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The Economic Implications of Advanced Manufacturing Technologies of the Industry 4.0 Wave

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Contents

Abstract

The present dissertation collects methodological and empirical works developed with the aim of moving forward the debate on the diffusion and the economic implications of advanced manufacturing technologies (AMTs) of the Industry 4.0 (I4.0) wave. In line with current open research avenues in the literature, in the four Chapters we answer the following research questions: (i) How can we measure with precision both the adoption and the production – i.e. the overall diffusion – of AMTs across countries and over time? (ii) What is the relationship between the adoption of AMTs, total factor productivity (TFP) growth, and technological catch-up across manufacturing industries? (iii) Does the adoption of AMTs push or discourage manufacturing firms to restructure business activities through collective layoffs? (iv) What is the relationship between the growing diffusion of additive manufacturing (or 3D printing) innovations and employment across manufacturing industries? We address these questions with methodological and empirical rigour, providing novel insights on still underexplored research areas. On the one hand, our findings open up for further research across several streams of both the economics and management literature. On the other hand, they allow us to outline clear implications and potential suggestions for both institutional policymakers and managers, analysing the effectiveness of current policies targeting the I4.0 revolution and support managers in harnessing the benefits spurring from the adoption of AMTs.

Introduction

This dissertation collects methodological and empirical studies aiming at moving forward the understanding of the diffusion dynamics and the economic implications of advanced manufacturing technologies of the Industry 4.0 wave.

Over the last decade, the emergence and growing diffusion of new digital technologies has led governments, national and international institutions, industry practitioners and academic scholars to discuss the advent of a fourth industrial revolution (4IR) wave, also called Industry 4.0 (I4.0) (e.g. Brynjolfsson and McAfee, 2014; EIB, 2019; OECD, 2017; UNCTAD, 2020; WIPO, 2019). Specifically, the concept of Industry 4.0 (I4.0) was first introduced in 2011 by the German Government, synthesising the will to revitalise the manufacturing industry in the aftermath of the 2008 global financial crisis as a way to boost prosperity among developed economies, through to the adoption and integration of a set of advanced, smart and digital technologies (Kagermann et al., 2013; Rüßmann et al., 2015). The term ‘*fourth industrial revolution*’ is commonly used worldwide to address the unfolding and diffusion of such new digital transformation, while the use of the ‘*Industry 4.0*’ terminology has been relatively more adopted across European countries Nonetheless, the two terms are frequently used interchangeably referring to the same set of technologies. As such, ‘*Industry 4.0*’ can be considered as an umbrella term (Mariani and Borghi, 2019), grouping together a set of heterogeneous technologies as well as industrial policy initiatives that emerged to support their diffusion and adoption.

Within the spectrum of technologies embedded in the I4.0 wave – most frequently, industrial robots, additive manufacturing, internet of things, cyber-physical systems, cloud computing, big data analytics, virtual reality, machine learning and artificial intelligence – the works presented in the following Chapters focus on three of these technologies, namely advanced industrial robots (AIRs), additive manufacturing (AM) and industrial internet of things (IIoT). The choice of such technological focus and the related terminology lies at the intersection of three main considerations: first, the technical characteristics of these technologies make them internally homogeneous and externally different with respect to the other technologies of the 4IR, reflecting OECD's (2012) definition of "*computer-controlled or micro-electronics-based equipment used in the design, manufacture or handling of a product*". Second, from an economic standpoint, these three technologies represent forms of 'embodied technologies', meaning that their adoption entails the physical installation of a specific type of machinery and/or capital equipment. As also discussed by Foster-McGregor et al. (2019), this characteristic represents a crucial distinction relative to other technologies of the 4IR, where the physical component of the technology is usually standardised and multi-purpose (e.g. computers and servers). As further discussed later, such intrinsic feature makes these three technologies the most appropriate to be investigated through the devised methodology. Third and most importantly, from a conceptual standpoint, they represent a new and more advanced form of manufacturing technology, which can be thought of as the evolution of those advanced manufacturing technologies which diffused over the 90s and had been conceptualised in previous studies (e.g. Udo and Ehie, 1996; Cagliano and Spina, 2000; Kotha and Swamidass, 2000). Furthermore, since these three technologies of the I4.0 wave bear the highest potential impact on advanced manufacturing processes – ranging from the management of productive operations to the organisation of human work – they have also been defined as '*game-changing technologies*' (Eurofound, 2018). Throughout the dissertation, we will refer to these technologies as '*advanced manufacturing technologies*' (AMTs).

As we further discuss throughout the thesis, new technologies of the I4.0 wave are widely recognised to bring major benefits, such as higher operational flexibility, higher production efficiency and quality, lower set-up costs and integration along the value chain, resulting in higher productivity in manufacturing operations and better performance overall (e.g. Rüßmann et al., 2015; Schwab, 2016; Skilton and Hovsepian, 2017; Eurofound, 2018). At the same time, additional high-level impact resides in the world of work and, in general, the entire society. On the one hand, a general concern around the "*risks of new monopolies, mass redundancies, spying on workers, and the extension of precarious digital work*" (Davies, 2015, p. 9) emerges. On the other hand, this transformation calls for a policy debate on the upcoming changes in the task content and occupational profiles of manufacturing employment (Frey and Osborne, 2017; Eurofound, 2018).

The growing attention given to such technologies of the I4.0 wave has resulted in substantial body of both theoretical and empirical literature, exploring several research avenues. First and foremost, this work deals with the overall process of technology diffusion (e.g. Acharya and Keller, 2009; Caselli and Coleman, 2001; Caselli and Wilson, 2004; Comin and Hobijn, 2010; Eaton and Kortum, 1999; Keller, 2002; 2004), specifically with the development of technological innovations, the production of new and more advanced forms of technology and, ultimately, with their adoption. The term 'technology diffusion' is traditionally conceived as to describe the process by which innovations are first known and, eventually, adopted by individuals and/or firms in a place. However, such process is "*neither inevitable nor automatic*" (Keller, 2004, p. 753). New technologies usually emerge locally, due to the required presence of a certain level of tacit knowledge and a localised producing industry developing them. However, their diffusion might not necessarily imply actual adoption outside the geographical boundaries in which they originate: the essence of the diffusion concept does not just entail that a new technology is used abroad – actual adoption usually going along with overall economic integration (Keller, 2004) – but also allow for the simple spread of awareness of the existence of a new technology or innovation, thus enabling its use, in principle (Eaton and Kortum, 1999). Thus, the diffusion, production and adoption of a new technology are usually considered as distinct concepts: the latter two imply the first one, but not the other way round.

These concepts are of crucial importance in several areas of economic research: most cross-country differences in per capita income and inequality are due to differences in total factor productivity (TFP), rather than to differences in the levels of factor inputs (Comin and Hobijn, 2010; Keller, 2002). Such productivity differences, in turn, depends largely on technological differences (Comin and Hobijn, 2010; Keller, 2002; 2004). Thus, relatedly to the empirical work developed throughout this dissertation, a first stream of this literature delves into the relationship between the diffusion of some technologies of the I4.0 wave (mostly adoption of AIRs) and productivity gains happening at different levels of analysis, i.e. country, sector, and firm (Jäger et al., 2015; Graetz and Michaels, 2018; Edquist et al., 2019; Acemoglu et al., 2020; Alderucci et al., 2020; Benassi et al., 2020; Ballestar et al., 2020; Bonfiglioli et al., 2020; Espinoza et al., 2020; Cette et al., 2021; Damioli et al., 2021; Du and Lin, 2022; Venturini, 2022). One main finding from these works is that I4.0 technologies are, generally, positively associated with productivity. However, they also highlight that the magnitude of such relationship is largely sensitive to the way of measuring productivity, the specific technology investigated, the data source, the level of aggregation, and the estimation method. More specifically, all these studies fail in providing comparable estimates of the productivity gains associated with the diffusion of different technologies, alone and in bundle.

A second research stream investigates the role played by technologies of the 4IR in affecting the way firms operate and organise their activities both at a local level and on an international scale (Alcácer et al., 2016; Autio et al., 2021; de Beule et al., 2022; Hannibal and Knight, 2018; Laplume et al., 2016; Strange and Zucchella, 2017). These new digital technologies can affect firms in different ways, pushing businesses to either contract or expand the geographical scope of their activities, as well as to consider either expanding or restructuring current operations in a variety of ways. High-impact restructuring events like downsizing and closures have only received lateral attention, mainly in relation to the implications for laid-off employees in contexts of growing automation (Beer et al., 2019; Blien et al., 2021; Goos et al., 2021; Olsson and Tåg, 2017). Hence, so far, this remains a strongly under investigated area, still lacking a deeper analysis of the potential direct relationship between the diffusion of 4IR technologies and the occurrence of restructuring events, especially when such events entail collective layoffs.

Finally, a third stream of the literature on technologies of the I4.0 wave addresses the relationship between automation and employment, analysing how the diffusion of these technologies affects both the level of employment and its composition. Taking stock of previous works analysing how new forms of automation affect the different tasks necessary to perform jobs (e.g. Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018; 2019; Frey and Osborne, 2017), several empirical studies have analysed different employment-related outcomes, mainly at the sectoral and firm level (e.g. Acemoglu and Restrepo, 2020; Acemoglu et al., 2020; Bonfiglioli et al., 2020; Chiacchio et al., 2018; Dauth et al., 2021; Domini et al., 2021; 2022; Graetz and Michels, 2018; Mann and Püttmann, 2021; Ni and Obashi, 2021). While findings from sectoral analyses converge towards a negative effect of new automation technologies, firm-level studies provide mixed evidence resulting from differences in the investigated employment outcome, in the focal technology and measure, the data source and the methodology used. This calls for further work aimed at reconciling firm-level and more aggregate evidence. At the same time, as most studies focus on the effect of adopting AIRs, it becomes important to fill the research gap with respect to the relationship between employment and other, less investigated, technologies of the 4IR.

From a methodological perspective, most studies across all these bodies of research present limitations in the measurement of the diffusion of new technologies of the 4IR. While the last few years have witnessed a growing availability of comparable data on the diffusion of these technologies across countries, sectors and firms, high quality sources offering more opportunities to researchers remain either private or commercial (e.g. data from the International Federation of Robotics (IFR) or from the European Manufacturing Survey (EMS)). Such scarcity of accurate and freely available information stems from the dynamic nature of the transformation under analysis, which is relatively recent and still ongoing. In this context, clear trade-offs emerge between precision and coverage of different measures, as well as over the measurement scope, by addressing complementary yet distinct aspects of the diffusion of a new technology, namely production and adoption. As a result, the different measures and proxies used in the above-mentioned studies all bear pros and cons, making them more suitable to assess the implications of adopting (i.e. survey data, actual adoption data, or imports) or producing (i.e. actual production data or patents) a technology, yet complementary to the aim of measuring its overall diffusion.

Following these conversations, this dissertation aims at answering the following research questions:

i. How can we measure both the adoption and the production – i.e. the overall diffusion – of AMTs of the I4.0 wave across countries and over time?

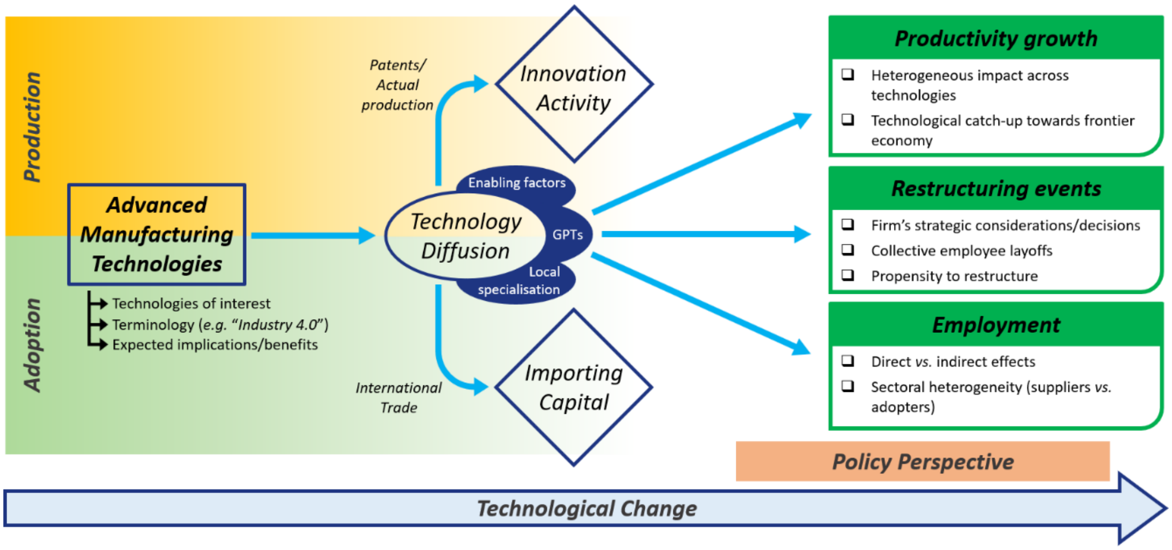
ii. What is the relationship between the adoption of AMTs, total factor productivity (TFP) growth, and technological catch-up across manufacturing industries?

iii. Does the adoption of AMTs push or discourage manufacturing firms to restructure business activities through collective layoffs?

iv. What is the relationship between the growing diffusion of additive manufacturing (or 3D printing) innovations and employment across manufacturing industries?

Figure 1 presents a conceptual map summarising the overall content of this dissertation and the research gap behind the above listed research questions.

Figure 1. Thesis' conceptual map



Notes: Authors' own elaboration.

The first Chapter addresses the above-discussed measurement issues and trade-offs, affecting existing measures of overall diffusion, adoption or production of AMTs at different level of analysis and based on different sources of information. Hence, building on previous works we present a new empirical perspective overcoming such limitations. Our study provides a refined methodological approach that allows us to precisely measure AMT adoption across countries and that can be continuously updated over time. Specifically, we build on the well-established idea in the international economics literature that trade of capital goods captures technology diffusion, and its adoption across countries. We combine data on trade (imports and exports) and production of highly disaggregated product categories (at the 8-digit level) strictly related to AMTs from Eurostat's Comext and Prodcom databases. Our identification of AMT-related product codes emerges from a comprehensive knowledge of the technologies, their technical characteristics and components involved in their application, and has been cross-validated with information provided by technology manufacturers worldwide, by the Italian Customs Agency, and by a private customs broker. We build different measures of adoption by using import data alone as well as all available information (i.e. import, export and production data), bearing different levels of precision. In so doing, we provide fresh comprehensive evidence on the adoption of AMTs in Europe, showing that import-based adoption measures highly correlate with more precise, yet more data demanding, proxies also accounting for the production and exports of AMTs. Ultimately, the use of import-based adoption measures enables a more extensive geographical coverage. We further check the robustness of our descriptive results by comparing them with evidence from other recent works, adopting similar approaches, but neglecting a precise identification, selection and validation process for product codes related to AMTs. All in all, we set the premise for monitoring the evolution of AMT adoption on a large scale and over time, and discuss its implications and potential research directions along a variety of research fields ranging from economics to innovation and international business studies.

In the second Chapter, we explore whether the adoption of AMTs affects the TFP growth rates across manufacturing industries. We explore the productivity effects associated with these new advanced technologies by looking at their direct contribution to TFP growth rates, as well as the role they play in the technological catching-up of those countries which are more distant from the technology frontier. To measure AMT adoption at the sectoral level, we move forward with the methodology discussed in Chapter 1 and build measures of sectoral adoption for each AMT, exploiting information on (i) a country's total imports of AMT-related goods, (ii) a country's total imports from AMT-producing sectors, and (iii) cross-country and cross-sector data on imported intermediates from world input-output tables. Using these measures we are able to both quantify the overall effect deriving from the adoption of these technologies and to disentangle potential heterogenous effects across technologies. The empirical analysis relies on a panel of 13 manufacturing industries across

14 European countries over the 2009–2019 period, and employs a robust empirical setting widely used in the literature studying aggregate productivity growth and technological catch-up. Our results suggest AMTs to be relevant contributors to sectoral TFP growth rates. When looking at AMTs as a bundle, they have statistically and quantitatively significant effects, however hiding heterogeneous contributions if looking at each technology alone. Specifically, we find that AM and AIRs are more beneficial on average for European countries, while IIoT seems to have a weaker effect on TFP growth rates, limited to technologically advanced countries. Most importantly, we find evidence that productivity gains associated with overall AMT adoption are mostly concentrated in more advanced economies, closer to the technology frontier. These findings add to recent contributions to the literature on the effect of AIRs and IIoT, shed light on the yet unexplored relationship between AM adoption and TFP growth, and contribute with novel evidence on the role played by these technologies on productivity convergence.

The third Chapter delves into the role played by AMT adoption in firms' decision to restructure their business activities by resorting to collective employee layoffs, implemented either through downsizing, offshoring or closure. We develop a conceptual framework to analyse how the benefits and implications associated with the adoption of AMTs affect a firm's operational activities and its organisation, ultimately influencing its propensity to undertake the decision to restructure. Specifically, we illustrate competing theoretical arguments predicting either a positive or a negative association between AMTs' technical features and a firm's propensity to restructure. The rising diffusion of new automation technologies may be seen, on the one hand, as threatening jobs and triggering the displacement of workers and, on the other hand, as a strategy that could sustain firm competitiveness, hence reducing the likelihood of collective layoffs. Furthermore, we contend that adopting these technologies may result in different types of restructuring events being pursued by firms. In order to test our hypotheses, we estimate a two-stage model where we first test whether AMT adoption influences a firm's propensity to undertake a restructuring decision, and then, once the decision to restructure has been taken, whether it influences a firm's propensity to either displace employees collectively (i.e. downsizing), move a part of its business activities abroad (i.e. offshoring), or layoff the whole workforce (i.e. closure). The study draws on 730 restructuring decisions implemented across about 12.000 European manufacturing firms between 2013 and 2020. Our findings reveal that AMTs influence a firm's strategy by lowering its propensity to restructure through collective layoffs. We find robust evidence that the adoption of AMTs helps save jobs by reducing a firm's propensity to close either the whole firm or part of its plants. Conditional on restructuring, AMT adoption is found to increase the probability of laying-off a part of the workforce and downsize firm's activities, as opposed to plant closure. Our results set the premise to further investigate the relationship between the adoption of AMTs of the I4.0 wave and firms' organisational and restructuring decisions, a research field still under-investigated, while still offering fresh and useful insights to both managers and policymakers.

Finally, the fourth Chapter focuses on additive manufacturing (AM) technologies and explores the relationship between the overall diffusion of AM innovations and sectoral employment. Our focus on this AMT is motivated by its unique technical characteristics and how they link to production processes in manufacturing industries. Specifically, AM represents a form of capital-embodied process innovation, similar to the widely investigated AIRs. Notwithstanding, due to its specific characteristics, the diffusion of AM innovations is motivated by market-seeking economic incentives, rather than the classical labour-saving aims behind AIRs. Specifically, AM innovations increase the potential for product customization and decrease the time-to-market, creating market expansion effects, ultimately fostering labour demand. In the empirical application, we build a novel database based on

AM patent information in order to analyse the origins and uses of all AM innovations (i.e. both product and process). We use patent application data from the USPTO to build a proxy of the overall diffusion of AM innovations and to estimate the relationship between this technology of the 4IR and employment across 21 manufacturing industries of 31 OECD countries, between 2009 and 2017. Our empirical strategy is based on the estimation of both unconditional and conditional labour demand functions. In the former, AM relates to employment *via* all potential channels: by affecting product demand and, in turn, production and employment levels, as well as by altering the relative intensity of the production factors used in the process; in the latter, the market expansion channel is 'switched off'. Furthermore, we explore the potential heterogeneity of these mechanisms across sectoral groups based on innovation sourcing and intensity, i.e. across categories of the Pavitt taxonomy (Pavitt, 1984). Our results highlight a positive relationship between AM innovations and employment at the industry level associated with both market expansion and complementarity between AM and labour. This represents a clear distinction as compared to findings from previous works on other AMTs like AIRs at the aggregate or sectoral level, where a dominant labour-saving effect in manufacturing have been observed. Conversely, our results go along recent firm-level evidence hinting at an overall positive relationship between technologies of the I4.0 wave and employment (Domini et al., 2021). Furthermore, we find such positive relationship to characterise manufacturing sectors differently, depending on the prevailing mechanism between market expansion and factor complementarity.

In sum, the present dissertation provides several insights and contribute to the above introduced streams of the literature. First, findings from Chapter 1 highlight that the envisioned methodology to measure AMT diffusion and adoption provides reliable results as compared to previous works in the literature, at the same time improving the measurement precision and coverage. One main advantage of our methodology is that it is easy to update over time, enabling continuous monitoring of the geographical and temporal patterns of AMT adoption. Furthermore, it can be extended to other countries outside Europe and, due to the increasing availability of transaction-level data, it can be used to precisely track AMT adoption at the firm level across large samples, avoiding the use of proxies or self-reported data from surveys. We take advantage of all these insights and outline an agenda for future research, spanning across different research fields.

Secondly, Chapter 2 moves forward the debate on the methodology by discussing a measure proxying sectoral adoption of AMTs. At the same time, it also provides new evidence on the relationship between TFP growth and new technologies of the I4.0 wave, taking into account both the overall effect of AMT adoption and that of every single technology alone. Furthermore, the Chapter explores how these technologies differentially affect TFP growth rates across manufacturing sectors of European countries, also taking into account their distance from the world technology frontier, showing that the observed effects across countries and sectors are far from being evenly spread.

To the best of our knowledge, Chapter 3 takes the first steps into a research area still untapped and looks at the relationship between AMT adoption and a firm's restructuring choices involving collective employee layoffs. Beyond the empirical results, one important contribution of this Chapter is the conceptualisation of the mechanisms linking together technical and economic features, benefits and implications associated with AMT adoption to those firm-level characteristics eventually pushing towards a business restructuring implemented through either downsizing, offshoring or closure.

To conclude, in the last Chapter we take a different perspective and try to analyse how the overall diffusion of one specific AMT, i.e. AM, relates to sectoral employment. One main contribution of this work is that it provides an in-depth analysis of AM innovations, their development, production, and industrial use, using detailed information contained in patent applications. Such insight enables to comprehensively measure the diffusion of both product and process innovations in the field of AM technologies and helps filling a gap in the extant literature, which has so far neglected a deeper economic analysis on this unique production method.

The contributions of this dissertation come with clear policy and managerial implications. First, Chapter 2 highlights the need for firms not to take benefits associated to AMT adoption for granted and to carefully consider the right mix of technologies to adopt relatively to their stage of maturity and level of technological readiness, as well as for policymakers to set proper incentives towards the adoption of I4.0-related technologies with the final goal of boosting productivity. Secondly, Chapter 3 shows how AMTs provide new tools and opportunities for managers to keep up with rising competition and increase chances of business success, simultaneously enabling firms to avoid the worst-case scenario, implying firm's closure. Under this light, industrial and innovation policies launched across Europe in the past decade may have resulted in a secondary positive effect beyond a relaunch of productivity growth, by reducing jobs lost through corporate restructuring. Finally, Chapter 4 provides valuable insights for policymakers aiming to foster the diffusion of welfare-enhancing innovations and job creation, considering the sectors more likely to experience employment-related gains from AM. Similarly, it informs managers of the potential synergies resulting from the integration of AM technologies in their production processes, leading to a deeper understanding of the related benefits.

Table 1 summarises the content of the four Chapters presented in this dissertation.

Table 1. Thesis chapters' overview and status

	Chapter 1	Chapter 2	Chapter 3	Chapter 4
Title	Measuring Adoption of Advanced Manufacturing Technologies via International Trade Data: Insights from European Countries	Advanced Manufacturing Technologies and Productivity Growth: Evidence from Europe	Firm Restructuring Modes and Advanced Manufacturing Technologies: Evidence from Collective Layoffs across Europe	The Employment Implications of Additive Manufacturing
Topic	Measurement of advanced manufacturing technology adoption	Advanced manufacturing technology and productivity growth	Advanced manufacturing technology and firm's restructuring decisions	Additive manufacturing and employment
Broad research question	How can we measure both the adoption and the production – i.e. the overall diffusion – of AMTs of the I4.0 wave across countries and over time?	What is the relationship between the adoption of AMTs, total factor productivity (TFP) growth, and technological catch-up across manufacturing industries?	Does the adoption of AMTs push or discourage manufacturing firms to restructure business activities through collective layoffs?	What is the relationship between the growing diffusion of additive manufacturing (or 3D printing) innovations and employment across manufacturing industries?
Level of analysis	Country	Country-sector	Firm	Country-sector
Main data sources	Eurostat's Comext and Prodcom	Eurostat's Comext and Prodcom, WIOD, EU KLEMS	Eurofound's ERM, Eurostat's Comext and Prodcom, WIOD, Bureau van Dijk's Amadeus	PATSTAT, WIOD, OECD's STAN
Sample	EU 27 countries and the UK	14 European countries, 13 manufacturing industries	730 restructuring decisions implemented across manufacturing firms in 19 European countries	31 OECD countries, 21 manufacturing industries
Time period	2009-2018	2009-2019	2013-2020	2009–2017
Dependent variable(s)	-	TFP growth	Dummy indicating if the firm restructured *via* layoffs	Employment
Empirical methods	Descriptive statistics	Panel data fixed effect regressions (equilibrium correction model)	Two-stage model (first-stage probit model and second-stage multinomial logit model), propensity score matching	Cross-sectional regressions with multiple fixed effects, instrumental variable (2SLS)
Co-authors	Davide Castellani, Katiuscia Lavoratori	Davide Castellani, Katiuscia Lavoratori	Davide Castellani, Katiuscia Lavoratori	Giulia Felice, Lucia Piscitello
Status	Published in Journal of Industrial and Business Economics	Target Journal: Technological Forecasting and Social Change	Target Journal: British Journal of Management	Published in Industry and Innovation

Chapter 1

Measuring Adoption of Advanced Manufacturing Technologies via International Trade Data: Insights from European Countries†*

Abstract

The investigation of the adoption of advanced manufacturing technologies (AMTs) of the Industry 4.0 (I4.0) wave and their implications, both at the macro and micro level, has attracted growing interest in the recent literature. Most studies have looked at the overall diffusion or the production of related innovations and knowledge, but what do we know about the adoption of these technologies over time and across countries? In this Chapter, we look at three technologies of the I4.0 wave and present a new empirical perspective able to overcome the limitations of existing attempts at measuring their adoption, generally based on small-scale and country-specific studies. Our study provides a methodology that allows measuring adoption across countries for a relatively long time period. In so doing, we build on the well-established idea in the international economics literature that trade of capital goods captures technology diffusion, and thus adoption across countries. We provide preliminary and comprehensive evidence on the adoption of these AMTs in Europe and set the premise for monitoring its evolution and implications on a large scale and over time.

Keywords: Advanced manufacturing technologies; Industry 4.0; technology diffusion; advanced industrial robots; additive manufacturing; industrial internet of things; Covid-19.

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† This Chapter is a slightly revised version of Castellani, D., Lamperti, F., & Lavoratori, K. (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. The Journal article has been edited to reduce redundancies with the overall thesis.
* This Chapter is co-authored with Katiuscia Lavoratori (Henley Business School, University of Reading, UK) and Davide Castellani (Henley Business School, University of Reading, UK). Contributions: Fabio Lamperti 55% (Conceptualisation, Methodology, Investigation, Data curation, Formal analysis, Writing – Original draft, Visualisation); Katiuscia Lavoratori 35% (Conceptualisation, Methodology, Validation, Writing – Review/editing, Visualisation, Supervision); Davide Castellani 10% (Conceptualisation, Methodology, Writing – Review/editing, Supervision).

1.1. Introduction

While there is no universal agreement about what an industrial revolution is, there is consensus that three major technological shocks had a substantial impact on the way goods were manufactured throughout history. That is, the introduction of water and steam-powered manufacturing facilities; the electrically powered technologies enabling mass production; the introduction of Information and Communication Technology (ICT) in the manufacturing process. More recently, governments, industries and academic scholars have highlighted the emergence of a new set of digital (and '*smart*') technologies as the key players of a fourth industrial revolution (4IR) wave, also called Industry 4.0 (I4.0) (Brynjolfsson and McAfee, 2014; Davies, 2015; Schwab, 2016; OECD, 2017; WIPO, 2019; UNCTAD, 2020).[1]

Within the industrial manufacturing domain, the term of '*Industry 4.0*' was coined in 2011 by the German Government to embrace the challenge of revitalising the manufacturing industry and boosting prosperity among developed economies, driven by the adoption and integration of a set of enabling advanced technologies (Kagermann et al., 2013; Rüßmann et al., 2015; Mariani and Borghi, 2019). In this Chapter, we will refer to '*advanced manufacturing technologies*' (AMTs) as a group of key player technologies driving such changing environment. AMTs are defined as "*computer-controlled or micro-electronics-based equipment used in the design, manufacture or handling of a product*" (OECD, 2012).

These technologies are seen as able to enhance operational flexibility, production efficiency and quality, and to reduce set-up costs, and so in turn to boost productivity and performance (Rüßmann et al., 2015; Schwab, 2016; Skilton and Hovsepian, 2017; Büchi et

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[1] Several initiatives from national governments have taken place worldwide, starting with the 'Advanced Manufacturing Partnership' in the USA and the 'High-tech Strategy 2020' in Germany, followed by 'La Nouvelle France Industrielle' in France, the 'Future of Manufacturing' in the United Kingdom, 'Industria 4.0' in Italy, the 'Factories of the Future' as part of the European Programme Horizon 2020 (Liao et al., 2017; Mariani and Borghi, 2019); some, emerging also in developing countries like Morocco (Gallab et al., 2021).

al., 2020), and create the conditions for sustainable operation management among supply chain operators (Lopes de Sousa Jabbour et al., 2018). In addition, they also allow for flexibility and speed in prototyping and responding to unpredictable demand needs and uncertainty. This has become extremely important since consumer needs and, more generally, the economic external environment have become more and more volatile. Indeed, the role of technologies under the recent unprecedented global event of the Covid-19 pandemic is an inspiring example (The Guardian, 2020; European Commission, 2020; UNCTAD, 2020).

Despite the growing popularity of the matter across policy institutions, media and academic scholars, a clear picture of the adoption of AMTs on the global economy is still an under-investigated research area. Some evidence is provided using data collected from surveys in specific countries or looking at specific technologies or on a small number of firms, through case studies (Sandström, 2016; Dachs et al., 2019; Delic and Eyers, 2020, among others). The main motivation for such paucity of evidence is the lack of reliable and precise measures of adoption on a large scale across countries and over time.

Beyond measurement issues, the process of technology diffusion itself is "*neither inevitable nor automatic*" (Keller, 2004, p. 753). New technologies usually emerge locally, due to the required presence of a certain level of tacit knowledge and a localised producing industry developing them. However, their diffusion might not necessarily imply actual adoption outside the geographical boundaries in which they originate: the essence of the diffusion concept does not just entail that a new technology is used abroad – actual adoption usually going along with overall economic integration (Keller, 2004) – but also allow for the simple spread of awareness of the existence of a new technology or innovation, thus enabling its use, in principle (Eaton and Kortum, 1999). Thus, in this study we consider the diffusion, production and adoption of a new technology as distinct concepts: the latter two imply the first one, but not the other way round.

With this respect, some studies have looked at the overall diffusion and the production of innovation and knowledge associated with the 4IR (Benassi et al., 2020; Balland and Boschma, 2021; Corradini et al., 2021; Felice et al., 2022;[2] Venturini, 2022), with special reference to the technological and geographical aspects of the origin and diffusion of I4.0 knowledge and innovations (Ciffolilli and Muscio, 2018; Balland and Boschma, 2021; Corradini et al., 2021; Martinelli et al., 2021). However, more effort is needed to enhance our understanding of the magnitude and evolution over time, geographical spread across countries and the presence of specialisation patterns in the adoption of AMTs. This becomes extremely important for understanding a relatively new phenomenon and to provide suggestions both for policymakers and managers that are dealing with such technological changes.

From a methodological perspective, tracking the growth and evolution of emerging technologies is particularly complicated since there are no available data, especially when the transformation is still ongoing and the technology is not yet mature. Our empirical approach addresses this problem by relying on the well-established idea that cross-country technology transfer can occur *via* international trade of capital goods.

In a seminal work, Caselli and Coleman (2001) investigate the technology diffusion of computers in the 70s–80s. At that time, computers represented a revolutionary innovation and a direct measure of capital investments was not available on a large scale. As an embodied technology, computers are an ideal case of technology diffusion to investigate, and as the authors do remark "*technology diffusion takes place through imports of the equipment embodying the technology*" (Caselli and Coleman, 2001, p. 328). Inspired by their intuition, we measure adoption of AMTs with import flows of selected products and machinery that

[2] I.e. Chapter 4.

embody such technologies, and we corroborate this measure with the use of production data able to capture the component of adoption, related to domestically produced goods. The idea of using imports as a proxy of technology adoption and diffusion has been developed in the literature (e.g. Caselli and Wilson, 2004; Acemoglu and Restrepo, 2022; Domini et al., 2021), and since these technologies belong to complex and high value categories of capital goods, the problem concerning re-exporting activities of imports in the form of intermediate inputs is very unlikely (Bernard et al 2015).

In a nutshell, our methodology consists of identifying the fine-grained (8-digit) product codes of capital goods related to advance industrial robots (AIRs), additive manufacturing (AM) and industrial internet of things (IIoT), i.e. the three capital-embodied AMTs will we focus on. Based on these product codes, we can quantify the adoption of these technologies for 28 European countries over the 2009–2018 period. Our evidence suggests that the most advanced European economies have been investing in these technologies over the years with different degrees and technology specialisation. Interestingly, we also uncover a growing presence of a cluster of Central and Eastern European countries as AMT adopters. Two reasons can explain this finding: first, national industrial policies are massively supporting the adoption of such technologies to sustain long-term international competitive advantages; second, the increasing participation of these countries in global value chains (GVCs) facilitates the multinational enterprise (MNE) transfer of sophisticated production technologies to their foreign subsidiaries through imports of capital goods or encourages local suppliers to adopt advanced technologies in their production processes.

The main contribution of this work resides in moving forward the conversation about the adoption of AMTs within the I4.0 context, by introducing and improving an empirical measure able to capture the phenomenon. We provide prima facie empirical evidence of the diffusion of AMTs across European countries over the period 2009–2018. At the same time, we provide a discussion about possible extensions of such methodology at the industry and firm level, alongside a further research agenda.

The Chapter is organised as follows. Section 1.2 briefly describes the advanced manufacturing technologies under investigation. Section 1.3 describes the data and the methodology employed to create the measure of adoption and to identify AMTs from trade data. Section 1.4 provides an empirical application of the proposed methodology illustrating the relevance, evolution and geographical diffusion of AMT adoption across European countries. Section 1.5 concludes, summarizing the main findings and proposing possible research directions.

