al.*, 2021). This viewpoint suggests that new digital technologies can enhance productivity, curtail operational costs, and mitigate the risk of closure (Sinha and Noble, 2008; Marcucci *et al.*, 2021).

Despite extensive research, these two strands of literature have not fully engaged with each other. Firm-level studies (Acemoglu *et al.*, 2020, 2023; Bonfiglioli *et al.*, 2024) estimate the positive effects of automation on productivity but overlook the additional benefits beyond productivity gains, with a more granular insight into how firms achieve them. The digital transformation brought by AMTs may lead to: (i) automated and flexible production, logistics, and supply chain tracking; (ii) interconnected communication between machines, components, and final products; (iii) mass customization and enhanced human–machine interaction; and (iv) a digitally optimized smart factory that is integrated with the supply chain (Shafiq *et al.*, 2016). These transformations can lead to internal restructuring aimed at operational, organizational, and financial optimization, often resulting in business restructuring and layoffs (Coucke *et al.*, 2007; Coucke and Sleuwaegen, 2008; Bandick, 2016). Although large-scale business restructuring events attract media attention due to widespread layoffs, the role of AMTs in driving these transformations remains underexplored, with only a few studies addressing the issue. For instance, Beer *et al.* (2019) and Goos *et al.* (2021) examined the impact of automation on employment following major plant closures in the Australian and Belgian automotive industries. They found that workers in routine tasks and with limited digital skills face greater reemployment challenges. Similarly, Blien *et al.* (2021) and Olsson and Tåg (2017) analyzed mass layoffs in Germany and Sweden, showing that while automation does not increase unemployment, it exacerbates worker polarization, reducing reemployment prospects and wages. Overall, these studies pave the way to analyze the intersection between AMTs and business restructuring events, which is crucial to our investigation. Nonetheless, they neglect a deeper analysis of the relationship between AMT adoption, the occurrence and the mode of restructuring events, and their employment effects.

2.3 AMTs and business restructuring

To investigate the relationship between AMTs and restructuring strategies, we build our conceptual framework upon the previous work of Coucke *et al.* (2007), who theoretically modeled how a firm's characteristics affect preferences towards, and trade-offs between, different and alternative restructuring strategies involving significant collective layoffs. Specifically, *closure* represents the most drastic restructuring mode: companies may choose to terminate all their activities when they incur losses, and/or other restructuring options are either impossible or expensive (Coucke *et al.*, 2007; O'Brien and Folta, 2009). The second type of restructuring strategy resulting in layoffs is *downsizing* (Coucke *et al.*, 2007; Cascio, 2012; Freeman and Ehrhardt, 2012), defined as 'a planned set of organizational policies and practices aimed at workforce reduction with the goal of improving firm performance' (Datta *et al.*, 2010, p. 282). Finally, firms may decide to relocate their manufacturing operations abroad as a survival strategy. Most often, this offshoring decision results from an efficiency-seeking strategy, aimed at lowering costs and raising productivity (Coucke and Sleuwaegen, 2008; Sethupathy, 2013; Bandick, 2016), or following resource-seeking aims (i.e., specialized personnel, new knowledge and innovations; Lewin *et al.*, 2009).

2.3.1 AMTs and the probability of restructuring

Continuing the discussion on dual perspectives (Section 2.2), AMTs might have profound implications for a firm's operational strategies as they have an impact on productivity, flexibility, and resilience. However, their influence on restructuring remains a complex issue with competing perspectives. On the one hand, AMTs can enhance competitiveness, reducing the need for disruptive adjustments; on the other hand, their integration may lead to workforce displacement, skill-biased employment shifts, and business reorganization.

One key finding from the literature is that the extent of AMTs and their perceived benefits are highly dependent on contextual factors such as firm size, sector, and geographical location. Most studies emphasize that the well-planned integration of AMTs into business practices yields significant advantages, outweighing the drawbacks of partial implementation. Technologies such as AIRs enhance flexibility, efficiency, and reliability in production (Dalenogare *et al.*, 2018; Frank *et al.*, 2019). AM accelerates prototyping, fosters innovation, supports mass customization, and promotes sustainability by reducing resource consumption and waste (Weller *et al.*, 2015; Bogers *et al.*, 2016). Similarly, integrating the IoT with other I4.0 technologies enables the creation of cyber-physical systems that seamlessly connect machines, computers, and products, leading to cost reductions, improved safety, and enhanced productivity (Kagermann *et al.*, 2013; Alcácer and Cruz-Machado, 2019). These advancements contribute to higher productivity levels (Lamperti *et al.*, 2024), allowing firms to adapt more effectively to economic uncertainty, demand fluctuations (Müller *et al.*, 2018) and economic shocks, as they improve organizational resilience (Marcucci *et al.*, 2021). Consequently, AMTs provide firms with competitive advantages that enhance their survival prospects without requiring disruptive restructuring measures, such as mass layoffs.

Based on the above discussion of firm-level mechanisms through which AMTs could influence the propensity to restructure, our first hypothesis follows as:

> H1a. *A high level of a firm's exposure to AMTs is negatively associated with its probability of restructuring through collective layoffs.*

Taking a different perspective, several authors emphasize that AMTs require firms to commit to capital investments in specialized hardware and software infrastructures (Marcucci *et al.*, 2021). Müller *et al.* (2018) argue that although these technologies entail high short-term costs, benefits materialize in the long run. Additionally, AMTs might shift the skill content of tasks, particularly in production, affecting both employment levels and required skills (Frey and Osborne, 2017). This shift may lead to retraining, upskilling, or job displacement. AIRs enhance working conditions by reducing human error, operating autonomously, and improving safety in hazardous environments (Złotowski *et al.*, 2017). AM increases demand for highly skilled workers in design, R&D, and operations, reinforcing skill-biased technological change (Felice *et al.*, 2022). Likewise, the IoT reduces the need for manual labor as machines self-adapt without human intervention (Porter and Heppelmann, 2014, 2015). These patterns align with broader automation trends in Industry 4.0 (Acemoglu and Restrepo, 2018, 2019, 2020) where AMTs drive capital–labor substitution, while requiring new skill sets (Acemoglu and Autor, 2011).

Beyond labor dynamics, AMTs allow firms to explore new markets, expand product portfolios, and adopt innovative business models (Bogers *et al.*, 2016; Müller *et al.*, 2018). While product innovations are linked to positive employment effects (Montobbio *et al.*, 2024), AMTs reshape both organizational and manufacturing processes. AM, for instance, facilitates co-creation with consumers, altering traditional production workflows and redefining geographic and organizational boundaries (Strange and Zucchella, 2017). Some studies suggest that AM fosters decentralized production, enabling firms to locate operations closer to consumers, reducing logistic costs and delivery times (Laplume *et al.*, 2016; Hannibal and Knight, 2018). Specifically, De Beule *et al.* (2022) show that firms using AM maintain more foreign production subsidiaries than non-AM firms, even when compared to similarly innovative companies. IoT further transforms value chain integration by linking manufacturers, suppliers, and customers through seamless data exchange, reducing the need for intermediaries and lowering coordination costs (Porter and Heppelmann, 2014, 2015). This enhances the efficiency of geographically dispersed operations, reducing barriers to relocating value-adding activities to cost-efficient or market-proximate locations (Strange and Zucchella, 2017). This reorganization can lead to the relocation of value-adding activities closer to final markets or cost-effective locations, potentially triggering layoffs.

Given these arguments, AMTs may drive restructuring efforts through job displacement and geographical shifts, leading to an alternative hypothesis:

H1b. *A high level of a firm's exposure to AMTs is positively associated with its probability of restructuring through collective layoffs.*

2.3.2 AMTs and alternative restructuring choices

AMTs may provide firms with new sources of competitive advantage over non-adopters (Porter and Heppelmann, 2014, 2015), ultimately increasing their chances of future survival (Sinha and Noble, 2008; Marcucci *et al.*, 2021). Notwithstanding, firms face challenges and uncertainties related to their surrounding market conditions, new (or evolution of existing) technological trajectories (e.g., the emergence of the I4.0 paradigm; Martinelli *et al.*, 2021), as well as industry or macroeconomic downturns (e.g. the 2008 financial crisis, the 2020 Covid-19 pandemic). By using AMTs, these events can be mitigated by a firm's ability to develop specific and unique capabilities (resulting in higher levels of organizational resilience) (Marcucci *et al.*, 2021), but managers may still deem it necessary to undertake drastic strategic decisions.

Once the decision to restructure is taken, the (rational) managerial decision-making process involves the evaluation of gains and costs associated with each restructuring opportunity and the choice of a restructuring alternative that allows the maximization of the future value of the firm's business activities (Coucke *et al.*, 2007). In this context, we consider the worst-case scenario (*closure*) as a reference to compare alternative restructuring modes and analyze the implications of AMTs in such evaluations.

When comparing *downsizing* and *closure*, managers evaluate the net present value obtained by continuing operations, net of the adjustment costs associated with the adaptation of business activities to the reduced workforce due to the layoff. Such costs are then compared to the scrap value of current assets in the case of closure. We argue that there are three main mechanisms in place.

First, (as discussed in previous sections) adopting automated and advanced production methods results in capital deepening that can lead to collective employee layoffs (Coucke *et al.*, 2007; Cascio, 2012; Freeman and Ehrhardt, 2012). Furthermore, AMTs may require less human involvement in production (especially in downstream industries; Dosi *et al.*, 2021; Felice *et al.*, 2022) and a different mix of more qualified human capital (Frey and Osborne, 2017; Pedota *et al.*, 2023).

Second, AMTs can lead to reduced production and logistic costs, optimized workflows, and deeper integration of different business activities within the firm and across the value chain (Porter and Heppelmann, 2014, 2015; Dalenogare *et al.*, 2018; Frank *et al.*, 2019), resulting in improved resilience and a firm's ability to absorb shocks (Marcucci *et al.*, 2021).

Third, AMTs require onerous investments in both physical (i.e. capital-intensive machinery and equipment; Benassi *et al.*, 2022; Müller *et al.*, 2018) and human capital (i.e. upskilling and training of employees; Pedota *et al.*, 2023). While the former may be common to all firms (depending on their investment capabilities), the latter is crucial for a complete and effective adoption of AMTs. As in the case of other ICTs (Brynjolfsson and Hitt, 1996; Fichman, 2004), a large share of costs relates to: the technical training of employees (to use new machines/systems and learn new practices); hiring professional consultants to support the transformation; the organizational effort made to adapt to the transformation; and to absorbing the productivity losses incurred during the transition. These additional investments associated with employee training and establishing new routines and practices are considered sunk costs, since they are strictly specific to the firm's organization (Kogut and Kulatilaka, 2001; Presidente, 2023), hence lost in case of closure. Thus, the decision to invest in these technologies usually entails sunk costs that make plant closure particularly onerous.