1.2. Defining advanced manufacturing technologies

As discussed in the previous Section, the I4.0 wave (or 4IR) gathers a heterogeneous set of technologies, bearing different levels of complementarity as well as different degrees of relatedness with specific industrial operations. These underlying similarities and differences, together with the characteristics of each new digital technology associated with the I4.0 wave, motivate our focus on those technologies that have the highest potential impact in advanced manufacturing processes.[3] Keeping this as our starting point, we embrace the definition provided by the European Foundation for the Improvement of Living and Working Conditions, which identifies five '*game-changing technologies*', namely, advanced industrial

[3] While we already acknowledged the impact new technologies of the I4.0 wave have on manufacturing operations – e.g. higher operational flexibility, higher production efficiency and quality, lower set-up costs and integration along the value chain, resulting in higher productivity and better performance overall (Rüßmann et al., 2015; Schwab, 2016; Skilton and Hovsepian, 2017; Eurofound, 2018) – additional high-level impact resides in the world of work and, in general, the entire society. On the one hand, a general concern around the "*risks of new monopolies, mass redundancies, spying on workers, and the extension of precarious digital work*" (Davies, 2015, p. 9) emerges. On the other hand, this transformation calls for a policy debate on the upcoming changes in the task content and occupational profiles of manufacturing employment (Frey and Osborne, 2017; Eurofound, 2018).

robots (AIRs), additive manufacturing (AM), industrial internet of things (IIoT), electric vehicles and industrial biotechnologies (Eurofound, 2018). As anticipated, this Chapter focuses on the first three technologies given their potential to impact significantly all manufacturing sectors to the core of their operations, being key components of the 4IR.

Moreover, these are embodied technologies, so that their adoption requires a physical installation of a specific type of capital equipment. This is a crucial distinction concerning other new digital technologies of the 4IR (e.g. artificial intelligence, machine learning, cloud computing, big data, etc.), whose physical component of the technology is usually standardised and multi-purpose (Foster-McGregor et al., 2019). In turn, this further intrinsic feature of the three AMTs we investigate makes them more appropriate for the methodology that we devised in this Chapter.

Advanced industrial robots (AIRs): This category includes advanced industrial robots, which leverage high-level and dynamic programming (i.e. able to perform '*smarter*' tasks) and enable more flexibility in production (Eurofound, 2018). Thanks to the falling cost of hardware and software experienced during the last decade, there has been a huge improvement in the technical features of industrial robotics. Advanced robots existing nowadays can perform a wider set of tasks compared to their predecessors, especially those requiring high flexibility and accuracy. The possibility of equipping robots also with advanced sensors and functionalities, and the potential for human-machine interactions has enabled their adoption to spread from traditional sectors of usage (e.g. automotive and electronics) to several others (e.g. agriculture and logistics).

Additive manufacturing (AM): The International Organization for Standardization (ISO) defines additive manufacturing as "the general term for those technologies that based on a geometrical representation creates physical objects by successive addition of material" (ISO, 2015). Currently, these technologies are used for various applications in the engineering industry, but also in other areas such as medicine, architecture, education, and several handcrafted segments (Wohlers Associates, 2014). This category includes highly flexible and adaptable machinery leveraging on digital production technique enabling reduced material consumption and waste as compared to ‘traditional’ subtracting methods (Tuck et al., 2008; Atzeni and Salmi, 2012; Achillas et al., 2015; Chekurov et al., 2018), technically enhanced and highly customised products (Diegel et al., 2010; Atzeni and Salmi, 2012; Petrick and Simpson, 2013; Mellor et al., 2014; Khorram Niaki and Nonino, 2017), as well as fewer manufacturing steps, especially reducing assembly operations (Weller et al., 2015; Sandström, 2016; Cuellar et al., 2018; Singamneni et al., 2019). Additive manufacturing (also referred to as 3D printing) techniques work by following a reversed logic than traditional manufacturing processes (Attaran et al., 2017), adding or melting subsequent 2D layers of material to generate the final product. Already implemented in the production of plastic consumer products, aerospace and human prosthetics, additive manufacturing is increasingly adopted in other manufacturing sectors (Laplume et al., 2016; OECD, 2017; EIB, 2019).

Industrial Internet of Things (IIoT): The Industrial Internet of Things is used to identify the industrial specializations of the Internet of Things (IoT). The latter consists of “*a global infrastructure for the information society, enabling advanced services by interconnecting (physical and virtual) things based on existing and evolving interoperable information and communication technologies*” (ITU, 2012). This category includes wireless (and not) sensors, actuators, control and regulation systems, microchips and distributed systems such as Near Field Communication (NFC) chips, Radio-Frequency Identification (RFID) tags and Global Positioning Systems (GPS) (Atzori et al., 2010; Gubbi et al., 2013). IoT systems can be applied to several different contexts to create smart environments (e.g. smart cities, smart homes, smart factories, smart vehicles, etc.). Specifically, Industrial IoT refers to the creation of a digital environment in which (1) controlling machines (i.e. computers), (2) process machinery (e.g. '*traditional*' automatic manufacturing stations, additive manufacturing machines and industrial robots) and (3) smart products (i.e. products incorporating an RFID tag, NFC chip, GPS or alike systems) are all connected. Hence, IIoT integrates a high-level processing and communication potential able to elaborate huge data amount, collected and transferred between each node of a widespread, seamless network (Atzori et al., 2010; Gubbi et al., 2013). In turn, this creates opportunities for enhanced working conditions, more flexible operations and digital integration along the value chain (Stock and Seliger, 2016; Wang, Wan, Li and Zhang, 2016; Wang, Wan, Zhang, Li and Zhang, 2016).

1.3. Data and methodology

1.3.1. Building measures of AMT technology adoption

So far, the empirical literature has been strongly limited by the absence of an extensive, precise and comprehensive measure of adoption to capture such a complex phenomenon, across technologies, across countries and over time.

In particular, some evidence comes from data collected through surveys in specific countries or looking at specific technologies. For instance, data collected by the European Investment Bank (EIB, 2019) and from Eurostat (Eurostat, 2021) provide cross-country insights from a representative sample of firms adopting various technologies of the 4IR – at the aggregate and sectoral level, respectively, at the same time providing only cross-sectional evidence. Conversely, survey data providing insight at a finer level – cross-country, sectoral, or even firm-level adoption – cover long time-series although focusing on single technologies (like industrial robots in the case of data from the International Federation of Robotics (IFR)) or for more technologies but on a shorter period (such as for data from the European

Manufacturing Survey (EMS)[4]), but are only available either privately or for commercial use. Alternatively, several contributions have addressed the implications of adopting technologies of the I4.0 through case studies based on specific sectors or a small number of firms (e.g. Sandström, 2016; Khorram Niaki and Nonino, 2017), by small-scale firm-based surveys (e.g. Kianian et al., 2016; Delic and Eyers, 2020), or by extrapolation from alternative sources (e.g. Ancarani et al., 2019). In turn, these limits associated with the existing data sources hamper the comparison across countries and sectors, as well as across technologies. We aim at overcoming such data and methodology limitations.

Drawing from Caselli and Coleman (2001), we create two measures as a proxy of adoption: first, we measure adoption by the *import* of AMT capital goods, using bilateral trade data at the finest level of disaggregated product classes. However, we acknowledge that imports may underestimate adoption in countries that have a large local production of AMTs, since these countries already feature local producing firms, potentially selling domestically. Similarly, measuring adoption *via* imports could overestimate adoption in countries where the import of these technologies does not translate into local adoption, but in re-export, since importing capital goods does not necessarily mean that technology is successfully transferred and assimilated. To assess the extent of this potential measurement issue, we also resort to a different measure of adoption, which we call *net consumption*, based on the formula: $net\ consumption = (production + import - export)$. In this way, we can account for both sources of capital investments determining adoption of AMTs, that is domestic and foreign production, and also for how much of this remains in the country (i.e. is not exported). This second measure is not available for all countries and technologies considered, as production data on goods embodying AMTs are in some cases missing or not reliable.

[4] See Dachs et al. (2019) for a recent application.

Therefore, this measure is mainly used to validate our *import* measure of AMT adoption, which is more widely available (also outside the EU) and thus allow us to extend the application of this methodology.

After completing the data collection on trade and production information, we create these adoption proxies for each of the three AMTs we look at (i.e. AIRs, AM and IIoT). First, we compute *import* variables by creating three '*synthetic*' measures computed as the sum of all 8-digit product codes relating to the same technology (as illustrated in detail in Section 1.3.3), for each country-year observation in our EU28 sample. Following the same logic, we build our second proxy measuring adoption (i.e. the *net consumption* variables) by combining import, export and production data for each AMT.

We finally adjusted values for PPP and converted them in constant 2011 USD using exchange rates and PPP conversion factors from Eurostat and the World Development Indicator (WDI) data set of the World Bank, respectively, to allow for intertemporal and geographical comparison and to filter out cross-country differences in prices.

1.3.2. Data

We rely on two main sources of data to generate measures of AMT adoption. First, we use highly disaggregated trade data collected from the Comext data set, available from the Eurostat website. Comext provides statistics on the value of goods traded between the EU28 member states (i.e. intra-EU trade) and traded by the EU member states with non-EU countries (i.e. extra-EU trade) (Eurostat, 2019). Goods are classified according to the Combined Nomenclature (CN) classification, which is based on the harmonised Commodity Description and Coding System (HS). The HS provides information up to the 6-digits level of commodity disaggregation, and then the CN builds on the HS by adding a further breakdown at the 8-digit level. This extension allows us to consider around 9,500 8-digit product codes, which are subject to annual revisions that ensure the CN to be up to date to changes in technology or patterns of international trade (Eurostat, 2019).[5] As our interest lies in the identification of very specific capital goods associated with three technologies, the use of 8-digit disaggregated data provides the insight needed to identify with a sufficient deal of precision those product categories in which it is more likely that these AMTs are traded.

Second, we use production data from the Prodcom data set (Eurostat, 2018) to provide further detail to our analysis and build a measure of *net consumption*. The Prodcom data set provides information on the value of goods produced and sold in EU28 countries. Differently from the data reported in Comext, Prodcom data follow the Classification of Products by Activity (CPA). As in the case of the CN classification, the CPA is revised every year and consists of around 3,900 products; hence, one CPA product may correspond to one or more CN goods (even though in the case of some product categories the CPA features a higher level of detail as compared to the CN). Furthermore, the CPA classification differentiates itself from the CN one as it is based on the NACE Rev.2 classification. This means that the first 4-digits of each product code in the CPA corresponds to the 4-digit sector in which the product is manufactured.

As further discussed later in this Section, we took the 2017 release of both the CN and the CPA as reference for our initial identification of AMT-related product codes. Further details on the methodology followed to reconcile the two classifications over time and to build a unique time series for each identified product code are reported in the following Section.

Both Comext and Prodcom databases also report data on quantities of 8-digit products, traded and produced. Though quantities would represent a more desirable measure

[5] Data included in the Comext data set are converted in Euros for reporting purposes by Eurostat and expressed in current prices.

as they are not affected by inflation dynamics or conversions for international and intertemporal comparison, our preferred measures are based on value data. There are two main reasons for this choice: first, quantities are frequently reported in different ways in the two data sets,[6] thus not allowing for comparison on the quantities of all product categories we look at. Second, data on quantities present a high share of missing values in our country-year observations for many of the disaggregated product codes we consider. Hence, we decided to employ value data as they enable higher comparability across the two sets of data.

We acknowledge that the informations provided by Comext and Prodcom bear different level of precision: while trade data are collected by customs and hence represent the universe of cross-border transactions (Eurostat, 2019), production data are collected through a survey of a representative sample of firms in each country's 4-digit NACE sector, making up at least 90% of real national production (Eurostat, 2018). Despite we recognise that such difference may represent a potential source of measurement bias, we highlight that Comext and Prodcom databases represent the most precise, detailed and updated sources of information for the purpose of our analysis.

1.3.3. Identifying AMTs via trade data

Our identification of the specific types of machinery, equipment and components related to AMTs starts from the analysis of several sources of information. In particular, we relied on: i) the relevant engineering literature both from the practitioner – for instance, the standard international terminology approved by ASTM International (2013) and ISO (2015) for AM technologies, concepts and definitions on IIoT provided by ITU (2012) – and an academic point of view; ii) product catalogues of representative producing firms for AIRs, IIoT and

[6] For instance, in Comext, quantities are usually reported in 100 kg, while in Prodcom are reported in different units such as kg, m2 or number of items.

AM;[7] iii) the World Customs Organisation (WCO), and; iv) Eurostat.[8] From these sources, we were able to develop a list of keywords related to our AMTs of interest. This keyword-based approach has been widely used lately, and applied to different data sources – e.g. patents, business registers, scientific publications, trade and industrial records (Craglia et al., 2018; De Prato et al., 2019; Van Roy et al., 2019). The list of identified keywords is reported in Table B1 in Appendix B.

The identified keywords were then used to define an initial list of 25 8-digit CN product codes.[9] We acknowledge that some of the technologies we focus on may be embedded also in other product classes not included in our shortlist. However, we adopt a conservative approach that allows us to consider only those product codes reporting a precise, coherent and unquestionable description, and to underestimate rather than overestimate the phenomenon. At the same time, the selected keywords might also lead to false-positive results or matches with product codes at a lower level of disaggregation (e.g. 6- or 4-digit codes). Hence, we performed a second stage of manual screening in which we exclude potential false-positive matches and identify the relevant 8-digit codes included in the less disaggregated categories matching with our keywords. More specifically, we focus on trade in capital goods of product codes included in the 4-digit CN codes 8463 (Machine tools for working metal or cermets, without removing material), 8471 (Automatic data-processing machines and units thereof […]), 8477 (Machinery for working rubber or plastics or for the manufacture of products from these materials), 8479 (Machines and mechanical appliances

[7] Given its wider discussion in the existing literature (e.g. Acemoglu and Restrepo, 2022), the identification of the relevant nomenclature is a lesser problem in the case of AIRs; hence, as a reference, we looked at ABB Ltd product catalogue. Concerning AM, we looked at product catalogues from three main producers worldwide, namely Stratasys Ltd., 3D Systems Inc. and EOS GmbH. Finally, relatively to IIoT, given that it is the technology bearing the widest set of capital goods among the technologies we focus on, we consulted product catalogues from Intel Corp., ABB Ltd., Siemens AG, Hewlett Packard Enterprise LP, Bosch GmbH, GE Digital Plc., Cisco System Inc. and Rockwell Automation Inc.

[8] For more details, see https://trade.ec.europa.eu/tradehelp/classifying-computers-software.

[9] We define the product categories of interest starting from CN-2017 classification (that following the latest revision of the HS classification, HS-2017).

having individual functions), 8515 (Electric, laser or other light or photon beam, electron beam […] machines and apparatus for hot spraying of metals or cermets), 8517 (Apparatus for the transmission or reception of voice, images or other data, including apparatus for communication in a wired or wireless network […]), 8526 (Radar apparatus, radio navigational aid apparatus and radio remote control apparatus), 8542 (Electronic integrated circuits) and 9032 (Automatic regulating or controlling instruments and apparatus). The full list of product codes initially identified and the related descriptions are reported in Table B2 in Appendix B.

In the case of AIRs, our initial research brought to the identification of a single, main, code – since we do not aim at considering other forms of more traditional automation like non-robotics handling machines or conveyor belt systems. The other two cases present more challenges: specific codes for AM machines and IIoT devices do not yet exist in either the HS or the CN classifications. In the case of AM, the World Customs Organisation recognises the lack of a specific chapter in the HS classification encompassing these types of machinery, thus resulting in their categorisation being spread in several other product codes (Yuk, 2018). To the best of our knowledge, the identified codes are those most suitable to be used in practice and reflect the specific characteristics of the existing AM processes, as described above. The case of IIoT is even more challenging as the variety of devices is larger than in the case of AM, and cases of our focus goods being matched to a wider set of product categories greatly increases. Nonetheless, based on further validation discussed below, we believe the set of codes shortlisted here should capture much of the trade associated with IIoT components as product descriptions of the shortlisted goods refer to very specific products, classified in a highly detailed way.

To validate the selection process for the shortlisted CN codes, we first developed a survey to collect information on the CN (and/or CPA) product codes used by producers of the three AMTs when exporting (and/or producing) their products. Then, we consulted experts and practitioners from the Italian Customs Agency and a private customs broker. Overall, the large majority of the 8-digit codes originally identified (21 out of 25) were confirmed, hinting to the goodness of the overall identification procedure. Appendix A provides further details on the validation process.

After the validation process, we matched the 21 CN codes considered in Table B2 (see Appendix B) with 22 codes in the CPA nomenclature, according to the 2017 correspondence table provided by Eurostat. A crucial task for our analysis lies indeed in the identification of the correct product codes associated with our AMTs, when looking at past and subsequent years. Hence, we first used year-to-year correspondence tables provided by Eurostat, and we manually checked for forward and backwards changes that occurred in each of the two classifications along the period considered (2009–2018), for each identified code starting from the 2017's release of the CN and CPA. Second, for each product code we cross-checked the correspondence between the CN and the CPA classifications year-by-year in order to track any potential change in the identified codes and to reconcile 'within nomenclature' correspondences along the time series.

Changes in the CN and CPA classifications are of two types: (1) new products are added to the classifications with new codes; (2) existing product codes are converted into new product codes. Changes of this second type are problematic, as they might imply not just the 'recoding' of certain products but also the elimination of 'old' product codes, whose related products are then absorbed in one (or more) new codes. Specifically, in cases in which multiple CN codes correspond to one or more CPA codes (or vice versa), as well as for cases in which the classification has changed over time, we followed the methodology by Van Beveren et al. (2012). This methodology proceeds by creating '*synthetic*' codes by grouping together the codes which are subject to changes. In this way, we ensure full consistency in the correspondence between trade and production data over time.

When looking at the product codes we have identified as capturing AMTs, this procedure resulted in the reduction of our product codes from 21 to 18 following the CN nomenclature, and from 22 to 18 following the CPA nomenclature. Our cross-checking procedure highlighted a mostly consistent correspondence of the product codes, across both years and classifications, with only a few cases in our list of codes subject to either type (1) or type (2) changes. Table 1 reports the correspondence table between CN and CPA codes, in 2017.

Table 1 around here

1.4. Discussion of findings

In this Section, we present the main trends over time and across countries characterising the adoption of AIRs, AM and IIoT across EU28 countries, between 2009 and 2018. The choice of focussing on the period after 2009 is driven by the following considerations. In 2006 the German government has launched the High-Tech Strategy to drive innovation actions and technological innovation. In 2009, after the global financial crisis, the demand for mechanical engineering products returned to normal (Kagermann et al., 2013). In the same year, Korea has launched a five-year plan to encourage Research and Development (R&D) investments in the intelligent robot industry aiming at expanding the adoption of industrial robots in other industrial sectors, since industrial robotics can be considered the first key technological driver (De Backer et al., 2018). Furthermore, several core patents protecting additive manufacturing technologies, such as fused deposition modelling and selective laser sintering, expired between 2009 and 2014 (Laplume et al., 2016). This created the right conditions for many new producers of additive manufacturing machinery to start their business about spill-over inventions (Wohlers Associates, 2014). Thus, we start the period of observation from 2009, which can be reasonably recognised as the beginning of a global interest on this technological wave.

1.4.1. Preliminary insights on AMT adoption

Our first focus is on the relationship between *import* and *net consumption* measures in our EU28 sample, over the 2009–2018 period. This relationship can be explored only on the subsample of countries for which production data are available for the product codes described in Section 1.3; hence, for which *net consumption* can be computed.

Rooting our argument in the literature on technology diffusion (e.g. Caselli and Coleman, 2001; Caselli and Wilson, 2004; Acharya and Keller, 2009),[10] we argue that *import* represents a good proxy of AMT adoption, especially for those countries not characterised by a strong local production for such technologies. Conversely, when local producers account for a substantial share of adoption, the *net consumption* proxy should provide more precise insights into the phenomenon.

Figure 1 plots values of our two adoption proxies at the beginning and the end of the observation period, showing that *import* and *net consumption* are highly correlated, with pairwise correlation coefficients of 0.83 for AIR, 0.65 for AM and 0.66 for IIoT. With the exception of The Netherlands in IIoT, where import is much larger than net consumption, probably due to the export of imported components, import and net consumption largely coincide for all three AMTs. Indeed, the Figure reveals our two measures to be largely

[10] See also Keller (2004) for an extensive review.

comparable across European countries for which we have production data – because the net difference between production and export of AMTs is negligible in the case of most countries and technologies – and *import* to be an almost perfect measure of adoption.

Figure 1 around here

Despite some differences across the three technologies, this first descriptive evidence suggests that *import* can be a good proxy of adoption for AMTs across EU countries. Furthermore, looking at the relative positioning of most EU28 countries in the initial and final year in our sample highlight a proportional change in both *import* and *net consumption* proxies. This suggests that the large majority of European countries have been increasingly adopting AMTs. In the following, we argue that this measure indeed captures the patterns of adoption over time and across countries.[11]

1.4.2. Temporal and geographical patterns of AMT adoption

As discussed in the previous Sections, these technologies have received considerable attention from businesses and policymakers, and they have been at the core of several industrial initiatives worldwide after the 2009 financial crisis. Hence, we expect the adoption of AMTs across EU28 countries to have significantly increased over our observation period.

[11] As a further robustness check, since virtually all European countries in our sample (with the exception of Cyprus, Greece and Malta in the case of AIRs) are also exporters of AMTs – similarly to what found by Caselli and Coleman (2001) in the case of computing equipment already in the mid-90s – we computed import to export ratios for each country and each technology in order to show which countries are net importers of AMTs (ratios above 1) and which countries are exporters of AMTs (ratios below 1). To show the evolution of this dynamics over the observation period we computed initial (2009-2011) and final (2016-2018) three-year averages, to smooth potential peaks in the data. We report this additional analysis in Table B3 in Appendix B. Most countries in our sample (14 in the case of AIRs, 17 in the case of AM and 20 in the case of IIoT) consistently import more AMTs than they export.

Figure 2 around here

Figure 2 explores the change in the flow of *import* (panel A) and *net consumption* (panel B) measures between 2009 and 2018, in the aggregate of the European countries for which we have production data (those for which we can compute the *net consumption* measure). The Figure reports shares of *import* and *net consumption* per 1,000 workers to account for differences in country size; we express them as an index (2009=1). Panel A reveals that the adoption of all three AMTs has increased by about 2.1 times, with a peak in the *import* proxy for AIRs that reached a 3.5-fold increase. The observed pattern looking at the *net consumption* adoption proxies (panel B) is quite similar (i.e. adoption increasing by between 2 and 2.7 times), although revealing a more homogeneous growth across the three AMTs until 2015, with AM then growing relatively more than its peer AMTs in 2017 and 2018.

Foster-McGregor et al. (2019) highlight that while there has been a rise in the absolute value of technologies related to the 4IR over the last two decades, the share of these products in total imports remains very small, actually declining over time. To test our measures to this prior finding, panel C in Figure 2 reports the shares of the AMT *import* measures in import of reference benchmark categories. As a benchmark, we use the aggregate of the 2-digit product category(ies) in the CN classification to which our product codes (for each AMT) belong (i.e. product category 84 for AIRs and AM, and the sum of product categories 84, 85 and 90 for IIoT). Specifically, we compare AMT imports with imports of similar and related, yet highly aggregated, goods; this allows to avoid confounding effects due to trends in import flows of goods that are completely unrelated with AMTs. When compared with the product category(ies), we observe that all three technologies have experienced a trend of increasing shares of imports over the period 2009–2018 relative to their benchmark, with AIRs increasing from 0.11% to 0.24% (+114%), AM imports rising from 0.11% to 0.17% (+56.3%) and IIoT increasing from 4.75% to 7.36% (+55.1%).

As an additional robustness check, Figure B1 in Appendix B replicates the analysis in Figure 2 but looking at the full sample of all EU28 countries: panel A explores the change in the flow of *import* measure for our three AMTs between 2009 and 2018, while panel B analyses the trend in the ratio between imports in each AMT and imports of the related benchmark category(ies). Also in this case, as compared to 2009 all three AMTs have increased consistently, with AM and IIoT rising by 2.2 and 1.5 times respectively, and AIRs even peaking at about 4.9 times. Looking at the share of AMTs in imports of the related benchmarks, the trend is very similar to that observed for the smaller sample of EU countries for which we can compute the *net consumption* measure, with all AMTs increasing their import components in the benchmark categories (AIRs rising by 126.8%, AM by 63.2% and IIoT increasing by 53%).

To provide further insight, in Appendix B, we analyse the composition of the observed trend for AIRs, AM and IIoT, by looking at the shares of aggregate imports across all EU28 countries in single product codes included in each of our adoption measures. Specifically, Table B4 reports shares for each year in the observation period and product code composing *import* measures for AM and IIoT, as well as the observed percentage change between 2009 and 2018 (for AIRs, Table B4 reports the same data presented in panel B of Figure B1 since the measure includes a single CN/CPA product code). Such analysis provides insights about some heterogeneity in the trends for individual product codes building our adoption measures: overall, in the vast majority of specific product codes, imports have grown faster compared to the related 2-digit benchmark category(ies), thus leading to an increase in the shares. Specifically, in the case of AM, 3 out of 4 product codes experience an increase in their shares of import (between +11.9% and +85%), while only 1 product code experiences a slight drop (–18.9%); similarly, in the case of IIoT, 11 out 13 product codes feature an increase in their share of imports relative to the benchmarks (ranging between +8.3% and +225.7%).

Tables 2, 3 and 4 provide detailed data on cross-country differences in the importance of *import* and *net consumption* flows per 1,000 workers of AMTs in 2009 and 2018 (AIRs, AM and IIoT, respectively), as well as their growth over this period.

Tables 2, 3 and 4 around here

Table 2 shows the *import* value of AIRs in 2009 and 2018. Among the European countries, we can observe the central role played by Germany, Italy, Sweden, and Austria during the period, although some Central and Eastern European countries (CEECs) such as the Czech Republic, Hungary, Slovakia and Slovenia complete the scenario, featuring as important players in the adoption of AIRs.[12] The *net consumption* data return a very similar picture to the *import* measure, supporting the strong correlation between the two adoption proxies. Moving to AM, Table 3 shows that the biggest importer is Slovakia, followed by Czech Republic, Hungary, Lithuania and Slovenia. It is worth highlighting the increasing role of CEECs at the end of the period in the *imports* of AM, underlining the importance of the adoption of advanced technologies in these transition countries. Among the most advanced and industrialised countries in the EU, Austria, Denmark, Germany and Italy present the highest growth rate of AM adoption when looking at the *net consumption* measure. Finally, looking at data for the IIoT adoption proxies in Table 4, we can observe a more widespread adoption, based on both the *import* and the *net consumption* data, across Europe. Austria, the

[12] We suggest caution in the interpretation of values for Cyprus, Malta, and Luxemburg. In such cases the accuracy of our adoption measure may be lower, for instance given the presence of pass-on trade practices eventually inflating national statistics.

United Kingdom (UK), Hungary, Poland, and Romania have registered a substantial increase also in *net consumption*, representing the major consumers of IIoT at the end of the period. It is worth noting that among the advanced European economies, the UK registers not only the lowest initial values of adoption across technologies but also lower growth rates in terms of *import* and *net consumption*, except for IIoT. On the contrary, countries that report important growth rates over the years are located in Central and Eastern Europe. In particular, some of these countries emerge as strong AMT adopters not just when looking at our *import* measure (as one would expect), but consistently also when looking at the more precise *net consumption* proxy for adoption. Notably, Czech Republic and Hungary in the case of AIRs, Poland and Slovakia in the case of AM, and Czech Republic, Hungary, Lithuania, Poland, Romania and Slovakia in the case of IIoT.

In Figure 3, we further confirm these insights with the cumulated rates of AMT adoption at the end of the period, computed as the stock over the 2009–2018 period per 1,000 workers of both *import* (left-hand side, in green) and *net consumption* (right-hand side, in red) measures. Figure 3 shows the coverage and scale, leaders and laggards in the adoption of AMTs in Europe. The combined graphical representation of both measures makes even clearer the role of Central and Eastern Europe (mainly Hungary, Slovakia, and the Czech Republic) as key adopters, followed by Western European countries such as Germany, Italy, Austria, France and Sweden.

Figure 3 around here

To provide further insight and robustness to our analysis on the adoption and diffusion of I4.0 technologies, we compute normalised relative import propensity (RIP) indexes[13] in each country and AMT in our sample, following Foster-McGregor et al. (2019). Such complementary analysis provides insight into the evolution of relative intensity in the adoption of each AMT across EU28 countries, at the beginning and the end of our observation period. Results, which are reported in Figure B2 in Appendix B, denote remarkable stability in the propensity to import AMTs across countries, but with a handful of countries, mostly among the new member states, that have significantly increased their propensity to import AIRs (e.g. Croatia, Czech Republic, Lithuania and Poland) and AM (Hungary).

Two main factors can help explain this pattern. On the one hand, governments of these countries are strongly supporting the investment in the adoption of such *game-changing* technologies given the industrial composition of their manufacturing industries. For example, the Czech Republic is one of the most industrialised countries, where the automotive industry has an important weight in the industrial composition.[14] Investing in these technologies is crucial for maintaining the (international) competitiveness of the country and for the long run economic growth, as part of future innovation strategies and industrial policy objectives (Ministry of Industry and Trade of the Czech Republic, 2019).

On the other hand, over the last two decades, CEECs have massively strengthened the link with Western European countries through global value chain participation. At the end of 2005, Western European firms were responsible for around 80% of foreign direct investment

[13] These indexes are positive (negative) if the share of imports more of a certain AMT in total import of a given country is higher (lower) than the corresponding share in the EU as a whole.
[14] After the global financial crisis in 2009, car manufacturers worldwide started to restructure their business operations, investing heavily in new digital technologies. For instance, since 2010 the automotive industry has witnessed rising investments in new production capacities as well as investments in modern production technologies, resulting in major car-producing countries driving the demand for industrial robots (IFR, 2020).

(FDI) stock in CEECs, with Germany, Austria, France and Italy accounting for the majority of shares (ECB, 2013). The large-scale investment flow directed from Western European countries towards several CEECs over the last 10 to 15 years is, in fact, the result of their economic transition from planning and control economies into market economies over the 90s, combined with the benefits of the European Single Market integration policies, as a result of their access to the EU in 2004 (Cséfalvay, 2020). Furthermore, countries like the Czech Republic, Hungary, Slovakia and Poland are the preferred host locations, especially due to their relatively higher political and institutional stability, the availability of relatively skilled workers and the low unit labour costs (Carstensen and Toubal, 2004).

On a complementary perspective, Western European countries are the main destinations of CEECs total exports, 45% related to foreign value-added or domestic value-added for the exports of other countries, suggesting that participation in GVCs is mostly associated with western (particularly European) MNEs (ECB, 2013, 2020). A strong interdependence with parent firms allows the transfer of sophisticated machinery and capital goods to local affiliates through imports, able to boost productivity upgrading and develop a domestic industry operated by major productive firms in the sector (Chiacchio et al, 2019). Seen under this light, our evidence points at Europe to be the perfect case to understand how MNEs organize and reconfigure the geographical structure of their supply chains over time – for instance, from global to regional, nearshoring activities in CEECs (Pavlínek, 2018) – and how this can have implications also relatedly to the adoption of new technologies.[15] Recent evidence from Cséfalvay (2020) on AIRs confirms this to be one of the critical factors driving the diffusion of technologies related to the I4.0 across CEECs.

[15] The latest data from Eurostat seems to corroborate our evidence, highlighting that, across European countries, AMT adoption is mostly concentrated in large firms. In 2020, across EU27 countries, only 4% of small enterprises (10–49 employees) employ AIRs, while this share grows to 23% among large enterprises (250+ employees). Similarly, these shares amount to 4% and 17% in the case of AM, to 16% and 38% in the case of IIoT, respectively for small and large firms (Eurostat, 2021).

In sum, these findings provide first evidence of the geographical pattern and scale of AMT adoption in Europe: while the most advanced countries have been steadily investing in these technologies in the whole period, we uncover the growing importance of CEECs as AMT adopters. At the same time, together with the descriptive statistics provided in Section 1.4.1, our findings provide additional evidence that our *import* and *net consumption* measures return consistent results, with the major advantage of the *import* adoption proxy of being available for an enlarged sample of countries.

1.5. Conclusions, future developments and applications

This Chapter proposes a fine-grained methodology to measure the adoption of AMTs using trade and production data and provides some descriptive evidence on the patterns of adoption over the last decade across EU countries. Our findings suggest the importance of further investigating the topic and intensifying research efforts to find better, more refined and precise measures able to proxy the adoption of these new technologies. In this respect, the methodology presented here outlines a potential way of overcoming data limitations associated with technologies like AIRs, AM and IIoT. The use of highly disaggregated and detailed trade and production data seems to hold promising opportunities to fill a knowledge gap and offer a powerful tool to investigate how these AMTs are affecting several economic aspects in developed countries, as well as developing countries. At the same time, if compared to prior works in the field (e.g. Foster-McGregor et al., 2019), our findings also highlight how crucial it is to: i) properly understand the technologies involved, and; ii) develop precise and structured identification methodologies aimed at tracking their trade and production, hence eliminating the most possible sources of measurement error.

Our methodology, although not free from caveat (as discussed in Section 1.3), is easily scalable and can provide up-to-date information on the adoption of AMTs across countries and over time. Considering that the production of AMTs is highly geographically concentrated in a few countries,[16] in most countries imports represent a perfect proxy of adoption. This means that our analysis can be easily extended using 6-digit UN COMTRADE data, which are available for all countries in the world and updated regularly to enlarge the sample with non-European countries. Notwithstanding, we recognise that the findings presented here are specific to European countries, hence the validity of such insight outside the EU boundaries is still to be assessed. Furthermore, while the focus of this Chapter is at a macro-level, trade data are available at the sector and, increasingly, at the establishment level. Indeed, several statistical offices worldwide are allowing researchers to access detailed import and export data at the transaction level. This opens up the opportunity to build measures of the adoption of AMTs at the firm/establishment level (e.g. Domini et al. 2021), which so far have been hampered by a chronic lack of information.