We argue that, on the one hand, AMTs can push firms to downsize through collective layoffs, but on the other hand, they increase a firm's efficiency and resilience, while creating sunk costs and irreversible investment, thus reducing the likelihood of plant closure. This leads to our second hypothesis:

H2. *Conditional on restructuring, a high level of a firm's exposure to AMTs is associated with a higher probability of choosing to downsize over closing.*

Comparing the *offshoring* decision with the *closure* scenario, the new business opportunities created by AMTs enable firms to better serve new markets, facilitating the extent to which they are able to serve geographically distant locations, and the coordination between dispersed activities (Strange and Zucchella, 2017; Hannibal and Knight, 2018; De Beule *et al.*, 2022). From this perspective, new AMT-related assets can act as catalysts for an offshoring decision: they allow companies to reduce the logistic costs when they offshore production activities abroad (Kinkel and Maloca, 2009), while also pursuing an efficiency-seeking strategy that benefits from the lower production costs in the offshoring location (Coucke and Sleuwaegen, 2008; Sethupathy, 2013; Bandick, 2016). At the same time, the benefits gained from the adoption of AMT may also result in additional productivity effects from value-adding activities retained in the home country. For example, as discussed by Porter and Heppelmann (2015), IoT-enabled connectivity between the firm and its customers makes it easier to manage remote customer services due to the continuous data exchange between smart products and a firm's monitoring systems, enabling such services to be outsourced to lower-wage, but high IT-skilled locations. These mechanisms should further encourage increased competitiveness from non-offshored activities (Barba Navaretti *et al.*, 2010) and improve a firm's chances of survival (Grazzi *et al.*, 2022).

In sum, the characteristics of these technologies should make it convenient for a firm to offshore production activities and seek a more efficient and productive business structure, avoiding the closure of the business. Hence, we hypothesize:

H3. *Conditional on restructuring, a high level of a firm's exposure to AMTs is associated with a higher probability of choosing to offshore activities over closing.*

3. Data and methodology

3.1 Data

Our empirical investigation relies on data from three main sources. First, we sourced data on restructuring events from Eurofound's European Restructuring Monitor (ERM) database, which provides rich information about business restructuring events involving businesses operating in the 27 European Union (EU) countries, the United Kingdom (UK; until the end of 2019) and Norway, from 2002 onwards. The information on restructuring events reported in the ERM database is collected by checking daily newspapers and business news and integrated with online resources, such as company websites (Eurofound, 2025). The data provided satisfies strict criteria, aimed at publishing information only on significant, large-scale, restructuring events taking place across the EU: '*an event is included if it entails the announced destruction or creation of at least 100 jobs, or at least 10% of the workforce at sites employing more than 250 people*' (Eurofound, 2025). The ERM database collects data on large-scale restructuring events reported in the principal national media and company websites in each European country, including business expansion, closure, merger/acquisition, and offshoring/delocalization. It provides information on the type of event, the home country, and the name of the focal company, together with the employment impact of the restructuring decision (e.g., job losses and/or gains, locations). It continuously monitors the evolution of the restructuring decisions over time and updates the details related to the execution of the events and their impact.[2]

The structure of the ERM data allows for the presence of cross-country events, where consequences affect more than one European country or even countries outside of Europe (i.e. flagged as 'European Union' or 'World' in the ERM data). We discarded all events outside of Europe or in multiple countries, as well as those events reporting either incomplete or insufficient information to allow a precise identification of where the employment effect happened. Furthermore, business

[2] Updates on subsequent changes in the implementation of restructuring events are reported directly in the event description as follow-up information.

restructuring events in the ERM data can indicate the displacement of a part of the workforce (i.e. a collective layoff), the hiring of new employees, or a mix of both.[3] For consistency with our study's conceptual framework, we focus only on those restructuring events that imply a net negative effect on the workforce (i.e. when the difference between new hirings and the total layoffs associated with the restructuring event is negative).

As reported by Eurofound (2025), we look at: closure/bankruptcy, '*when a company goes bankrupt/a company or an industrial site is closed for economic reasons not directly connected to relocation or outsourcing*'; internal restructuring/downsizing, '*when the company undertakes a job-cutting plan, which is not linked to another type of restructuring [...]*', and offshoring/delocalization, '*when the activity is relocated or outsourced outside of the country's borders*'. We acknowledge that offshoring can be viewed as a combination of a firm deciding to set up activities abroad (i.e. to a host country) and close or downsize in the home country. However, data on offshoring events reported in the ERM database is not affected by such issues, hence not subject to double counting (i.e. the same event is not recorded twice as a closure or downsizing in the home country and offshoring in the host country), which could in turn bias our results. Indeed, the ERM event categories reflect the full extent of the main employment effect behind the restructuring decision at the time of the announcement. In the case of offshoring, events are recorded in the home country, job losses (and, potentially, hirings) refer to the home country, and the only information about the host country lies in the destination country and, potentially, the location within the host country. In our empirical analysis, we focus on restructuring events taking place in manufacturing sectors (i.e. 2-digit NACE codes from 10 to 33).

Second, we sourced detailed firm-level longitudinal information from Moody's Orbis Europe database for the period 2012–2020. We initially identified firms engaged in the three layoff-related restructuring events from the ERM database within Orbis Europe, as well as a sample of non-restructuring firms. First, we downloaded information for manufacturing firms active in the 27 EU countries, the UK and Norway, with at least nine employees, and having non-missing values for key financial and balance sheet variables over the observation period. Specifically, we considered the number of employees, tangible and intangible fixed assets, operating revenue, and profit/loss. This initial step resulted in 217,377 firms respecting such criteria. Second, we matched data on the three layoff-related restructuring events from the ERM database with firm-level data from Orbis Europe, discarding all observations for which it was not possible to obtain non-missing firm data necessary to compute the variables of interest. Third, we dropped all observations for firms in Orbis Europe matching with firms reporting other types of restructuring events in the ERM database (i.e. those not reporting any type of restructuring under investigation in our study but undertaking other types of restructuring, but not necessarily implying collective employee layoffs, for example, mergers and acquisitions or business expansions). This process returned a sample of 77,317 observations (12,663 firms), including both restructuring and non-restructuring firms. Finally, we used the resulting subset of non-restructuring European firms to create a counterfactual sample with comparable characteristics for our group of restructuring firms by implementing propensity score matching. We report details in the Online Appendix.

Third, to build the main explanatory variable of exposure to the technology, we combine information on sectoral AMT adoption with firm-level capital composition. We follow the methodology from Lamperti *et al.* (2024) to compute industry-level AMT adoption, using highly detailed information (8-digit level of product disaggregation) on imports of AMT-related goods sourced from Eurostat's Comext database and inter-country and inter-sector intermediate imports from the World Input–Output Database dataset (Timmer *et al.*, 2015). The final sample includes 3,224 observations for 1,888 firms operating across 24 manufacturing industries and located in 19 European countries between 2013 and 2020. This sample includes 728 restructuring events undertaken by 563 firms.[4]

[3] Unfortunately, the information provided via the ERM data does not allow us to consistently identify which type of workers are laid off or hired.

[4] Our sample coverage is reduced from 27 EU countries, the UK and Norway, to 18 EU countries and the UK after discarding non-missing observations in Orbis Europe data for restructuring firms and as a by-product of our econometric strategy controlling for several FE, which results in several 'singleton' observations across country-sector-year units to be dropped because perfectly predicted.

3.1.1 Variables

3.1.1.1 *Dependent variables.*

Restructuring decision: Our first dependent variable is a dummy variable assuming a value of 1 in the presence of any restructuring event involving layoffs, and a value of 0 in the absence of a restructuring event.

Restructuring mode: Our second dependent variable is a categorical variable describing the mode of restructuring undertaken by the company. It assumes a value of 0 in the case of the reference category (closure), a value of 1 in the case of downsizing, and a value of 2 in the case of offshoring. This is a one-time restructuring decision.

3.1.1.2 *Main explanatory variable*

Firm-level AMT exposure: Firm-level data on the adoption of AMTs are rarely available, and most studies rely on dedicated surveys[5] or proxy measures (e.g. Castellani *et al.*, 2022; Lee *et al.*, 2023). To test our hypotheses, we construct a measure of firm-level exposure to AMTs, building on the idea that firms operating in industries with higher AMT adoption and that are more capital-intensive, are more likely to pursue further capital deepening and adopt AMTs (Coucke *et al.*, 2007; Coucke and Sleuwaegen, 2008; Cascio, 2012; Freeman and Ehrhardt, 2012; Bandick, 2016). The level of technological and capital intensity that characterizes the surrounding environment represents an important factor in determining industry competitive dynamics (Malerba and Orsenigo, 1997; Breschi *et al.*, 2000; Dosi *et al.*, 2022) and also shapes a firm's technological investment decisions (Datta *et al.*, 2010; Porter and Heppelmann, 2014).

Based on this premise, we define firm-level exposure to AMTs as the combination of two factors: (i) industry-level AMT adoption, measured as the (natural logarithm of) *AMT import stock* of the industry in which the firm operates (Lamperti *et al.*, 2024). To construct the *AMT import stock*, we use data from 2009 up to year t, when the restructuring event occurs (see the Online Appendix for more details). This approach aligns with the well-established idea that imports of equipment embodied with the technology, indicate technology diffusion and, therefore, technology adoption (for recent applications, see Acemoglu and Restrepo, 2022; Bisio *et al.*, 2025; Lamperti *et al.*, 2025); (ii) the firm's level of capital intensity (i.e. *tangible capital-to-labor (K/L)* ratio), measured by the natural logarithm of tangible fixed assets per employee. The rationale behind this exposure measure is that firms with higher capital intensity, operating in industries with greater AMT adoption, are more likely to adopt AMTs due to their greater exposure to the technology and their capital-intensive structure (to our knowledge, the most closely related papers are Acemoglu and Restrepo, 2020; Bonfiglioli *et al.*, 2024; Gihleb *et al.*, 2022). Following this idea, we operationalize the exposure to AMTs of firm i, operating in sector s of country c at time t as:

$$AMT\_\exp_{i,t} = \left[\ln\left(AMT\ Import\ Stock\right)_{s,c,t} \times \underbrace{\ln\left(\frac{Tangible\ Fixed\ Assets}{Number\ of\ Employees}\right)_{i,t}}_{Tangible\ K/L} \right] \quad (1)$$

Since this measure is effectively an interaction between sectoral *AMT import stock* and firm *tangible K/L* ratio, we also include these two variables in all our models as controls for the main effects.

3.1.1.3 *Firm-level characteristics and country-sector controls*

We control for a set of firm-level and sectoral characteristics, following the relevant literature on the restructuring choices of firms, their survival, and their employment dynamics. Specifically, we include measures of *intangible K/L* ratio, in order to measure a firm's intellectual property, R&D expenditure, licenses and other reputational assets, which build up a firm's set of resources and

[5] We note that survey data, despite providing highly detailed information, features well-known limitations, such as limited comparability across countries and over time.

know-how and can lead to new products, services, and competitive advantage. We further include a measure of firm-level *productivity,* capturing the firm's ability to use its assets to produce the desired output, which generally enhance a firm's efficiency level, as well as firm-specific routines and processes.[6] Additionally, we include controls for the firm's *age*, *size*, *return on assets (ROA)*, *leverage*, if the firm is part of a *corporate group*, if it is an *innovator* (i.e. it holds patents) and if it performed *recent investments*. We further control for other relevant sectoral characteristics, such as overall *investment intensity* and the level of *product differentiation* characterizing the industry in which the firm operates. All these variables are described in detail in the Online Appendix.