From a policy perspective, we provide evidence on the adoptionof AMTs across countries within the European region in a relatively large time window, especially considering countries that are linked through the participation to GVCs orchestrated by western European countries, and the industrial strategies targeting these technologies adopted by CEECs. Yet, given the purely descriptive nature of the analysis reported in this Chapter, the presence of context-specific and/or conditioning factors (e.g. economic integration, R&D investments and investments in enabling technologies, potentially building AMT-specific absorptive capacity) affecting the adoption pattern observed across CEECs is still to be explored and represents an avenue for future research. Coherently, our data can also provide

[16] Our production data indicates that, even within the sample of countries featuring some AMT production (i.e. those reported in the scatterplots in Figure 1), the large majority of EU production is concentrated in few countries, particularly in the case of AIRs (mostly Austria, Denmark, France, Germany, Italy, Hungary and Sweden) and AM (mostly Austria, Denmark, Germany and Italy). Conversely, production of IIoT is much more evenly distributed across all EU producers.

suggestions and be used to investigate statistically robust causation of the effectiveness of policy incentives put in place to stimulate the adoption of such technologies across countries.

Our effort can provide a set of insights and help define a further research agenda. There are several research areas in the context of I4.0 and the adoption of its technologies, which are still under-investigated and that can be explored using the methodology proposed in this Chapter.

Productivity**, **occupation and growth. The transition to a digital economy may boost the competitiveness of a country, create new opportunities for business and entrepreneurial initiatives, as well as a new way to reach international markets, affecting productivity and economic growth as a consequence (UNCTAD, 2017, 2020). The manufacturing sector is still recognised as crucial and remains one of the main drivers of employment and economic growth. For this reason, national and supra-national institutions should devote their effort to incentivising and supporting ‘digital development’ investments (Davies, 2015; European Commission, 2017), also monitoring the returns and response to incentives already in place. As existing evidence suggests, new digital manufacturing technologies can boost productivity and sustain GDP growth (e.g. Dauth et al., 2021; Graetz and Michaels, 2018; Edquist et al., 2019). This can be particularly important for emerging economies and their catching-up process, since the adoption of digital technologies may facilitate access to production means and the creation of local (new) enterprises and entrepreneurial initiatives, to contribute to sustainable country development and international competitiveness. However, such technologies can asymmetrically contribute to the growth process, since some countries can have easier access and the ability to use some technologies (e.g. additive manufacturing) rather than others (e.g. advanced industrial robots), due to their particular characteristics. Furthermore, these technologies require high-skilled labour (especially with science, technology, engineering, and mathematics (STEM) education). As a form of knowledge-intensive, skill-biased technologies, these could affect occupations, education systems, job profiles and labour rewards (Frey and Osborne, 2017). Digitalisation may change jobs, their nature and tasks, the skills required, and new jobs may emerge as a result of a digital revolution (Brynjolfsson and Mitchell, 2017). This may affect the employment patterns and the demand for skills associated with both existing and new jobs (Grundke et al., 2018). Thus, policy interventions should also operate to create the necessary skills and capabilities to promote and support such digital transition, properly mixing economic and social policy actions to balance potentially rising inequality and managerial control over the workforce (Cetrulo and Nuvolari, 2019).

International business and global value chains. Nowadays, companies require more operational flexibility, reduced time-to-market and closer proximity to their consumption markets to be more responsive to local tastes. This may result in the need of reshaping the organisation of global networks and location advantages toward shorter GVC configurations. The higher capital-intensive nature of these digital and automated technologies can change the landscape of country competitive advantages, since the location of manufacturing facilities in low labour-cost countries becomes less and less attractive (Laplume et al., 2016). Besides, these peculiar characteristics may affect the dynamics and drivers of inward/outward FDI, MNEs' internationalisation strategy and location decisions for different value chain activities, and in turn, this may affect GVC organisations (UNCTAD, 2017; Hannibal and Knight, 2018; Castellani et al. 2021). Following this argument, the adoption of AMTs can incentivize the reshoring of manufacturing operations – i.e. relocation decision back to the firm’s home country (Kinkel and Maloca, 2009; Ellram et al. 2013) – especially when the company aims at increasing its productivity and flexibility (Dachs et al., 2019), or at enhancing the quality of manufactured products, brand recognition and post-sales processes (Ancarani et al., 2019). Thus, sound empirical evidence can help with the development of effective policies and incentives to boost the digital transformation and influence inward and outward FDI flows. In this respect, the intra-firm co-location of production and R&D activities is considered crucial to facilitate knowledge transfer across units within the firm's network and to enhance innovation capabilities, especially when the knowledge is tacit and hard to codify (Pisano and Shih, 2012). However, AMTs can make some knowledge-intensive and production-related research activities more codified and standardised, therefore easy to be transferred across value chain activities and borders. As a consequence, this could affect national and international location and co-location decisions, and the concentration/dispersion of R&D activities and collaboration across places (Castellani and Lavoratori, 2020).

Covid-19 and current challenges. The unprecedented disruptions created by the Covid-19 pandemic have strongly challenged businesses across countries and highlighted how sensitive to external shocks particularly dispersed GVCs are, as well as how difficult the management of global organisational structure can be. Recently, the picture has been fuelled by the global shortage of critical components across industries (e.g. semiconductors), and the huge increase in shipping costs per container (UNCTAD 2021; Forbes, 2021). This has revived the conversation about GVC configurations and more 'regionalised' global networks, and how automation and digitalisation can speed such restructuring process, although the sticky nature of GVCs needs to be considered (The Economist, 2020; Antràs, 2021). Furthermore, the Covid-19 shock has caused a 'wake-up call' for late digital adopters and the need to start rethinking their operational strategies and business models (McKinsey, 2021; Amankwah-Amoah et al., 2021). Understanding how single AMTs can respond to specific challenges, and whether such technologies can help firms to be more resilient and agile in the long run becomes crucial to create incentives aiming at stimulating timely investment and speeding recovery. Finally, the pandemic has accelerated the call for more environmentalfriendly production processes and sustainable manufacturing, where global warming and higher environmental pollution are ascribable to traditional manufacturing technologies, therefore AMTs can play a pivotal role (Bai et al., 2020). In the years to come, rich and up-to-date data are necessary to address all these open questions, and trade data can provide invaluable help in this regard.

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1.7. Tables and Figures

Table 1. Correspondence between CN and CPA product codes related to AMTs

8-digits product codes CN	CPA product codes	CPA product descriptions
Advanced Industrial Robots		
84795000	28993935	Industrial robots for multiple uses (excluding robots designed to perform a specific function (e.g. lifting, handling, loading or unloading))
Additive Manufacturing		
84639000	28413471	Swaging machines and spinning lathes for working metal, machines for manufacturing flexible tubes of spiral metal strip and electro-magnetic pulse metal forming machines, and other machine tools for working metal without removing metal (excluding riveting machines)
	28491360	Riveting machines
	289900Z0	Riveting machines, swaging machines and spinning lathes for working metal, machines for manufacturing flexible tubes of spiral metal strip and electro-magnetic pulse metal forming machines, and other machine tools for working metal without removing metal
84778011	28961082	Machines for processing reactive resins
84778019	28961084	Machines for the manufacture of foam products (excluding machines for processing reactive resins)
84778099	28961097	Machinery for working rubber or plastics or for the manufacture of products from these materials, n.e.c.
Industrial Internet of Things		
84718000	26122000	Network communications equipment (e.g. hubs, routers, gateways) for LANs and WANs and sound, video, network and similar cards for automatic data processing machines
84718000 / 84719000	26203000	Other units of automatic data processing machines (excluding network communications equipment (e.g. hubs, routers, gateways) for LANs and WANs and sound, video, network and similar cards for automatic data processing machines)
84719000	269900Z0	Other units of automatic data processing machines
85176200	26302320	Machines for the reception, conversion and transmission or regeneration of voice, images or other data, including switching and routing apparatus
85269120	26512050	Radio navigational aid apparatus (including radio beacons and radio buoys, receivers, radio compasses equipped with multiple aerials or with a directional frame aerial)
85269200	26512080	Radio remote control apparatus (including for ships, pilotless aircraft, rockets, missiles, toys, and model ships or aircraft, for machines, for the detonation of mines)
85423111 85423119	26113003	Multichip integrated circuits: processors and controllers, whether or not combined with memories, converters, logic circuits, amplifiers, clock and timing circuits, or other circuits
85423190	26113006	Electronic integrated circuits (excluding multichip circuits): processors and controllers, whether or not combined with memories, converters, logic circuits, amplifiers, clock and timing circuits, or other circuits
85423911 85423919	26113091	Other multichip integrated circuits n.e.c.
85423990	26113094	Other electronic integrated circuits n.e.c.
90321020	26517015	Electronic thermostats
90321080	26517019	Non-electronic thermostats
90322000	26517030	Manostats
90328100	26516500	Hydraulic or pneumatic automatic regulating or controlling instruments and apparatus
90328900	26517090	Instruments and apparatus, regulating or controlling, n.e.c.

Notes: The reference CN and CPA classifications are 2017 versions.

Table 2. *Import* and *net consumption* of AIRs by European country and growth rates between 2009 and 2018

	Import			Net consumption		
	2009	2018	Growth Rate (%)	2009	2018	Growth Rate (%)
	(1)	(2)	(3)	(4)	(5)	(6)
Austria	9.6	22.3	133.7	19.5	35.1	79.8
Belgium	10.9	21.5	97.7	12.0	7.4	-38.3
Bulgaria	2.5	6.1	148.8			
Croatia	1.2	6.3	424.5	1.4	3.4	147.5
Cyprus	0.6	0.0	-98.2			
Czech Republic	4.0	53.9	1262.2	2.7	55.7	1950.6
Denmark	4.3	10.2	138.6	5.6	5.4	-3.6
Estonia	1.6	4.3	162.4			
Finland	2.9	8.5	198.2	4.8	0.3	-93.1
France	2.1	6.7	226.0	17.1	25.2	47.6
Germany	4.7	14.6	211.9	11.9	33.4	180.2
Greece	0.8	1.5	86.6			
Hungary	4.2	17.6	321.9	9.6	31.7	231.3
Ireland	1.0	4.5	326.2			
Italy	4.3	12.8	201.9	20.9	69.0	230.7
Latvia	1.4	2.5	76.9			
Lithuania	2.4	7.2	203.9	2.0	3.0	49.4
Luxemburg	16.7	204.5	1123.0			
Malta	6.4	3.9	-38.8			
Netherlands	8.5	18.8	121.6	0.6	12.9	1916.0
Poland	2.2	10.9	387.6			
Portugal	4.6	21.4	363.9	1.8	18.2	904.3
Romania	4.3	10.3	137.8			
Slovakia	8.0	73.6	817.4			
Slovenia	5.5	35.8	556.9			
Spain	2.8	9.1	221.8	3.8	9.5	150.5
Sweden	4.3	13.0	198.6	25.7	7.0	-72.9
United Kingdom	1.8	3.1	74.7	3.0	2.9	-3.3
All Countries Mean	4.4	21.6	390.0	8.9	20.0	124.7

Notes: Authors' own computations based on Comext and Prodcom data. *Import* and *net consumption* measures converted in constant PPP USD and reported per 1,000 workers.

Table 3. *Import* and *net consumption* of AM by European country and growth rates between 2009 and 2018

	Import			Net consumption		
	2009	2018	Growth Rate (%)	2009	2018	Growth Rate (%)
	(1)	(2)	(3)	(4)	(5)	(6)
Austria	10.4	19.6	88.1	15.6	37.0	137.2
Belgium	7.0	17.1	143.3			
Bulgaria	3.7	13.0	250.7	2.7	8.6	214.8
Croatia	2.2	3.9	76.1			
Cyprus	4.9	3.0	-38.5			
Czech Republic	11.0	32.1	191.6	5.1	0.6	-88.1
Denmark	2.2	6.8	205.1	1.0	10.2	899.5
Estonia	3.8	8.4	122.7			
Finland	7.8	4.4	-43.0	6.9	5.4	-21.8
France	2.9	4.4	50.2	5.1	3.4	-32.0
Germany	3.0	10.2	244.4	6.1	38.0	525.5
Greece	4.5	5.8	27.4			
Hungary	4.8	26.0	446.0			
Ireland	4.0	5.9	49.6			
Italy	2.8	7.3	161.8	20.8	60.7	192.1
Latvia	1.1	14.0	1162.0			
Lithuania	6.3	28.9	359.7			
Luxemburg	12.1	4.5	-62.9			
Malta	5.7	2.4	-57.0			
Netherlands	2.0	6.6	227.8			
Poland	6.2	14.0	125.4	2.1	12.2	482.6
Portugal	4.2	13.4	220.5	0.9	7.1	677.3
Romania	4.2	13.0	212.5			
Slovakia	21.5	40.3	87.0	0.4	3.1	659.5
Slovenia	7.9	18.2	129.5			
Spain	3.9	5.4	38.2	5.0	9.2	82.9
Sweden	2.0	3.6	77.9	0.3	2.1	698.5
United Kingdom	1.2	2.2	78.3	0.5	1.4	173.6
All Countries Mean	5.5	11.9	163.4	5.2	14.2	328.7

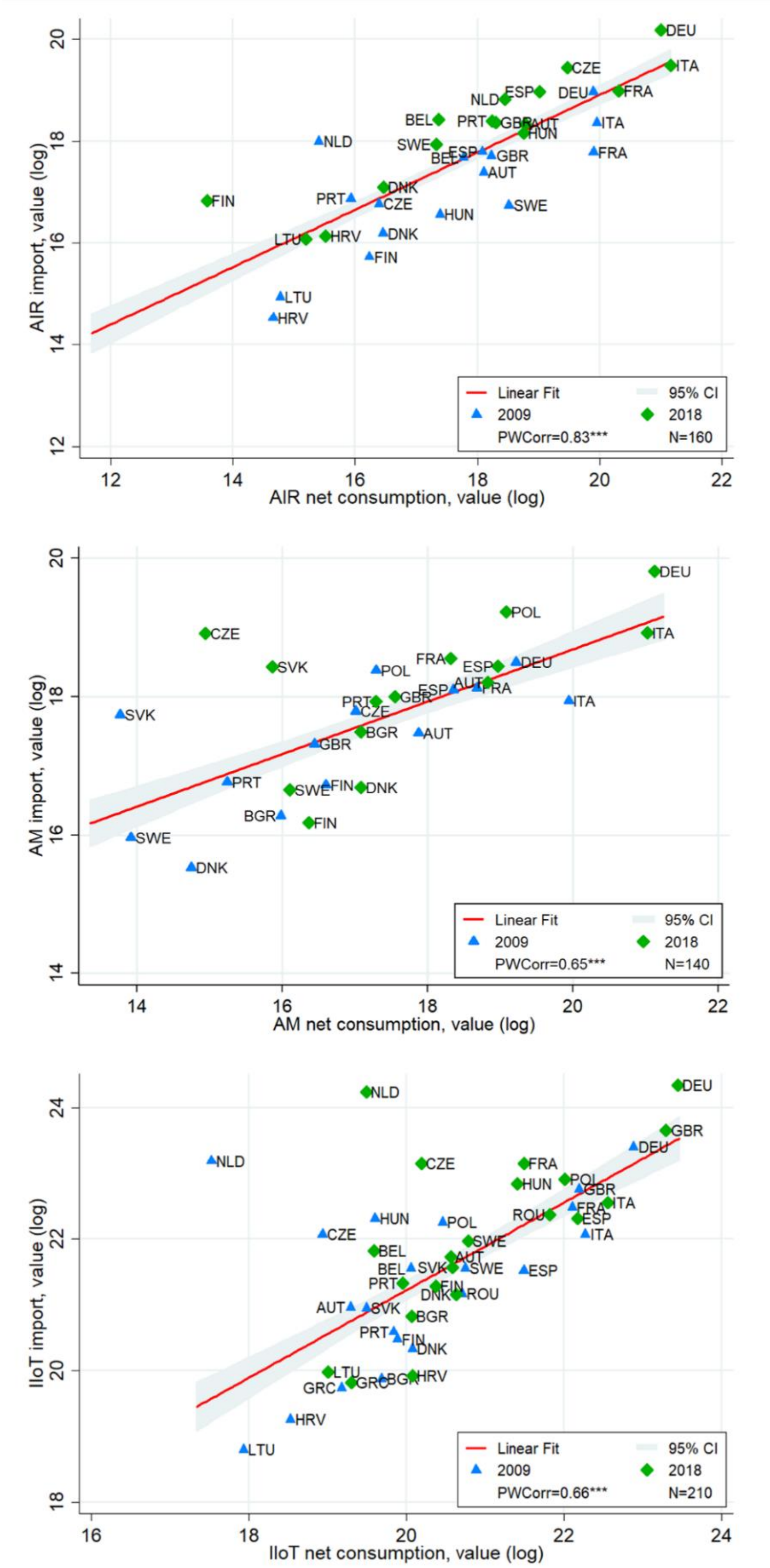
Notes: Authors' own computations based on Comext and Prodcom data. *Import* and *net consumption* measures converted in constant PPP USD and reported per 1,000 workers.

Table 4. *Import* and *net consumption* of IIoT by European country and growth rates between 2009 and 2018

	Import			Net consumption		
	2009	2018	Growth Rate (%)	2009	2018	Growth Rate (%)
	(1)	(2)	(3)	(4)	(5)	(6)
Austria	341.3	671.0	96.6	64.1	207.5	223.4
Belgium	526.9	644.5	22.3	118.0	69.0	-41.5
Bulgaria	134.5	360.6	168.1	111.7	170.1	52.3
Croatia	136.9	277.7	102.9	66.1	325.9	392.9
Cyprus	94.3	166.6	76.6			
Czech Republic	798.9	2208.9	176.5	34.7	114.7	230.3
Denmark	270.4	591.3	118.7	210.3	349.2	66.1
Estonia	332.3	1154.2	247.4			
Finland	331.3	735.6	122.0	183.5	294.2	60.3
France	225.5	430.4	90.8	155.2	82.1	-47.1
Germany	397.3	939.2	136.4	236.1	382.8	62.1
Greece	84.1	108.0	28.5	48.0	64.5	34.3
Hungary	1324.6	1903.3	43.7	88.0	452.9	414.5
Ireland	626.3	824.8	31.7			
Italy	173.1	276.8	59.9	211.7	277.0	30.9
Latvia	113.2	652.8	476.6			
Lithuania	113.6	361.6	218.4	47.8	137.1	186.7
Luxemburg	742.4	528.9	-28.8			
Malta	4892.0	1763.2	-64.0			
Netherlands	1527.9	4224.5	176.5	5.3	36.8	590.7
Poland	297.6	555.6	86.7	49.5	225.5	355.6
Portugal	190.6	402.2	111.0	90.2	101.6	12.7
Romania	179.4	626.0	249.0	113.1	360.9	219.0
Slovakia	534.7	929.9	73.9	124.8	344.3	175.9
Slovenia	269.5	488.4	81.2			
Spain	118.2	257.1	117.6	114.6	224.1	95.4
Sweden	541.4	728.9	34.6	240.0	221.9	-7.5
United Kingdom	281.4	624.5	122.0	159.4	434.3	172.4
All Countries Mean	557.1	837.0	50.2	117.7	232.2	97.2

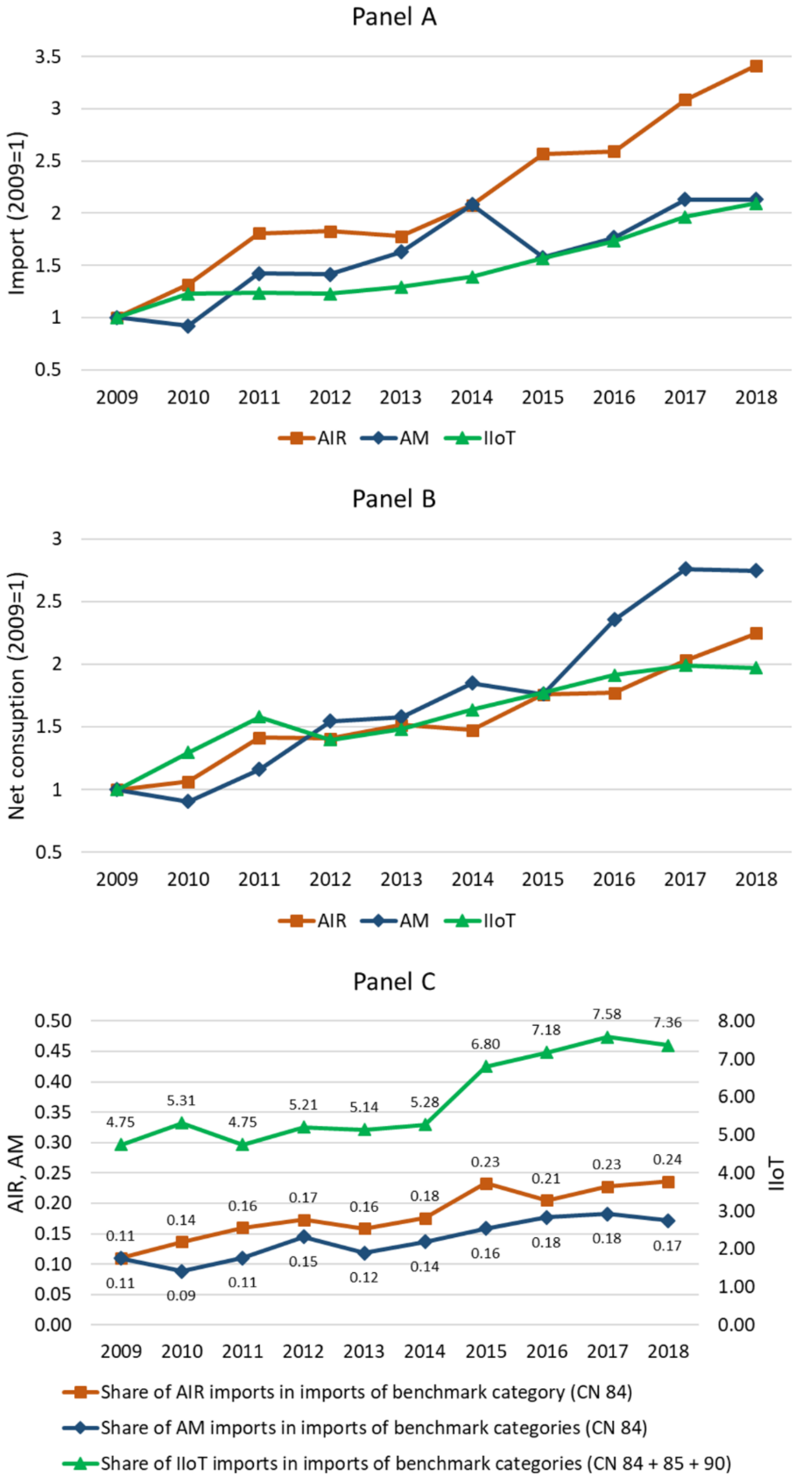
Notes: Authors' own computations based on Comext and Prodcom data. *Import* and *net consumption* measures converted in constant PPP USD and reported per 1,000 workers.

Figure 1. Relationship between *import* and *net consumption* measures of AMT adoption, 2009 and 2018 values and pairwise correlation coefficients



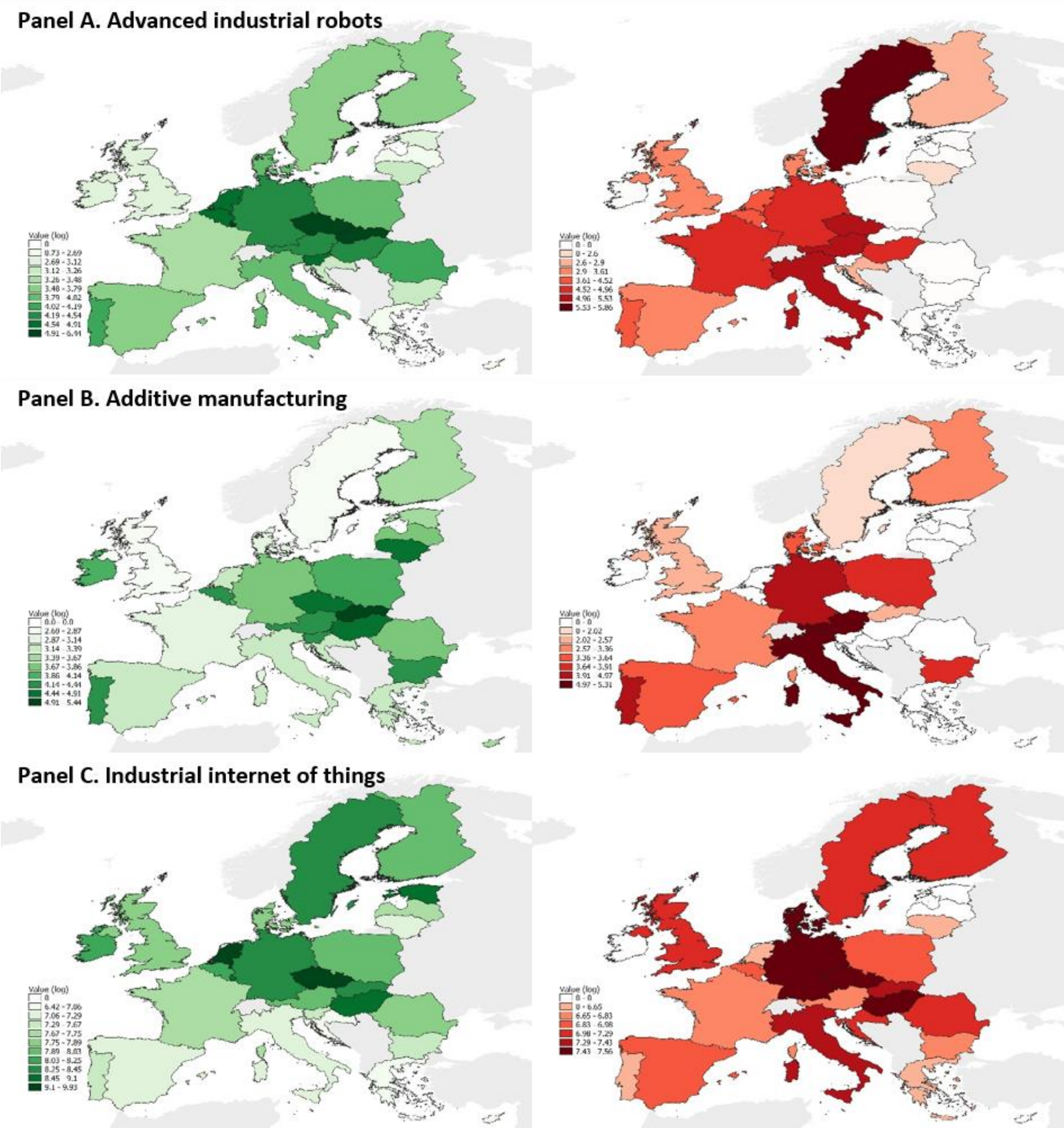
Notes: Authors' own computations based on Comext and Prodcom data. *Import* and *net consumption* measures converted in constant PPP USD to increase comparability over time and filter out cross-country differences in prices.

Figure 2. Change in *import* and *net consumption* measures of AMT adoption and shares of AMT imports in imports of the reference benchmark categories (%) – sample of AMT producers in the EU28 sample, 2009–2018 period



Notes: Authors' own computations based on Comext and Prodcom data. Panel A reports *import* measures converted in constant PPP USD and reported per 1,000 workers. Panel B reports *net consumption* measures converted in constant PPP USD and reported per 1,000 workers. Panel C reports the share of imports of each AMT in imports of the reference benchmark categories (%); 2-digit benchmark categories are product category 84 for AIRs and AM, and the sum of product categories 84, 85 and 90 for IIoT. Given the high level of aggregation characterising our benchmark product categories in the CN classification, reconstructing similar benchmark codes from the CPA classification using the methodology presented in Section 1.3 would result in extensive overlapping and the creation of a high number of synthetic codes (resulting from the aggregation of hundreds of 8-digit CPA product codes), in turn not enabling the computation of a precise benchmark.

Figure 3. Import and net consumption of AMTs by EU28 country, 2009–2018 period stocks



Notes: Authors' own computations based on Comext and Prodcom data. *Import* (in green) and *net consumption* (in red) measures converted in constant PPP USD, reported per 1,000 workers and expressed as 2009–2018 period stocks (in log). Maps created using QGIS software.

1.8. Appendix A: Data Validation

In order to validate the selection process for the CN codes reported in Table 1, we consulted a pool of experts composed of both scientists and practitioners, whose expertise relates to the technologies under investigation, as well as to both trade and customs procedures through which CN codes are assigned to capital goods when they are shipped. Overall, the large majority of the 8-digit codes originally identified were confirmed, hinting at the goodness of the overall identification procedure.

As a first step, we checked if and which product codes are used in practice when goods related to our three AMTs of interest are shipped from their producers to clients worldwide. Clearly, CN codes – as any other national or international trade classification – are only used when the shipment of goods involves a cross-border transaction. Conversely, domestic transactions are not recorded on trade registers. Bearing this in mind, we created a survey aimed at confirming the 25 8-digit CN product codes matching with our keywords list and collecting information on any other code used in practice. We sent the survey to 229 worldwide producers of industrial robots, additive manufacturing/3D printing machines, and industrial IoT and automation equipment on the 3rd of June 2020, followed by a first reminder sent on the 10th of June and a final reminder on the 17th of June. Respondents were asked to select one or more technologies associated with products in their catalogues and report which CN codes they use when they export abroad. To maximize the response rate and coverage, as well as provide respondents with the widest range of options, we allowed respondents to choose among other major classifications used in the accounting of both trade and production statistics, alongside the CN classification.[17] Unfortunately, despite the response period

[17] Other trade classifications listed as option were: The Standard International Trade Classification (SITC), the Harmonized System (HS) classification, the Broad Economic Categories (BEC) classification, the U.S. Schedule B number classification, the Japanese Commodity Classification for Foreign Trade Statistics (CCFTS), the

overlapped with the ease of lockdown measures following the Covid-19 pandemic and with many firms starting back their operations, the response rate was heavily penalised as only 3.5% of the firms surveyed completed the questionnaire. Nonetheless, the few answers collected allowed us to validate two product codes associated with our AMTs: the 8-digit CN code 84795000 covering the trade of industrial robots and the 8-digit Prodcom code 28413471, corresponding to the CN code 84639000 and supposedly capturing one of the processes related to additive manufacturing. A further takeaway from the survey came from conversations with a few respondents, carried out via email exchange, who highlighted scarce familiarity with the trade and production nomenclatures we suggested as options in the survey.

As a second step, we consulted practitioners and experts working for the Italian Customs Agency (Agenzia delle Dogane e dei Monopoli) and a private customs broker and logistic service provider.[18] Phone conversations with these experts helped clarify the steps through which CN product codes are assigned to goods when these transit customs in or outbound. Specifically, goods are classified under a unique classification (e.g. CN, SITC, BEC, etc.) code that describes the product and not its use or specific function. Since incorrect classification can lead to delays in clearing goods, unnecessary overpayment or potential underpayment of duties (the latter resulting in penalties for the shipping firm), this procedure is generally carried out with the highest care and the high majority of firms trading abroad relies on custom brokers to determine the correct product code to be used. In principle, if the

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Chinese HS classification. Other product classification commonly used in production accounting, listed as option were: the Central Product Classification (CPC), the Statistical Classification of Products by Activity (CPA), the Community Production (PRODCOM) classification, the Austrian OEPRODCOM, the Croatian NIP, the Czech CZ-PRODCOM, the Finnish PRODCOM, the French PRODFRA, the German GP, the Hungarian ITO, the Italian ATECO, the Latvian PRODCOM LV, the Lithuanian PGPK, the Polish PRODPOL, the Romanian PRODROM, the Slovak PRODSLOV, the Slovenian NIP.

[18] We contacted the private custom broker and logistic provider Sebi S.r.l. based at the two Milan (IT) airports, Malpensa and Linate.

shipped good belongs to a very specific category, univocally defined by a product code in the classification adopted, there is little space for errors during the matching procedure.

Conversely, in cases where the classification is not up to date with newly developed goods, the identification of the correct product code can suffer from potential misallocations. As custom operators are generally not experts of products, machinery or equipment specificities, when doubts arise, the matching is performed taking the 8-digit product code whose description is the most similar to the in- or outbound good, a more general 6- or 4-digit code, or even the one corresponding to the lowest custom duty among the range of potentially appropriate product codes.

In our specific case, further phone calls with these experts validated other product codes initially selected and associated with our AMTs, upon consultation of private databases to which we could not otherwise get access. Specifically, this second consultation unambiguously validated the selected CN product code for industrial robots (i.e. 84795000) and several codes presumably related to industrial IoT (i.e. all 8-digit codes shortlisted and included in the 4-digit categories 8471, 8526 and 9032), thanks to the high specificity of capital goods associated to these technologies. Furthermore, some procedures were also recorded for the 8-digit code belonging to categories 8517 and 8542, even though only some of them were univocally related to IoT applications. We nonetheless deem these codes validated for the purpose of our investigation, as we are not interested in the actual percentage of matches for each product code in relation to a specific AMT, but rather in confirming that a specific product code was indeed used at least once in trade related to these technologies. From our understanding, the validation of product codes linked to industrial robots and industrial IoT capital goods was possible thanks to the high specificity of good descriptions in both shipment orders and the CN classification, allowing for an unambiguous match in the majority of cases.

The case of additive manufacturing/3D printing machines is relatively more complex as specific CN product codes do not exist yet (as described above). In this specific case, our phone conversation with the custom experts highlighted a lack of expertise on the technology specificities illustrated in Section 1.2, which guided our initial selection. In turn, only three additional product codes associated with additive manufacturing were validated (i.e. CN codes belonging to the 6-digit HS product category 847780), having got confirmed records of trade of 3D printers under this codes. Finally, further conversations with one of the experts also confirmed the potential goodness of the selected 8-digit codes 85158010 and 85158090 upon fit with the specific additive manufacturing process for which they were initially shortlisted, however, we could not get confirmation of any custom practice specifically using these codes in relation to shipments of 3D printers using powder bed fusion processes (e.g. laser sintering, laser metal deposition, etc.). Thus, we discarded CN codes 85158010 and 85158090, together with CN codes 84772000 and 84775980 for which we did not get any confirmed match.