3.2 Empirical strategy

To test our hypotheses, we first analyze the role of AMT exposure on the firm's decision on whether to restructure or not, conditionally to firm and industry characteristics. Second, we observe the role of AMT exposure when a firm chooses which restructuring mode to pursue, conditional on undertaking a restructuring decision. We follow a two-stage procedure based on Heckman's (1979) approach: in the first stage, we estimate a probit model describing the selection problem (i.e. whether to restructure through employee layoff or not) using a counterfactual sample of non-restructuring firms, followed by a second stage where we estimate a multinomial logit model describing the choice problem (i.e. to choose among the three alternative restructuring modes discussed here). In this second stage, we include the inverse Mills ratio (IMR) to account for the mechanisms described by the first selection problem. This procedure helps us to control for the potential bias in the second stage arising from unobservable factors leading some firms to restructure their business activities and achieve partial identification even in situations where proper exclusion restrictions are not easy to identify (Honoré and Hu, 2020, 2022).[7] Therefore, our baseline specification follows the set of equations:

$$\begin{aligned} &P\left(Rest_{i,t} = 1 | AMT\_\exp_{i,t-1}, \boldsymbol{X}_{i,t-1}, \boldsymbol{Z}_{s,c,t-1}\right) \\ &= \Phi\left[\alpha_0 + \beta_0 AMT\_\exp_{i,t-1} + \gamma_0 \boldsymbol{X}_{i,t-1} + \delta_0 \boldsymbol{Z}_{s,c,t-1} + \varepsilon_{i,t}\right] \end{aligned} \tag{2}$$

$$\begin{aligned} &P\left(Rest\_mode_{i,t} = J | AMT\_\exp_{i,t-1}, \boldsymbol{X}_{i,t-1}, \boldsymbol{Z}_{s,c,t-1}, IMR_{i,t-1}\right) \\ &= \frac{1}{1 + \sum_{m=1}^{J-1} \exp\left(\alpha_m + \beta_m AMT\_\exp_{i,t-1} + \gamma_m \boldsymbol{X}_{i,t-1} + \delta_m \boldsymbol{Z}_{s,c,t-1} + \vartheta_m IMR_{i,t-1}\right)} \end{aligned} \tag{3}$$

where the dependent variable in the first stage, $Rest_{i,t}$, is a dummy variable assuming value 1 if firm i performs a restructuring decision at time t and 0 otherwise. In the second stage, each firm i engaging in a restructuring event at time t, faces alternative $J = 3$ choices: *closures (baseline)*, *downsizing* and *offshoring*, as described by $Rest\_mode_{i,t}$. $AMT\_\exp_{i,t-1}$ captures the firm-level exposure to AMTs; $\boldsymbol{X}_{i,t-1}$ and $\boldsymbol{Z}_{s,c,t-1}$ represent vectors of firm-level characteristics and country-sector controls, respectively. Following from H1a/b, we expect β_0 to be either < 0 or > 0 in Eq. (2), and with H2 and H3, we expect β_1 and β_2 to be > 0 in Eq. (3). We further include a set of country, sector fixed effects (FE) in all our specifications to control for unobserved heterogeneity. Furthermore, in our robustness checks we also test specifications, including country-by-sector FE. Each estimation includes a set of year dummies to capture any time FE that may affect the probability of a specific restructuring event in a given year. We do not observe firms over time, so our model can be considered as a pooled cross-section.

[6] We measure productivity in two ways. First, we compute labor productivity, calculated as the natural log of the ratio of the firm's turnover and number of employees, which we use in our main analysis. Second, as an alternative measure, we estimate total factor productivity (TFP), as a measure of a firm's capabilities, using the methodology proposed by Ackerberg *et al.* (2015) and implemented through STATA's `acfest` routine.

[7] We further test a different estimation method based on a conditional mixed-process model (using STATA's `cmp` command, see Roodman, 2011) where Eq. (2) and (3) are simultaneously estimated and a formal check of the presence of self-selection is tested via significance of the cross-equation correlation of error terms. Notably, here Eq. (3) is estimated via the multinomial probit model. Results are reported in Table A5 in the Online Appendix and are qualitatively and statistically in line with the main results presented in Table 7.

All variables included in our specifications for Eq. (2) and (3) are lagged by one year to avoid simultaneity issues. Table 1 presents the summary statistics and correlation matrix for the variables used in our main analysis, highlighting no multicollinearity concerns. We only uncover a high correlation between the *AMT exposure* and the *Tangible K/L* variables, which is, however, expected given that the former results from the interaction of the latter with sectoral *AMT import stock*. We further check for potential multicollinearity issues by computing variance inflation factor (VIF) values for all variables in our model, which are never above the critical value of 10.

Additionally, to corroborate our main findings, we extend our analysis by investigating the role played by AMT exposure on the magnitude of layoffs, distinguishing between net layoffs (new hirings minus total layoffs), total layoffs and new hirings associated with each restructuring event (see Section 4.2). Coherently with H2 and H3, we expect an overall negative relationship between AMT exposure and the number of laid-off employees, since the firm should be less likely to close, laying-off either the whole or a large portion of the workforce; we assume they would rather opt for a downsize, laying-off only a portion of the workforce.

3.3 Descriptive evidence on restructuring events

Tables 2, 3, and 4 highlight the distribution of restructuring events of each category across years, sectors, and countries, respectively. Specifically, Table 2 shows that downsizing events are the most frequent mode of restructuring (545), while closure and offshoring are less numerous (125 and 58, respectively). The frequency of all three types of restructuring events has been relatively stable during the observation period, although we observe a higher percentage at the beginning and at the end of the observation period. This insight reinforces the idea that there is a correlation between economic shocks and restructuring through collective layoffs (as discussed in Section 2.3.1). Specifically, early years in our time series (2013 and 2014) bear the aftermath of the local (sovereign debt) crises affecting European countries, starting from 2011, while the steep increase witnessed in 2020 is clearly related to the Covid-19 pandemic. The tables also include the distribution of non-restructuring firms over the years.

Table 3 highlights that restructuring events cover all manufacturing industries, except for offshoring cases, which are more concentrated in some sectors. A notable concentration of restructuring events characterizes sector 10 (manufacturing of food products), sector 28 (manufacturing of machinery and equipment) and sector 29 (manufacturing of motor vehicles, trailers, and semi-trailers). Likewise, Table 4 presents the geography of the restructuring events: across the 19 European countries in our data, most closure cases are concentrated in Germany, France, the UK, and Poland. Cases of restructuring through downsizing present a similar pattern, with the notable addition of northern EU countries like Finland and Sweden, which also present a relatively large number of cases. Finally, offshoring, which is the less frequent type of event, appears in a few countries, mostly Germany, France and, to a lesser extent, Belgium, the UK, and Austria.

Looking at the size of collective layoffs across our sample, Figure 1 describes the frequency distribution of normalized employee layoffs.[8] We expressed the size of layoffs as a share of the previous year's number of employees of the firm. Collective layoffs in our sample involve a large portion of the firm workforce: on average about 71%, ranging between 38% and full dismissal of the workforce, which represents about the top fifth percentile of the distribution. This suggests that only a few cases of closure involve the closure of the whole firm. At the same time, it also highlights that employee reductions following downsizing or offshoring decisions have resulted in a large proportion of the workforce being laid off. Table 5 reports summary statistics of normalized employee layoffs reported in Figure 1 and the log value of layoff size: mean normalized employee layoffs rank highest in the case of closure (0.803) but remain high also in the case of downsizing (0.694) and offshoring (0.710), supporting the insight from Figure 1. Closure events feature the highest (log) mean layoff size as compared to the other restructuring events considered: specifically, the magnitude of layoffs associated with closure events is larger than that observed for downsizing and offshoring events at any point up to the 90th percentile of the layoff distribution, while it remains larger than the one for downsizing events up to the 75th

[8] We note that, by construction, normalized employee layoffs can also be seen as a firm's employment growth. Consistent with prior literature on growth rates for several firm-level variables, Figure 1 presents the typical tent-shape distribution characterized by fat tails (see, for instance, Barba Navaretti *et al.*, 2022; Bottazzi and Secchi, 2003).

Table 1. Descriptive statistics: correlation matrix, variance inflation factors, and summary statistics

Variable	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]
Firm-level variables														
[1] AMT exposure	1.000													
[2] Tangible K/L	0.886	1.000												
[3] Intangible K/L	0.280	0.220	1.000											
[4] Productivity (LP)	0.366	0.390	0.200	1.000										
[5] Age	0.186	0.162	0.051	0.074	1.000									
[6] Size	0.314	0.240	0.472	−0.019	0.204	1.000								
[7] ROA	0.119	0.108	0.042	0.074	0.046	0.095	1.000							
[8] Leverage	0.123	0.115	0.193	−0.081	−0.010	0.133	−0.200	1.000						
[9] Corporate group dummy	0.221	0.177	0.376	0.105	0.213	0.379	0.014	0.123	1.000					
[10] Innovator dummy	0.171	0.117	0.210	0.067	0.302	0.237	−0.005	0.007	0.269	1.000				
[11] Recent investments dummy	0.171	0.032	0.192	0.040	0.028	0.218	0.054	0.043	0.122	0.096	1.000			
Sectoral variables														
[12] AMT import stock	0.159	−0.086	0.226	0.102	0.140	0.221	−0.020	−0.001	0.156	0.258	0.117	1.000		
[13] Investment intensity	0.042	0.034	0.042	0.073	0.014	0.030	0.012	−0.039	−0.044	0.035	0.027	0.086	1.000	
[14] Product differentiation	0.000	−0.020	−0.005	−0.041	0.072	−0.034	−0.006	0.032	−0.059	0.000	0.011	0.081	0.169	1.000
VIFs	6.91	6.94	1.53	1.33	1.18	1.58	1.08	1.14	1.32	1.23	1.16	1.55	1.05	1.05
N	3,224	3,224	3,224	3,224	3,224	3,224	3,224	3,224	3,224	3,224	3,224	3,224	3,224	3,224
Mean	71.931	3.568	1.709	5.575	3.385	7.074	0.011	0.073	0.730	0.645	0.377	20.338	21.468	0.792
SD	27.412	1.294	1.676	0.907	0.869	1.733	0.295	0.121	0.444	0.479	0.485	1.955	12.312	0.163
Min	−182.056	−10.352	−0.535	1.883	0	1.792	−8.683	−0.874	0	0	0	13.435	2.710	0.150
Max	241.353	11.077	11.895	12.651	5.606	13.393	1.057	2.459	1	1	1	25.263	119.550	1.000

Notes: Authors' own computations based on ERM and Orbis Europe data. All statistics refer to 1-year lagged variables. Statistics only refer to firm-year observations for restructuring events; statistics for the full sample, including non-restructuring firms, are available upon request. AMT, advanced manufacturing technologies; ERM, European Restructuring Monitor; ROA, return on assets

Table 2. Distribution of restructuring events, by year

	Closure		Downsizing		Offshoring		Non-restructuring		Total
Year	N	%	N	%	N	%	N	%	N
2013	12	2.92	73	17.76	10	2.43	316	76.89	411
2014	19	4.57	60	14.42	7	1.68	330	79.33	416
2015	11	3.23	58	17.01	6	1.76	266	78.01	341
2016	9	2.55	57	16.15	7	1.98	280	79.32	353
2017	17	4.80	58	16.38	7	1.98	272	76.84	354
2018	16	5.41	42	14.19	5	1.69	233	78.72	296
2019	20	4.42	75	16.56	4	0.88	354	78.15	453
2020	21	3.50	122	20.33	12	2.00	445	74.17	600
Total	125	3.88	545	16.90	58	1.80	2,496	77.42	3,224

Notes: Authors' own computations based on European Restructuring Monitor and Orbis Europe data. Data on non-restructuring firms refer to firm-year observations.

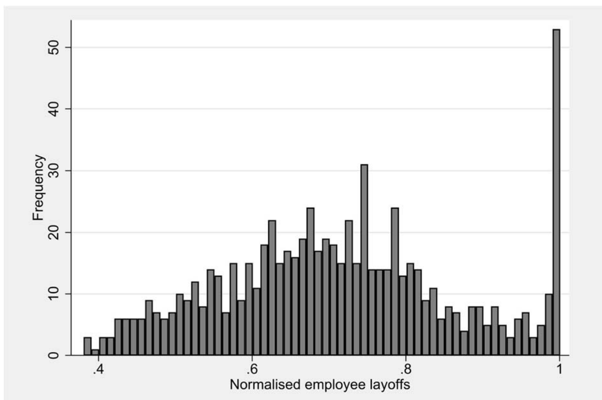

Figure 1. Frequency distribution of normalized employee layoffs. *Notes*: Authors' own computations based on ERM and Orbis Europe data. Employee layoffs have been normalized using the firm's number of workers in the year preceding the restructuring event

percentile. These insights suggest that downsizing and offshoring firms are, on average, larger than those of closing ones, resulting in higher absolute layoffs at the top of the distribution.

Finally, Table 6 presents descriptive statistics for the variables used in our main analysis, distinguishing firm and industry characteristics across the three restructuring modes investigated. Notably, AMT exposure is significantly higher across downsizing firms as compared to those who decided to close, coherently meeting our expectations discussed in Section 2.3. It is also interesting to note that the size of the firms involved in closure events is smaller than that of the downsizing firms.

4. Results

4.1 Restructuring

Table 7 reports the main results of the regression analysis estimating the two-stage selection model described by Eqs. (2) and (3). Column (1) reports the estimated coefficients from the probit model used in the first stage, while column (2) reports the estimated average marginal effects (AME). The coefficient for AMT exposure in column (1) is negative and statistically significant at the 5% level, suggesting that exposure to AMT has a significant relationship with lower probabilities of pursuing any type of restructuring decision involving collective layoffs, as compared to non-restructuring firms—thus supporting hypothesis H1a. The estimated AME in column (2) highlights that a 10% increase in AMT exposure relates to a 0.02 percentage point (p.p.) drop in the probability of undertaking restructuring.

Table 3. Distribution of restructuring events, by 2-digit NACE code

NACE 2-digit code	Closure		Downsizing		Offshoring		Non-restructuring		Total
	N	%	*N*	%	*N*	%	*N*	%	*N*
10 – Man. of food prod.	26	6.19	49	11.67	7	1.67	338	80.48	420
11 – Man. of beverages	6	5.88	9	8.82	2	1.96	85	83.33	102
12 – Man. of tobacco prod.	1	4.76	3	14.29	1	4.76	16	76.19	21
13 – Man. of textiles	1	2.44	7	17.07	1	2.44	32	78.05	41
14 – Man. of wearing apparel	3	7.32	5	12.20	0	0.00	33	80.49	41
15 – Man. of leather and related prod.	1	5.88	2	11.76	0	0.00	14	82.35	17
16 – Man. of wood and of prod. of wood and cork	2	3.13	7	10.94	1	1.56	54	84.38	64
17 – Man. of paper and paper prod.	9	6.57	21	15.33	1	0.73	106	77.37	137
18 – Printing and reproduction of recorded media	1	2.27	5	11.36	0	0.00	38	86.36	44
19 – Man. of coke and refined petroleum prod.	1	2.86	7	20.00	0	0.00	27	77.14	35
20 – Man. of chemicals and chemical prod.	3	1.85	29	17.90	4	2.47	126	77.78	162
21 – Man. of basic pharmaceutical prod. and pharmaceutical preparations	4	3.57	20	17.86	3	2.68	85	75.89	112
22 – Man. of rubber and plastic prod.	6	4.72	14	11.02	3	2.36	104	81.89	127
23 – Man. of other non-metallic mineral prod.	6	6.19	14	14.43	1	1.03	76	78.35	97
24 – Man. of basic metals	4	2.19	34	18.58	2	1.09	143	78.14	183
25 – Man. of fabricated metal prod., except machinery and equipment	4	3.33	18	15.00	2	1.67	96	80.00	120
26 – Man. of computer, electronic and optical prod.	5	2.70	34	18.38	2	1.08	144	77.84	185
27 – Man. of electrical equipment	9	4.46	31	15.35	10	4.95	152	75.25	202
28 – Man. of machinery and equipment n.e.c.	13	3.24	73	18.20	5	1.25	310	77.31	401
29 – Man. of motor vehicles, trailers and semi-trailers	15	3.99	90	23.94	8	2.13	263	69.95	376
30 – Man. of other transport equipment	0	0.00	54	31.76	0	0.00	116	68.24	170
31 – Man. of furniture	1	1.85	7	12.96	2	3.70	44	81.48	54
32 – Other manufacturing	2	3.85	4	7.69	3	5.77	43	82.69	52
33 – Repair and installation of machinery and equipment	2	3.28	8	13.11	0	0.00	51	83.61	61
Total	125	3.88	545	16.90	58	1.80	2,496	77.42	3,224

Notes: Authors' own computations based on European Restructuring Monitor and Orbis Europe data. Data on non-restructuring firms refer to firm-year observations.

Table 4. Distribution of restructuring events, by country

	Closure		Downsizing		Offshoring		Non-restructuring		Total
ISO	*N*	%	*N*	%	*N*	%	*N*	%	*N*
AUT	5	4.90	13	12.75	5	4.90	79	77.45	102
BEL	9	10.00	27	30.00	7	7.78	47	52.22	90
CZE	2	2.35	11	12.94	1	1.18	71	83.53	85
DEU	24	4.15	131	22.63	10	1.73	414	71.50	579
DNK	1	1.72	8	13.79	1	1.72	48	82.76	58
EST	0	0.00	4	12.12	0	0.00	29	87.88	33
FIN	7	1.99	58	16.48	3	0.85	284	80.68	352
FRA	20	5.21	109	28.39	13	3.39	242	63.02	384
GBR	29	4.95	59	10.07	5	0.85	493	84.13	586
GRC	1	10.00	1	10.00	0	0.00	8	80.00	10
HUN	4	6.56	4	6.56	1	1.64	52	85.25	61
IRL	1	10.00	0	0.00	0	0.00	9	90.00	10
LTU	0	0.00	7	17.50	0	0.00	33	82.50	40
LVA	0	0.00	2	15.38	1	7.69	10	76.92	13
NLD	1	1.11	10	11.11	3	3.33	76	84.44	90
POL	12	4.55	33	12.50	0	0.00	219	82.95	264
SVK	4	4.40	8	8.79	2	2.20	77	84.62	91
SVN	2	1.92	14	13.46	1	0.96	87	83.65	104
SWE	3	1.10	46	16.91	5	1.84	218	80.15	272
Total	125	3.88	545	16.90	58	1.80	2,496	77.42	3,224

Notes: Authors' own computations based on European Restructuring Monitor and Orbis Europe data. Data on non-restructuring firms refer to firm-year observations.

Table 5. Employee layoffs by type of restructuring event

	Closure		Downsizing		Offshoring		Total	
	Normalized	log	Normalized	log	Normalized	log	Normalized	log
Mean	0.803	5.388	0.694	5.352	0.710	5.193	0.714	5.346
SD	0.162	0.670	0.143	1.015	0.174	0.616	0.154	0.940
p10	0.558	4.625	0.509	4.277	0.449	4.564	0.509	4.394
p25	0.680	4.883	0.597	4.644	0.578	4.736	0.606	4.710
Median	0.801	5.247	0.690	5.142	0.729	5.075	0.709	5.176
p75	0.964	5.832	0.780	5.861	0.844	5.525	0.809	5.832
p90	1.000	6.293	0.895	6.553	0.947	6.256	0.956	6.399

Notes: Authors' own computations based on European Restructuring Monitor and Orbis Europe data. Observations: 125 closures; 545 downsizing; 58 offshoring. Normalized (%) values expressed as employee layoffs over firm's number of workers in the year preceding the restructuring event (corresponding to values reported in Figure 1).

Our findings for the other firm-level variables in our model are in line with the existing literature (Coucke *et al.*, 2007; Coucke and Sleuwaegen, 2008; Barba Navaretti *et al.*, 2010; Bandick, 2016; Grazzi *et al.*, 2022). Even after the matching procedure—discussed in the Online Appendix, which extensively reduces the potential heterogeneity existing between restructuring and non-restructuring firms—we find evidence that restructuring firms are, on average, more productive, bigger, and less profitable than their counterfactual. While we uncover no significant difference between restructuring and non-restructuring firms when looking at a firm's age and (tangible and intangible) capital intensity, our results suggest that firms which are part of a corporate group are less likely to restructure through employee layoffs, and that those firms that have recently invested in physical assets are less likely to pursue collective layoffs; this emphasizes the role of recent capital investments in lowering incentives to restructure. Finally, none of the three additional sectoral controls in our model are significantly different from zero, suggesting that the combination of FE in our specification captures the underlying sectoral and country-specific trends, in particular, those related to technological and investment intensity.

Table 6. Descriptive statistics: *T*-test for differences in sample means across restructuring events

Variable		Closure		Downsizing		Offshoring		Closure versus downsizing	Closure versus offshoring
		Mean	SD	Mean	SD	Mean	SD	*T*-test (*P*-value)	*T*-test (*P*-value)
Firm-level variables									
	AMT exposure	61.839	36.574	76.365	25.876	71.943	26.429	0.000	0.036
	Tangible K/L	3.348	1.172	3.720	1.249	3.610	1.059	0.002	0.136
	Intangible K/L	1.647	1.674	2.084	1.806	2.349	1.869	0.010	0.016
	Productivity (LP)	5.597	0.938	5.642	0.896	5.712	0.998	0.628	0.463
	Age	3.305	0.972	3.572	0.874	3.626	1.024	0.005	0.047
	Size	6.848	1.859	7.928	2.097	7.765	2.152	0.000	0.006
	ROA	−0.037	0.260	0.001	0.185	−0.003	0.128	0.124	0.230
	Leverage	0.069	0.115	0.081	0.116	0.100	0.159	0.281	0.188
	Corporate group dummy	0.640	0.482	0.796	0.403	0.759	0.432	0.001	0.098
	Innovator dummy	0.584	0.495	0.728	0.445	0.724	0.451	0.003	0.060
	Recent investments dummy	0.296	0.458	0.396	0.490	0.328	0.473	0.031	0.672
Sectoral variables									
	AMT import stock	20.533	1.746	20.613	1.937	20.506	1.852	0.650	0.926
	Investment intensity	20.271	10.213	23.035	12.008	22.564	8.575	0.009	0.116
	Product differentiation	0.787	0.175	0.794	0.161	0.831	0.154	0.658	0.083

Notes: Authors' own computations based on ERM and Orbis Europe data. Observations: 125 closures; 545 downsizing; 58 offshoring. All statistics refer to 1-year lagged variables. AMT, advanced manufacturing technologies; ERM, European Restructuring Monitor