1.9. Appendix B: Additional Tables and Figures

Table B1. List of Keywords Related to AMTs

Keywords related to AMTs		
Advanced Industrial Robots		
Robot*	Industrial robot*	
Additive Manufacturing		
First tier keywords (General terminology, processes, technologies)		
Additive manufacturing	Additive process*	3d print*
3-d print*	3-dimensional print*	3d manufacturing
3-d manufacturing	3-dimensional manufacturing	Three-d print*
Three-dimensional print*	Three-d manufacturing	Three-dimensional manufacturing
Binder jetting	Direct energy deposition	Material extrusion
Material Jetting	Powder bed fusion	Sheet lamination
Vat photopolymerization	Fused deposition modelling	Fused filament fabrication
Laser sintering	Laser melting	Direct metal laser deposition
Laser metal deposition	Electron beam melting	Laser engineering net shaping
Stereolithography	Poly-jet matrix	Multi-jet modelling
Continuous liquid interface production		
Second tier keywords (Components, tools, methods, materials)		
Laser*	Electron beam*	Plasma
Extrusion	Extruder*	Metal*
Plastic*	Resin*	Photopolymer*
Wax*	Powder*	
Industrial Internet of Thighs		
First tier keywords (General terminology, acronyms, concepts, technologies)		
Internet of thing*	IoT	Industrial Internet of thing*
IIoT	Industrial Internet	Communication network*
Automatic network*	Wireless network*	Controller area network
CAN	Public switched telephone network	PSTN
Local area network	LAN	Wireless local area network
WLAN	Long-term evolution network	LTE
Digital subscriber line	DSL	Second generation network
2G	Third generation network	3G
Fourth generation network	4G	Fifth generation network
5G	Next generation network	NGN
Ethernet	Wi-Fi	Advanced sensor*
Automatic sensor*	Advanced actuator*	Automatic actuator*
Advanced communication system*	Automatic regulator*	Automatic controller*
Integrated circuit*	System on chip	SOC
Microcontroller	MCU	Radio-frequency identification
RFID	Near-field communication	NFC
Global positioning system	GPS	Switcher*
Router*	Gateway*	Cable*
Optical fibre*	Data processing machine*	
Second tier keywords (Components, tools, methods)		
Communication*	Network*	Automatic
Sensor*	Actuator*	Reception*
Transmission*	Transfer*	Regulator*
Regulating	Controller*	Controlling
Processor*	Converter*	Amplifier*
Integrated chip*	Chip*	Circuit*
Identifier*	Transponder*	Tag*
Microchip*	Card*	Reader*
Radar*	Navigation*	Switching
Routing	Wire*	Connector*
Optical fiber*	Data	

Notes: Keyword selection based on the engineering literature, terminology from ruling bodies and product catalogues on AMTs.

Table B2. List of initially identified CN product codes related to AMTs

4-digits HS product codes, 8-digits CN product codes and CN product descriptions		
Advanced Industrial Robots		
8479	Machines and mechanical appliances having individual functions, not specified or included elsewhere in this chapter	
	84795000	Industrial robots, not elsewhere specified or included
Additive Manufacturing		
8463	Other machine tools for working metal or cermets, without removing material	
	84639000	Other machine tools for working metal or cermets, without removing material; Other
8477	Machinery for working rubber or plastics or for the manufacture of products from these materials, not specified or included elsewhere in this chapter	
	84772000†	Extruders
	84775980†	Other machinery for moulding or otherwise forming; Other; Other
	84778011	Machines for the manufacture of foam products; Machines for processing reactive resins
	84778019	Machines for the manufacture of foam products; Others
	84778099	Other machinery; Other; Other
8515	Electric (including electrically heated gas), laser or other light or photon beam, ultrasonic, electron beam, magnetic pulse or plasma arc soldering, brazing or welding machines and apparatus, whether or not capable of cutting; electric machines and apparatus for hot spraying of metals or cermets	
	85158010†	Other machines and apparatus; For treating metals
	85158090†	Other machines and apparatus; Other
Industrial Internet of Things		
8471	Automatic data-processing machines and units thereof; magnetic or optical readers, machines for transcribing data onto data media in coded form and machines for processing such data, not elsewhere specified or included	
	84718000	Other units of automatic data-processing machines
	84719000	Other
8517	Telephone sets, including telephones for cellular networks or for other wireless networks; other apparatus for the transmission or reception of voice, images or other data, including apparatus for communication in a wired or wireless network (such as a local or wide area network), other than transmission or reception apparatus of heading 8443, 8525, 8527 or 8528	
	85176200	Machines for the reception, conversion and transmission or regeneration of voice, images or other data, including switching and routing apparatus
8526	Radar apparatus, radio navigational aid apparatus and radio remote control apparatus	
	85269120	Radio navigational aid apparatus; Radio navigational receivers
	85269200	Radio remote control apparatus
8542	Electronic integrated circuits	
	85423111	Processors and controllers, whether or not combined with memories, converters, logic circuits, amplifiers, clock and timing circuits, or other circuits; Goods specified in note 9(b)(3 and 4) to chapter 85; Multi-component integrated circuits (MCOs)
	85423119	Processors and controllers, whether or not combined with memories, converters, logic circuits, amplifiers, clock and timing circuits, or other circuits; Goods specified in note 9(b)(3 and 4) to chapter 85; Other
	85423190	Processors and controllers, whether or not combined with memories, converters, logic circuits, amplifiers, clock and timing circuits, or other circuits; Other
	85423911	Other; Goods specified in note 9(b)(3 and 4) to chapter 85; Multi-component integrated circuits (MCOs)*
	85423919	Other; Goods specified in note 9(b)(3 and 4) to chapter 85; Other*
	85423990	Other; Other
9032	Automatic regulating or controlling instruments and apparatus	
	90321020	Thermostats; Electronic
	90321080	Thermostats; Other
	90322000	Manostats
	90328100	Other instruments and apparatus; Hydraulic or pneumatic
	90328900	Other instruments and apparatus; Other

Notes: The reference CN classification is the 2017 version. Product codes denoted with * have been checked through assessment of the related additional notes. Product codes denoted with † did not satisfy our validation procedure; all other codes were validated.

Table B3. Import to export ratios for each AMT, by country and time period

	AIR		AM		IIoT	
	2009-2011	2016-2018	2009-2011	2016-2018	2009-2011	2016-2018
Austria	0.51	0.44	0.25	0.21	1.06	0.93
Belgium	2.61	1.41	1.83	1.70	1.43	1.10
Bulgaria	11.87	1.25	7.83	3.04	1.98	1.21
Croatia	9.36	0.79	0.87	0.20	1.83	2.21
Cyprus			729.67	1.19	10.14	9.59
Czech Republic	2.39	10.72	1.46	0.72	1.28	1.38
Denmark	0.80	0.17	0.27	0.19	1.53	1.48
Estonia	3.00	2.23	3.92	5.20	1.47	0.54
Finland	0.38	0.48	1.78	7.37	1.61	1.46
France	0.60	0.42	1.05	0.96	0.98	0.88
Germany	0.64	0.61	0.12	0.19	1.01	1.05
Greece			4.24	6.96	5.59	4.83
Hungary	0.66	2.21	5.69	17.44	1.29	0.92
Ireland	7.65	3.76	3.33	3.80	0.40	0.23
Italy	0.81	0.50	0.11	0.17	1.67	1.76
Latvia	4.98	2.65	2.13	1.47	1.64	0.82
Lithuania	2.81	1.77	4.94	2.39	2.05	1.27
Luxemburg	0.85	0.61	38.08	68.19	1.05	1.74
Malta			22.97	11496.44	32.16	0.47
Netherlands	0.99	0.73	0.60	0.55	0.91	0.91
Poland	16.80	15.94	2.92	4.14	4.44	2.08
Portugal	1.23	3.17	3.52	5.88	7.60	1.63
Romania	2.51	4.72	6.78	9.69	3.59	1.97
Slovakia	8.63	16.02	0.69	0.82	3.61	2.16
Slovenia	3.92	2.73	2.83	1.83	1.14	1.33
Spain	1.50	1.23	1.55	1.76	4.30	2.91
Sweden	0.21	0.29	0.56	1.20	1.26	1.31
United Kingdom	1.54	1.09	0.76	1.34	1.42	2.17

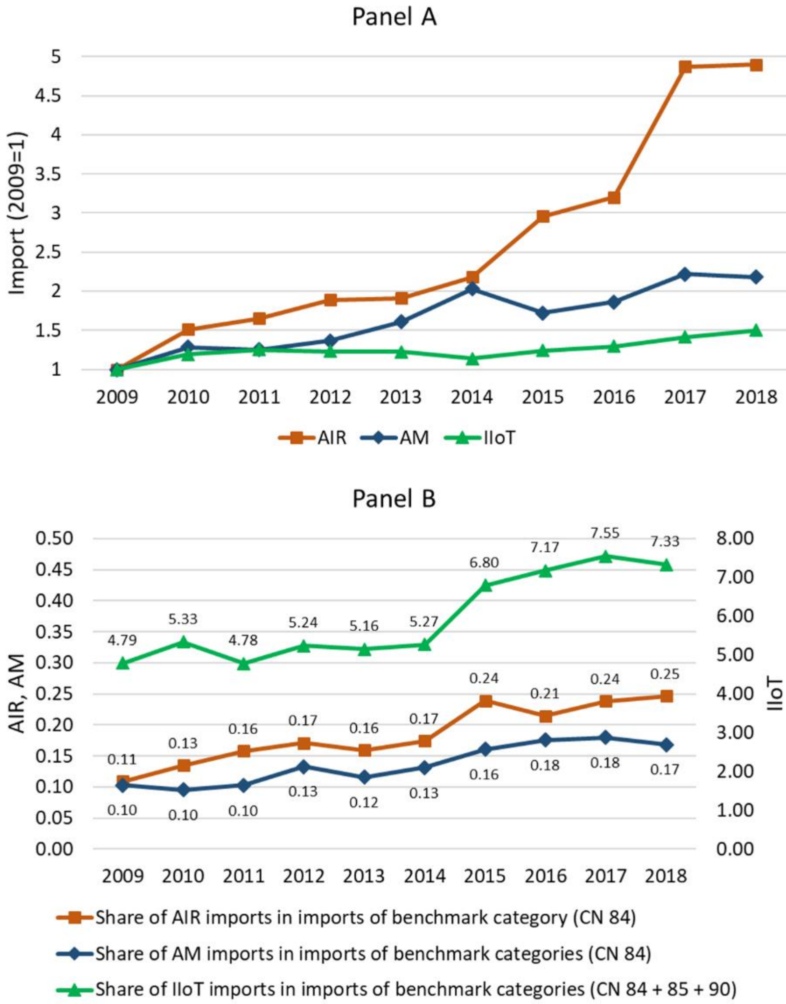
Notes: Authors' own computations based on Comext and Prodcom data. We compute three-year averages of import to export ratios as simple averages. Ratios above 1 indicates net importers of AMTs, conversely ratios below 1 indicates net exporters of AMTs.

Table B4. Shares of CPA/CN product codes imports in imports of the reference benchmark categories (%) and changes between 2009 and 2018 (%), full sample of EU28 countries

		2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	Δ(2009-2018)
AIR	CPA 28993935/ CN 84795000	0.109	0.135	0.158	0.171	0.159	0.175	0.239	0.215	0.238	0.247	126.8
AM	CPA 28961082/ CN 84778011	0.004	0.002	0.002	0.003	0.003	0.002	0.004	0.005	0.004	0.004	11.9
	CPA 28961084/ CN 84778019	0.011	0.009	0.007	0.007	0.008	0.005	0.009	0.009	0.008	0.009	-18.9
	CPA 28961097/ CN 84778099	0.070	0.065	0.075	0.087	0.082	0.104	0.122	0.132	0.142	0.129	85.0
	Synthetic CPA for 28413471, 28491360, 289900Z0/ CN 84639000	0.019	0.018	0.019	0.035	0.022	0.020	0.026	0.030	0.026	0.026	38.8
IIoT	CPA 26113003/ Synthetic CN for 85423111, 85423119	0.121	0.102	0.079	0.102	0.094	0.066	0.071	0.125	0.107	0.152	25.5
	CPA 26113006/ CN 85423190	0.971	1.110	0.995	1.036	0.972	0.974	1.211	1.307	1.530	1.475	51.9
	CPA 26113091/ Synthetic CN for 85423911, 85423919	0.020	0.036	0.033	0.024	0.023	0.025	0.029	0.030	0.059	0.065	225.7
	CPA 26113094/ CN 85423990	0.729	1.000	0.803	0.839	0.830	0.863	1.082	1.073	1.153	1.141	56.6
	CPA 26302320/ CN 85176200	1.617	1.769	1.635	1.887	1.947	2.054	2.865	3.066	3.097	3.021	86.8
	CPA 26512050/ CN 85269120	0.309	0.266	0.237	0.242	0.224	0.240	0.298	0.300	0.294	0.258	-16.3
	CPA 26512080/ CN 85269200	0.028	0.029	0.032	0.040	0.041	0.045	0.054	0.056	0.056	0.052	89.8
	CPA 26516500/ CN 90328100	0.013	0.017	0.020	0.022	0.024	0.027	0.032	0.041	0.046	0.039	198.8
	CPA 26517015/ CN 90321020	0.028	0.029	0.029	0.031	0.032	0.033	0.044	0.049	0.049	0.045	63.3
	CPA 26517019/ CN 90321080	0.050	0.050	0.047	0.050	0.048	0.048	0.055	0.057	0.050	0.045	-9.5
	CPA 26517030/ CN 90322000	0.024	0.026	0.029	0.034	0.031	0.029	0.034	0.036	0.034	0.036	51.0
	CPA 26517090/ CN 90328900	0.332	0.371	0.361	0.408	0.393	0.380	0.449	0.455	0.454	0.404	21.6
	Synthetic CPA for 26122000, 26203000, 269900Z0/ Synthetic CN for 84718000, 84719000	0.552	0.527	0.481	0.521	0.499	0.489	0.574	0.579	0.622	0.598	8.3

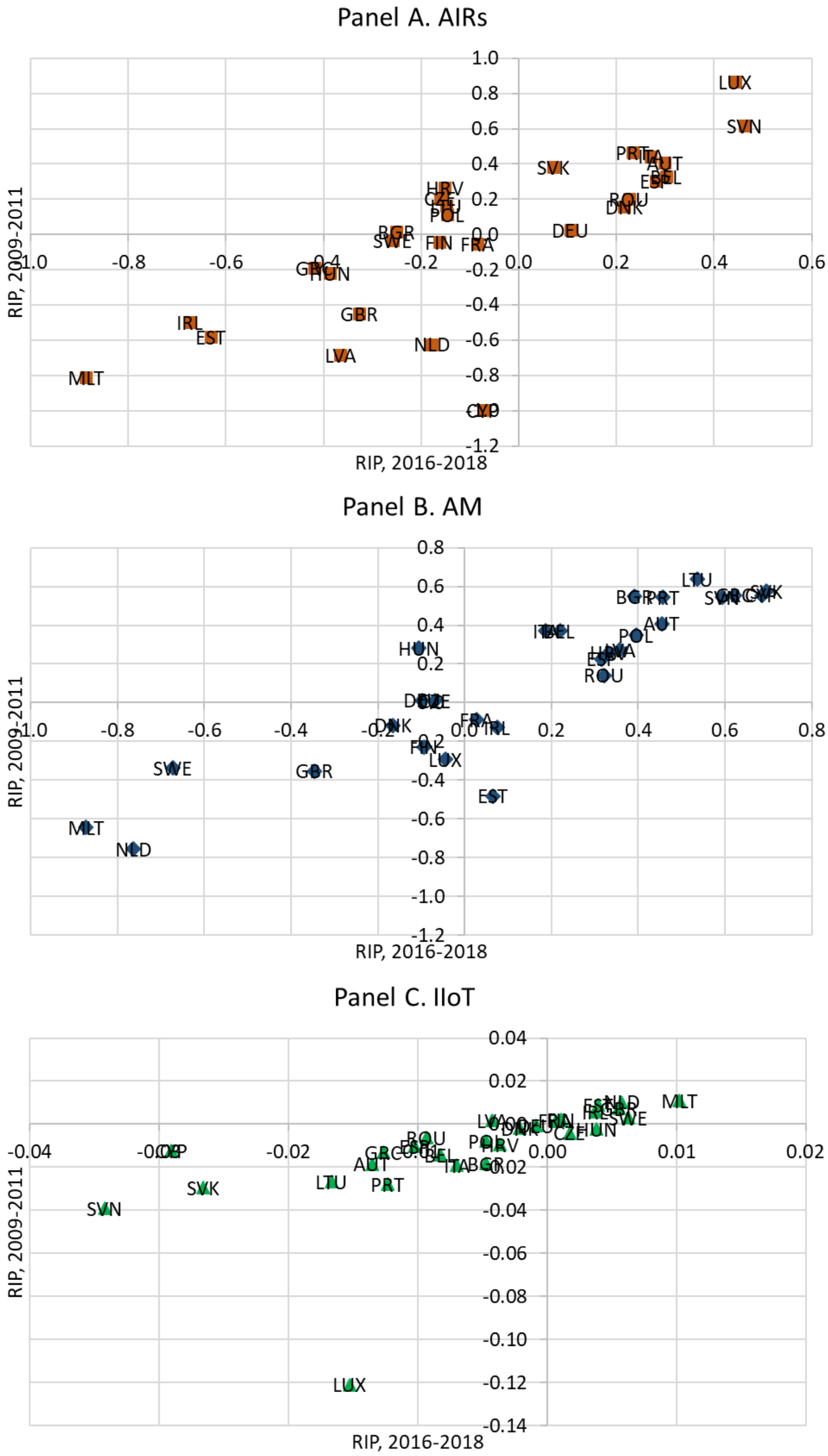
Notes: Authors' own computations based on Comext and Prodcom data. We take the CN-CPA correspondence in 2017 as the reference. Whenever a change in the classifications impacts the identified product codes in 2017, we highlight any data manipulation with '*Synthetic*', following the methodology by Van Beveren et al. (2012). Any other change in the classifications which is related to the years before and after 2017 (e.g. a change in the product code identifying a specific product category) are not highlighted here. 2-digit benchmark categories are product category 84 for CPA/CN codes related to AIRs and AM, and the sum of product categories 84, 85 and 90 for CPA/CN codes related to IIoT.

Figure B1. Change in *import* measures of AMT adoption and shares of AMT imports in imports of the reference benchmark categories (%), full sample of EU28 countries, 2009–2018 period



Notes: Authors' own computations based on Comext and Prodcom data. Panel A reports *import* measures converted in constant PPP USD and reported per 1,000 workers. Panel B reports the share of imports of each AMT in imports of the reference benchmark categories (%); 2-digit benchmark categories are product category 84 for AIRs and AM, and the sum of product categories 84, 85 and 90 for IIoT.

Figure B2. Comparison between the initial and final three-year averages in the relative import propensity (RIP) indexes for each AMT



Notes: Authors' own computations based on Comext and Prodcom data. We compute three-year averages of RIP indexes as simple averages. RIPs for each AMT are transformed as (RIP-1)/(RIP+1) to increase symmetry and comparability so that RIPs above 0 indicates indicate a comparative advantage.

Chapter 2

Advanced Manufacturing Technologies and Productivity Growth: Evidence from Europe*

Abstract

Do advanced manufacturing technologies (AMTs) boost TFP growth? This Chapter explores whether the adoption of advanced technologies affects the sectoral TFP growth rates across the manufacturing industries of 14 European countries, during the period 2009–2019. We rely on a novel measure of adoption of advanced manufacturing technologies (namely, advanced industrial robots, additive manufacturing and industrial internet of things), exploiting information on imports of capital goods embodying such technologies. Our results suggest that the adoption of AMTs of the Industry 4.0 wave spurs quantitatively important and statistically significant gains in TFP growth rates. These productivity gains are mostly concentrated in countries closer to the technology frontier.

Keywords: Advanced manufacturing technologies; Industry 4.0; technology diffusion; total factor productivity (TFP); economic growth; technological convergence.

* This Chapter is co-authored with Katiuscia Lavoratori (Henley Business School, University of Reading, UK) and Davide Castellani (Henley Business School, University of Reading, UK). Contributions: Fabio Lamperti 75% (Conceptualisation, Methodology, Investigation, Data curation, Formal analysis, Writing – Original draft, Visualisation); Katiuscia Lavoratori 15% (Conceptualisation, Methodology, Validation, Writing – Review/editing, Supervision); Davide Castellani 10% (Conceptualisation, Methodology, Writing – Review/editing, Supervision).

2.1. Introduction

Over the last decade, academics, policymakers, and practitioners ranging from engineers to managers and entrepreneurs have been increasingly focused on the latest wave of technological change in production processes, embodied by the advent of new digital and smart technologies (Brynjolfsson and McAfee, 2014; Liao et al., 2017; EIB, 2019).

This new stage in the technological progress is nowadays advocated to be the fourth industrial revolution (4IR), also known as Industry 4.0 (I4.0) in manufacturing (Skilton and Hovsepian, 2017), leading to new digital paradigms and guided by the diffusion of a vast array of automation technologies. The combination of industrial robots, additive manufacturing (or 3D printing), internet of things, cloud computing, big data, machine learning, artificial intelligence, virtual and augmented reality enables the creation of cyber-physical systems which integrate seamlessly physical operations with digital insight (Lee et al., 2015; Rajkumar et al., 2010; Alcácer and Cruz-Machado, 2019), enabling the creation of smart factories (Lucke et al., 2008; Wang et al., 2016).

In the factory shop floor, the use of sensors, paired with today's improvements in dynamic programming, enables advanced industrial robots to perform a broader range of tasks as compared to their predecessors, offering accuracy, flexibility, and collaborative human-machine applications (Davies, 2015; Stock and Seliger, 2016; Eurofound, 2018). At the same time, additive manufacturing provides firms with the possibility to expand their product range – for instance, by creating new niche markets, offering new opportunities for real-time customization and enabling to speed-up the entire product development cycle (Atzeni and Salmi, 2012; Mellor et al., 2014; Bogers et al., 2016; Rayna and Striukova, 2016), while also reducing the number of production stages and material consumption (Atzeni and Salmi, 2012; Weller et al., 2015; Cuellar et al., 2018). On top of this, the extensive implementation of sensors, actuators and distributed systems (e.g. Near Field Communication microchips, Radio-Frequency Identification tags and Global Positioning Systems) enables the creation of industrial internet of things environments (Atzori et al., 2010; Gubbi et al., 2013), resulting in a high potential for communication and integration and, ultimately, into more efficient management of industrial operations, and in higher digital integration along the value chain (Stock and Seliger, 2016; Wang et al., 2016).

The OECD defines advanced manufacturing technologies (AMTs) as "*computer-controlled or micro-electronics-based equipment used in the design, manufacture or handling of a product*" (OECD, 2012). This definition reflects the role of applications based on Information and Communication Technologies (ICTs), developed with the third industrial revolution started in the 1950s and later became the mainstream industrial paradigm throughout the 70s and the 90s, which paved the way for today's core technologies of the 4IR. In this Chapter, we focus on three new AMTs, which are well-suited for manufacturing applications and bear a high potential in revolutionising the industrial landscape of advanced economies: industrial robots (AIRs), additive manufacturing (AM) and industrial internet of things (IIoT).

The revolutionary role that these digital technologies have on manufacturing operations is well recognised: the European Foundation for the Improvement of Living and Working Conditions (Eurofound) highlights them as '*game-changing*' or disrupting technologies as they can find widespread application across every manufacturing industry due to their '*versatility and complementarity*' (Eurofound, 2018, p. 3). Beyond that, a critical factor characterising these three AMTs is that they are technologies usually embodied in capital goods. This characteristic makes it possible to measure their adoption across countries using data on imports of the capital goods embodying such technologies.[19]

AMTs and other automation technologies of the 4IR can boost firms' capabilities to perform flexibly, collaboratively and resiliently (Lee et al., 2014; Schuh et al., 2014; Lee et al., 2015; Stock

[19] In line with recent descriptive evidence (e.g. Foster-McGregor et al., 2019), we do not consider other new digital technologies like cloud computing, big data, machine learning and artificial intelligence. As the most important component of these technologies resides in the software, while the hardware used is usually standard and multi-purpose (e.g. computers, servers, etc.), it is very difficult to trace and measure the adoption of these technology on a large scale.

and Seliger, 2016; Lee et al., 2018). Overall, the digital transformation brought by the 4IR is expected to lead to higher cost-efficiency and rising productivity (Kagermann et al., 2013; Schuh et al., 2014; Müller et al., 2018; Dachs et al., 2019), while also benefitting market competition and contribute to overall GDP growth, particularly in advanced economies.

However, despite the attention given to the 4IR by academics and institutional actors, the empirical evidence concerning these phenomena is still limited, along with suitable measures of adoption of such technologies allowing an investigation of the effects of AMTs on a large scale across countries, industries and over time. Guided by these premises, our research question is: *What is the relationship between the adoption of AMTs of the 4IR, total factor productivity (TFP) growth and technological catch-up across manufacturing industries of European economies?*

We attempt to fill this gap following the intuition by Caselli and Coleman (2001) and subsequent studies – such as Blanas et al. (2019) and Acemoglu and Restrepo (2022) at the country-level; Acemoglu et al. (2020), Bonfiglioli et al. (2020) and Domini et al. (2021, 2022) at the firm-level – who relied on import data for product categories (mostly, at the 6-digit level) to build proxies of technology adoption. However, these studies exploit a much broader definition of automation technologies, reaching outside the boundaries of the 4IR, thus capturing a large share of machinery and equipment already in use and potentially to be considerate as enabling technologies. Conversely, we move forward such approch by adopting a structured methodology to identify capital and intermediate goods specifically related to the three digital technologies of interest, using highly disaggregated data on 8-digit product codes. Through these precise measures, we provide fresh empirical evidence on the productivity gains and the technological convergence associated with the adoption of a bundle of AMTs, strictly related to the I4.0 wave.

The 4IR-productivity nexus has attracted an increasing amount of research (e.g. Graetz and Michaels, 2018; Edquist et al., 2019; Acemoglu et al., 2020; Damioli et al., 2021; Venturini, 2022). However, these studies have mostly focused on the adoption of specific technologies (namely AIRs). We build on this growing literature by exploring the role played by a larger set of technologies, including AIRs, AM and IIoT, in generating productivity growth and convergence[20] using a panel of 13 manufacturing industries across 14 European countries over the 2009–2019 period.

Moving forward the methodology developed in Chapter 1, our contribution is twofold: first, we provide suitable proxies to measure the adoption of the three (capital-embodied) AMTs across countries and sectors, as well as to explore empirically how they affect productivity growth, a research area still severely under investigated. Second, we explore the productivity effects associated with AMTs by looking at their direct contribution (i.e. through domestic adoption) to TFP growth rates and the role they play in the technological catching-up of European economies more distant from the technology frontier.

Our results highlight that AMTs are relevant contributors to TFP growth rates over the investigation period. When taken together, AMTs have statistically and quantitatively significant effects. Looking at individual AMTs, we find that AM (and, to a lower extent, AIRs) the more beneficial on average for European economies, while the effect of IIoT on TFP growth is weaker and limited to technologically advanced countries. One main result emerging from the analysis is that the productivity gains from AMT adoption mostly concentrate in countries closer to the technology frontier. Furthermore, our results are robust to different measures of TFP growth, to the presence of cointegration, and to the use of both alternative AMT adoption proxies and estimation methods.

The rest of the Chapter is structured as follows. Section 2.2 briefly discusses the relevant literature on the topic, Section 2.3 highlights the analytical framework and the empirical strategy for our empirical investigation. Section 2.4 discusses the data used, while Section 2.5 presents and discusses the results of our econometric analysis and the related robustness tests. Finally, Section

[20] See, for instance, Griffith et al. (2004), Cameron et al. (2005), Griffith et al. (2009), Minniti and Venturini (2017) and Mason et al. (2020) for recent empirical studies on productivity convergence.

2.6 discusses results, the related policy implications, and concludes discussing limitations and outlining future research.

2.2. Background literature

The 4IR and its technologies have been at the core of academics' debate for over a decade now. From a conceptual standpoint, AMTs of the I4.0 wave represent a new and more advanced form of capital, which can be thought of as the evolution of those advanced manufacturing technologies which diffused over the 90s and had been conceptualised in previous studies (e.g. Udo and Ehie, 1996; Cagliano and Spina, 2000; Kotha and Swamidass, 2000). By substituting or complementing traditional types of automated machinery, AMTs can perform a growing number of tasks in a faster and more efficient way, in turn, rising productivity. In addition, other forms of automation like artificial intelligence (AI) may also contribute to the generation of new ideas and innovations – for instance, continuously improving other forms of automation – and in the production of goods, generating economic and productivity growth (see Aghion et al., 2019, for a detailed discussion).

There is an emerging agreement among academics to consider the digital technologies of the I4.0 wave as new general purpose technologies (GPTs). The distinctive trait of GPTs is that they can generate sustained economic growth by boosting continuous innovation and co-invention, spreading to every sector of the economy (Bresnahan and Trajtenberg, 1995; Carlaw and Lipsey, 2002; Jovanovic and Rousseau, 2005; Bresnahan, 2010). For instance, AIRs and AI are now commonly seen as a technological platform for innovation (Cockburn et al., 2019), which enable firms to define new productive ways of recombining existing technologies (Agrawal et al., 2019) and improve forecast-making, reducing uncertainty and harness more and new opportunities (Agrawal et al., 2019). However, the view of AMTs as GPTs is still very much in its infancy, both on a theoretical (Trajtenberg, 2019; Aghion et al., 2019) and empirical ground (Brynjolfsson et al., 2019b; Martinelli et al., 2021).

Over the last few years, data on the diffusion of these technologies have become increasingly available from different sources. For instance, the 2019 European Investment Bank Investment Survey (EIBIS) shows consistent adoption shares for these three technologies across European manufacturing firms: AIRs have the highest uptake (around 47% of firms), followed by IIoT and AM (around 34% and 28% of firms, respectively). Conversely, 2020 Eurostat's data hints at more conservative figures, suggesting actual adoption to be lower across EU27 countries (i.e. among manufacturing firms 17% use AIRs, 19% use IIoT and 12% use AM).

This anecdotal evidence suggests that these technologies have reached non-negligible diffusion rates and have the potential to affect different aspects of the economy. Nonetheless, it also highlights how sensitive these insights can be depending on the sources of data and survey design (i.e. sample size, composition, timing of the data collection).

Prima facie empirical evidence hints at the larger ecosystem created by the bundle of technologies of the 4IR to be the next GPT, rather than a single highly promising technology. For instance, Venturini (2022) finds that the stock of innovations related to I4.0 can generate productivity spillovers, whose pattern conforms to the productivity '*J-curve*' typically observed in the early stage of diffusion of new GPTs. Nonetheless, the lack of reliable and precise measures capturing the diffusion of I4.0-related technologies has so far hampered empirical investigations, and only few works have contributed to the identification of the real economic impact brought by the 4IR. Given the lack of extensive and detailed sources of information (Brynjolfsson et al., 2019a; Cockburn et al., 2019), most of the studies in the field have focused on AIRs using data from the International Federation of Robotics (IFR), mostly looking at the occupational and wage effects of robotisation at different level of analysis (e.g. Graetz and Michaels, 2018; Dauth et al., 2021; Acemoglu and Restrepo, 2020).

Recently, some works have looked at the productivity effects (both labour productivity and TFP) deriving from either adopting or producing specific automation technologies or I4.0-related innovations (Jäger et al., 2015; Graetz and Michaels, 2018; Edquist et al., 2019; Acemoglu et al., 2020; Alderucci et al., 2020; Benassi et al., 2020; Ballestar et al., 2020; Bonfiglioli et al., 2020; Espinoza et al., 2020; Cette et al., 2021; Damioli et al., 2021; Du and Lin, 2022; Venturini, 2022). Overall, these studies highlight the magnitude of the expected effect to depend largely on the technology investigated, the data source and the estimation method, thus not providing a unified view of their implications. Importantly, most evidence currently comes either from surveys (mostly cross-sections) conducted in selected countries, case studies on a small number of firms, or from empirical works looking at specific technologies for which data are currently available (e.g. IFR data). This limits comparison across countries, sectors, and technologies.

Studies investigating adoption-related productivity effects are those most closely related to our work. Using the growth accounting approach and looking at 30 OECD countries, Cette et al. (2021) find that aggregate AIR adoption does not appear to have been a quantitatively significant source of productivity growth between 1975 and 2019. Similarly, also Edquist et al. (2019) and Espinoza et al. (2020) leverage on growth accounting to investigate productivity gains associated with the adoption of IoT yet taking different approaches to measure technology adoption. On the one hand, Edquist et al. (2019) uses data on licensed IoT connections across 82 countries for the period 2010–2017 to investigate the relationship between IoT adoption and cross-country TFP growth, finding that a 10% increase in the growth rate of IoT connections per inhabitant is associated with a 0.23% increase in the rate of growth of TFP. On the other hand, Espinoza et al. (2020) combine earlier findings on the estimated contribution of ICT capital investments to labour productivity growth and new cross-country data on IoT expenditure in the attempt to single out the proportion of ICT-related productivity gains coming from investments in IoT. Their findings point at negligible contributions to annual labour productivity growth of about 0.01 and 0.006 percentage points in the US and across EU10 countries, respectively.

Along this aggregate evidence, other works attempt to provide a more precise picture by also considering sectoral heterogeneity. Graetz and Michaels (2018) estimate that the rising adoption of AIRs can explain between 0.4 and 1% of the increase in labour productivity and between 0.3 and

0.8% of TFP growth, between 1993 and 2007, across manufacturing and non-manufacturing sectors in a sample of 17 advanced economies. Similarly, Du and Lin (2022) exploit sectoral data on installed AIR to measure robotisation rates across Chinese regions – following the empirical approach by Acemoglu and Restrepo (2020) – and uncover a U-shaped relationship between AIR adoption and TFP growth: quantitatively significant productivity gains are associated mostly with regions featuring a sufficiently high level of robotisation.

Looking at a finer unit of analysis, firm-level evidence highlights similar findings. Jäger et al. (2015) find significant higher labour productivity gains associated with AIR adoption in manufacturing operations by looking at around 1,400 Swiss and Dutch businesses. Similarly, Ballestar et al. (2020) analyse a sample of Spanish firms between 2008 and 2015, uncovering a rise in productivity of about 3% across small and medium sized firms (SMEs) associated with AIR adoption, but no effect on large companies. The works by Acemoglu et al. (2020) and Bonfigliolo et al. (2020) look at AIR adoption across French firms, although uncovering mixed findings: while the former find unconclusive and not robust evidence on the impact of AIR adoption on TFP growth between 2010 and 2015, the latter find a positive and significant effect over a longer period from 1994 to 2013, robust to several checks.

Although previous studies have moved the debate forward, they bear some limitations. First, they measure the adoption of single technologies (mostly AIR and, in some cases, IoT) and neglect the implications coming from a wider and more complete nexus of technologies. Second, they focus on different levels of aggregation (country vs sector vs firm level) and on different periods, thus making it hard to compare insights. Furthermore, while providing interesting insights, these works base their analysis on different and only partially comparable measures for the same technology: e.g. IFR data in Graetz and Michaels (2018), Cette et al. (2021) and Du and Lin (2022), AIR adoption dummy in Ballestar et al. (2020), and AIR imports in Acemoglu et al. (2020) and Bonfigliolo et al. (2020). Finally, some of these works bear important limitations from and empirical standpoint: on the one hand, cross-sectional data (e.g. Jäger et al., 2015; Ballestar et al.,

2020) or too short time series (e.g. Edquist et al., 2019) do not allow to investigate causal relationships; on the other hand, broad assumptions[21] do not enable to produce accurate estimates (e.g. Espinoza et al., 2020). This study addresses these limitations by providing a unified measurement framework for different AMTs and testing their effect on productivity growth of 14 European countries and 13 2-digit manufacturing industries over a decade (2009–2019) employing panel data econometric modelling that allows to investigate causal relationships. We model the technological change associated with AMTs by studying how the adoption of the latest technologies of the 4IR, embodied in capital and intermediate goods, relates to sectoral productivity growth.[22] As such, our work also relates to the literature on investment-specific technological change (Greenwood et al., 1997, 2000), which recognises the role of capital investments in specific types of machinery and equipment as one of the most relevant sources of productivity growth. This literature has investigated thoroughly the role played by ICT (vs non-ICT) investments in determining productivity growth over the last few decades (e.g. Bakhshi and Larsen, 2005; Martínez et al., 2010; Venturini, 2015; Chung, 2018). In this work, we take stock of this literature and investigate the distinct contribution to productivity of the capital and intermediate goods embodying AMTs from other more traditional types of ICT investments.

This study also relates to two other well-established literatures. On one hand, it deals with the study of endogenous innovation, economic growth (e.g. Romer, 1990; Aghion and Howitt, 1992; 1997) and productivity gains coming from different sources, such as traditionally, research and development (R&D), imports and human capital (e.g. Coe and Helpman, 1995; Keller, 1998; Eaton and Kortum, 2001; Caselli and Wilson, 2004; Caselli and Coleman, 2006; Acharya and

[21] The authors use existing survey data on installed IoT devices by region (e.g. North America, Western Europe, Asia/Pacific, etc.), combined with earlier published estimates of the contribution of ICT capital to labour productivity growth, in order to estimate how much of such ICT contribution relates to IoT capital by developing different scenarios (i.e. assuming different percentage of ICT expenditure devoted to IoT).

[22] This approach enables a more general formalisation of the adoption phenomena, as well as a scalable methodology which can be used to trace AMT adoption at different level of aggregation (i.e. from the macro to the micro), depending on data availability.

Keller, 2009). On the other hand, it links with the debate on the source of differences in income and productivity across countries (e.g. Acemoglu and Zilibotti, 2001; Caselli and Coleman, 2006) and their implications for economic and technological convergence (e.g. Griffith et al., 2004; Cameron et al., 2005; Griffith et al., 2009; Madsen et al., 2010; Bourlès et al., 2013; Bergeaud et al., 2016; Minniti and Venturini, 2017; Mason et al., 2020).

These literatures propose that variables like R&D, imports and investments in new and more advanced technologies (e.g. ICTs or AMTs) play a role in determining both productivity growth and the speed of convergence of TFP levels across countries. In past decades, between the 70s and the 90s, both R&D and imports have been important sources of productivity growth across countries and sectors, although not reaching consensus on the role of trade patterns as a way for R&D-related technology transfer and productivity growth (Coe and Helpman, 1995; Coe et al., 1997; Keller, 1998; Griffith et al., 2004; Acharya and Keller, 2009). Other studies recognise that the role of imports is particularly important for countries away from the technology frontier (Keller, 2000) and that the composition of imports matters in determining productivity gains, which are mostly associated with trade in more advanced capital goods (Eaton and Kortum, 2001; Caselli and Wilson, 2004). The role of ICT investments is also well documented in these literatures and found to be a leading source of productivity growth across countries and sectors ever since the 80s (Bakhshi and Larsen, 2005; Martínez et al., 2010; Venturini, 2015; Bergeaud et al., 2016). However, decreasing productivity gains from ICTs are documented over the past decades (Bergeaud et al., 2016; Chung, 2018), and mixed findings on the overall effect associated with these type of capital investments emerge when focusing on manufacturing industries alone (e.g. Mc Morrow et al., 2008; Edquist and Henrekson, 2017).

While all these studies represent the starting point of our empirical investigation, our aim is to move forward the debate by exploring which role is played by new AMTs of the I4.0 wave. Specifically, we address the limitations of prior studies looking at technologies of the 4IR by providing a unified measurement framework for different AMTs, hence making the observed effect comparable across technologies, and testing their potential role as enablers of productivity catch-up (convergence) across manufacturing industries of European economies leveraging on the well-established distance-to-frontier framework.

2.3. Empirical setting

An established approach to model country-sector productivity growth (e.g. Bernard and Jones, 1996a,b) posits that TFP in sector j of country i grows both as a result of domestic investment and of the opportunities offered by being relatively more distant from the technological frontier (i.e. catching-up).[23] Hence, TFP growth (ΔlnA_{ijt}) can be modelled as follows:

$$\Delta lnA_{ijt} = \beta_{ij} + \gamma_{ij} ln\left(\frac{A_F}{A_i}\right)_{jt-1} \quad (1)$$

where A represents total factor productivity (TFP) as an index of technical efficiency (i.e. technological progress). TFP is allowed to vary across countries, industries and time and derived from the following production function:

$$Y_{ijt} = A_{ijt} G_{ij}(X_{ijt}, L_{ijt}, K_{ijt}) \quad (2)$$

where, in each time period, Y denotes gross output produced in each country using intermediate inputs X, labour L and capital K inputs; function $G(\cdot,\cdot)$ is assumed to be homogeneous of degree one and to exhibit diminishing marginal returns to the accumulation of each individual production factor and constant returns to scale. At any time t, one of the countries i will feature the highest level of TFP in sector j, i.e. the technological frontier (A_F). β_{ij} and γ_{ij} (with $\beta_{ij}, \gamma_{ij} \geq 0$) are parameters capturing the rate of country-industry-specific innovation and the speed of technological catch-up, respectively; the term $ln(A_F/A_i)_{jt-1}$ represents the catch-up component of productivity growth in country i, expressed as a function of the lagged productivity differentials in sector j

[23] See Islam (1999) for a review of theories, approaches, and measurement issues.

between country i and country F. The rationale for equation (1) is that, for a non-frontier country i the catch-up term ($ln(A_F/A_i)_{jt-1}$) is positive and larger the further away country i lies far from the frontier in sector j, making greater the potential for productivity gains. In the case of frontier countries instead, the sole source of productivity growth resides in domestic innovation, such that the second term in the right-hand side of equation (1) is null.

According to the model, in steady-state equilibrium, TFP in each sector j in all countries will grow at the same constant rate, such that in each non-frontier country TFP growth from domestic innovation and from technological catch-up equals TFP growth from domestic innovation alone for the technological leader. The model also allows any country i to switch endogenously from being a frontier to a non-frontier country and vice versa, in a way that in steady state the frontier for sector j will be whichever country featuring the highest TFP level in that sector. Each non-frontier country will be at an equilibrium distance behind the leader such that all countries feature the same TFP growth rate.

Equation (1) can be thought as an equilibrium correction model (ECM) representation featuring a first-order autoregressive distributed lag model (ADL(1,1)), which assumes a long-run cointegrating relationship between a country's own TFP and technological leader's TFP:[24]

$$lnA_{ijt} = \lambda_1 lnA_{ijt-1} + \lambda_2 lnA_{Fjt} + \lambda_3 lnA_{Fjt-1} + \beta_{ij} + \varepsilon_{ijt} \tag{3}$$

Assuming long-run homogeneity ($\lambda_1 + \lambda_2 + \lambda_3 = 1$), this equation can be expressed as:

$$\Delta lnA_{ijt} = \lambda_2 \Delta lnA_{Fjt} + (1 - \lambda_1) ln\left(\frac{A_F}{A_i}\right)_{jt-1} + \beta_{ij} + \varepsilon_{ijt} \tag{4}$$

so that equation (4) is identical to (2) with $1 - \lambda_1 = \gamma$ and $\lambda_2 = 0$. This ECM representation offers a straightforward interpretation: TFP growth in country i and industry j increases with TFP growth of the industry featuring as frontier (i.e. F) and with the distance of each country-sector pair from the frontier sector (Bourlès et al., 2013).

[24] See Hendry (1996) for further details.

As discussed in Section 2.2, following the extensive literature on endogenous innovation and growth we recognise the role variables such as R&D, international trade and ICTs have in determining productivity growth. At the same time, following the literature on technological convergence, we assume these variables can affect TFP growth through both domestic innovation and technological catch-up. In addition to these traditional determinants of TFP growth, in this Chapter we augment the model with the introduction of a variable measuring the adoption of AMTs. We account for these sources of productivity growth by allowing parameters β_{ij} and γ_{ij} in equation (1) to be functions of R&D, international trade, investments in ICTs and in AMTs. Hence, our final econometric specification becomes:

$$\Delta lnA_{ijt} = \alpha_1 \Delta lnA_{Fjt} + \alpha_2 lnDTF_{ijt-1} + \alpha_3 AMT_{ijt-1} + \alpha_4 AMT_{ijt-1} \times lnDTF_{ijt-1} + \alpha_5 X_{ijt-1} + \alpha_6 X_{ijt-1} \times lnDTF_{ijt-1} + \eta_{ij} + \tau_t + \varepsilon_{ijt} \quad (5)$$

where ΔlnA_{ijt} and ΔlnA_{Fjt} represent the TFP growth rate in sector j of country i and the TFP growth rate in sector j of the frontier, respectively; $lnDTF_{ijt-1}$ is the distance from the frontier (the empirical counterpart of $ln(A_F/A_i)_{jt-1}$), AMT_{ijt-1} is our main explanatory variable capturing the stock of investments in the three I4.0-related technologies (i.e. AIRs, AM and IIoT) at the country-sector level and X_{ijt-1} is a vector of control variables (i.e. R&D, overall sectoral imports, ICT investments). We further explore specification of our model where we estimate equation (5) by substituting overall AMT investments AMT_{ijt-1} with single technologies (i.e. AIR_{ijt-1}, AM_{ijt-1} and $IIoT_{ijt-1}$) in order to explore potential heterogeneities across technologies.

A positive value for α_2 implies that technology transfers are relevant for technological laggards, thus translating in productivity catch-up. If AMT adoption spurs productivity gains, α_3 should be positive; at the same time, if it brings greater TFP growth for countries closer to (farther away from) the frontier α_4 should be negative (positive). As described in Chapter 1, the AMTs under investigation show a distinct pattern of diffusion across Europe. Since AMTs embody some of the most recent forms of technological change, they require absorptive capacity and complementarity with existing enabling technologies to be efficiently adopted (Ciffolilli and Muscio, 2018; Corradini et al., 2021). Hence, while we expect positive TFP gains from AMT adoption (i.e. a positive α_3), it is likely that the effect on the speed of catching-up will be very limited and not beneficial for technological laggard (i.e. we expect a negative α_4).

The information on AMT imports is available only at the country-year level for the sample of European countries included in our analysis. In order to have variation across sectors we exploit: (i) data on the share of AMT-related capital and intermediate goods produced by AMT-producing industries and (ii) sectoral information on the share of intermediates imported from AMT-producing industries. In this way we can build a measure of sectoral AMT imports, which should well approximate true sectoral imports for disaggregated 8-digit product codes, otherwise not available.[25] Section 2.4.2 provides a detailed description on how we compute the AMT_{ijt} variable. In Section 2.5.3 we provide a robustness test to our main results, by exploring specifications of our model in which we allow AMT adoption to vary only across countries and years. Equation (5) includes unobserved heterogeneity arising from country-industry characteristics not captured by our explanatory variables, affecting rates of TFP growth, and possibly correlated with our controls. For instance, there may be some specific characteristics related to the production technology in specific countries and sectors that might push TFP to grow faster in exactly those country-sector pairs showing higher intensities in investments in AMTs, R&D or trade patterns. For this reason, we include country-sector fixed effects (η_{ij}), i.e. use the within-groups estimator. We further include time fixed effects (τ_t) to capture the potential component of technical change, evolving over time, which is common to all countries and sectors, as well as common macroeconomic trends and shocks. Since heteroskedasticity is pervasive in our industry-level data, and hypotheses tests on our sectoral variables indicates that variances are heterogeneous across country-sector groups, we

[25] This measure is close in spirit to the robot exposure index proposed by Acemoglu and Restrepo (2020) to measure robot adoption at the local labour market level, also used by several empirical studies in the automation-employment literature.

estimate all specifications of equation (5) by Weighted Least Squares (WLS) using value added shares in total economy as weights. As robustness check, in Section 2.5.3, we also explore unweighted specifications, estimated *via* Ordinary Least Squares (OLS).

2.4. Data

2.4.1. TFP growth and levels

To compute our dependent variable, TFP growth rate, we use 2-digit sectoral data on gross output, value added, labour, total capital stock and intermediate inputs for European countries, the US and Japan from the 2021 release of EU KLEMS database (February 2022 revision). We complement EU KLEMS data with comparable information from OECD STAN data set.

Following an established approach (Islam, 1999), we adopt the superlative index approach by Caves et al. (1982a,b). The approach assumes that the underlying production function is translog, allowing a more flexible specification of the production technology and outperforming other measures assuming alternative production function (e.g. Cobb-Douglas technologies) in terms of comparability (e.g. Griffith et al., 2004; Keller, 2004; Venturini, 2015). Following Jorgenson et al. (2005), we compute TFP growth rates as:

$$\Delta lnA_{ijt} = \Delta lnY_{ijt} - \breve{v}_{ijt}^{X}\Delta lnX_{ijt} - \breve{v}_{ijt}^{K}\Delta lnK_{ijt} - \breve{v}_{ijt}^{L}\Delta lnL_{ijt} \quad (6)$$

where $\breve{v}_{ilt}^{X}$, $\breve{v}_{ilt}^{K}$ and $\breve{v}_{ilt}^{L}$ represent the share of nominal intermediate inputs, the share of capital compensation and the share of labour compensation in gross output, respectively. Terms $\breve{v}_{ijt}$ represent the '*divisia index*'[26] and are computed as $\breve{v}_{ijt} = 0.5(v_{ijt} + v_{ijt-1})$. Due to assumption on constant returns to scale it holds that $\breve{v}_{ijt}^{X} + \breve{v}_{ijt}^{K} + \breve{v}_{ijt}^{L} = 1$.

[26] The '*divisia index*' is used in economic modelling to account for changes over time (e.g. quantity, price) related to subcomponents of a production function, which are usually measured in different units (e.g. labor hours, investments in capital equipment and purchase of intermediates).

We measure TFP levels using the same approach, evaluating TFP relative to a common reference point (i.e. the geometric mean of the TFP levels of all other countries):

$$\ln A_{ijt} = ln\left(\frac{Y_i}{\bar{Y}}\right)_{jt} - \tilde{v}_{ijt}^{X} ln\left(\frac{X_i}{\bar{X}}\right)_{jt} - \tilde{v}_{ijt}^{K} ln\left(\frac{K_i}{\bar{K}}\right)_{jt} - \tilde{v}_{ijt}^{L} ln\left(\frac{L_i}{\bar{L}}\right)_{jt} \tag{7}$$

where $\bar{Y}$, $\bar{X}$, $\bar{K}$ and $\bar{L}$ denote the geometric means of gross output, intermediate inputs, aggregate capital stock and labour, and $\tilde{v}_{ijt} = 0.5(v_{ijt} + \bar{v}_{ijt})$ are the averages of nominal input cost shares and their geometric means. In each time t and sector j, we take the country with the highest TFP level as the frontier, so that the $lnDTF_{ijt}$ term is computed as the difference between lnA_{Fjt} and lnA_{ijt}. Coherently, ΔlnA_{Fjt} is the TFP growth rate observed at the frontier, in each sector j at each time t.

Given the characteristics of our model, despite our geographical focus is on Europe, we also use data on the US and Japan in the computation of TFP levels and growth rates to expand the range of advanced economies possibly featuring as the frontier, being these two countries worldwide technological champions. Similar studies take a similar approach (e.g. Griffith et al., 2004), thus omitting them and constrain the range of countries featuring as frontier to Europe only could result in a serious bias in our results.

We also deal with important measurement issues related to differences across countries in hours worked and skills levels. To support the robustness of our results, we compute alternative measures of TFP that adjust for differences in hours worked and skills levels. Appendix A reports details on how we compute these alternative TFP measures.

2.4.2. Measuring AMT adoption

The main variables of interest, the adoption of the three AMTs considered in this Chapter (i.e. AIRs, AM and IIoT), are computed by starting from country-level highly disaggregated trade data from Eurostat's Comext database, thanks to the availability of fine-grained 8-digit product codes related to such technologies. Product codes in Comext data follow the Combined Nomenclature

(CN), a further breakdown of the Harmonised System. We checked for changes occurred in the classification between 2009 and 2019 in each year, in order to track all potential changes related to the selected codes. Whenever the CN classification changed over time, we followed the methodology by Van Beveren et al. (2012), creating '*synthetic*' codes grouping together the relevant CN codes. This procedure grants full consistency in the correspondence between trade data over time and resulted in a slight reduction in the number of 8-digit product codes considered (shrinking from 21 to 18). Further details on technical caveats related with Comext data, along with the list of identified product used in our analysis are reported in Chapter 1.

Starting from this harmonised list of product codes, we computed our measure to proxy the adoption of AMTs by creating one summary measure for the three technologies as the sum of the value of imports for all product codes relating to AIRs AM and IIoT, for each country and year of observation. In this way, we can identify for each European country in our panel a unique measure embodying all the imported goods associated with AMTs. This measure is inspired by Caselli and Coleman (2001) and similar measures of technology adoption have been used in several recent studies (e.g. Blanas et al., 2019; Acemoglu et al., 2020; Bonfiglioli et al., 2020; Domini et al., 2021; 2022; Acemoglu and Restrepo, 2022).

Caselli and Coleman (2001) also argue that an alternative approach would be to exploit both production and trade data, to account for both domestic and foreign sources of adoption of a technology. Such a measure would capture the *net consumption* (i.e. *production* + *import* – *export*) of a technology. For AMTs, we highlighted in Chapter 1 that the availability of production data is constrained by the actual presence of local producers, resulting in this alternative measure to be available for a restricted sample of European countries. We also showed that, imports and net consumption are highly correlated, and the former represents a good proxy of AMT adoption across European countries.

As anticipated in Section 2.3, in order to measure AMT adoption at the sector level we build an exposure index by using: (i) the information on each country's share of imported AMT-related goods over total imports from AMT-producing sectors;[27] (ii) cross-country and cross-sector data on imported intermediate inputs from WIOD data set (Timmer et al., 2015). In doing so, we assume that each industry adopts AMT in the same proportion as it uses AMT-related inputs from the 2-digit sector producing each specific AMT (i.e. 28 for AIRs and AM, 26 for IIoT):

$$M_{i,j,t}^{AMT} = \left(M_{i,t}^{AIR} \times \varphi_i^{AIR} \times \frac{\sum_c int_{i,j}^{c,28}}{\sum_c \sum_s int_{i,j}^{c,s}} \right) + \left(M_{i,t}^{AM} \times \varphi_i^{AM} \times \frac{\sum_c int_{i,j}^{c,28}}{\sum_c \sum_s int_{i,j}^{c,s}} \right) + \left(M_{i,t}^{IIoT} \times \varphi_i^{IIoT} \times \frac{\sum_c int_{i,j}^{c,26}}{\sum_c \sum_s int_{i,j}^{c,s}} \right) \tag{8}$$

where i and j denote the country and the sector buying intermediates (i.e. the destination); c and s denote the country and the sector selling intermediates (i.e. the source); $\varphi_i^{AIR} = M_i^{AIR}/M_i^{28}$ denotes, in each country i, the share of AIR imports in all imports of goods produced by sector 28; $\varphi_i^{AM} = M_i^{AM}/M_i^{28}$ denotes the same share for AM; $\varphi_i^{IIoT} = M_i^{IIoT}/M_i^{26}$ denotes the share of IIoT imports in all imports of goods produced by sector 26.

For each country i, sector j and year t, AMT imports (M_{ijt}^{AMT}) are then equal to the sum of imports of each AMT in each country, weighted by the ratio of AMT-related intermediate goods bought by sector j of country i from the sector producing each specific AMT (i.e. 28 for AIRs and AM, 26 for IIoT) in all other countries ($c \neq i$) over total intermediate goods used by sector j in country i (int_{ij}). We take predetermined weights (i.e. in 2008) in order to avoid potential biases associated with reverse causality. The idea behind this measure is that true sectoral AMT adoption (unfortunately, not available) should be positively correlated with our measure, i.e. the more a sector buys AMT-related inputs from AMT producing sectors, the larger its AMT adoption.

We then compute the stock of sectoral AMT imports (AMT_{ijt}) following the perpetual inventory method as $AMT_{ijt} = M_{ijt}^{AMT} + (1-\delta)AMT_{ijt-1}$, assuming a depreciation rate or 15%.

[27] As discussed in Chapter 1, this information can be computed by matching the 8-digit CN product codes for AMT-related capital and intermediate goods with the corresponding 8-digit codes in Prodcom classification. In the Prodcom list, the first 4 digits of each product code coincide with the 4-digit NACE sector producing the good (Eurostat, 2021).

We also test specifications of our model in which we delve into the specific relationship, and related magnitude, of each single AMT. The related measures for AIRs, AM and IIoT are built following the same methodology used for the total AMT variable.

2.4.3. Other independent variables

In addition to country-sector and year fixed-effects, we include controls for R&D and ICT capital stocks as shares of value added. To avoid that our AMT adoption variables pick up a general effect from imported goods, we also control for the share of imports in value added. All these variables vary over countries, sectors, and years. We sourced this information from EU KLEMS database, OECD STAN, ANBERD and BTDIxE data sets. When building all our variables, we adjusted current values using specific sectoral deflators from OECD STAN and converting all data in USD.[28] This allows for more precise intertemporal and geographical comparison while performing our sectoral empirical analysis.

Our sample consists of 14 European countries[29] and 13 2-digit manufacturing industries[30] over the 2009–2019 period. Table 1 below reports a detailed description of all variables and a summary description, while Table 2 presents summary statistics.

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[28] We do not use sectoral PPPs, which would enable a more precise comparison across countries and sectors, since these are hardly available for all countries, sectors and years in our analysis. However, this is a lesser concern for our work as by using the within-groups estimator we should be able to filter out cross-country and cross-sector differences in prices.

[29] Country list: Austria (AUT), Belgium (BEL), Czech Republic (CZE), Germany (DEU), Denmark (DNK), Spain (ESP), Finland (FIN), France (FRA), United Kingdom (GBR), Italy (ITA), Netherland (NLD), Portugal (PRT), Slovak Republic (SVK), Sweden (SWE).

[30] Manufacturing industries list (NACE rev.2): 1 - Food products, beverages and tobacco (10-12); 2 - Textiles, wearing apparel, leather and related products (13-15); 3 - Wood and paper products; printing and reproduction of recorded media (16-18); 4 - Coke and refined petroleum products (19); 5 - Chemicals and chemical products (20); 6 - Basic pharmaceutical products and pharmaceutical preparations (21); 7 - Rubber and plastics products, and other non-metallic mineral products (22-23); 8 - Basic metals and fabricated metal products, except machinery and equipment (24-25); 9 - Computer, electronic and optical products (26); 10 - Electrical equipment (27); 11 - Machinery and equipment n.e.c. (28); 12 - Transport equipment (29-30); 13 - Other manufacturing; repair and installation of machinery and equipment (31-33).

Tables 1 and 2 around here

2.5. Results

2.5.1 Main results

Table 3 shows our estimates of the model described by equation (5) in Section 2.3. Our starting point is to estimate a benchmark model including only determinants of TFP growth extensively studied in the literature, i.e. R&D, imports and ICT intensity.

We begin in column (1) by estimating the long-run relationship between TFP growth rates and R&D, import and ICT variables between 1995 and 2019. This baseline model provides us with a robust starting point for the analysis, directly connects our work to the existing literature and increases comparability with prior studies. TFP growth of the frontier (ΔlnA_F) and the $lnDTF$ terms are positive and statistically significant at the 1% level. This indicates that, within each manufacturing industry, while all European countries benefit from technological progress at the frontier, countries lagging behind the frontier also experience additional productivity gains (i.e. TFP grows faster) as a result of catching-up. This result is in line with prior sector-level evidence for developed economies spanning between the 70s and early 2000s (e.g. Griffith et al., 2004; Cameron et al., 2005; Mc Morrow et al., 2008; Bourlès et al., 2013; Minniti and Venturini, 2017; Mason et al., 2020), and persistent up to before the Covid-19 pandemic, as shown by our results.

In line with other studies (e.g. Griffith et al., 2004; Madsen et al., 2010), we find a positive and statistically significant (at the 1% level) relationship between R&D investments and TFP growth across all countries and sectors, but these gains are concentrated in countries closer to the frontier (i.e. the interaction with the $lnDTF$ term is also statistically significant and negative). Conversely, import intensity seems to feature a negative relationship with TFP growth and a catching-up effect due to a positive contribution to the speed of technology transfer (both significant at the 5% level). Although these effects are small in magnitude, our findings are broadly in line with works looking at earlier decades (e.g. Keller, 2000; Griffith et al., 2004). Finally, in line with other studies (e.g. Bakhshi and Larsen, 2005; Martínez et al., 2010; Venturini, 2015; Bergeaud et al., 2016), our estimates highlight that ICT investments had a positive effect on TFP growth rates (significant at the 5% level), yet mostly concentrated in more advanced European economies.

In columns (2) and (3) we then split the sample period, looking at the period 1995–2008 in column (2) and at the period 2009–2019 in column (3). As discussed in Chapter 1, the year 2009 represents a meaningful starting point for our investigation since: (i) only after the 2008 global financial crisis these technologies started receiving increasing attention from European policymakers and the worldwide demand for advanced mechanical and automation equipment returned to normal (Kagermann et al., 2013; De Backer et al., 2018); (ii) several core patents protecting AM technologies, such as fused deposition modelling and selective laser sintering, expired between 2009 and 2014 (Laplume et al., 2016), leading to a proliferation of spill-over inventions and machinery producers.

Comparing column (2) with (1), we note that imports had a no significant effect between 1995 and 2008. Similarly, the effect of ICT investments is estimated less precisely and turns out not significant, pointing at similar results as found in some studies looking at manufacturing industries over the same period (e.g. Mc Morrow et al., 2008; Edquist and Henrekson, 2017). Conversely, looking at the 2009–2019 period in column (3), ICT investments appear to have a large positive and significant effect on TFP growth rates across manufacturing industries, concentrated in more advanced countries. This finding provides updated evidence of the role of ICTs as a driver of productivity, highlighting that the trend of diminishing gains observed in previous studies (e.g. Bergeaud et al., 2016; Chung, 2018) has turned in the case of European countries in our sample.

Next, in columns (4) and (5), we augment the baseline catch-up model by including our measure of sectoral AMT adoption (column (4)) and by allowing it to have an effect on the speed of technology transfer from the frontier (column (5)). In column (4), the effect of AMT adoption alone is negative, very small in magnitude and not statistically different from zero. However, in column (5), when we also consider its relationship with TFP growth mediated by the distance from the technology frontier ($AMT \times lnDTF$), the AMT adoption variable increases in magnitude and become statistically significant at the 1% level, while the interaction term enters our specification with a negative and statistically significant (1% level) coefficient. This result suggests that, AMT adoption spurs positive productivity gains for economies closer to the frontier while countries lagging behind the frontier do not benefit from AMT-related technological catch-up.

In columns from (6) to (8) we explore specifications similar to that in column (5) where our TFP measures reflect cross-country differences in the skill composition of the workforce (column (6)), in hours worked and skill composition (column (7)), and also for an alternative definition of the technology frontier[31] (column (8)). Our main results are robust and qualitatively unchanged cross these specifications, confirming a positive effect of AMT adoption on TFP growth rates across manufacturing industries of European countries.

The specifications correcting TFP measurement for hours worked and skills also highlight that accounting for these factors reduces the importance of spill-overs from the leader's growth (i.e. ΔlnA_F's coefficient reduces in magnitude and is no longer significant), while it also uncovers a much bigger role of R&D investments (e.g. in column (6), RD's coefficient becomes three times bigger than in column (5), while its interaction with $lnDTF$ remains virtually unchanged) and a more uncertain role of ICTs (e.g. ICT's coefficients are less precisely estimated in column (7)).

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[31] The model described in Section 3 assumes that it is not the identity of the technology frontier that is relevant in equation (5), but the distance from the frontier itself, capturing the potential for technological catch-up. As the model allows for any country to switch endogenously from being a frontier to a non-frontier country and vice versa, only requiring that the $lnDTF$ term correlates with the potential for technology transfer and productivity gains from catching-up. Thus, in column (8) we test an alternative specification of our model in which we measure $lnDTF$ using the average TFP level for the two countries featuring the highest value as the frontier, and by computing ΔlnA_F as the average growth rate between these two countries.

Table 3 around here

In Table 4, we test the sensitivity of our main results when using three different and disaggregated measures for each AMT, i.e. we report estimates of equation (5) in which we consider disaggregated measures for AIRs, AM and IIoT. In column (1) we only consider the direct relationship between AIR adoption on TFP growth, which results to be positive and statistically significant, although only at the 10% level. When we also consider the $(AIR \times lnDTF)$ interaction term in column (2), we observe a positive direct effect of AIR investments, which also increase in magnitude, and a negative sign for the interaction term (both statistically significant at the 10% level). This result suggests similar implications as for the aggregate AMT variable: while AIRs spur TFP gains across manufacturing industries, these gains are larger for European economies closer to the frontier.

Columns (3) and (4), (5) and (6) replicate the same specifications considering the adoption of AM and IIoT, respectively. Results for both the main and the moderated relationships are qualitatively unchanged across specifications reported in Table 4 as compared to the main results in Table 3, however the estimates presented in columns (2), (4) and (6) of Table 4 highlight relationships of different magnitude with TFP growth, depending on the specific technology.

Table 4 around here

2.5.2. Quantitative importance of the estimated effects

In this Section, we focus on the interpretation of the estimated coefficients for the specifications just presented and on their quantitative importance.

Figure 1 around here

The average marginal effect of AMT adoption on TFP growth rates across all countries and sectors in our sample computed as $\alpha_3 + \alpha_4 \times \overline{lnDTF}$ is positive (i.e. $0.329 - 0.313 \times 0.899 = 0.047$), based on estimates from column (7) of Table 3. To get a more detailed view, Figure 1 plots the marginal effects of AMT adoption, considering heterogeneity across countries by computing marginal effects for each country-sector pair. The box-plot graph shows, for each country, the mean, the median, the interquartile range and the upper and lower adjacent values (excluding outliers).

Between 2009 and 2019, imports of AMT-related technologies had a positive effect on TFP growth in many sectors and countries in our sample. In 5 out of 14 countries (i.e. Germany, the UK, France, Italy and Spain), productivity growth has been boosted by imports of AMTs in virtually all manufacturing industries. In the Netherlands, about 75% of the sector-year distribution experience positive gains, together with just more than 50% of the distribution for Austria, Belgium and Sweden. Conversely, in Finland and Czech Republic, more than 50% of the sector-year distribution experience a negative effect on TFP growth rates. Denmark, Portugal and Slovakia are the European countries less able to harness benefits from the adoption of the three AMTs we consider, with about 75% of sector-year observations showing a negative effect on TFP growth.[32]

In quantitative terms, more AMT-advanced countries like Germany, the UK, France and Italy experienced a positive average (black dots) marginal effects across all manufacturing industries ranging between +0.1 and +0.18 percentage points (pp) associated with a 10% increase in

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[32] While such result may be related to the yet mentioned lack of necessary conditions (e.g. a certain level of absorptive capacity) in the case of Slovakia and, to a certain extent, Portugal, the findings for Denmark may relate to the sectoral composition of the country, with a small and decreasing share of manufacturing as compared to services (similarly to other Nordic countries in our sample, i.e. Sweden and Finland). With this respect, we acknowledge that our analysis of the *import-technology transfer-productivity growth* is conditional on the local specific industrial structure.

AMT adoption. Conversely, Portugal and Slovakia seems to have suffered a negative average marginal effect deriving from AMT adoption, mild in the case of Portugal (i.e. about –0.024 pp), more severe for Slovakia (i.e. about –0.062 pp).

Figure 2 explores differences in the average marginal effect of adopting each AMT singularly (i.e. AIRs, AM and IIoT) on TFP growth, based on estimates from columns (2), (4) and (6) of Table 4. Decomposing the aggregate measure helps identifying which technology of the 4IR has contributed more – on average across manufacturing industries of European countries – to productivity growth between 2009 and 2019. Our estimates highlight that a 10% increase in the adoption of AIRs resulted, on average, in about +0.194 pp rise in TFP growth (black dot), while the same increase in AM adoption spurred a mean growth of about +0.308 pp. The lower contribution we estimate is associated with IIoT adoption (i.e. +0.062 pp, on average). In the case of AIRs and IIoT, the estimated marginal effects are positive for the large majority of the country-sector distribution (i.e. more than 75%), although productivity gains from the former spans over a larger positive range (i.e. up to about +0.7), while those associated with the latter are much lower (i.e. only up to about +0.22 pp). Most strikingly, our results highlight that TFP growth rates in manufacturing industries of the analysed European countries are mostly boosted by AM adoption, as virtually no country-sector pair experience a negative marginal effect, the bottom percentiles of the distribution experience moderate positive marginal effects and TFP gains above the 25th percentile of the distribution range between +0.23 and +0.55 pp.

Our results on AIR and IIoT adoption are on average more conservative, but in line with evidence from more comparable studies Graetz and Michaels (2018) and Edquist et al. (2019). To the best of our knowledge, so far there is no evidence on the relationship between AM adoption and productivity measures and this work represents the first attempt of quantifying AM contribution to TFP growth.

Figure 2 around here

In Figure 3, we further delve into the heterogeneity of effects associated with each different AMT by plotting marginal effects for the European countries in our sample. In the case of AIRs and IIoT, most countries enjoy net TFP gains from their adoption above the 25th percentile of the distribution. Only Portugal and Slovakia have a consistent portion of the distribution (i.e. about 50% or more) experiencing negative marginal effects of TFP growth. However, TFP gains and losses from IIoT adoption spans over a narrower range compared to that resulting from AIR adoption, reflecting the pattern seen in Figure 2. Similarly, the insight presented here on AM adoption is in line with that discussed above: almost all countries and sectors experience positive marginal effects (except the bottom percentiles of the Slovak distribution).

To conclude, findings presented in Figure 3 suggest that AM adoption spurs a more homogeneous positive effect on productivity growth across countries and manufacturing sectors, while the effect of AIRs and IIoT is positive for most (if not all) sectors in more advanced European countries and negative in many industries in countries lagging behind the frontier. The latter effect is generally smaller in magnitude in the case of IIoT, according to our findings.