Table 7. Main results: two-stage multinomial logit model

	1st stage: Probit model		2nd stage: Multinomial logit				
	H1		H2	H3	Marginal effects		
	Coefficients	Marginal effects	Closure versus Downsizing	Closure versus Offshoring	Closure	Downsizing	Offshoring
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Firm-level variables							
AMT exposure	−0.006**	−0.002**	0.066**	0.077**	−0.007**	0.006*	0.002
	(0.003)	(0.001)	(0.028)	(0.033)	(0.003)	(0.003)	(0.002)
Tangible K/L	0.076	0.021	−0.921**	−1.060**	0.101**	−0.082*	−0.020
	(0.065)	(0.018)	(0.381)	(0.460)	(0.040)	(0.048)	(0.025)
Intangible K/L	−0.011	−0.003	0.039	0.232	−0.006	−0.006	0.013
	(0.029)	(0.008)	(0.106)	(0.160)	(0.011)	(0.013)	(0.009)
Productivity (LP)	0.107**	0.029**	−0.567	−1.191**	0.068	−0.022	−0.047
	(0.053)	(0.014)	(0.491)	(0.570)	(0.052)	(0.060)	(0.030)
Age	0.050	0.014	−0.080	−0.179	0.010	−0.003	−0.007
	(0.049)	(0.013)	(0.273)	(0.325)	(0.029)	(0.033)	(0.017)
Size	0.201***	0.055***	−1.043	−1.734*	0.121	−0.064	−0.056
	(0.033)	(0.009)	(0.872)	(0.986)	(0.092)	(0.107)	(0.050)
ROA	−0.275***	−0.075***	2.458*	2.998*	−0.272*	0.209	0.063
	(0.105)	(0.028)	(1.488)	(1.661)	(0.159)	(0.172)	(0.075)
Leverage	−0.040	−0.011	0.154	0.487	−0.021	−0.003	0.023
	(0.294)	(0.080)	(0.977)	(1.668)	(0.105)	(0.129)	(0.094)
Corporate group dummy	−0.186**	−0.051**	1.526*	1.840*	−0.169*	0.131	0.038
	(0.089)	(0.024)	(0.889)	(1.052)	(0.095)	(0.110)	(0.054)
Innovator dummy	0.027	0.007	0.000	0.205	−0.002	−0.011	0.013
	(0.090)	(0.025)	(0.328)	(0.521)	(0.035)	(0.043)	(0.029)
Recent investments dummy	−0.144**	−0.039**	0.887	1.248	−0.100	0.067	0.033
	(0.064)	(0.018)	(0.733)	(0.888)	(0.078)	(0.088)	(0.044)
Sectoral variables							
AMT import stock	−0.008	−0.002	−0.936***	−0.683	0.098***	−0.104***	0.005
	(0.077)	(0.021)	(0.300)	(0.477)	(0.032)	(0.037)	(0.025)
Investment intensity	−0.003	−0.001	−0.009	0.009	0.001	−0.002	0.001
	(0.004)	(0.001)	(0.020)	(0.033)	(0.002)	(0.002)	(0.002)
Product differentiation	−0.112	−0.030	0.223	1.238	−0.036	−0.032	0.068
	(0.290)	(0.079)	(1.149)	(1.602)	(0.121)	(0.149)	(0.090)
Inverse Mills ratio			−8.581	−13.631**			
			(5.797)	(6.805)			
Country FE	Yes		Yes		Yes		
Sector FE	Yes		Yes		Yes		
Year FE	Yes		Yes		Yes		
Observations	3,224		728		728		
Firms	1,888		563		563		
(pseudo) R^2	0.093		0.229		-		
Log-likelihood	−1,563		−404.7		-		

Notes: All variables are 1-year lagged. Robust standard errors in brackets are clustered at the firm level. Significance levels: ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$. AMT, advanced manufacturing technologies

Looking at the multinomial logit model in the second stage, columns (3) and (4) report model coefficients comparing closure to downsizing, and closure to offshoring, respectively. Furthermore, columns (5), (6), and (7) report AMEs from the multinomial logit model, estimated for each category taken alone. The IMR from the first stage is statistically significant at the 5% level in column (4), suggesting that unobservable factors potentially implying a selection mechanism in the comparison between closure and offshoring events are properly captured. Conditional on restructuring, the estimated coefficient for the AMT exposure variable is positive and statistically significant at the 5% level in column (3), supporting H2 and suggesting that those restructuring firms that are more exposed to AMTs are more likely to downsize rather than close an entire plant, laying off only a portion of the workforce. Similarly, the AMT exposure coefficient in column (4) is positive and precisely estimated (5% level), providing support for H2. This suggests that exposure to AMTs is linked to a firm's propensity to offshore as an alternative to closure.

Focusing on other firm-level characteristics and sectoral controls, findings are consistent with previous studies (Coucke *et al.*, 2007; Bandick, 2016). After controlling for self-selection mechanisms, we find that differences in (tangible) capital composition and profitability mostly explain the propensity to pursue downsizing or offshoring as opposed to closure. We also find that differences in sectoral AMT import stocks correlate with the propensity to downsize as compared to terminate activities, while other industry characteristics, such as general investment intensity and product differentiation, are not statistically significant.

To further explore the mechanisms behind these results, in columns (5), (6), and (7), we present the AMEs of exposure to AMTs on the probability of pursuing each specific restructuring mode, computed from the second-stage multinomial logit model. H2 and H3 argue that AMTs can influence the firm's propensity towards downsizing and offshoring over closure as a result of a double mechanism: the benefits (e.g., increased efficiency, flexibility, and productivity) and underlying mechanisms (e.g., automation deepening, higher integration along the value chain, upskilling, and sunk costs) accompanying the adoption may raise incentives to downsize or offshore activities, while also raise barriers to closure. On average, a 10% increase in the level of AMT exposure is associated with a 0.07 p.p. drop in the probability of closure (column (5)), a 0.06 p.p. increase in the probability of downsizing (column (6)), but with no significant effect on the probability of offshoring. This insight suggests that the observed relationship with AMT exposure in column (3) emanates from both a positive role of AMT-related benefits and mechanisms on the probability of downsizing, and a reduced probability of closure derived from the resources committed to automation technologies, resulting in higher sunk costs, when exposure to AMTs is high. Conversely, the support for H2 (see column (4)) results solely from a lower probability of closure.

4.1.1 Robustness checks

Alternative FE specification. Column (3) of Table 7 shows that, beyond the firm's AMT exposure, the sectoral AMT import stock is also related to the propensity to downsize and shut down business activities. To exclude the possibility that the results of the firm-level AMT exposure variable are conditional on the significance of sectoral AMT import stock control, we conduct a robustness check including country-sector FEs. In contrast, the AMT import stock variable could capture unobserved trends that are simultaneously country- and sector-specific. Table A1 in the Online Appendix shows that our results are qualitatively and statistically unchanged in comparison with the same specifications of Table 7.[9]

Productivity measured by TFP. Key to our analysis is accounting for differences in the level of efficiency of usage of input factors characterizing restructuring firms, since such differences allow us to isolate the potential contribution of AMT exposure towards shaping firm restructuring decisions. Although in our main estimates we account for differences in labor productivity across restructuring firms, we acknowledge that such measure neglects a more precise accounting of the efficiency of usage of other productive factors. Hence, we conduct a robustness test by considering

[9] Additionally, we tested a specification of the two-stage model including country-by-year and sector FE, as well as a specification including sector-by-year and country FE. These additional checks produced results in line with those reported in Table A1 and are available upon request from the authors. We note that the combination of FE tested in Table A1 is the less parsimonious and more robust among the FE combinations we tested.

a measure of TFP. However, since computing firm-level TFP requires more information, it results in a reduction of about 30% of our sample. The results (reported in Table A2 in the Online Appendix) support the findings presented in Table 7 on H2 and H3, while the coefficient for AMT exposure in the first stage is less precisely estimated.

AMT import spikes. One potential concern in our analysis is that the firm-level AMT exposure results from the combination of sectoral AMT import stock and the firm capital intensity level, hence, potentially not proxying investments in AMTs accurately. To tackle this issue, we exploit the information on sectoral AMT import flows (then interacted with the firm's level of capital intensity), following the well-established idea and empirically observed pattern that investments in digital/automation technologies are not constant over time, but rather happen in spikes (Domini *et al*., 2021, 2022; Bisio *et al*., 2025). Following this approach, the resulting alternative proxy for firm-level AMT exposure assumes higher values for more capital-intensive firms which operate in more AMT-intensive countries and sectors, but only in periods when the country-sector flow of AMT imports spikes. Specifically, we identify spikes in the flow of AMT imports as higher values (at the top five percent) in the distribution of year-on-year growth rates of AMT import flows. Results from this additional robustness check are reported in Table A3 in the Online Appendix, showing support for our main results.

Excluding 2020. Descriptive statistics on the distribution of restructuring events in our data reveal that 155 events (about 21% of all events) occurred in 2020, during the Covid-19 pandemic. This number represents a consistent spike in the number of yearly restructuring events, which may be caused by an exceptional exogenous event consistently affecting employment levels across firms and resulting in a surge of collective layoffs. To evaluate the robustness of our findings to such exceptional circumstances, we replicate our main estimates by excluding the year 2020 from the analysis. Results are reported in Table A4 in the Online Appendix and support the robustness of our main findings.

4.2 Layoffs

Here we explore the relationship between AMT exposure and the employment implications of business restructuring events. Specifically, we look at the magnitude of the related layoffs, expressed as the natural logarithm of the net number of employees laid-off (i.e. total laid-off workers minus newly hired workers), total layoffs, and new hirings. We treat it as the second stage of our econometric strategy, and we estimate sample-selection models following Heckman's (1979) methodology. Specifically, while the first stage is specified as in Eq. (2), the second stage can be estimated via OLS and formalized as follows:

$$Y_{i,t} = \alpha + \beta AMT\_\exp_{i,t-1} + \gamma \mathbf{X}_i + \delta \mathbf{Z}_{s,c,t-1} + \vartheta IMR_{i,t-1} + \varepsilon_{i,t} \tag{4}$$

where $Y_{i,t}$ represents either the magnitude of layoffs involved in restructuring decisions of firms i at time t, as measured by the natural logarithm of the net number of employees laid-off, the natural logarithm of total laid-off workers, or the natural logarithm of newly hired workers; all explanatory variables correspond to those described in Eq. (2) and (3), and $\varepsilon_{i,t}$ represents the idiosyncratic error term. We also test different combinations of FE, productivity measures, and proxies for firm-level AMT exposure.

Coherently with our hypotheses, we expect a negative relationship between AMT exposure and the number of laid-off workers, which is driven by a reduced propensity to undertake closure (involving the larger toll for workers, as described in Tables 5 and 6) and a larger propensity to undertake alternative strategies.

Table 8 reports the results from the second stage in Eq. (4). Columns (1), (2), and (3) present the coefficients describing the average relationship between AMT exposure and the magnitude of net layoffs associated with the restructuring modes discussed above (column (1)), the magnitude of total layoffs (column (2)), and the magnitude of new hirings (column (3)) accounting for country, sector, and time FE, and measuring productivity as labor productivity. Columns (4), (5), and (6) replicate the analysis by accounting for country-by-sector and time FE. Conditional on restructuring, on average, we find a negative relationship between exposure to AMTs and the size of net layoffs, small in magnitude, and statistically significant at the 5% level (columns (1)

Table 8. Relationship between magnitude of net layoffs, total layoffs, new hirings, and AMT exposure

	Net layoffs (1)	Total layoffs (2)	New hirings (3)	Net layoffs (4)	Total layoffs (5)	New hirings (6)
AMT exposure	−0.025***	−0.024***	0.003	−0.009**	−0.009**	0.000
	(0.007)	(0.007)	(0.003)	(0.004)	(0.004)	(0.003)
Inverse Mills ratio	5.011***	4.903***	−0.827	1.187*	1.181	−0.645
	(1.458)	(1.467)	(0.604)	(0.699)	(0.732)	(0.578)
Firm-level controls	YES			YES		
Sectoral controls	YES			YES		
Country FE	YES			-		
Sector FE	YES			-		
Country-Sector FE	-			YES		
Year FE	YES			YES		
Observations	728			648		
Firms	563			493		
R^2	0.402	0.408	0.121	0.520	0.527	0.265

Notes: Productivity measured as labor productivity. All variables are 1-year lagged. Firm-level controls: Tangible K/L, Intangible K/L, Productivity, Age, Size, ROA, Leverage, Corporate group dummy, Innovator dummy, Recent investments dummy. Sectoral controls: AMT import stock, Investment intensity, Product differentiation. Robust standard errors in brackets are clustered at the firm level. Significance levels: $^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.1$. AMT, advanced manufacturing technologies; ROA, return on assets

and (4)). Similar results emerge when looking at the magnitude of total layoffs (columns (2) and (5)). Conversely, no statistically significant relationship is found in columns (3) and (6), where we look at the relationship between AMT exposure and new hirings. Additional robustness checks (Table A7) are reported in the Online Appendix.

Coherently with our main findings, we uncover a negative association with collective layoffs, suggesting that higher AMT exposure is associated with layoff events involving fewer workers. Considered together with our main results, this suggests that not only AMTs relate to a lower probability of closure relative to other restructuring events, but they also associate with fewer displaced workers. Overall, these findings highlight a less explored potential effect of AMTs on employment: while extensive evidence suggests new digital automation technologies displace jobs, we uncover a secondary relationship that works in the opposite direction by reducing the overall number of laid-off employees via business restructuring.

4.3 Sectoral outcomes

We next examine the relationship between AMTs, sectoral employment, the cumulated number of firms' restructuring events and the cumulated number of layoffs at the sector-country level. As discussed (see Section 3.1.1), AMT adoption at the industry level is proxied by (the natural logarithm of) *AMT import stock*, while other sectoral outcomes and explanatory variables are computed using firm-level data available for both restructuring and non-restructuring firms in the complete sample of 77,317 observations (12,663 firms—see Section 3.1 and the Online Appendix for further details). Using this analysis, the significant relationship between AMTs and restructuring/layoffs should hold, even when we move to a higher level of aggregation—the sector-country level. We first start with a broader analysis on the association between AMTs and sectoral employment, considering the direct relationship between the two and the potential composition dynamics taking place between restructuring and non-restructuring firms. Thus, we estimate different specifications of a simple (conditional) labor demand equation, where we regress sectoral employment on AMT adoption, turnover (proxying gross output), other sectoral controls, country-year, and sector-year FE:

$$Emp_{s,c,t} = \alpha + \beta AMT\_is_{s,c,t-1} + \delta \mathbf{Z}_{s,c,t-1} + \varepsilon_{s,c,t} \quad (5)$$

where $Emp_{s,c,t}$ is the natural logarithm of employment in sector s of country c, $AMT\_is_{s,c,t}$ is *AMT import stock*, $\mathbf{Z}_{s,c,t}$ is a vector of country-sector explanatories, and $\varepsilon_{s,c,t}$ is the idiosyncratic error

Table 9. Sectoral analysis of the relationship between employment and AMT adoption, by restructuring group

	Emp total (1)	Emp restructuring (2)	Emp non-restructuring (3)	Emp total (4)	Emp restructuring (5)	Emp non-restructuring (6)
AMT import stock	0.029**	−0.131***	0.039***	−0.001	−0.160***	0.028**
	(0.012)	(0.035)	(0.011)	(0.015)	(0.049)	(0.014)
Sectoral controls	YES			YES		
Productivity measure	LP			TFP		
Country-Year FE	YES			YES		
Sector-Year FE	YES			YES		
Observations	2,664	1,190	2,520	2,639	951	2,519
R^2	0.945	0.921	0.960	0.927	0.895	0.925

Notes: All variables are 1-year lagged. Sectoral controls: Total turnover, Tangible K/L, Intangible K/L, Mean productivity, Mean age, Mean ROA, Mean leverage, Share of firms in a corporate group, Share of innovating firms, Share of firms with recent investments. Robust standard errors in brackets are clustered at the firm level. Significance levels: $^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.1$. AMT, advanced manufacturing technologies; ROA, return on assets

term. We further explore sectoral differences between restructuring and non-restructuring firms. This distinction helps us gauge the heterogeneous relationship that AMTs might have across the two groups.

Our estimates of the *AMT import stock* coefficient, reported in Table 9, highlight a mixed overall relationship between AMT adoption and sectoral employment (columns (1) and (4)), depending on the productivity measure used. Conversely, a negative and statistically significant relationship emerges when looking at sectoral aggregates from the restructuring sample (columns (2) and (5)), while a positive and significant relationship is found when considering the non-restructuring sample (columns (3) and (6)).

Following this preliminary insight, we further develop our sectoral analysis by examining the relationship between AMT adoption and two key outcomes from our firm-level analysis: the number of restructuring events and the total amount of layoffs by sector. Specifically, we estimate the following equation via OLS:

$$Y_{s,c,t} = \alpha + \beta AMT\_is_{s,c,t-1} + \delta \mathbf{Z}_{s,c,t-1} + \varepsilon_{s,c,t} \tag{6}$$

where $Y_{s,c,t}$ is either the total number of restructuring events in sector s of country c, at time t, or the corresponding total layoff (in natural logarithm). Every other element in Eq. (6) is defined as in Eq. (5), and we include country-year and sector-year FE.

Results (reported in Table 10) are consistent with our firm-level insights and suggest a negative and significant relationship between the number of restructuring events and AMT adoption (columns (1) and (2)). We find consistent and robust results even looking at the total sectoral layoff outcome (columns (3) and (4)). In conclusion, these findings add to the discussion on the employment effect of automation technologies, providing insight on the heterogeneous relationship between employment and AMTs across sectoral breakdowns based on restructuring events, further supporting the view that AMTs play a role in reducing the propensity to restructure and lower the number of corresponding layoffs.

5. Discussion and conclusions

In this study, we investigate the relationship between exposure to Industry 4.0 advanced manufacturing technologies and those restructuring strategies that lead to collective employee layoffs. While a large body of literature has investigated the complex and multifaceted nature of the relationship between new automation technologies and employment, it has overlooked one of the potential channels through which such relationship works: business restructuring events. Specifically, the decision to restructure business activities and to lay off employees stems from the interplay of several diverse strategic considerations around the firm's performance, its financial

Table 10. Sectoral analysis of the relationship between number of restructuring events, magnitude of layoffs, and AMT adoption

	Number of restructuring events		Layoffs	
	(1)	(2)	(3)	(4)
AMT import stock	−0.024* (0.014)	−0.023* (0.014)	−0.094** (0.042)	−0.084** (0.042)
Sectoral controls	YES		YES	
Productivity measure	LP	TFP	LP	TFP
Country-Year FE	YES		YES	
Sector-Year FE	YES		YES	
Observations	2,664	2,639	2,664	2,639
R^2	0.351	0.353	0.374	0.379

Notes: All variables are 1-year lagged. Sectoral controls: Tangible K/L, Intangible K/L, Mean productivity, Mean age, Total employment, Mean ROA, Mean leverage, Share of firms in a corporate group, Share of innovating firms, Share of firms with recent investments. Robust standard errors in brackets are clustered at the firm level. Significance levels: $^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.1$. AMT, advanced manufacturing technologies; ROA, return on assets.

status, and its competitive position in the market. Prior research has largely focused on either understanding the organizational and contextual features that influence the strategic decision process leading to the restructuring of business activities (Coucke *et al.*, 2007; O'Brien and Folta, 2009; Bandick, 2016), or on the analysis of the employment implications in the aftermath of a restructuring event (Olsson and Tåg, 2017; Beer *et al.*, 2019; Blien *et al.*, 2021; Goos *et al.*, 2021).

We propose a conceptualization of the mechanisms through which the benefits, barriers, and implications of AMTs affect a firm's propensity to engage in alternative restructuring choices and assess the resulting relationship between technology and layoffs. We present a dual perspective on the automation-employment nexus: while investments in AMTs may foster the displacement of workers (e.g., via automation deepening, Acemoglu and Restrepo, 2018, 2019; see also Cascio, 2012; Coucke *et al.*, 2007; Freeman and Ehrhardt, 2012), they may also provide new tools and opportunities for managers to sustain competition and increase a firm's chances of success, creating incentives to avoid restructuring decisions and large collective layoffs.

Our findings suggest that exposure to AMTs relates to a lower probability of pursuing any restructuring decision involving layoffs. Although the estimated marginal effect is relatively small in magnitude, the underlying relationship is statistically robust. Furthermore, conditional on restructuring, AMT exposure is also associated with a lower probability of permanently closing a firm's plant or even terminating activities, and a higher probability of pursuing downsizing as an alternative. Such changes are relatively small in magnitude but highly robust across specifications. Looking at restructuring alternatives, our findings on closure are consistent with the view that investments in specialized technologies (Coucke *et al.*, 2007; O'Brien and Folta, 2009), and the related investments in human capital (Brynjolfsson and Hitt, 1996; Fichman, 2004), ultimately set up barriers to closure. Results on downsizing, instead, agree with the view that investments in I4.0 technologies enable firms to achieve higher efficiency, flexibility and productivity, higher customization, reduced time-to-market, and deeper digital integration along the supply chain, within and across organizations (Weller *et al.*, 2015; Dalenogare *et al.*, 2018; Müller *et al.*, 2018; Frank *et al.*, 2019).

Finally, our findings reveal that these mechanisms result in layoff events of a smaller magnitude. Insights from the aggregate, sectoral-level, analysis are consistent with firm-level results, highlighting a negative relationship with both the overall number of restructuring events and layoffs.

5.1 Policy and managerial implications

Our findings can help define policy recommendations aimed at mitigating the negative consequences of collective employee layoffs. Industrial and innovation policies have been launched by almost every EU country over the last decade to promote the adoption of new digital and automation technologies, to increase the efficiency and productivity of firms and, ultimately, to achieve sustained economic growth. We argue that, because of such policies, the diffusion of

AMTs may entail a secondary positive effect by providing firms with the means to sustain their operations, become more competitive and productive, and avoid economic hardship. This has generated a countervailing force, reducing jobs lost through corporate restructuring. Therefore, policymakers should carefully assess the technologies bearing the highest potential benefits, depending on the industrial context in which firms operate, and boost the local penetration of I4.0 technologies and related competencies (e.g. via competence hubs or industry–university partnerships).