Figure 3 around here

2.5.3. Robustness checks

In this Section, we address different econometric issues, which might affect our empirical strategy.

Serial correlation: The first concern might relate with the effect of AMTs on TFP growth rates being overestimated because firms operating within sectors in our sample might import, invest in, and adopt more AMTs in periods characterised by a faster productivity growth. Since our specifications in Tables 3 and 4 highlight a strong correlation between our measures proxying the AMT adoption and TFP growth, we need to be cautious in interpreting our results as causal, as we cannot rule out simultaneity bias and reverse causality. The relevant assumption needed here is that lagged values of AMT adoption should be predetermined to TFP growth in equation (5) (i.e. $E\left(AMT_{ijt-1}, \varepsilon_{ijt}\right) = 0$), while current shocks on productivity growth are allowed to feed back to both current and future values of AMT adoption (i.e. $E\left(AMT_{ijt+s}, \varepsilon_{ijt}\right) \neq 0, s \geq 0$). Such condition could be violated if, for example, firms would be able to predict a positive shock on TFP one period in advance and be instantly able to increase their investments in AMTs. In this scenario, the condition $E\left(AMT_{ijt-1}, \varepsilon_{ijt}\right) = 0$ would be violated and residuals in equation (5) would result being serially correlated.

Furthermore, since our empirical model is designed as an ECM – thus capturing the long-run (cointegrating) relationship between TFP growth and our explanatory variables – testing the presence of serial correlation in the residuals (i.e. stationarity) is equivalent to a cointegration test.

We test each specification for the presence of first-order serial correlation in the residuals by using Born and Breitung (2014) version of the Lagrange Multiplier (LM) test, which allows for bias correction in fixed effect panel data models with relatively short T periods like ours. We report *p*-values of the test at the bottom of each specification in Tables 3 and 4.[33] *p*-values are always above the critical value for the test of 0.05, thus suggesting our model not to be affected by serial correlation. In addition, we formally tested for the presence of unit roots in our data and we tested the long-run cointegrating relationship among the variables included in our model by using the appropriate tests. Finally, to further address reverse causality concerns, we estimated the model in equation (5) using the (System-)GMM estimator, which provided confirmatory results.[34]***Aggregate AMT variables:*** Our main explanatory variables capturing overall AMT adoption and the adoption

[33] We report results of the LM test for the presence of first-order serial correlation in the residuals also at the bottom of Tables B1, B2, B3 and B4 in Appendix B.
[34] Further detail on the tests and GMM model's results are available upon request.

AIRs, AM and IIoT at the sector level are built as exposure measures, in the spirit of Acemoglu and Restrepo (2020), by accounting for the existing linkages between aggregate AMT imports and sectoral trade patterns. Despite these variables should proxy sufficiently well true sectoral imports of AMTs, not otherwise available, their construction is based on the assumption that each industry adopts AMT in the same proportion as it uses AMT-related inputs sourced from the 2-digit sector producing each specific AMT from every other country. To provide further robustness to our main results, we relax this assumption and use observed AMT imports at country level as a measure of adoption.

We estimate specifications of the model described in equation (5) in which our AMT adoption variable is allowed to vary only across countries and time. This means that differently from our main results, these estimates should be interpreted only as the average relationship between AMT adoption and TFP growth across countries. Table B1 in Appendix B presents our estimates using aggregate AMT adoption and replicating specifications in Table 3 and 4. Overall, Table B1 confirms our main findings: results for both our main AMT adoption variables and other variables included in the model are qualitatively unchanged and statistically robust.

Alternative TFP growth measure: In our econometric analysis we account for two main factors which might lead to deviations from real patterns when measuring TFP growth (i.e. differences in hours worked and skill composition). At the same time, we acknowledge that there are other potential sources of measurement error which might affect the measurement of TFP growth rates. In order to provide robustness the methodology we adopted to measure TFP growth (Caves et al., 1982a;b) and to our main results by using an alternative approach, we use data on TFP growth rates provided by EU KLEMS[35] to measure our dependent variable (ΔlnA_{ijt}) and one of the explanatories (i.e. the contemporaneous TFP growth at the frontier, ΔlnA_{Fjt}). Table B2 in

[35] Computed following a different growth accounting approach as described Stehrer et al. (2019).

Appendix B reports estimates comparable to that in Table 3 and 4, using EU KLEMS's TFP growth measure: our main results are robust to the use of this alternative measure.

Unweighted regressions: Our main results are estimated through WLS-FE (i.e. using the within-groups estimator). We use industry-level shares of value added in total economy to account for the fact that manufacturing industries might have different size and relative weight when compared across countries, according to the local industrial structure. Coherently, in our model, AMT adoption might have a relatively more important role in some countries and sectors, depending on their relative importance in the whole economy.

To further test the robustness of our main results, in Tables B3 and B4 in Appendix B, we report estimates from unweighted regressions, estimated through OLS-FE. In so doing, we test the less restrictive assumption that all sectors have the same relative weight across countries. Table B3 shows results comparable to those reported in Table 3 and 4, while Table B4 shows results obtained using aggregate AMT adoption variables (i.e. comparable to those in Table B1). Our main findings are robust to this further check.

2.6. Discussion and conclusions

Total factor productivity has been stagnating across European economies ever since the second half of the 90s and throughout the early 2000s as a result of the inability of European countries to harness the benefits of investments R&D, human capital accumulation and the diffusion of ICTs. (Mc Morrow et al., 2008). Although we can still find evidence of β-convergence and σ-convergence[36] within specific manufacturing sectors, economic convergence in manufacturing as a whole has been hampered by institutional factors (e.g. weak policy), existing structural rigidities

[36] β-convergence occurs when TFP rises faster in countries far from the technological frontier than in countries closer to it, i.e. technological laggards experiencing catch-up; σ-convergence refers to the reduction of the sample dispersion (i.e. standard deviation) of relative TFP levels across countries over time.

and the economic downturns observed in Europe after the 2008 global financial crisis (ECB, 2015; Bergeaud et al., 2016; Eurofound, 2020), culminating in 2020 with the Covid-19 pandemic. This evidence signs a clear break with the pattern of TFP growth and convergence observed in several empirical works looking at earlier decades, i.e. between the 70s and early 90s (e.g. Griffith et al., 2004; Cameron et al., 2005).

This study investigates to what extent the adoption of AMTs could contribute to end this pattern of sluggish productivity growth. In line with other recent works (e.g. Venturini, 2022) our results suggest that AMTs of the I4.0 wave could play an important role in the long run to reverse the observed productivity growth stagnation. However, we find that gains related to the rising adoption of embodied AMT are unevenly distributed across Europe, with more technologically advanced countries benefitting more, while technological laggards lack enough absorptive capacity and technological capabilities to harness the related productivity gains. For instance, one of the most advanced European economies, Germany, is a leading actor in AMTs (UNIDO, 2018; Martinelli et al., 2021). Conversely, other European countries like Portugal and Slovakia – despite showing not negligible adoption levels, as seen in Chapter 1 – still lag behind in the adoption of enabling technologies, in the development of 4IR-related competences and policies (Ciffolilli and Muscio, 2018; Corradini et al., 2021), thus hampering productivity gains potentially deriving from investments in AMTs. In turn, this pattern may contribute to widen the productivity gap between more advanced and laggard countries, ultimately increasing inequalities.

We also highlight some heterogeneity across technologies. Our results on AIRs and IIoT are in line with previous evidence from comparable works (e.g. Graetz and Michaels, 2018; Edquist et al., 2019), although our estimates point at more conservative average productivity gains associated with the adoption of these technologies. At the same time, to the best of our knowledge, our work provides a first quantification of productivity gains deriving from the adoption of AM. Our results suggest such gains to be positive and quantitatively important as much as that coming from AIRs.

The adoption of AIRs and AM seem to bring higher and, in the case of AM, more evenly distributed contributions to TFP growth rates across European countries studied here, while gains spurred from IIoT adoption are suggested to be lower and even more concentrated in the most advanced economies. Possible reasons behind these heterogeneous results might relate with either the level of technological maturity associated with different AMTs or with the differences in the associated investment costs.[37] In fact, also Chiacchio et al. (2019) and Martinelli et al. (2021) discuss how high investment costs and lack of sufficient absorptive capacity remain two of the main factors limiting the adoption of these technologies, especially for SMEs, while large companies (mostly multinationals) are better suited to efficiently adopt AMTs.

Another barrier to the adoption of AMTs is the lack of precise and unified standards (above all, technical) across countries and industries (Martinelli et al., 2021), enabling interoperability between different technologies. While leading AMT producers sponsor proprietary standards, adopters ask for more open and universal standards like the Reference Architectural Model Industrie 4.0 (Schweichhart, 2017) or alternatives emerging under the supervision of international bodies like the International Telecommunication Union (ITU) or the ISO. This issue is particularly important for IIoT, given its crucial and infrastructural role within the I4.0 architecture (Atzori et al., 2010).

This leads directly to the debate on whether the bulk of policy initiatives put in place by European countries over the last decade has led to significant results in boosting the diffusion of such advances technologies. Surely, developing policy incentives fostering innovation and adoption of AMTs across SMEs would bring more widespread benefits across European economies, given

[37] According to estimates from Acemoglu and Restrepo (2020), the average price of AIR ranges between 50,000 and 100,000 USD, while the average price for an industrial AM machine is between 200,000 and 250,000 USD according to our computations based on data from all major AM producers worldwide and reported by Senvol. Senvol's data are available at http://senvol.com/machine-search/. Concerning IIoT, the total cost of deployment greatly varies depending on the sector and on the scale of the project. Using total cost of ownership (TCO) calculator for IoT applications by NOKIA, we estimate cost for a medium-sized factory to range between 1.6mln and 0.8mln USD. NOKIA's IoT TCO calculator is available at https://pages.nokia.com/T007K9-Compare-Wireless-Critical-Connectivity-Options.

the major role played by this class of firms: a more integrated approach across different AMTs must go along with dedicated incentives and approaches for individual technologies, which are more exposed to inefficient implementation. At the same time, these needs to be paired with a broader recognition among policymakers that integrating economic incentives with local dissemination of competencies and specific I4.0 knowledge content, and coordinated national and regional policies across the continent (i.e. following a common framework and standards) would create the potential for larger gains. The latter realising not just in terms of productivity growth but also in terms of aggregate economic growth and better employment conditions in the decades ahead.

To sum up, this Chapter adds to other recent contributions in the literature proposing a precise measure that uses fine-grained information (8-digit product codes) on the import of capital and intermediate goods related to AMTs. Our methodology allows the highest precision in the identification of such product codes, removing potential noise brought by all unrelated product codes otherwise considered when looking at more aggregated trade data (e.g. at the 4- or 6-digit level). The resulting measures enable us to study how these technologies affect TFP growth and technological convergence when actual adoption data are not publicly available. By doing so, our contribution is twofold: on the one hand, we provide new robust measures to study the adoption of multiple AMTs; on the other hand, we analyse the related implications for productivity growth, providing insight of the effects of different technologies (one of which, AM, has not been investigated before) across manufacturing sectors of European countries.

Our findings should be considered under the light of the caveats that characterise our analysis: as trade data for highly disaggregated products are not directly available at the industry level, we can only link them to the importing sector by means of input-output tables, i.e. by creating proxies of sectoral adoption. Furthermore, although we provide several econometric checks to our model of catching-up (e.g. testing for cointegration), our relatively short panel poses limits to the use of more sophisticated and robust econometric techniques accounting for cross-sectional dependence, and enabling a robust analysis of the long run effects of adopting AMTs. Furthermore, our findings highlight that ex-ante (i.e. prior to 2009) more advanced countries, like Germany, are those benefitting the most from AMT adoption. Arguably, such pre-existing trend may have led firms in more advanced economies to massively adopt AMTs to further sustain and increase productivity growth, making the evaluation of the net contribution of AMT adoption to productivity growth hard to quantify. With respect to such potential reverse causality issue we provide reassuring evidence, although we acknowledge the limitations of our work and leave a more accurate evaluation for future research.

To conclude, as our import-based, sectoral measure of AMT adoption provides robust results which are in line with prior findings in the literature, it could be used to delve into several possible avenues for future research. Since import data at the fine-grained product level are available for a growing number of countries and for long and constantly updated time series, our methodology is scalable and can be used to analyse larger samples of countries and industries. Furthermore, international transaction-level data are available and increasingly accessible in many countries. This can allow an extension of this analysis to the firm level, possibly link adoption of AMTs to firm productivity, international competitiveness, offshoring and reshoring or employment dynamics and composition.

Further research in this area might investigate the role of different contextual conditions in explaining why we witness heterogeneous results in the way European countries benefits from adopting AMTs. As discussed in above, following the wave of I4.0 policy initiatives introduced by European countries during latest years, incentives targeted more towards some technologies than others might have had a role in explaining the differences documented here. Another interesting direction of research should investigate the underlying mechanisms at place, which might either help or hinder TFP growth associated with the adoption of AMTs, such as the degree of capital/labour complementarity featured by each of these technologies.

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2.8. Tables and Figures

Table 1. Description of the variables

Variable Label	Variable Description
ΔlnA_{ijt}	Growth rate of total factor productivity (TFP)
ΔlnA_{Fjt}	Growth rate of total factor productivity (TFP) of the frontier country
$lnDTF_{ijt-1}$	1-year lagged distance from the technology frontier
RD_{ijt-1}	1-year lagged ratio between sectoral stock of R&D investments and sectoral value added
M_{ijt-1}	1-year lagged ratio between sectoral imports from the rest of the world and sectoral value added
ICT_{ijt-1}	1-year lagged ratio between sectoral stock of ICT investments and sectoral value added
AMT_{ijt-1}	1-year lagged ratio between sectoral stock of advanced manufacturing technology imports (AIRs + AM + IIoT) and sectoral value added
AIR_{ijt-1}	1-year lagged ratio between sectoral stock of advanced industrial robot imports (AIRs) and sectoral value added
AM_{ijt-1}	1-year lagged ratio between sectoral stock of additive manufacturing imports (AM) and sectoral value added
$IIoT_{ijt-1}$	1-year lagged ratio between sectoral stock of industrial internet of thing imports (IIoT) and sectoral value added

Notes: Data on aggregate imports comes from Eurostat's Comext data sets; data on sectoral variables comes from EU KLEMS, STAN, ANBERD and BTDIxE data sets.

Table 2. Summary statistics of the main variables

	ΔlnA_{ijt}	ΔlnA_{Fjt}	$lnDTF_{ijt-1}$	RD_{ijt-1}	M_{ijt-1}	ICT_{ijt-1}	AMT_{ijt-1}	AIR_{ijt-1}	AM_{ijt-1}	$IIoT_{ijt-1}$
Mean	0.0082	0.0165	0.8992	0.0599	4.2768	0.0973	0.2436	0.3438	0.3583	0.2368
SD	0.0610	0.0844	0.3298	0.0938	24.2155	0.3909	0.2212	0.2394	0.4750	0.2190
Max	0.8993	0.6955	2.0327	1.8348	981.4395	15.6755	1.4864	2.7346	6.0443	1.4432
Median	0.0035	0.0064	0.9295	0.0299	2.1856	0.0648	0.1692	0.2667	0.2068	0.1637
Min	-0.4817	-0.1321	0.1303	-0.0043	0.2567	0.0003	0.0007	0.0013	0.0005	0.0007

Notes: Sample size for all variables is 1,760 observations over the 2009–2019 period. ΔlnA_{ijt}, ΔlnA_{Fjt} and $lnDTF_{ijt-1}$ variables include controls for differences in hours worked and skill composition.

Table 3. WLS-FE estimates: relationship between sectoral AMT adoption and TFP growth

	1995-2019	1995-2008	2009-2019					
ΔlnA_{ijt}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔlnA_{Fjt}	0.163***	0.199***	0.257***	0.258***	0.258***	0.021	0.029	0.299***
	(0.030)	(0.047)	(0.036)	(0.036)	(0.035)	(0.050)	(0.057)	(0.092)
$lnDTF_{ijt-1}$	0.102***	0.167***	0.243***	0.244***	0.238***	0.207***	0.223***	0.311***
	(0.012)	(0.026)	(0.036)	(0.036)	(0.036)	(0.029)	(0.037)	(0.042)
RD_{ijt-1}	0.177***	0.134***	0.282***	0.282***	0.243***	0.892***	1.236***	1.274***
	(0.039)	(0.045)	(0.071)	(0.071)	(0.067)	(0.173)	(0.250)	(0.216)
$(RD \times lnDTF)_{ijt-1}$	-0.248***	-0.175**	-0.965***	-0.970***	-0.849***	-0.874***	-1.150***	-1.228***
	(0.070)	(0.075)	(0.237)	(0.239)	(0.235)	(0.195)	(0.254)	(0.240)
M_{ijt-1}	-0.001**	0.004	-0.003***	-0.003***	-0.004***	-0.005***	-0.010***	-0.009***
	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)
$(M \times lnDTF)_{ijt-1}$	0.002**	-0.004	0.006***	0.006**	0.007***	0.005***	0.008***	0.009***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
ICT_{ijt-1}	0.052**	0.045	0.197***	0.189***	0.216***	0.181	0.491**	0.465**
	(0.025)	(0.037)	(0.061)	(0.058)	(0.045)	(0.129)	(0.234)	(0.198)
$(ICT \times lnDTF)_{ijt-1}$	-0.083*	-0.046	-0.387***	-0.379***	-0.400***	-0.157	-0.526*	-0.568**
	(0.046)	(0.055)	(0.143)	(0.137)	(0.114)	(0.163)	(0.279)	(0.262)
AMT_{ijt-1}				-0.007	0.292***	0.206***	0.329***	0.311***
				(0.029)	(0.057)	(0.059)	(0.102)	(0.089)
$(AMT \times lnDTF)_{ijt-1}$					-0.544***	-0.247***	-0.313***	-0.323***
					(0.096)	(0.059)	(0.089)	(0.087)
TFP controls	-	-	-	-	-	s	h,s	h,s,2c
Observations	4,048	2,291	1,757	1,757	1,757	1,757	1,760	1,760
R-squared (within)	0.488	0.577	0.423	0.422	0.439	0.324	0.305	0.339
Serial correlation (*p*-value)	0.264	0.302	0.328	0.337	0.401	0.093	0.143	0.282

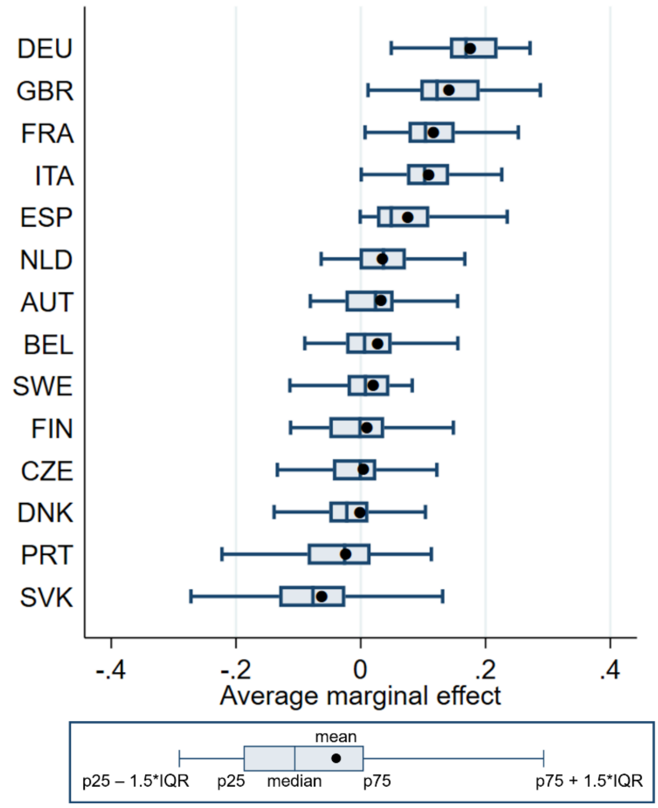
Notes: Robust standard errors in parentheses. All regressions include a full set of time and country-industry dummies (within-group estimator) and are estimated through WLS using value added shares in total economy as weights. Serial correlation is LM test for the presence of first-order serial correlation in the residuals. TFP controls are h: hours worked; s: skill composition; 2c: two-country frontier. The dependent variable is the growth rate of TFP. ΔlnA_{Fjt} is the contemporaneous growth rate of TFP for the frontier; $lnDTF_{ijt-1}$ is the lagged distance from the technology frontier; RD_{ijt-1} is the lagged sectoral R&D intensity; M_{ijt-1} is lagged sectoral import intensity; ICT_{ijt-1} is lagged sectoral ICT investments; AMT_{ijt-1} is lagged sectoral adoption of advanced manufacturing technologies. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 4. WLS-FE estimates: relationship between sectoral AIR, AM and IIoT adoption measures and TFP growth

ΔlnA_{ijt}	(1)	(2)	(3)	(4)	(5)	(6)
ΔlnA_{Fjt}	0.032	0.030	0.029	0.034	0.029	0.030
	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)	(0.057)
$lnDTF_{ijt-1}$	0.191***	0.202***	0.188***	0.209***	0.197***	0.219***
	(0.035)	(0.037)	(0.032)	(0.033)	(0.035)	(0.039)
RD_{ijt-1}	1.270***	1.323***	1.208***	1.260***	1.294***	1.254***
	(0.245)	(0.254)	(0.242)	(0.237)	(0.248)	(0.250)
$(RD \times lnDTF)_{ijt-1}$	-1.180***	-1.226***	-1.139***	-1.162***	-1.210***	-1.163***
	(0.249)	(0.256)	(0.245)	(0.235)	(0.252)	(0.254)
M_{ijt-1}	-0.009***	-0.011***	-0.005*	-0.008***	-0.009***	-0.010***
	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)	(0.003)
$(M \times lnDTF)_{ijt-1}$	0.007***	0.010***	0.004	0.006**	0.008***	0.008***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
ICT_{ijt-1}	0.435**	0.538**	0.189	0.357**	0.464**	0.493**
	(0.215)	(0.247)	(0.165)	(0.171)	(0.195)	(0.198)
$(ICT \times lnDTF)_{ijt-1}$	-0.481*	-0.589**	-0.250	-0.445*	-0.515**	-0.530**
	(0.265)	(0.296)	(0.213)	(0.234)	(0.249)	(0.247)
AIR_{ijt-1}	0.267*	0.788*				
	(0.160)	(0.424)				
$(AIR \times lnDTF)_{ijt-1}$		-0.661*				
		(0.401)				
AM_{ijt-1}			0.024	0.596***		
			(0.017)	(0.193)		
$(AM \times lnDTF)_{ijt-1}$				-0.320***		
				(0.109)		
$IIoT_{ijt-1}$					0.081**	0.248***
					(0.034)	(0.076)
$(IIoT \times lnDTF)_{ijt-1}$						-0.207***
						(0.068)
TFP controls	h,s	h,s	h,s	h,s	h,s	h,s
Observations	1,760	1,760	1,760	1,760	1,760	1,760
R-squared (within)	0.291	0.298	0.287	0.309	0.295	0.302
Serial correlation (*p*-value)	0.309	0.162	0.878	0.863	0.224	0.132

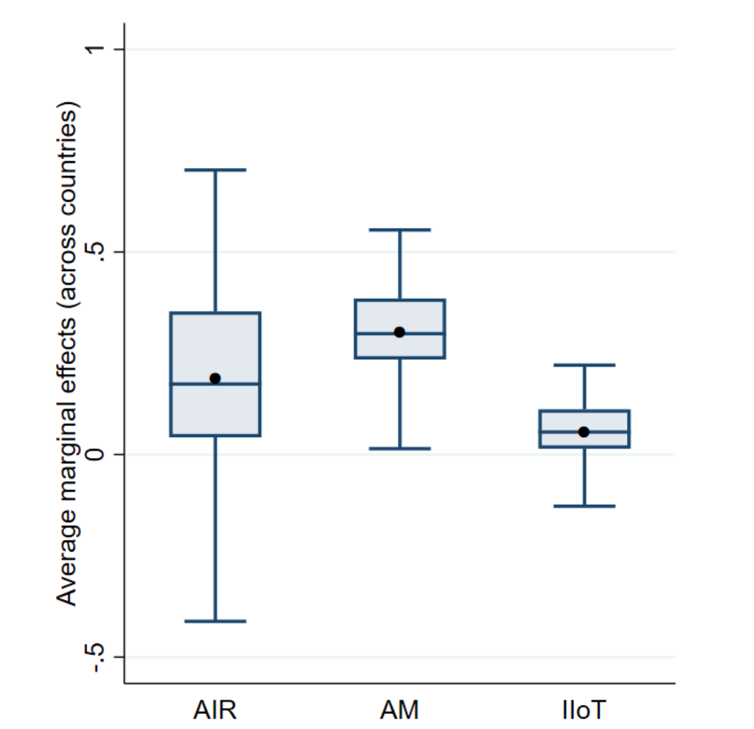
Notes: Robust standard errors in parentheses. All regressions include a full set of time and country-industry dummies (within-group estimator) and are estimated through WLS using value added shares in total economy as weights. Serial correlation is LM test for the presence of first-order serial correlation in the residuals. TFP controls are h: hours worked; s: skill composition. The dependent variable is the growth rate of TFP. ΔlnA_{Fjt} is the contemporaneous growth rate of TFP for the frontier; $lnDTF_{ijt-1}$ is the lagged distance from the technology frontier; RD_{ijt-1} is the lagged sectoral R&D intensity; M_{ijt-1} is lagged sectoral import intensity; ICT_{ijt-1} is lagged sectoral ICT investments; AIR_{ijt-1} is lagged sectoral adoption of advanced industrial robots; AM_{ijt-1} is lagged sectoral adoption of additive manufacturing; $IIoT_{ijt-1}$ is lagged sectoral adoption of industrial internet of things. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Figure 1. Marginal effect of AMT adoption on TFP growth rates, by country



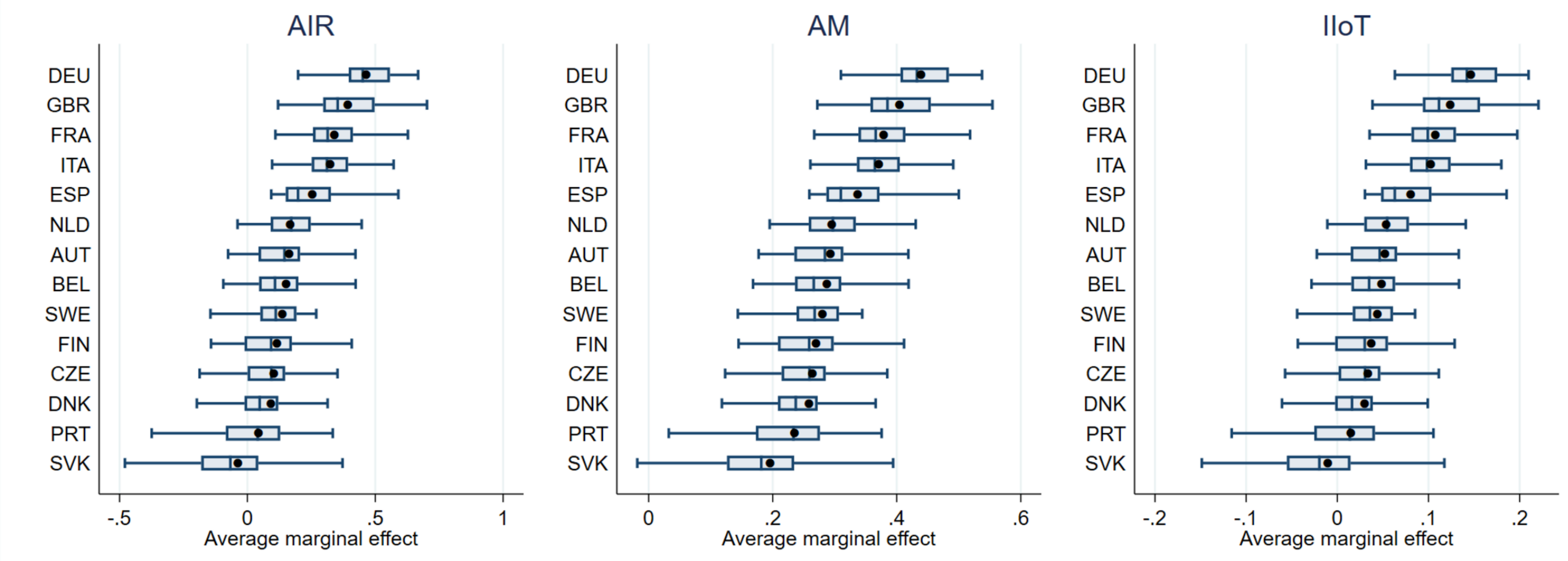
Notes: Authors' own estimates. Average marginal effects of AMT adoption on TFP growth rates computed as $\alpha_3 + \alpha_4 \times lnDTF_{ijt}$, using $\alpha_3 = 0.329$ and $\alpha_4 = -0.313$ from column (7) of Table 3. The black dot indicates the mean value across sectors; the line inside the box indicates the median sector; the box shows the interquartile range (IQR); the extreme values are the lower adjacent value (25th %ile – 1.5*IQR) on the left and the upper adjacent value (75th %ile + 1.5*IQR) on the right; outliers are excluded.

Figure 2. Marginal effect of AIR, AM and IIoT adoption on TFP growth rates



Notes: Authors' own estimates. Average marginal effects of AIR, AM and IIoT adoption on TFP growth rates computed as $\alpha_3 + \alpha_4 \times lnDTF_{ijt}$, using $\alpha_3^{AIR} = 0.788$ and $\alpha_4^{AIR} = -0.661$ from column (2) of Table 4, $\alpha_3^{AM} = 0.596$ and $\alpha_4^{AM} = -0.320$ from column (4) of Table 4, and $\alpha_3^{IIoT} = 0.248$ and $\alpha_4^{IIoT} = -0.207$ from column (6) of Table 4. The black dot indicates the mean value across sectors; the line inside the box indicates the median sector; the box shows the interquartile range (IQR); the extreme values are the lower adjacent value (25^{th} %ile – 1.5*IQR) on the left and the upper adjacent value (75^{th} %ile + 1.5*IQR) on the right; outliers are excluded.

Figure 3. Marginal effect of AIR, AM and IIoT adoption on TFP growth rates, by country



Notes: Authors' own estimates. Average marginal effects of AIR, AM and IIoT adoption on TFP growth rates computed as $\alpha_3 + \alpha_4 \times lnDTF_{ijt}$, using $\alpha_3^{AIR} = 0.788$ and $\alpha_4^{AIR} = -0.661$ from column (2) of Table 4, $\alpha_3^{AM} = 0.596$ and $\alpha_4^{AM} = -0.320$ from column (4) of Table 4, and $\alpha_3^{IIoT} = 0.248$ and $\alpha_4^{IIoT} = -0.207$ from column (6) of Table 4. The black dot indicates the mean value across sectors; the line inside the box indicates the median sector; the box shows the interquartile range (IQR); the extreme values are the lower adjacent value (25th %ile – 1.5*IQR) on the left and the upper adjacent value (75th %ile + 1.5*IQR) on the right; outliers are excluded.

2.9. Appendix A: Alternative TFP measures

We compute different TFP measures, correcting for two different characteristics which may be sources of cross-country differences: (a) we adjust the measure of labour inputs for differences in hours worked; (b) we adjust the measure of labour inputs for differences in the skill composition of the workforce.

Differences in the skill composition of the workforce: We control for differences in the quality of the labour inputs. Using a similar index to that proposed by Griffith et al. (2004), we express employment in each country, sector, and year as:

$$L_{ijt} = \left(E_{ijt} \times H\_h_{ijt}\right)^{W\_h_{ijt}} \times \left(E_{ijt} \times H\_m_{ijt}\right)^{W\_m_{ijt}} \times \left(E_{ijt} \times H\_l_{ijt}\right)^{W\_l_{ijt}}$$

where E_{ijt} denotes the number of people employed in sector j of country i, at time t; H_h_{ijt}, H_m_{ijt} and H_l_{ijt} denote shares of hours worked by employees with high, medium and low education level across manufacturing sectors, respectively; W_h_{ijt}, W_m_{ijt} and W_l_{ijt} denote shares of workers with high, medium and low education level in the wage bill across manufacturing sectors, respectively. Since our analysis only covers manufacturing industries and information on the skill composition of the workforce in EU KLEMS dataset are available only at the 1-digit level of sectoral aggregation (i.e. the whole manufacturing), shares of hours worked and wages by employees with different education are proportionally derived by weighting 1-digit manufacturing data on composition by the share of hours worked in each 2-digit manufacturing industry.

Differences in hours worked: Our baseline TFP measures uses the number of people employed in sector j of country i as a measure of the labour input in the production function. The first adjustment we make is using the number of hours worked by people employed. This is a sector-specific adjustment.