From a managerial standpoint, our work suggests that AMTs represent a key element managers should consider when evaluating strategic opportunities to sustain competition and increase their chances of survival and future success.

5.2 Limitations and future research

While we believe this study is a first step into the yet unexplored relationship between automation, restructuring events, and employment, we acknowledge it is not without limitations. First, the current lack of precise quantitative measures of firm-level adoption of AMTs, especially for a large enough sample covering several industries and countries, makes it necessary to resort to a proxy derived from a combination of industry-level information on AMT adoption and the firm level of capital intensity, based on the assumption that more capital-intensive firms operating in more AMT-intensive industries adopt more AMTs. Second, while focusing on an extensive sample of restructuring events allows us to better understand the phenomenon of interest, we acknowledge that restructuring data provided via the ERM database presents additional limitations: (i) the coverage of restructuring events, which are not necessarily fully representative of the whole population (Eurofound, 2025) and (ii) the lack of precise information on the type/occupation of workers that are laid-off or hired. Despite its limitations, the ERM data provides a rich set of unstructured information reported in the description and rationale of the event. Further research could dig into this richness, for instance, by analyzing the compositional effects of restructuring events over the affected workforce, as well as monitoring (with a higher degree of accuracy) specific mention of the role of automation and I4.0 technologies (Lamperti, 2024). To this end, machine learning techniques could prove to be helpful methodologies to extract value from unstructured text information and make them available to researchers. Finally, our study focuses solely on the job hires/losses of manufacturing firms during restructuring events; future research should explore the broader impact of these decisions on the labor market across the entire economy, including the services sector, and consider both backward and forward linkages, where the effects at the aggregate industry level may provide a more comprehensive understanding.

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Author contribution

Fabio Lamperti: Conceptualization; Data curation; Methodology; Formal Analysis; Visualization; Writing – original draft; Writing – review & editing. Katiuscia Lavoratori: Conceptualization; Methodology; Writing – original draft; Writing – review & editing. Davide Castellani: Conceptualization; Methodology; Writing – review & editing.

Supplementary data

Supplementary material is available at *Industrial and Corporate Change* online.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data are available from the corresponding author upon reasonable request.

References

Acemoglu D. and D. Autor (2011), 'Skills, tasks and technologies: Implications for employment and earnings', in D. Card and O. Ashenfelter (eds), *Handbook of Labor Economics* (**Volume 4, Part B**), Amsterdam, The Netherlands: Elsevier, pp. 773–1823. https://doi.org/10.1016/S0169-7218(11)02410-5

Acemoglu, D. and P. Restrepo (2018), 'Low-skill and high-skill automation,' *Journal of Human Capital*, **12**(2), 204–232. https://doi.org/10.1086/697242.

Acemoglu D. and P. Restrepo (2019), 'Artificial intelligence, automation, and work', in A. Agrawal, J. Gans and A. Goldfarb (eds), *They Economics of Artificial Intelligence: An Agenda*, University of Chicago Press: Chicago, pp. 197–236. https://doi.org/10.7208/chicago/9780226613475.003.0008

Acemoglu, D. and P. Restrepo (2020), 'Robots and jobs: evidence from US labor markets,' *Journal of Political Economy*, **128**(6), 2188–2244. https://doi.org/10.1086/705716.

Acemoglu, D. and P. Restrepo (2022), 'Demographics and automation,' *The Review of Economic Studies*, **89**(1), 1–44. https://doi.org/10.1093/restud/rdab031.

Acemoglu, D., C. Lelarge and P. Restrepo (2020), 'Competing with robots: firm-level evidence from France,' *AEA Papers and Proceedings*, **110**, 383–388. https://doi.org/10.1257/pandp.20201003.

Acemoglu, D., G. Anderson, D. Beede, C. Buffington, E. Childress, E. Dinlersoz, L. Foster *et al.* (2023), 'Advanced technology adoption: selection or causal effects?' *AEA Papers and Proceedings*, **113**, 210–214. https://doi.org/10.1257/pandp.20231037.

Ackerberg, D. A., K. Caves and G. Frazer (2015), 'Identification properties of recent production function estimators,' *Econometrica*, **83**(6), 2411–2451. https://doi.org/10.3982/ECTA13408.

Alcácer, V. and V. Cruz-Machado (2019), 'Scanning the industry 4.0: a literature review on technologies for manufacturing systems,' *Engineering Science and Technology, an International Journal*, **22**(3), 899–919. https://doi.org/10.1016/j.jestch.2019.01.006.

Alcácer, J., J. Cantwell and L. Piscitello (2016), 'Internationalization in the information age: a new era for places, firms, and international business networks?' *Journal of International Business Studies*, **47**(5), 499–512. https://doi.org/10.1057/jibs.2016.22.

Bandick, R. (2016), 'Offshoring, plant survival and employment growth,' *The World Economy*, **39**(5), 597–620. https://doi.org/10.1111/twec.12316.

Barba Navaretti, G., D. Castellani and A.-C. Disdier (2010), 'How does investing in cheap labour countries affect performance at home? Firm–level evidence from France and Italy,' *Oxford Economic Papers*, **62**(2), 234–260. https://doi.org/10.1093/oep/gpp010.

Barba Navaretti, G., D. Castellani and F. Pieri (2022), 'CEO age, shareholder monitoring, and the organic growth of European firms,' *Small Business Economics*, **59**(1), 361–382. https://doi.org/10.1007/s11187-021-00521-5.

Beer, A., S. Weller, T. Barnes, I. Onur, J. Ratcliffe, D. Bailey and M. Sotarauta (2019), 'The urban and regional impacts of plant closures: new methods and perspectives,' *Regional Studies, Regional Science*, **6**(1), 380–394. https://doi.org/10.1080/21681376.2019.1622440.

Benassi, M., E. Grinza, F. Rentocchini and L. Rondi (2022), 'Patenting in 4IR technologies and firm performance,' *Industrial and Corporate Change*, **31**(1), 112–136. https://doi.org/10.1093/icc/dtab041.

Bisio, L., A. Cuzzola, M. Grazzi and D. Moschella (2025), 'The dynamics of automation adoption: firm-level heterogeneity and aggregate employment effects,' *European Economic Review*, **173**, 104943. https://doi.org/10.1016/j.euroecorev.2024.104943.

Blien, U., W. Dauth and D. H. W. Roth (2021), 'Occupational routine intensity and the costs of job loss: evidence from mass layoffs,' *Labour Economics*, **68**, 101953. https://doi.org/10.1016/j.labeco.2020.101953.

Bogers, M., R. Hadar and A. Bilberg (2016), 'Additive manufacturing for consumer-centric business models: implications for supply chains in consumer goods manufacturing,' *Technological Forecasting and Social Change*, **102**, 225–239. https://doi.org/10.1016/j.techfore.2015.07.024.

Bonfiglioli, A., R. Crinò, H. Fadinger and G. Gancia (2024), 'Robot imports and firm-level outcomes,' *The Economic Journal*, **134**(664), 3428–3444. https://doi.org/10.1093/ej/ueae055.

Bottazzi, G. and A. Secchi (2003), 'Why are distributions of firm growth rates tent-shaped?' *Economics Letters*, **80**(3), 415–420. https://doi.org/10.1016/S0165-1765(03)00142-3.

Breschi, S., F. Malerba and L. Orsenigo (2000), 'Technological regimes and Schumpeterian patterns of innovation,' *The Economic Journal*, **110**(463), 388–410. https://doi.org/10.1111/1468-0297.00530.

Brynjolfsson, E. and L. Hitt (1996), 'Paradox lost? Firm-level evidence on the returns to information systems spending,' *Management Science*, **42**(4), 541–558. https://doi.org/10.1287/mnsc.42.4.541.

Calvino, F. and M. E. Virgillito (2018), 'The innovation-employment nexus: a critical survey of theory and empirics,' *Journal of Economic Surveys*, **32**(1), 83–117. https://doi.org/10.1111/joes.12190.

Cascio, W. (1993), 'Downsizing: what do we know? What have we learned?' *Academy of Management Executive*, **7**, 95–104. https://www.jstor.org/stable/4165111.

Cascio W. F. (2012), 'How does downsizing come about?', in C. L. Cooper, A. Pandey and J. C. Quick (eds), *Downsizing*, Cambridge University Press: Cambridge, pp. 51–75. https://doi.org/10.1017/CBO9780511791574.005

Castellani, D., F. Lamperti and K. Lavoratori (2022), 'Measuring adoption of industry 4.0 technologies via international trade data: insights from European countries,' *Journal of Industrial and Business Economics*, **49**(1), 51–93. https://doi.org/10.1007/s40812-021-00204-y.

Ciarli, T., M. Kenney, S. Massini and L. Piscitello (2021), 'Digital technologies, innovation, and skills: emerging trajectories and challenges,' *Research Policy*, **50**(7), 104289. https://doi.org/10.1016/j.respol.2021.104289.

Coucke, K. and L. Sleuwaegen (2008), 'Offshoring as a survival strategy: evidence from manufacturing firms in Belgium,' *Journal of International Business Studies*, **39**(8), 1261–1277. https://doi.org/10.1057/PALGRAVE.JIBS.8400403.

Coucke, K., E. Pennings and L. Sleuwaegen (2007), 'Employee layoff under different modes of restructuring: exit, downsizing or relocation,' *Industrial and Corporate Change*, **16**(2), 161–182. https://doi.org/10.1093/ICC/DTM002.

Dalenogare, L. S., G. B. Benitez, N. F. Ayala and A. G. Frank (2018), 'The expected contribution of industry 4.0 technologies for industrial performance,' *International Journal of Production Economics*, **204**, 383–394. https://doi.org/10.1016/J.IJPE.2018.08.019.

Datta, D. K., J. P. Guthrie, D. Basuil and A. Pandey (2010), 'Causes and effects of employee downsizing: a review and synthesis,' *Journal of Management*, **36**(1), 281–348. https://doi.org/10.1177/0149206309346735.

De Beule, F., A. Van Assche and J. Nevens (2022), 'Additive manufacturing and production internationalization: an internalization perspective,' *Journal of International Management*, **28**(4), 100952. https://doi.org/10.1016/j.intman.2022.100952.

Domini, G., M. Grazzi, D. Moschella and T. Treibich (2021), 'Threats and opportunities in the digital era: automation spikes and employment dynamics,' *Research Policy*, **50**(7), 104137. https://doi.org/10.1016/j.respol.2020.104137.

Domini, G., M. Grazzi, D. Moschella, T. Treibich and T. (2022), 'For whom the bell tolls: the firm-level effects of automation on wage and gender inequality,' *Research Policy*, **51**(7), 104533. https://doi.org/10.1016/J.RESPOL.2022.104533.

Dosi, G. (1982), 'Technological paradigms and technological trajectories,' *Research Policy*, **11**(3), 147–162. https://doi.org/10.1016/0048-7333(82)90016-6.

Dosi, G. (1988), 'Sources, procedures, and microeconomic effects of innovation,' *Journal of Economic Literature*, **26**(3), 1120–1171.

Dosi, G., M. Piva, M. E. Virgillito and M. Vivarelli (2021), 'Embodied and disembodied technological change: the sectoral patterns of job-creation and job-destruction,' *Research Policy*, **50**(4), 104199. https://doi.org/10.1016/j.respol.2021.104199.