2.10. Appendix B: Additional Tables

Table B1. WLS-FE estimates: relationship between aggregate AMT adoption measures and TFP growth

ΔlnA_{ijt}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ΔlnA_{Fjt}	0.257***	0.332***	0.040	0.040	0.354***	0.028	0.035	0.029	0.032	0.029	0.040
	(0.036)	(0.038)	(0.046)	(0.053)	(0.091)	(0.057)	(0.053)	(0.058)	(0.055)	(0.058)	(0.053)
$lnDTF_{ijt-1}$	0.244***	0.307***	0.246***	0.259***	0.358***	0.183***	0.237***	0.183***	0.221***	0.183***	0.258***
	(0.036)	(0.040)	(0.032)	(0.040)	(0.045)	(0.032)	(0.037)	(0.032)	(0.035)	(0.032)	(0.040)
RD_{ijt-1}	0.283***	0.248***	0.855***	1.168***	1.204***	1.239***	1.148***	1.251***	1.266***	1.262***	1.173***
	(0.071)	(0.064)	(0.153)	(0.224)	(0.195)	(0.245)	(0.227)	(0.243)	(0.228)	(0.242)	(0.226)
$(RD \times lnDTF)_{ijt-1}$	-0.969***	-0.816***	-0.793***	-1.046***	-1.122***	-1.164***	-1.041***	-1.176***	-1.159***	-1.185***	-1.051***
	(0.244)	(0.233)	(0.166)	(0.223)	(0.208)	(0.247)	(0.227)	(0.247)	(0.226)	(0.247)	(0.224)
M_{ijt-1}	-0.003***	-0.002***	-0.003***	-0.005***	-0.005***	-0.006***	-0.007***	-0.006***	-0.006***	-0.006***	-0.005***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$(M \times lnDTF)_{ijt-1}$	0.006***	0.006***	0.004***	0.006***	0.006***	0.007***	0.008***	0.007***	0.008***	0.007***	0.006***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ICT_{ijt-1}	0.196***	0.109**	0.060	0.183	0.180*	0.224	0.345**	0.256*	0.255**	0.256*	0.182
	(0.060)	(0.048)	(0.070)	(0.117)	(0.108)	(0.150)	(0.138)	(0.147)	(0.126)	(0.144)	(0.118)
$(ICT \times lnDTF)_{ijt-1}$	-0.384***	-0.171	-0.020	-0.209	-0.254	-0.280	-0.419**	-0.310	-0.327*	-0.314	-0.207
	(0.139)	(0.121)	(0.104)	(0.166)	(0.168)	(0.201)	(0.196)	(0.198)	(0.186)	(0.199)	(0.167)
AMT_{it-1}	-0.001	0.093***	0.288***	0.370***	0.401***						
	(0.014)	(0.026)	(0.054)	(0.079)	(0.083)						
$(AMT \times lnDTF)_{ijt-1}$		-0.367***	-0.438***	-0.507***	-0.600***						
		(0.082)	(0.079)	(0.104)	(0.118)						
AIR_{it-1}						-0.038***	0.229***				
						(0.013)	(0.054)				
$(AIR \times lnDTF)_{ijt-1}$							-0.262***				
							(0.051)				
AM_{it-1}								-0.003	0.113***		
								(0.008)	(0.025)		
$(AM \times lnDTF)_{ijt-1}$									-0.155***		
									(0.032)		
$IIoT_{it-1}$										0.006	0.376***
										(0.019)	(0.082)
$(IIoT \times lnDTF)_{ijt-1}$											-0.511***
											(0.106)
TFP controls	-	-	s	h,s	h,s,2c	h,s	h,s	h,s	h,s	h,s	h,s
Observations	1,757	1,757	1,757	1,760	1,760	1,760	1,760	1,760	1,760	1,760	1,760
R-squared (within)	0.422	0.457	0.376	0.359	0.409	0.289	0.353	0.285	0.323	0.285	0.357
Serial correlation (*p*-value)	0.328	0.453	0.153	0.114	0.130	0.781	0.327	0.563	0.260	0.496	0.116

Notes: Robust standard errors in parentheses. All regressions include a full set of time and country-industry dummies (within-group estimator) and are estimated through WLS using value added shares in total economy as weights. Serial correlation is LM test for the presence of first-order serial correlation in the residuals. TFP controls are h: hours worked; s: skill composition; 2c: two-country frontier. The dependent variable is the growth rate of TFP. ΔlnA_{Fjt} is the contemporaneous growth rate of TFP for the frontier; $lnDTF_{ijt-1}$ is the lagged distance from the technology frontier; RD_{ijt-1} is the lagged sectoral R&D intensity; M_{ijt-1} is lagged sectoral import intensity; ICT_{ijt-1} is lagged sectoral ICT investments; AMT_{it-1} is lagged aggregate adoption of advanced manufacturing technologies; AIR_{it-1} is lagged aggregate adoption of advanced industrial robots; AM_{it-1} is lagged aggregate adoption of additive manufacturing; $IIoT_{it-1}$ is lagged aggregate adoption of industrial internet of things. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table B2. WLS-FE estimates: relationship between sectoral AMT adoption measures and TFP growth using alternative measure from EU KLEMS

	1995-2019	1995-2008	2009-2019								
ΔlnA_{ijt}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
ΔlnA_{Fjt}	0.337***	0.416***	0.376***	0.349***	0.355***	0.308***	0.375***	0.361***	0.388***	0.350***	0.354***
	(0.089)	(0.096)	(0.059)	(0.069)	(0.069)	(0.073)	(0.069)	(0.061)	(0.063)	(0.069)	(0.070)
$lnDTF_{ijt-1}$	0.414***	0.538***	0.692***	0.719***	0.813***	0.709***	0.770***	0.590***	0.875***	0.719***	0.808***
	(0.068)	(0.094)	(0.160)	(0.168)	(0.164)	(0.144)	(0.151)	(0.169)	(0.189)	(0.169)	(0.164)
RD_{ijt-1}	0.900***	0.487***	0.704*	0.756**	0.654*	0.680*	0.633*	0.619	0.590	0.755**	0.652*
	(0.204)	(0.171)	(0.393)	(0.384)	(0.363)	(0.365)	(0.361)	(0.406)	(0.385)	(0.384)	(0.363)
$(RD \times lnDTF)_{ijt-1}$	-1.236***	-0.718***	-0.606	-0.776	-0.560	-0.697	-0.411	-0.229	-0.919	-0.770	-0.545
	(0.352)	(0.259)	(0.982)	(0.944)	(0.951)	(0.911)	(0.954)	(0.991)	(0.964)	(0.945)	(0.952)
M_{ijt-1}	0.022**	0.022**	0.018	0.017	0.016	0.019	0.018	0.013	0.006	0.017	0.016
	(0.009)	(0.009)	(0.016)	(0.015)	(0.012)	(0.015)	(0.014)	(0.015)	(0.012)	(0.015)	(0.012)
$(M \times lnDTF)_{ijt-1}$	-0.020*	-0.026***	-0.016	-0.014	-0.010	-0.017	-0.013	-0.008	0.002	-0.015	-0.010
	(0.010)	(0.009)	(0.028)	(0.028)	(0.021)	(0.028)	(0.024)	(0.026)	(0.022)	(0.028)	(0.021)
ICT_{ijt-1}	0.629***	-0.162	1.078***	0.998***	0.704*	0.998***	0.910**	1.070***	0.952***	1.000***	0.705*
	(0.197)	(0.178)	(0.412)	(0.375)	(0.363)	(0.379)	(0.388)	(0.383)	(0.368)	(0.377)	(0.363)
$(ICT \times lnDTF)_{ijt-1}$	-0.778**	0.270	-2.679***	-2.638***	-1.805**	-2.578***	-2.318**	-2.949***	-2.611***	-2.636***	-1.802**
	(0.315)	(0.243)	(0.933)	(0.889)	(0.871)	(0.887)	(0.911)	(0.911)	(0.873)	(0.890)	(0.869)
AMT_{ijt-1}				0.042	0.341***						
				(0.073)	(0.122)						
$(AMT \times lnDTF)_{ijt-1}$					-1.070***						
					(0.351)						
AIR_{ijt-1}						-0.051	0.126*				
						(0.031)	(0.066)				
$(AIR \times lnDTF)_{ijt-1}$							-0.430**				
							(0.189)				
AM_{ijt-1}								0.104*	0.301***		
								(0.053)	(0.073)		
$(AM \times lnDTF)_{ijt-1}$									-0.396***		
									(0.111)		
$IIoT_{ijt-1}$										0.041	0.338***
										(0.073)	(0.123)
$(IIoT \times lnDTF)_{ijt-1}$											-1.089***
											(0.361)
Observations	3,827	2,227	1,600	1,600	1,600	1,600	1,600	1,600	1,600	1,600	1,600
R-squared (within)	0.951	0.979	0.688	0.777	0.878	0.867	0.746	0.647	0.879	0.756	0.880
Serial correlation (p-value)	0.471	0.396	0.845	0.768	0.576	0.363	0.817	0.609	0.479	0.777	0.579

Notes: Robust standard errors in parentheses. All regressions include a full set of time and country-industry dummies (within-group estimator) and are estimated through WLS using value added shares in total economy as weights. Serial correlation is LM test for the presence of first-order serial correlation in the residuals. Data on TFP growth rate for manufacturing industries in Portugal are missing in EU KLEMS dataset. The dependent variable is the growth rate of TFP. ΔlnA_{Fjt} is the contemporaneous growth rate of TFP for the frontier; $lnDTF_{ijt-1}$ is the lagged distance from the technology frontier; RD_{ijt-1} is the lagged sectoral R&D intensity; M_{ijt-1} is lagged sectoral import intensity; ICT_{ijt-1} is lagged sectoral ICT investments; AMT_{ijt-1} is lagged sectoral adoption of advanced manufacturing technologies; AIR_{ijt-1} is lagged sectoral adoption of advanced industrial robots; AM_{ijt-1} is lagged sectoral adoption of additive manufacturing; $IIoT_{ijt-1}$ is lagged sectoral adoption of industrial internet of things. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table B3. OLS-FE estimates: relationship between sectoral AMT adoption measures and TFP growth

ΔlnA_{ijt}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔlnA_{Fjt}	0.029	0.029	0.032	0.030	0.029	0.033	0.029	0.030
	(0.061)	(0.061)	(0.061)	(0.061)	(0.062)	(0.061)	(0.061)	(0.061)
$lnDTF_{ijt-1}$	0.187***	0.227***	0.197***	0.206***	0.195***	0.215***	0.203***	0.224***
	(0.036)	(0.040)	(0.039)	(0.043)	(0.034)	(0.038)	(0.040)	(0.043)
RD_{ijt-1}	1.361***	1.274***	1.316***	1.354***	1.277***	1.320***	1.336***	1.294***
	(0.318)	(0.327)	(0.309)	(0.327)	(0.300)	(0.305)	(0.317)	(0.324)
$(RD \times lnDTF)_{ijt-1}$	-1.259***	-1.184***	-1.221***	-1.254***	-1.201***	-1.215***	-1.248***	-1.199***
	(0.309)	(0.314)	(0.305)	(0.319)	(0.296)	(0.293)	(0.309)	(0.314)
M_{ijt-1}	-0.009**	-0.010***	-0.009***	-0.011***	-0.005	-0.008**	-0.009***	-0.010***
	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
$(M \times lnDTF)_{ijt-1}$	0.008***	0.009***	0.007***	0.010***	0.004	0.007	0.008***	0.008***
	(0.003)	(0.003)	(0.002)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
ICT_{ijt-1}	0.474*	0.507*	0.450*	0.553*	0.201	0.368*	0.477**	0.505**
	(0.276)	(0.272)	(0.250)	(0.285)	(0.200)	(0.205)	(0.225)	(0.226)
$(ICT \times lnDTF)_{ijt-1}$	-0.524	-0.544*	-0.499	-0.605*	-0.267	-0.459	-0.530*	-0.545*
	(0.336)	(0.323)	(0.308)	(0.342)	(0.257)	(0.281)	(0.289)	(0.282)
AMT_{ijt-1}	0.087	0.338***						
	(0.060)	(0.127)						
$(AMT \times lnDTF)_{ijt-1}$		-0.319**						
		(0.126)						
AIR_{ijt-1}			0.282	0.829*				
			(0.190)	(0.441)				
$(AIR \times lnDTF)_{ijt-1}$				-0.700*				
				(0.396)				
AM_{ijt-1}					0.024	0.609***		
					(0.018)	(0.124)		
$(AM \times lnDTF)_{ijt-1}$						-0.328***		
						(0.071)		
$IIoT_{ijt-1}$							0.084**	0.254***
							(0.038)	(0.093)
$(IIoT \times lnDTF)_{ijt-1}$								-0.210**
								(0.087)
TFP controls	h,s	h,s	h,s	h,s	h,s	h,s	h,s	h,s
Observations	1,760	1,760	1,760	1,760	1,760	1,760	1,760	1,760
R-squared (within)	0.232	0.246	0.232	0.239	0.228	0.251	0.236	0.244
Serial correlation (*p*-value)	0.276	0.147	0.316	0.161	0.868	0.884	0.229	0.134

Notes: Robust standard errors in parentheses. All regressions include a full set of time and country-industry dummies (within-group estimator) and are estimated through OLS. Serial correlation is LM test for the presence of first-order serial correlation in the residuals. TFP controls are h: hours worked; s: skill composition. The dependent variable is the growth rate of TFP. ΔlnA_{Fjt} is the contemporaneous growth rate of TFP for the frontier; $lnDTF_{ijt-1}$ is the lagged distance from the technology frontier; RD_{ijt-1} is the lagged sectoral R&D intensity; M_{ijt-1} is lagged sectoral import intensity; ICT_{ijt-1} is lagged sectoral ICT investments; AMT_{ijt-1} is lagged sectoral adoption of advanced manufacturing technologies; AIR_{ijt-1} is lagged sectoral adoption of advanced industrial robots; AM_{ijt-1} is lagged sectoral adoption of additive manufacturing; $IIoT_{ijt-1}$ is lagged sectoral adoption of industrial internet of things. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table B4. OLS-FE estimates: relationship between aggregate AMT adoption measures and TFP growth

ΔlnA_{ijt}	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔlnA_{Fjt}	0.029	0.040	0.028	0.036	0.029	0.032	0.029	0.040
	(0.062)	(0.056)	(0.062)	(0.057)	(0.062)	(0.060)	(0.062)	(0.056)
$lnDTF_{ijt-1}$	0.190***	0.262***	0.189***	0.240***	0.189***	0.230***	0.190***	0.260***
	(0.036)	(0.045)	(0.035)	(0.042)	(0.036)	(0.040)	(0.036)	(0.045)
RD_{ijt-1}	1.318***	1.184***	1.297***	1.169***	1.311***	1.348***	1.319***	1.188***
	(0.305)	(0.262)	(0.303)	(0.266)	(0.307)	(0.305)	(0.305)	(0.262)
$(RD \times lnDTF)_{ijt-1}$	-1.235***	-1.060***	-1.215***	-1.058***	-1.230***	-1.232***	-1.236***	-1.064***
	(0.302)	(0.250)	(0.298)	(0.257)	(0.304)	(0.293)	(0.302)	(0.251)
M_{ijt-1}	-0.006***	-0.005***	-0.006**	-0.007***	-0.006***	-0.007***	-0.006***	-0.005***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$(M \times lnDTF)_{ijt-1}$	0.007***	0.006***	0.007***	0.008***	0.007***	0.008***	0.007***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ICT_{ijt-1}	0.264	0.185	0.233	0.351**	0.264	0.262*	0.265	0.183
	(0.167)	(0.129)	(0.178)	(0.153)	(0.168)	(0.145)	(0.167)	(0.130)
$(ICT \times lnDTF)_{ijt-1}$	-0.326	-0.211	-0.293	-0.427*	-0.323	-0.340	-0.327	-0.208
	(0.233)	(0.186)	(0.238)	(0.221)	(0.231)	(0.218)	(0.233)	(0.187)
AMT_{it-1}	0.005	0.375***						
	(0.013)	(0.120)						
$(AMT \times lnDTF)_{ijt-1}$		-0.513***						
		(0.158)						
AIR_{it-1}			-0.039***	0.235***				
			(0.013)	(0.068)				
$(AIR \times lnDTF)_{ijt-1}$				-0.267***				
				(0.062)				
AM_{it-1}					-0.002	0.116***		
					(0.007)	(0.035)		
$(AM \times lnDTF)_{ijt-1}$						-0.155***		
						(0.039)		
$IIoT_{it-1}$							0.007	0.381***
							(0.013)	(0.124)
$(IIoT \times lnDTF)_{ijt-1}$								-0.516***
								(0.162)
TFP controls	h,s	h,s	h,s	h,s	h,s	h,s	h,s	h,s
Observations	1,760	1,760	1,760	1,760	1,760	1,760	1,760	1,760
R-squared (within)	0.226	0.305	0.230	0.299	0.226	0.266	0.226	0.302
Serial correlation (*p*-value)	0.532	0.106	0.841	0.372	0.588	0.274	0.527	0.109

Notes: Robust standard errors in parentheses. All regressions include a full set of time and country-industry dummies (within-group estimator) and are estimated through OLS. Serial correlation is LM test for the presence of first-order serial correlation in the residuals. TFP controls are h: hours worked; s: skill composition. The dependent variable is the growth rate of TFP. ΔlnA_{Fjt} is the contemporaneous growth rate of TFP for the frontier; $lnDTF_{ijt-1}$ is the lagged distance from the technology frontier; RD_{ijt-1} is the lagged sectoral R&D intensity; M_{ijt-1} is lagged sectoral import intensity; ICT_{ijt-1} is lagged sectoral ICT investments; AMT_{ijt-1} is lagged aggregate adoption of advanced manufacturing technologies; AIR_{ijt-1} is lagged aggregate adoption of advanced industrial robots; AM_{ijt-1} is lagged aggregate adoption of additive manufacturing; $IIoT_{ijt-1}$ is lagged aggregate adoption of industrial internet of things. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Chapter 3

Firm Restructuring Modes and Advanced Manufacturing Technologies: Evidence from Collective Layoffs across Europe*

Abstract

Shifts in globalisation dynamics, rising international competition, worldwide economic crises and, lately, new challenges posed by the recent Covid-19 pandemic, have pushed firms to pursue different restructuring strategies, including downsizing, offshoring or plant closure, aiming at improving operational and financial performances and resulting in collective employee layoffs. In this context, the rising diffusion of new automation technologies is seen, on the one hand, as threatening jobs and triggering the displacement of workers and, on the other hand, as a strategy that could sustain firm competitiveness, hence reducing the likelihood of collective layoffs. This Chapter adds to the extant literature by analysing how the adoption of advanced manufacturing technologies (AMTs) of the Industry 4.0 wave (namely, advanced industrial robots, additive manufacturing, and industrial internet of things) (i) influence a firm's propensity to undertake restructuring decisions, and (ii) once the decision to restructure is taken, influence a firm's propensity to either reduce its workforce significantly (downsizing), move a part of its activities abroad (offshoring), or dismiss all employees (closure). Our findings, based on 730 restructuring decisions implemented across 12.000 European manufacturing firms between 2013 and 2020, reveal that the adoption of AMTs contribute to saving jobs by lowering the propensity to engage in restructuring strategies that involve collective layoffs. In addition, conditional on restructuring, we find robust evidence that the adoption of AMTs contribute reduce a firm's probability of pursuing the 'worst-case scenario' strategy, i.e. closure, while increasing the probability of downsizing. We do not uncover any significant effect on firm's offshoring decisions.

Keywords: Advanced manufacturing technologies; Industry 4.0; collective layoffs: restructuring; closure; downsizing; offshoring.

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3.1. Introduction

The current debate on new digital technologies has devoted much attention to the understanding of the mechanisms through which the adoption of new forms of automation triggers a displacement mechanism affecting jobs whose tasks can now be performed by capital (Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018; 2019; Frey and Osborne, 2017). Likewise, the adoption of new digital technologies is also changing the way businesses operate and are organised (Dalenogare et al., 2018; Porter and Heppelmann, 2014; 2015) both at a local level and on an international scale (Alcácer et al., 2016; Autio et al., 2021; de Beule et al., 2022; Hannibal and Knight, 2018; Laplume et al., 2016; Strange and Zucchella, 2017), and pushing firms to reorganise and rationalise their productive operations. With disruptive technologies of the Industry 4.0 (I4.0) wave (Kagermann et al., 2013) like advanced industrial robots (AIRs), additive manufacturing (AM) and industrial internet of things (IIoT) – which we refer to as advanced manufacturing technologies (AMTs) – firms can build upon intelligent production systems and digitally integrated value chains in order to increase operational efficiency, implement new business models and improve their strategic and competitive advantage (Bogers et al., 2016; Dalenogare et al., 2018; Frank et al., 2019; Lee et al., 2015; Müller et al., 2018; Porter and Heppelmann, 2014; 2015; Rayna and Striukova, 2016; Schuh et al., 2014; Weller et al., 2015). These changes are happening at an ever-faster pace and have lately received much attention from academics, businesses, and institutions.

Along with the diffusion of new digital technologies, past decades have been characterised by fast changes in the global configuration of production activities and growing international competition, pushing firms to adopt quick and drastic strategic decisions in order to survive these challenges (Coucke et al., 2007). The negative effect and rising uncertainty associated with conjunctural macroeconomic events – ranging from the 2008 global financial crisis to the latest outbreak of the Covid-19 pandemic – have added to this trend, producing long-lasting consequences on the organisation of firms (Antràs, 2020; Blit, 2020; di Stefano et al., 2022; Kwak and Lee, 2017).

As a result, ever more frequently, restructuring strategies aimed at improving operational and financial performance have turned into collective employee layoffs.

From a pure economic perspective, a firm's decision to undertake a strategic restructuring resulting in a collective layoff may signal a process of adjustment from the current workforce's size to that which would enable the firm to operate in the most efficient way and, hence maximize its market value (Coucke et al., 2007). However, such workforce reductions may result from the implementation of different and alternative strategies. Concurrently, when firms face uncertainty, competitive market condition, low profitably or a mix of these factors, both the strategic analysis of the different choices managers can pursue (Coucke and Sleuwaegen, 2008; Datta et al., 2010; O'Brien and Folta, 2009), and the formal microeconomic evaluation of alternative restructuring choices (Bandick, 2016; Coucke et al., 2007) can provide insights on the conditions under which one alternative prevails on the others.

In this Chapter, we focus on three types of events which produce collective employee layoffs, namely: (i) the dismissal of a proportion of the workforce (i.e. downsizing); (ii) the dismissal of either the entire workforce or a part of it as a result of relocating activities abroad, either maintaining ownership on the relocated activities or not (i.e. offshoring), and; (iii) the worst-case option, implying the cessation of activities in a plant resulting in the dismissal of the entire firm workforce (i.e. closure). Managers will evaluate the optimal strategy to pursue by comparing costs and gains associated with each of these alternatives. Such costs and gains directly depend both on firm's characteristics and industry conditions. Rational managers should undertake the strategy which, by providing the maximum net gain, dominates any other restructuring alternative. Clearly, if such evaluation results in negative prospects, they will refrain from pursuing any restructuring decision, holding to the existing conditions.

Within this context, our analysis focuses on the role played by the adoption of AMTs on firms' decision to undertake any of the above cited restructuring modes. While a substantial body of the labour economics literature points at a negative effect of automation technologies on employment – even more so when manufacturing activities are concerned –, in some cases, past decisions to adopt new digital technologies may turn out to be beacons of hope for workers. In particular, the adoption of AMTs brings several benefits (e.g. higher efficiency, flexibility and productivity), higher competitiveness, and sets operational and economic implications (e.g. affecting firm's cost structure) which might prevent the realisation of the worst-case scenario, i.e. a firm's closure. As such, we argue that a firm's decision to adopt AMTs and the associated benefit interplay with several strategic and operational considerations which managers should take into account when evaluating whether restructuring or not and, eventually, which is the optimal restructuring mode to implement.

Our analysis deals with multilevel restructuring decisions, whereby we assess the role of AMT adoption when a firm first face the decision whether restructuring or not, given its operational and financial characteristics as well as other industry- and country-specific factors. Then, once a firm's managers have decided to restructure, it faces a second decision on which restructuring mode to undertake between the three options discussed above. Furthermore, we assess the role of adopting AMTs on the magnitude of collective layoffs triggered by restructuring decisions.

This multilevel decision problem implies a first selection problem (i.e. whether a firm decides to restructure or not) and a second choice problem (i.e. which restructuring mode to pursue among downsizing, offshoring and closure) which needs to account for the self-selection mechanisms described by the first selection problem. We address this scenario by modelling the selection problem following Heckman's (1979) two-step procedure, first estimating a probit model, then by estimating a multinomial logit modelling the choice problem, and finally by evaluating the role of AMT adoption on the number of laid-off employees. To test the robustness of our findings we perform several checks, by: (i) testing alternative and more demanding specifications including a different combination of fixed effects; (ii) checking the consistency of the underlying model's assumptions, estimating an alternative specification of the first selection problem by means of a logit model; (iii) estimating the multinomial logit model by using a control group of non-restructuring firms featuring comparable characteristics as benchmark.

The central message of this work is that, while a growing body of evidence suggests that new automation technologies like AMTs and other I4.0-related technologies trigger employment displacement effects and foster job cuts among workers performing particularly exposed tasks, the same technologies may also act as a countervailing force by creating benefits (e.g. productivity growth, as discussed in Chapter 2) and by setting incentives which allow companies to avoid closure and, ultimately, to save jobs.

We examine a large sample of 12,162 manufacturing firms located across 19 European countries and including 730 restructuring events over the period 2013–2020, finding robust evidence that AMT adoption has a negative effect on their probability of pursuing any of the restructuring modes discussed above and involving collective layoffs. Conditional on restructuring, we find robust evidence of a negative effect of AMT adoption on the probability of closure and a positive effect on the probability of continuing business activity by pursuing downsizing. We also find no significant evidence that adopting AMTs spurs incentives pushing firms to offshore as an alternative to end business activities. Consistently with our prior results, when looking at the effect of AMT adoption at the intensive margin of restructuring choices, we find evidence that these technologies play a mitigating role by reducing the magnitude of layoffs associated with restructuring strategies.

Industrial and innovation policies have promoted the adoption of new digital technologies of the I4.0 wave to increase firms' efficiency and productivity; ultimately, to achieve sustained economic growth. The main implication of this research is that these same policies have a secondary positive effect by providing firms with means to sustain their operations, become more competitive, productive and avoid economic hardship. Furthermore, the magnitude of such phenomenon may have been underdiscussed in the current literature, being overshadowed by the major debate on the negative employment effects associated with new automation technologies of the fourth industrial revolution (4IR).

The remainder of this Chapter is structured as follows: Section 2 presents the literature and frame the hypotheses. Section 3 presents our empirical setting, the data and variables used, and provides descripting evidence. Section 4 discussed the results of the empirical analyses and Section 5 concludes.

3.2. Background literature and hypotheses

In this work, we focus on advanced manufacturing technologies (AMTs) of the I4.0 wave and on their impact on firm business activities in terms of performances, the organisation of their operations and their strategic choices concerning restructuring. The industrial application of AMTs includes advanced industrial robots (AIRs), additive manufacturing (AM) and industrial internet of things (IIoT) (Alcácer and Cruz-Machado, 2019; Mariani and Borghi, 2019). To date, these new digital technologies of the 4IR – along with several others – have been increasingly investigated in many fields, ranging from international business and economics to industrial economics, operations and technology management. Notwithstanding, to the best of our knowledge, a thorough investigation on the relationship between AMTs, the reorganisation strategies and the associated restructuring decisions that firms pursue to increase their competitiveness, performances, and future chances of success has been neglected to date.

Restructuring events can be thought as the visible consequences of management actions taken in order to improve firm's current operational, organisational and financial conditions (Coucke et al., 2007). Yet, restructuring decisions can be implemented in different ways depending on the specific underlying goal, thus bearing different consequences. Specifically, looking at the implications they bear for employees, these strategic decisions can lead to very different outcomes and, hence gather either a positive or a negative connotation. For instance, restructuring events that usually happen on a large scale, entailing the displacement of a large portion of a firm or plant workforce, result in extensive media coverage due to their negative consequences. With respect to this type of events, some studies have devoted attention to the implication of adopting AMTs and other automation technologies of the I4.0 wave for laid-off workers in the aftermath of closures (Beer et al., 2019; Goos et al., 2021) and downsizing decisions (Blien et al., 2021; Olsson and Tåg, 2017). Nonetheless, these studies have neglected a deeper investigation of the potential direct relationship between AMT adoption and the occurrence of restructuring events. Besides, AMTs have also been advocated to play a role in other types of restructuring decisions which, conversely, entails a positive connotation, generally associated with bringing back to the home country jobs and business activities previously offshored. As such, we acknowledge that the current debate has also focused on the implications that new technologies of the I4.0 have on decisions such as reshoring or backshoring (e.g. Ancarani et al., 2019; Barbieri et al., 2022; Dachs et al., 2019; Kinkel, 2020; Krenz et al., 2021).

3.2.1. Restructuring through collective layoffs

Hereafter, we summarise the main building blocks enabling us to study the potential impact of AMT adoption on the firm decision to restructure its current operation through employee layoffs by either downsize, offshore or close.

The economics and management literatures have devoted much attention to the different types of restructuring events associated with collective layoffs (Bandick, 2016; Brauer and Zimmermann, 2017; Coucke et al., 2007; Coucke and Sleuwaegen, 2008; Datta et al., 2010; O'Brien and Folta, 2009; Powell and Yawson, 2012; Reynaud, 2013). Although these works resort to several different theoretical backgrounds, they provide us with the key concepts, strategic factors, and economic variables which are of crucial importance to analyse how managers and firms evaluate and compare different restructuring options.

Closure represents the most drastic restructuring mode. Companies may choose to terminate all their activities when they incur in losses and any other restructuring option is not possible or is too costly (Coucke et al., 2007; O'Brien and Folta, 2009). They may decide to permanently divest – for instance, by closing a plant – to increase performances and strengthen remaining business activities (Atkins and Favreau, 2022; Powell and Yawson, 2012). Reaching such strategic and operational decision implies accounting for critical factors like sunk costs, uncertainty about the future value of business (i.e. computing the net present value of assets), recent investments, and the scrap value of the company (Coucke et al., 2007; O'Brien and Folta, 2009). Likewise, several works emphasise the role of industry-specific characteristics such as asset specificity, the presence of economies of scale, high capital and/or technology intensity, profitability, and import competition strategies, as these are expected to play a role in determining the firm's propensity to either exit or continue its operations (Colantone et al., 2015; Colombo and Delmastro, 2001; Fichman, 2004; O'Brien and Folta, 2009; Porter, 1980). Once such considerations have been accounted for, rational managers will decide to close a plant if the scrap value is low, there have been no or little recent investments, and the firm has few technological assets or innovations to leverage on as a source of future competitive advantage (Colombo and Delmastro, 2001; Coucke et al., 2007; O'Brien and Folta, 2009). Conversely, since investments in technology and new specialised capital equipment are generally considered as highly irreversible (Fichman, 2004), firms will refrain from closing when recent investments are high, thus raising sunk costs.

Underperforming firms may also opt for *downsizing* through employee layoffs. Companies mostly take this decision when the market presents declining demand and investment opportunities or when they experience high costs and need to improve efficiency, frequently because of rising global competition or as a result of economic cycles (Cascio, 2012; Datta et al., 2010; Freeman and Ehrhardt, 2012). Resorting to collective layoffs may also denote a defensive reaction to sudden macroeconomic shocks (Datta et al., 2010; Reynaud, 2013). On the one hand, the literature highlights that several industry characteristics – namely, capital and innovation intensity, research and development (R&D) expenditure, market concentration, rivalry, and the influence of industry trends (e.g. competitors or peers' restructuring strategy) – are likely to influence the downsizing decision (Brauer and Zimmermann, 2017; Cascio, 2012; Datta et al., 2010). On the other hand, crucial firm-specific factors that managers take into consideration are profitability (e.g. return on assets, return on equity), debt level, capital intensity, productivity, and internationalisation strategies (Campos-García et al., 2020; Cascio, 2012; Coucke et al., 2007; Freeman and Ehrhardt, 2012; Reynaud, 2013). Nonetheless, many studies highlight one further and critical mechanism associated with the downsizing decision: the substitution of labour for capital (Cascio, 2012; Coucke et al., 2007; Datta et al., 2010; Freeman and Ehrhardt, 2012). As emphasised by many authors (Brynjolfsson et al., 1994; Budros, 2004; Coucke et al., 2007; Fligstein and Shin, 2007; Wagar, 1997; Yoo and Mody, 2000), this mechanism entails increasing investments in information and communication technologies (ICTs) and automation (usually, labour-saving technologies) – motivated by cost saving and efficiency increase aims – result in internal adjustment processes and, ultimately, in workforce reductions.

Finally, firms may decide to *offshore* their manufacturing operations most often to pursue an efficiency-seeking strategy, aimed at lowering costs and rise productivity (Sethupathy, 2013). When the offshored activities are manufacturing ones, this is usually done by moving existing assets to those locations which enable to exploit labour cost differential *vis-à-vis* the home country (Bandick, 2016; Coucke et al., 2007; Coucke and Sleuwaegen, 2008), or to increase proximity with the final market, lowering logistic costs (Kinkel and Maloca, 2009). Alternatively, when offshored activities are not (or not only) manufacturing ones but rather IT or R&D, the decision usually entails a strategy aimed at seeking access to qualified personnel (Lewin et al., 2009), or new knowledge sources (Jensen, 2009). The implications of moving abroad different firm activities have been extensively analysed in the literature. On the one hand, mixed evidence emerges when manufacturing activities are offshored: while some authors call the attention on how moving productive operations abroad lowers home countries' capabilities to be competitive and innovative

(Pisano and Shih, 2012), others emphasize how outward investments in cheap labour countries lead to overall firm and employment growth thanks to higher competitiveness, innovation and value added from activities retained in the home country (Lee and Jung, 2015; Barba Navaretti et al., 2010). On the other hand, the assessment of offshoring strategies related to high value adding activities, like advanced services or innovation activities, has resulted in growing consensus towards the positive impact these choices have on overall business performances (Castellani and Pieri, 2013; Dachs et al., 2015; D'Agostino et al., 2013; Jensen, 2009; Lewin et al., 2009; Mihalache et al., 2012). Instead, looking at the determinants behind the offshoring decision, while the literature highlights the critical role that variables like access to a multinational network, international sourcing from developed and/or developing countries, the skill level of the workforce, and the role of prior physical investments play in the choice of moving activities abroad (Bandick, 2016; Coucke et al., 2007; Coucke and Sleuwaegen, 2008; Pennings and Sleuwaegen, 2000), some authors also point out how neglecting considerations on organisational complexity and experience may lead firms to take biased decisions due to a wrong assessment of the true costs associated with the offshoring decision (Larsen et al., 2013).

3.2.2. AMT adoption and restructuring choices

The literature looking at AMTs and other technologies of the I4.0 wave agrees that the digital transformation these technologies bring forward is creating profound and disruptive changes to business processes, industrial operations, supply chains, and business models (Marcucci et al., 2021). The key principles behind the adoption of AMTs can be reconnected to concepts such as advanced manufacturing processes, optimisation, flexible adaptation, data integration and interoperability. However, firms may adopt different AMTs following these principles to achieve different and/or more specific objectives. As discussed by Shafiq et al. (2016), some of these objectives may relate to: implementing automatic systems enabling the flexible adaptation of productive activities, the supply chain and products tracking in logistics; setting up a communication network between machines, parts, and final products; achieve mass-customisation in manufacturing; facilitating human-machine interaction; creating a digital and optimised smart factory networked and readily interacting with the rest of the supply chain. These goals bear a varying level of pervasiveness in the adoption of technologies of the 4IR, entailing different potential level of achieving the associated benefits, hence various degrees of transformation within the company organisation.