Dosi, G., M. C. Pereira, A. Roventini and M. E. Virgillito (2022), 'Technological paradigms, labour creation and destruction in a multi-sector agent-based model,' *Research Policy*, **51**(10), 104565. https://doi.org/10.1016/j.respol.2022.104565.

Eurofound (2025), *Restructuring events: European Restructuring Monitor (ERM)*. Available at: https://apps.eurofound.europa.eu/restructuring-events/methodology (Accessed: 23 April 2005).

Eurofound (2018), 'Game changing technologies – exploring the impact on production processes and work,' *Publications Office*. https://data.europa.eu/doi/10.2806/36769.

Felice, G., F. Lamperti and L. Piscitello (2022), 'The employment implications of additive manufacturing,' *Industry and Innovation*, **29**(3), 333–366. https://doi.org/10.1080/13662716.2021.1967730.

Fichman, R. G. (2004), 'Real options and IT platform adoption: implications for theory and practice,' *Information Systems Research*, **15**(2), 132–154. https://doi.org/10.1287/isre.1040.0021.

Frank, A. G., L. S. Dalenogare and N. F. Ayala (2019), 'Industry 4.0 technologies: implementation patterns in manufacturing companies,' *International Journal of Production Economics*, **210**, 15–26. https://doi.org/10.1016/j.ijpe.2019.01.004.

Freeman S. J. and K. Ehrhardt (2012), 'The antecedents of downsizing', in C. L. Cooper, A. Pandey and J. C. Quick (eds), *Downsizing*, Cambridge University Press: Cambridge, pp. 76–100. https://doi.org/10.1017/CBO9780511791574.006

Freeman, C. and L. Soete (1994), *Work for All or Mass Unemployment? Computerized Technical Change in the 21st Century*. Pinter: London,

Freeman, C., J. Clark and L. Soete (1982), *Unemployment and Technological Innovation*. Pinter: London,

Frey, C. B. and M. A. Osborne (2017), 'The future of employment: how susceptible are jobs to computerisation?' *Technological Forecasting and Social Change*, **114**, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019.

Gihleb, R., O. Giuntella, L. Stella and T. Wang (2022), 'Industrial robots, workers' safety, and health,' *Labour Economics*, **78**(1), 102205. https://doi.org/10.1016/j.labeco.2022.102205.

Goos, M., E. Rademakers and R. Röttger (2021), 'Routine-biased technical change: individual-level evidence from a plant closure,' *Research Policy*, **50**(7), 104002. https://doi.org/10.1016/j.respol.2020.104002.

Grazzi, M., C. Piccardo and C. Vergari (2022), 'Turmoil over the crisis: innovation capabilities and firm exit,' *Small Business Economics*, **59**(2), 537–564. https://doi.org/10.1007/s11187-021-00485-6.

Hannibal, M. and G. Knight (2018), 'Additive manufacturing and the global factory: disruptive technologies and the location of international business,' *International Business Review*, **27**(6), 1116–1127. https://doi.org/10.1016/j.ibusrev.2018.04.003.

Heckman, J. J. (1979), 'Sample selection bias as a specification error,' *Econometrica*, **47**(1), 153–161. https://doi.org/10.2307/1912352.

Honoré, B. E. and L. Hu (2020), 'Selection without exclusion,' *Econometrica*, **88**(3), 1007–1029. https://doi.org/10.3982/ecta16481.

Honoré, B. E. and L. Hu (2022), 'Sample selection models without exclusion restrictions: parameter heterogeneity and partial identification,' *Journal of Econometrics*, **243**(1–2), 105360. https://doi.org/10.1016/j.jeconom.2021.07.017.

Kagermann H., W. Wahlster and J. Helbig (2013), *Securing the Future of German Manufacturing Industry: Recommendations for Implementing the Strategic Initiative INDUSTRIE 4.0. Final Report of the Industrie 4.0 Working Group*. Forchungsunion, acatech. Available at: http://alvarestech.com/temp/RoboAseaIRB6S2-Fiat/CyberPhysicalSystems-Industrial4-0.pdf (Accessed: 24 April 2025).

Kinkel, S. and S. Maloca (2009), 'Drivers and antecedents of manufacturing offshoring and backshoring – a German perspective,' *Journal of Purchasing and Supply Management*, **15**(3), 154–165. https://doi.org/10.1016/j.pursup.2009.05.007.

Kogut, B. and N. Kulatilaka (2001), 'Capabilities as real options,' *Organization Science*, **12**(6), 744–758. https://doi.org/10.1287/orsc.12.6.744.10082.

Lamperti, F. (2024), 'Unlocking machine learning for social sciences: the case for identifying industry 4.0 adoption across business restructuring events,' *Technological Forecasting and Social Change*, **207**, 123627. https://doi.org/10.1016/j.techfore.2024.123627.

Lamperti, F., K. Lavoratori and D. Castellani (2024), 'The unequal implications of industry 4.0 adoption: evidence on productivity growth and convergence across Europe,' *Economics of Innovation and New Technology*, **33**(8), 1051–1075. https://doi.org/10.1080/10438599.2023.2269089.

Lamperti, F., K. Lavoratori and L. Tredicine (2025), 'From globalization to reshoring? The role of industry 4.0 in global value chains across Europe,' *Economics of Innovation and New Technology*, **1–23**, 1–23. https://doi.org/10.1080/10438599.2025.2487145.

Laplume, A. O., B. Petersen and J. M. Pearce (2016), 'Global value chains from a 3D printing perspective,' *Journal of International Business Studies*, **47**(5), 595–609. https://doi.org/10.1057/jibs.2015.47.

Lee, J. Y., D. Kim, B. Choi and A. Jiménez (2023), 'Early evidence on how industry 4.0 reshapes MNEs' global value chains: the role of value creation versus value capturing by headquarters and foreign subsidiaries,' *Journal of International Business Studies*, **54**(4), 599–630. https://doi.org/10.1057/s41267-022-00596-6.

Lewin, A. Y., S. Massini and C. Peeters (2009), 'Why are companies offshoring innovation? The emerging global race for talent,' *Journal of International Business Studies*, **40**(6), 901–925. https://doi.org/10.1057/jibs.2008.92.

Malerba, F. and L. Orsenigo (1997), 'Technological regimes and sectoral patterns of innovative activities,' *Industrial and Corporate Change*, **6**(1), 83–118. https://doi.org/10.1093/icc/6.1.83.

Marcucci, G., S. Antomarioni, F. E. Ciarapica and M. Bevilacqua (2021), 'The impact of operations and IT-related industry 4.0 key technologies on organizational resilience,' *Production Planning & Control*, **33**(15), 1417–1431. https://doi.org/10.1080/09537287.2021.1874702.

Martinelli, A., A. Mina and M. Moggi (2021), 'The enabling technologies of industry 4.0: examining the seeds of the fourth industrial revolution,' *Industrial and Corporate Change*, **30**(1), 161–188. https://doi.org/10.1093/icc/dtaa060.

Montobbio, F., J. Staccioli, M. E. Virgillito and M. Vivarelli (2024), 'The empirics of technology, employment and occupations: lessons learned and challenges ahead,' *Journal of Economic Surveys*, **38**(5), 1622–1655. https://doi.org/10.1111/joes.12601.

Müller, J. M., O. Buliga and K.-I. Voigt (2018), 'Fortune favors the prepared: how SMEs approach business model innovations in industry 4.0,' *Technological Forecasting and Social Change*, **132**, 2–17. https://doi.org/10.1016/j.techfore.2017.12.019.

O'Brien, J. and T. Folta (2009), 'Sunk costs, uncertainty and market exit: a real options perspective,' *Industrial and Corporate Change*, **18**(5), 807–833. https://doi.org/10.1093/ICC/DTP014.

Olsson, M. and J. Tåg (2017), 'Private equity, layoffs, and job polarization,' *Journal of Labor Economics*, **35**(3), 697–754. https://doi.org/10.1086/690712.

Pedota, M., L. Grilli and L. Piscitello (2023), 'Technology adoption and upskilling in the wake of industry 4.0,' *Technological Forecasting and Social Change*, **187**, 122085. https://doi.org/10.1016/j.techfore.2022.122085.

Pianta, M. (2005), 'Innovation and employment,' in J. Fagerberg and R. Nelson (eds), *The Oxford Handbook of Innovation*. Oxford University Press: Oxford.

Porter, M. E. and J. E. Heppelmann (2014), 'How smart, connected products are transforming competition,' *Harvard Business Review*, **92**(11), 64–88. https://www.hbs.edu/faculty/Pages/item.aspx?num=48195.

Porter, M. E. and J. E. Heppelmann (2015), 'How smart, connected products are transforming companies,' *Harvard Business Review*, **93**(10), 97–114. https://hbr.org/2015/10/how-smart-connected-products-are-transforming-companies.

Presidente, G. (2023), 'Institutions, holdup, and automation,' *Industrial and Corporate Change*, **32**(4), 831–847. https://doi.org/10.1093/icc/dtac060.

Roodman, D. (2011), 'Fitting fully observed recursive mixed-process models with cmp,' *The Stata Journal*, **11**(2), 159–206. https://doi.org/10.1177/1536867X1101100202.

Sethupathy, G. (2013), 'Offshoring, wages, and employment: theory and evidence,' *European Economic Review*, **62**, 73–97. https://doi.org/10.1016/j.euroecorev.2013.04.004.

Shafiq, S. I., C. Sanin, E. Szczerbicki and C. Toro (2016), 'Virtual engineering factory: creating experience base for industry 4.0,' *Cybernetics and Systems*, **47**(1–2), 32–47. https://doi.org/10.1080/01969722.2016.1128762.

Sinha, R. K. and C. H. Noble (2008), 'The adoption of radical manufacturing technologies and firm survival,' *Strategic Management Journal*, **29**(9), 943–962. https://doi.org/10.1002/smj.687.

Stornelli, A., S. Ozcan and C. Simms (2021), 'Advanced manufacturing technology adoption and innovation: a systematic literature review on barriers, enablers, and innovation types,' *Research Policy*, **50**(6), 104229. https://doi.org/10.1016/j.respol.2021.104229.

Strange, R. and A. Zucchella (2017), 'Industry 4.0, global value chains and international business,' *Multinational Business Review*, **25**(3), 174–184. https://doi.org/10.1108/MBR-05-2017-0028.

Timmer, M. P., E. Dietzenbacher, B. Los, R. Stehrer and G. J. de Vries (2015), 'An illustrated user guide to the world input-output database: the case of global automotive production,' *Review of International Economics*, **23**(3), 575–605. https://doi.org/10.1111/roie.12178.

Vivarelli, M. (1995), *The Economics of Technology and Employment: Theory and Empirical Evidence*. Aldershot: Elgar,

Weller, C., R. Kleer and F. T. Piller (2015), 'Economic implications of 3D printing: market structure models in light of additive manufacturing revisited,' *International Journal of Production Economics*, **164**, 43–56. https://doi.org/10.1016/j.ijpe.2015.02.020.

Złotowski, J., K. Yogeeswaran and C. Bartneck (2017), 'Can we control it? Autonomous robots threaten human identity, uniqueness, safety, and resources,' *International Journal of Human-Computer Studies*, **100**, 48–54. https://doi.org/10.1016/j.ijhcs.2016.12.008.

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