For instance, Dalenogare et al. (2018) investigate how the adoption of different I4.0-related technologies associates with expected benefits for product, operations, and side-effects aspects, by analysing secondary survey data on more than 2.000 Brazilian companies across 27 industrial sectors. Their findings highlight that different AMTs are beneficial under different perspectives: for instance, while AM brings product-related benefits and positive side-effects potentially related with sustainability of the production process, the benefits of adopting IIoT are more concentrated in operations due to the digital integration of manufacturing systems and data exchange. Likewise, Frank et al. (2019) look at the Brazilian context by exploring adoption patterns of I4.0 technologies across 92 manufacturing companies. They highlight wide differences in the extent of adoption of different technologies: while AMTs like AIRs and AM are more widely adopted – being considered as base investments to build up the I4.0 technological infrastructure of the firm – other complementary technologies like IIoT or big data analytics are still relatively less frequently implemented, eventually hampering the achievement of higher levels of productivity and efficiency. In Europe, Marcucci et al. (2021) use survey data from 160 Italian manufacturing firms to analyse the relationship between I4.0 technology adoption, firm's organisational resilience and company performances, finding that a positive effect on both dimensions is associated only with more IT-related technologies, like IIoT, which also ensure higher survival chances in the long-run *via* to increased resilience. Müller et al. (2018) qualitatively analyse 68 German firms across three industries (i.e. automotive, mechanical and plant engineering, ICTs) by looking at changes in the business models following adoption and find that most I4.0-related technologies are highly influential on all the elements of business models (i.e. value creation, value capture and values offer). The authors' results support previous findings from Bogers et al. (2016) and Rayna and Striukova (2016), who look specifically at AM, yet highlighting that the driver of adoption (i.e. internal motivation vs external pressure) influence the extent of effective implementation of these technologies.

3.2.2.1. AMT adoption and the probability of restructuring

One main finding from the extant literature is that the extent of adoption of different AMTs and the perceived associated benefits are highly dependent on contextual factors (e.g. firm's location, sectors, size, as well as the survey and sample design). Notwithstanding, most authors emphasize how benefits of well-designed adoption and integration with business practices outweigh the drawbacks associated with an only partial implementation. For example, AMTs like AIRs create new space for firms to improve flexibility and efficiency, while also increasing reliability and quality standards in productive activities (Dalenogare et al., 2018; Frank et al., 2019). AM allows to speed up the prototyping stage, foster the development and innovation of new and enhanced products, the adoption of new business models featuring co-design with costumers, and mass-customisation (Bogers et al., 2016; Rayna and Striukova, 2016), while also adopting a more sustainable production regime consuming and wasting less resources (Weller et al., 2015). At the same time, the combination of AMTs, particularly IIoT, with other technologies of the 4IR enables the creation of cyber-physical systems which entail the seamless digital integration of different physical components (i.e. machines, computers and products) and provide digital insight (Alcácer and Cruz-Machado, 2019; Lee et al., 2015; Schuh et al., 2014). Such integration brings twofold gains: first, it allows to reduce set-up, production, and maintenance costs as well as improving safety conditions, reliability, and eventually boosts productivity (Kagermann et al., 2013; Müller et al., 2018; Schuh et al., 2014). Second, it creates the condition to extend integration along the supply chain, reducing logistic costs and making operations more sustainable (Frank et al., 2019; Lee et al., 2015; Müller et al., 2018). For instance, implementing IIoT helps companies to enrich their business offer by adding new smart features and enabling connection between products and with the firm, helps traceability along the supply chain and optimise inventory management, and provide the base elements to enable autonomous production and self-monitoring of machines along the production chain (Wang et al., 2016).

These benefits translate in overall higher levels of productivity (see also Chapter 2) and thus enable companies to quickly adapt to uncertainty, unforeseen demand shifts (Müller et al., 2018), as well as economic shocks by improving their organisational resilience (Marcucci et al., 2021). In turn, by providing new sources of competitive advantage (Porter and Heppelmann, 2015), AMTs increase firm's chances to survive without resorting to disruptive adjustment processes involving an extensive restructuring of business activities, based on collective layoffs of employees. Coherently, we hypothesize:

> H1a. *A higher level of AMT adoption is negatively related with a firm's probability of restructuring through collective layoffs*.

Taking a different perspective, several authors emphasize that adopting AMTs requires firms to increasingly commit to capital investments in highly specialised hardware and software infrastructures (Marcucci et al., 2021). For instance, Müller et al. (2018) discuss how adopting these technologies is generally perceived as costly in the short run, whereas their benefits require longer time to be achieved. Besides, AMT adoption leads to a shift in the skill content of tasks performed in several activities, above all in production (Frey and Osborne, 2017). This shift in the labour content is likely to affect both the skills required and the overall level of employment, potentially resulting in either retraining and up-skilling programs for employees, in the layoff of some jobs, or in a mix of both. For example, AIRs also improve working conditions by limiting space for human errors, by carrying out operations without any worker's assistance, and ensuring safer working standards and higher reliability in harmful situations (Koos et al., 2013; Złotowski et al., 2017). AM requires more highly specialised workers in both high value-adding activities like design, R&D, and operations, making it skill-biased in favour of high-skilled workers (Felice et al., 2022). Similarly, adopting cyber-physical systems enabled by IIoT devices push in the same direction of a reduced and skill-upgraded need for human labour in manufacturing activities, considering new machines' ability to self-adapt without resorting to human interventions (Lee et al., 2015; Schuh et al., 2014). These arguments are further supported by the extensive recent literature on new automation technologies of the 4IR and their effect on labour (e.g. Acemoglu and Restrepo, 2018; 2019; 2020; Frey and Osborne, 2017): AMTs and other companion technologies of the I4.0 wave substantially represent a mechanism of automation deepening, which entails a substitution between capital and labour inputs in production and, at the same time, requires employees to possess a different mix of skills, i.e. they are skill-biased (Acemoglu and Autor, 2011).

Furthermore, as already discussed above, AMTs provide companies with the opportunity to tackle new markets by enriching their product portfolio at reduced costs, enhancing product characteristics, or adopting new business models (Bogers et al., 2016; Müller et al., 2018; Rayna and Striukova, 2016). While the literature on the innovation-employment nexus (see, among the others, Vivarelli, 2014) traditionally associates product innovations with positive employment effects, here we focus on the changes in both organisational and manufacturing processes that lie behind the new product- and business model-related opportunities. For instance, AM shifts the relative weight of in-house product development due to co-creation with consumers, hence changing the nature of the production process and management perceptions of the related geographical and organisational boundaries (Strange and Zucchella, 2017). Specifically, some authors point out that AM makes production more suitable to be decentralised and located closer to final customers, creating conditions for saving on logistic costs and delivery times (Hannibal and Knight, 2018; Laplume et al., 2016; Strange and Zucchella, 2017). Findings from de Beule et al. (2022) support this argument by highlighting how AM firms have more foreign production subsidiaries than non-AM companies, especially when compared to similarly innovative firms. Besides, IIoT allows firms to achieve greater integration along the value chain by connecting manufacturers with suppliers and customers worldwide thanks to seamless and instantaneous data exchange, lowering the need for intermediaries and reducing transaction and coordination costs (Porter and Heppelmann, 2014; 2015). This eventually makes the management of geographically dispersed value chain activities more effective and less costly (Strange and Zucchella, 2017), lowering perceived barriers towards locating different value-adding activities in different locations (e.g. closer to the final market, or in lower cost locations).

These arguments thus support a view of AMTs as triggers of more profound changes to the organisation of production than those solely associated with the flexibility, efficiency, and productivity gains highlighted above. These changes pertain the organisation of labour within and across countries by changing the relative weight of human content in production and control tasks, and the geographical location of different activities. Following this alternative perspective, we argue that AMT adoption is likely to push firms towards a restructuring of their activities, resulting in layoffs associated with the potential displacement of workers or the delocalisation of some activities. This leads to formulate a competing hypothesis to H1a:

> H1b. *A higher level of AMT adoption is positively related with a firm's probability of restructuring through collective layoffs*.

3.2.2.2. AMT adoption and alternative restructuring choices

As highlighted above, benefits deriving from AMT adoption are likely to provide firms with new sources of competitive advantage over non-adopters (Porter and Heppelmann, 2014; 2015), ultimately increasing their chances of future survival (Marcucci et al., 2021). Notwithstanding, AMT adopters and non-adopters alike face the same challenges and uncertainty related to the surrounding market conditions and the same risk of being exposed to sudden macroeconomic shocks (e.g. the 2008 financial crisis, the 2020 Covid-19 pandemic) as well as industry- or market-specific downturns. Although these unforeseen events can be mitigated by the firm's ability to develop higher level of organisation resilience thanks to AMTs (Marcucci et al., 2021), managers can still decide to undertake drastic strategic decisions. Thus, hereafter we focus on the implications of AMT adoption for companies, once they have decided to restructure by resorting to collective layoffs.

In this context, as anticipated in Section 2.1, rational managers' decision boils down to the evaluation of gains and costs associated with each restructuring opportunity and eventually choosing the restructuring alternative that allows to maximise the future value of the firm's business activities (Coucke et al., 2007). While taking stock of the bulk of literature on the topic and acknowledging the role played by different firm and industry characteristics, we take the worst-case scenario (i.e. plant or firm closure) as reference to compare alternative restructuring modes and analyse the implications AMTs have in such evaluation.

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 because of the layoff. This is then evaluated against the scrap value of current assets in the case of closure. Considering downsizing, as discussed earlier, AMT-enabled efficiency, flexibility, higher productivity, and deeper integration of different business activities within the firm and across the value chain make companies more resilient and able to absorb shocks (Marcucci et al., 2021), lowering the organisational and operational costs of adapting firm's activities after the restructuring while also increasing their competitiveness *vis-à-vis* non-adopters. At the same time, AMTs require less human content in production (e.g. due to AIRs), as well as a different mix of more qualified workforce. Likewise, adopting automatised and integrated production methods allows to carry on operations reducing both production and logistic costs (e.g. thanks to AM and IIoT) and achieve optimised work-flows, further reducing adjustment costs. This eventually results in a higher intensity of capital relatively to labour due to this process of automation deepening (Cascio, 2012; Coucke et al., 2007; Freeman and Ehrhardt, 2012).

Considering closure, the adoption of AMTs represents an investment in capital intensive machinery and equipment, which are generally expensive (Müller et al., 2018). Furthermore, the decision to invest in these technologies usually entails a long-term perspective, necessary to realise the above-mentioned benefits. Consequently, once a firm adopts AMTs, the costs associated with such decision are largely sunk. As discussed in Section 2.1, sunk costs associated with past capital investments play a critical role in managers' decision to pursue any restructuring option (Coucke et al., 2007; O'Brien and Folta, 2009). As argued by Fichman (2004), investments in technologies are usually tailored on firm's needs around specific production settings and/or monitoring systems, generally making them highly irreversible. Likewise, while capital assets like AIRs or AM can be sold or more easily adapted and redeployed, IIoT investments in digital sensors and automation systems are not easily re-assembled and readily made productive after closure.[38] Additionally, as in the case of other ICTs (Fichman, 2004), additional costs relate to the technical training of employees to use new machines and systems, learning new practices, hiring professional consultants to support the transformation, the organisational effort put on adapting to the transformation, and absorbing productivity losses incurred over the transition. These additional investments associated with employees' training, establishing new routines and practices are generally considered largely sunk, since they are strictly related to the firm's organisation (Kogut and Kulatilaka, 2001), hence lost in case of closure.

While some of these arguments are more settled in the literature on companies' restructuring decisions, others follow from our discussion of the implications and benefits associated with the adoption of AMTs. Overall, while AMT characteristics should push firms towards a smoother and less disruptive adaptation to downsizing through collective layoffs – thus increasing the likelihood

[38] As highlighted in Chapter 2 (footnote 33, p. 100), we note that IIoT investments are, generally, substantially more expensive than those in AIRs or AM, thus bearing a more important weight in the computation of sunk costs.

of preferring such option –, other considerations like sunk costs and investments' irreversibility should make the option of terminating business activities less appealing to managers. Thus, we hypothesize that:

> H2. *Conditional on restructuring, a higher level of AMT adoption is associated with a higher probability of firms choosing downsizing over closure*.

To complete our conceptual framework, we analyse the role of AMTs in the decision to restructure *via* offshoring, as compared to closure. New business opportunities created by AMTs like AM and IIoT 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 (de Beule et al., 2022; Hannibal and Knight, 2018; Laplume et al., 2016; Strange and Zucchella, 2017). Under this perspective, these technologies of the 4IR may act as catalysts of the traditional motives behind the offshoring decision: they allow companies to reduce the costs associated with these decisions by reducing logistic costs when they offshore production activities abroad (Kinkel and Maloca, 2009), while also pursuing an efficiency-seeking strategy benefitting from the lower production costs in the offshoring location (Bandick, 2016; Coucke and Sleuwaegen, 2008; Sethupathy, 2013). At the same time, the benefits gained through their adoption may also result in additional productivity effects for those value-adding activities retained in the home country: for example, as pointed out by Porter and Heppelmann (2015), IIoT enabled connectivity between the firm and its customers makes it easier to manage remote customer services thanks to the continuous data exchange between smart products and firm's monitoring systems, enabling such services to be outsourced to lower wage but high IT skills locations. All in all, these mechanisms should further facilitate achieving higher competitiveness from not offshored activities (Barba Navaretti et al., 2010), overall business performances, productivity (Castellani and Pieri, 2013) and chances of survival (Grazzi et al., 2022).

Coherently, combining these considerations with the above discussion about the implications of AMT adoption on closure decisions, the characteristics of these technologies should make it rather convenient for a firm to offshore production activities, laying-off employees and seeking a more efficient and productive business structure. Hence, we hypothesize:

H3. *Conditional on restructuring, a higher level of AMT adoption is associated with a higher probability of firms choosing offshoring over closure*.

3.3. Empirical model and data

3.3.1. Modelling restructuring decisions

To test empirically our hypotheses, first we analyse the role of AMT adoption on the firm's decision on whether to restructure or not, conditionally to other firm and industry characteristics. Second, we observe the role of AMTs when a firm chooses which restructuring mode to pursue among downsizing, offshoring and closure. This multilevel decision problem implies accounting for the selection bias deriving from firm's characteristics which may naturally lead to a higher propensity to restructure. To account for this selection bias problem, we follow Heckman's (1979) two-step procedure: in the first stage of our empirical analysis, we estimate a probit model describing the selection problem (i.e. whether to restructure through employee layoff or not), while in then the second stage 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 need to account for the self-selection mechanisms described by the first selection problem by including the inverse Mills ratio (IMR).

Besides AMT adoption, following the relevant literature discussed in Section 2.1, our model includes a set of firm-level controls, the level of sectoral AMT investments describing the AMT-related technological environment in which the firm operates, other key industry characteristics and a full set of country, sector and year fixed effects (FEs). Heckman's (1979) model obtains formal identification from the inclusion of at least one explanatory variable in the model describing the first selection problem which does not appear in the model for the second selection problem, i.e. an exclusion restriction. Our conceptual framework implies that firms will be able to achieve higher productivity levels because of AMT adoption, thus lowering chances that they will resort to restructuring *via* layoffs. Nonetheless, while economic theory suggests that firms which are more productive *per se* will naturally be less prone to any restructuring, the managerial decision-making processes frequently results in *ex ante* more productive firms to proactively undertake restructuring decisions with the aim of pursuing a further a productivity increase. Thus, we include *labour productivity* in the probit model as the main exclusion restriction which should help identifying the self-selection mechanism. Besides, in the first-stage probit model we further include two additional control variables – i.e. *investment intensity* and *product differentiation* – which should capture any industry characteristic related to technology and competitive dynamics (e.g. Datta et al., 2010) not purely related to AMTs, but which could affect the firm's propensity to restructure.

In the first-stage probit model, our dependent variable is a dummy variable which equals 1 if a firm undertake any restructuring decision entailing a collective layoff, 0 otherwise. Similarly, in the second-stage multinomial logit model the dependent variable is a categorical variable assuming value $k = 0$ in case of the reference category (i.e. closure), value $k = 1$ in case of downsizing and value $k = 2$ in case of offshoring.

In addition, we explore alternative specifications of the second-stage model featuring an OLS regression in which the dependent variable is the size of the collective layoff (i.e. the number of displaced workers). The dependent variable is here expressed as the natural logarithm of the number of employees laid-off, i.e. $ln(laid\text{-}off)$. We expect a negative relationship between AMT adoption and the number of laid-off employees, because firms adopting more AMT are less likely to close – laying-off either the whole workforce or a large share of it – and rather more likely to opt for a downsize – laying-off only a portion of the workforce.

To sum up, we estimate the following equations:

$$P\left(Restructuring_{i,j,c,t} = 1\right) = \frac{\exp\left(\beta_0 + \beta_1 AMT\ adoption_{i,j,c,t-1} + \beta_2 FLC_{i,j,c,t-1} + \beta_3 SLC_{j,c,t-1} + FEs\right)}{1 + \exp\left(\beta_0 + \beta_1 AMT\ adoption_{i,j,c,t-1} + \beta_2 FLC_{i,j,c,t-1} + \beta_3 SLC_{j,c,t-1} + FEs\right)} \tag{1}$$

$$P\left(Restructuring_{i,j,c,t} = k\right) = \frac{\exp\left(\beta_{k0} + \beta_{k1} AMT\ adoption_{i,j,c,t-1} + \beta_{k2} FLC_{i,j,c,t-1} + \beta_{k3} SLC_{j,c,t-1} + \beta_{k4} IMR_{i,j,c,t} + FEs\right)}{\sum_{m=1}^{k} \exp\left(\beta_0 + \beta_{m1} AMT\ adoption_{i,j,c,t-1} + \beta_{m2} FLC_{i,j,c,t-1} + \beta_{m3} SLC_{j,c,t-1} + \beta_{m4} IMR_{i,j,c,t} + FEs\right)} \tag{2}$$

$$ln(laid\text{-}off) = \beta_0 + \beta_1 AMT\ adoption_{i,j,c,t-1} + \beta_2 FLC_{i,j,c,t-1} + \beta_3 SLC_{j,c,t-1} + \beta_4 IMR_{i,j,c,t} + FEs + \varepsilon_{i,t} \tag{3}$$

where FLC and SLC are vectors of firm-level and sector-level controls, respectively.

3.3.2. Variables

Hereafter, we introduce all the explanatory variables included in our econometric model and the related motivation. All variables included in our specifications are lagged by one year, to avoid simultaneity issues.

3.3.2.1. Main explanatory variable

AMT adoption: As pointed out by many authors, a firm's capital structure and intensity are likely to affect its propensity to adopt different restructuring modes. Specifically, several studies highlight that more capital-intensive firms, which use more advanced technologies and invest in automation, are more likely to pursue further capital deepening (Bandick, 2016; Cascio, 2012; Coucke et al., 2007; Coucke and Sleuwaegen, 2008; Freeman and Ehrhardt, 2012; Pennings and Sleuwaegen, 2000). Yet, capital intensity alone is not able to properly capture a process of capital deepening involving investments in advanced technologies of the 4IR. Besides, the level of technological and capital intensity characterising the external environment represent important factors determining industry competitive dynamics as well as shaping firm's technological and investment decisions (Porter, 1980; Porter and Heppelmann, 2014). In turn, firms operating in industries characterised by higher levels of AMT investments will also be likely to invest in AMTs to sustain competition and achieve supply chain integration with customers and suppliers (Müller et al., 2018; Porter and Heppelmann, 2014; 2015).

Exact data on AMT investments at the level of the firm are not available for an extensive sample covering several countries and years, but based the discussion above, we measure the adoption of AMTs as a combination of two elements. The first is the firm's level of *capital intensity*, measured by the natural log of tangible fixed assets over the number of employees. The second is the level of *AMT investment intensity* of the industry in which the firm operates, measured as the natural log of the stock of sectoral AMT imports.[39] Formally, AMT adoption in firm i, operating in industry j of country c is measured as:

$$AMT\ adoption_{i,j,c} = \left[\underbrace{ln\left(\frac{Tangible\ Fixed\ Assets}{Number\ of\ Employees}\right)_{i,j,c}}_{Capital\ Intensity} \times \underbrace{ln(AMT\ Import\ Stock)_{j,c}}_{AMT\ Investment\ Intensity}\right] \quad (4)$$

Sectoral AMT imports are computed using an exposure index in the spirit of Acemoglu and Restrepo (2020), following the approach described in Chapter 2. Since the measure is effectively an interaction between firm *capital intensity* and sectoral *AMT investment intensity*, we also include the two variables in both the first-stage probit model and in the second stage multinomial logit as controls for the main effects.

3.3.2.2. Firm-level controls

Size: Following the literature on firms' restructuring choices, larger firms will be more likely to restructure resorting to collective layoffs since they generally enjoy a larger pool of available resources and are relatively better suited to face uncertainty and fast-changing market conditions (Bandick, 2016; Brauer and Zimmermann, 2017; Coucke et al., 2007; Coucke and

[39] The stock of sectoral AMT imports is computed using the perpetual inventory method, assuming a depreciation rate of 15%.

Sleuwaegen, 2008; O’Brien and Folta, 2009). At the same time, they will prefer to downsize or offshore their activities rather than terminate activities and exit from the market. We include the natural log of the number of employees as a measure of firm’s size.

Age: Looking at the firm under an evolutionary perspective, younger firms enjoy faster potential growth conditional to their ability to learn from the market, to adopt the right organisational structure and routines. However, while younger firms may experience a higher pressure to restructure due to the lack of such experience, older firms with established business procedures and practices are more likely to endure weak performances, market turmoil and less likely to restructure (Coucke et al., 2007; Coucke and Sleuwaegen, 2008). We control for firm’s experience including the natural log of its age.

Return on assets (ROA): Many authors highlight that scarce business performances and the lack of profitability may signal a higher likelihood to restructure as compared to peer firms operating in the same market (Brauer and Zimmermann, 2017; Campos-García et al., 2020; Coucke et al., 2007; Kang and Shivdasani, 1997; O’Brien and Folta, 2009; Powell and Yawson, 2012; Reynaud, 2013). Coherently, in case of weak performance, managers will be pushed to restructure with the aim of achieving a higher profitability. Thus, we include the return on assets (ROA) as a measure of profitability, computed as the ratio of net income over total assets.

Leverage: Similarly, also the financial structure of a company has been largely observed to be influential on the restructuring decision (Brauer and Zimmermann, 2017; Campos-García et al., 2020; Coucke et al., 2007; Kang and Shivdasani, 1997; O’Brien and Folta, 2009; Powell and Yawson, 2012; Reynaud, 2013). In principles, highly leveraged firms may face debtholders’ pressure to liquidate or sell assets and, eventually, lay-off employees when financial obligations are not met. However, previous studies find mixed evidence on the role of financial leverage measures over the propensity to restructure, highly dependent on the type of restructuring decision under analysis, firm and industry characteristics (Coucke et al., 2007). We control for firm’s financial leverage, computed as the natural log of the ratio of long-term debt over total assets.

Labour productivity: More productive firms enjoy higher survival chances and future growth prospects, while less productive firms have higher probability to exit the market (Bandick, 2016; Coucke and Sleuwaegen, 2008). At the same time, higher productivity also comes with increasing capital investments and reduction in inefficiencies (Cascio, 2012; Datta et al., 2010; Freeman and Ehrhardt, 2012) potentially obtained through restructuring decision like downsizing or offshoring. Hence, depending on the prevailing relationship with the propensity to restructure, we are likely to see mixed results. We measure labour productivity with the natural log of the ratio of firm's turnover and the number of employees.

Corporate group: The literature extensively highlight how firms belonging to a multinational network are relatively better suited to survive through economic shocks and market downturns, benefit from their higher international experience, are more efficient, but also how they are more likely to benefit from a higher potential to relocate capacity across borders at a reduced cost, increasing their likelihood of pursuing flexibility through offshoring and/or relocations rather than *via* downsizing (Coucke et al., 2007; Coucke and Sleuwaegen, 2008; Pennings and Sleuwaegen, 2000). Overall, these firms enjoy higher survival chances. We control for a firm's being part of a corporate group by including a dummy variable which equals 1 if the firm has at least one subsidiary (both national and multinational), 0 otherwise.

Innovator: Several authors point out that firms competing over innovation are less likely to terminate activities, showing higher management commitment to remain on the market (Campos-García et al., 2020; O'Brien and Folta, 2009; Pennings and Sleuwaegen, 2000) and higher chances of preferring alternative restructuring measures to closure in case of declining performances. Likewise, innovators are more likely to achieve and maintain new sources of competitive advantage, further increasing survival chances. Conversely, restructuring options involving loss of human capital, like downsizing, may affect firm's innovative capabilities (Datta et al., 2010). We account for a firm's status as innovator, measured as a dummy equalling 1 if the firm has at least one granted patent, 0 otherwise.

Recent investments: As discussed by Coucke et al. (2007), capital investments represent a barrier to exit and downsizing, given the high sunk costs associated with specialised machinery and equipment, as well as intangible assets like employee technical training (see also the discussion in Section 2.2). Hence, recent investments are generally assumed to hamper firm's likelihood of restructuring, given the consistent adjustment costs incurred by the firm in case of high recent investments. We characterise firms having performed recent investments using a dummy variable, assuming value 1 if the growth rate of tangible fixed assets is positive, 0 otherwise.

3.3.2.3. Industry controls and other variables

Investment intensity: The general investment intensity, capturing technological and capital-related features of environment surrounding a firm, represents an important factor determining industry competitive dynamics, shaping both the future chances of success for firms operating in an industry, and potential factors influencing firms' restructuring decisions (Datta et al., 2010; O'Brien and Folta, 2009; Porter, 1980; Porter and Heppelmann, 2014). Thus, we include a measure of investment intensity computed as the ratio of gross fixed capital formation to value added, both expressed in real terms.

Product differentiation: Another feature that may affect the probability to restructure is the level of product differentiation in an industry (Datta et al., 2010). Specifically, competitive pressure is generally assumed to be lower in industry with a high degree of product differentiation, thus decreasing firm's incentives to restructure *via* layoffs (Coucke et al., 2007). We proxy product differentiation using intra-industry trade, measured following Marvel and Ray's (1987) formulation of the Grubel and Lloyd (1975) index, computed as $2min(X_j,\ M_j)/(X_j + M_j)$, where X_j and M_j represent total exports and total imports of sector j, respectively.

Fixed effects (FEs): We further control for potential unobserved heterogeneity including country, sector, and year FEs. Country FEs should capture all country-specific institutional factors that may affect the decision to restructure through collective employee layoffs, such as labour market institutions and union activity. Sector FEs should capture industry-specific factors which are common to all countries, e.g. efficiency in the use of natural resources, the presence of scale economies, and the level of market competition. Year FEs should capture all time specific shocks and trends, as well as the cost of capital, which should affect the propensity of investing in technologies like AMTs, is generally assumed to be equal for all firms, and to vary over time.

3.3.3. Data and descriptive evidence

As a first step to create the dataset used for the empirical analysis, we sourced data on restructuring events from the European Restructuring Monitor (ERM) database, which provides a rich set of information about business restructuring events involving firms operating within the European Union (EU) 27 countries, the United Kingdom (UK) (until the end of 2019) and Norway. The information on restructuring events reported in the ERM database is collected by an international team of researchers at Eurofound and affiliates, by checking daily newspapers and business press, and integrated with online resources like company websites (Eurofound, 2022). Eurofound ensures the quality of the data published in the ERM database by continuously monitoring and cross-checking the information they gather. At the same time, data published in the ERM satisfy 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, 2022).[40]

Eurofound granted us bulk data access on all restructuring events happened in the EU27, UK and Norway between 2002 and February 2021. As a first step in data preparation, we focus on restructuring events in manufacturing (i.e. 2-digit NACE codes from 10 to 33) and discarded

[40] We acknowledge this might represent a source of potential bias, making our results not fully representative of medium, small and micro firms.

information on cases pertaining service industries and all other sectors.[41] Second, since the structure of the data and of the collected information allows for the presence of cross-country events whose consequences affect more than one European country or even countries outside Europe (i.e. those flagged as ‘European Union’ or ‘World’ in the related variable included in the ERM database), we discarded all events taking place outside Europe or in more than one European country. This step is necessary to exclude events reporting either incomplete or not sufficiently detailed information, as well as to avoid double counting of events: if one event affect several European countries and the available information is sufficiently detailed to identify single-country implications, one event for each country is also created (Eurofound, 2022). Finally, we focused on restructuring events described by Eurofound (2022) as ‘closure/bankruptcy’ (i.e. “*when a company goes bankrupt/a company or an industrial site is closed for economic reasons not directly connected to relocation or outsourcing*”), ‘offshoring/delocalisation’ (i.e. “*when the activity is relocated or outsourced outside of the country’s borders*”), and ‘internal restructuring’ (i.e. “*when the company undertakes a job-cutting plan, which is not linked to another type of restructuring […]*”),. By looking at these categories of events, we acknowledge that some events entail both the hiring and the displacement of workers. Hence, given the purpose of our analysis, we computed the net impact of each restructuring decision on employment and discarded from our data all events not implying a net negative effect on the workforce, i.e. an employee layoff.

Furthermore, we acknowledge that offshoring events might be seen as the combination of a firm deciding to offshore activities abroad (i.e. to a host country) and to close or downsize in the home country. However, this is not a concern for our analysis as data on restructuring events reported in ERM database are mutually exclusive in nature, hence not subject to double counting (i.e. the same event is recorded twice in the dataset as a closure or downsizing in the home country and an offshoring in the host country). In fact, ERM event categories reflect the full extent of the

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[41] As discussed in Chapter 1, we focus on manufacturing firms since the AMTs analysed here are more likely to affect manufacturing operations.

ultimate goal behind the restructuring decision: 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 country.

As discussed in Chapter 1 and 2, we sourced the data used to build our main explanatory variable, AMT adoption, as well as sectoral AMT investment intensity from Eurostat's Comext database and from the World Input-Output Database (WIOD) (Timmer et al., 2015). From Comext database we took highly detailed information, at the 8-digit level of product disaggregation, on country-level imports of AMT-related goods and aggregate country imports from AMT-producing industries (i.e. NACE 2-digit sector 28 for AIRs and AM, 26 for IIoT). From WIOD database we sourced data on intermediate inputs imported across countries and sectors, necessary to build sectoral weights describing each sector and country's purchase of AMT-related intermediates.

The other firm-level data necessary to compute our main explanatory variable capturing AMT adoption, together with data used to construct all firm-level controls were sourced from Bureau van Dijk's Amadeus database. The database provides us with detailed firm-level longitudinal data over the period 2012–2020. First, we downloaded information for manufacturing firms active in the EU27 countries, the UK and Norway, with at least 9 employees, and having known values (i.e. non-missing) for key financial and balance sheet variables over the observation period.[42] Second, we matched data on the three layoff-related restructuring events from the ERM database with firm-level data from Amadeus database, 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 Amadeus database matching with firms reporting other restructuring events included in the ERM database, i.e. those not reporting any type of restructuring investigated here, but undertaking other types of restructuring not strictly implying collective

[42] Specifically, we considered: number of employees, fixed tangible assets, fixed intangible assets, operating revenue, and profit/loss. The resulting search featured 217,377 firms respecting such criteria.

employee layoffs (e.g. merger and acquisitions, business expansions, etc.). Finally, the information for European firms in our Amadeus data, but not matching with any restructuring firms in the ERM database, were used as counterfactual (i.e. non-restructuring firms) in our empirical analysis. Clearly, these preparation steps also resulted in a reduction of the sample our analysis to the 2012–2020 period. However, loosing information on the 2002-2011 period is not likely to represent a limitation to our empirical analysis on the role played by AMTs in affecting firm's restructuring decisions as the adoption of such technologies picked up in the last decade. First, it was only after the global financial crisis, driven by a fast-moving debate on new technologies and manufacturing models, virtually all most advanced economies – and, most importantly, almost all European countries – launched their industrial policy programmes targeting I4.0 (Mariani and Borghi, 2019). Second, only starting from 2009 the global demand for mechanical engineering goods, machinery and enabling equipment for I4.0 returned to their pre-crisis level (Kagermann et al., 2013). Third, the core patents protecting some AMTs – in particular, AM – expired in 2009 and in subsequent years, allowing a strong diffusion of these technologies worldwide (Buonafede et al., 2018; Felice et al., 2022; Laplume et al., 2016).

Finally, we also used data from the OECD's Structural Analysis (STAN) and Bilateral Trade by Industry and End-use (BTDIxE) datasets, which we used to compute the two additional industry controls, i.e. investment intensity and product differentiation.

Table 1 around here

Our final sample include 77,556 observations over 12,162 firms operating across 24 manufacturing industries and located across 19 European countries between 2013 and 2020.[43] This sample includes 730 restructuring events, pertaining to 565 firms. Tables 1, 2 and 3 highlight the distribution of

[43] We recall that all our explanatory variables are lagged by one year, so to avoid the risk of simultaneity issues, hence why the observation starts in 2013.

restructuring events of each category across years, sectors, and countries, respectively. These tables also provide information on the characteristics of a restricted control sample of 2,552 firm-year observations with highly similar characteristics of restructuring firms and used in one of the robustness tests of our main analysis (see Section 4.2).

Table 2 around here

Table 1 shows that downsizing events are the more frequent mode of restructuring (546), while closure and offshoring are less numerous (126 and 58 overall). All three types of restructuring events have been more frequent at the beginning and at the end of our observation period. This insight further reinforces the idea that there is a correlation between economic shocks and restructuring through collective layoffs. Specifically, early years in our time series (2013 and following) bear the aftermath of local sovereign debt crises affecting European countries, while the steep increase witnessed in 2020 is clearly related with the outbreak of the Covid-19 pandemic.

Table 3 around here

Table 2 highlights that restructuring events are well dispersed across all manufacturing industries, exception made for offshoring cases which appear to be more concentrated in some sectors. A notable concentration of restructuring events characterises sectors 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 3 presents the geography of the restructuring events discussed in this work: 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 consistent number of cases. Finally, offshoring, which is the less frequent event, appears also to be rather constrained to few countries, mostly Germany, France and, to a lesser extent, Belgium.

Figure 1 and Table 4 around here

Looking at the size of collective layoffs across our sample, Figure 1 describes the frequency distribution of normalised employee layoffs.[44] 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 69%, ranging between 38% and full dismissal of the workforce. This suggests that only few cases of closure involve the actual closure of the firm, but rather closure of a firm's plant. At the same time, it also highlights that employee reductions following downsizing or offshoring decisions have resulted in large portion of the workforce being laid-off. Table 4 reports summary statistics of normalised employee layoffs reported in Figure 1 and the log value of layoff size: mean normalised employee layoffs ranks highest in the case of closure (0.764), but remains high also in the case of downsizing (0.678) and offshoring (0.705), supporting the insight from Figure 1. At the same time, 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 offshoring events at any point of the layoff distribution, while it remains larger than that for downsizing events up to the 75th percentile. These insights suggest that downsizing firms are on average higher than that of closing ones, resulting in higher absolute layoffs at the top of the distribution.

Finally, Table 5 presents the summary statistics and the correlation matrix for the variables used in our main analysis, while Table 6 presents descriptive statistics distinguishing firm and

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

industry characteristics across the three restructuring modes we investigate. Notably, AMT adoption is significantly higher across downsizing firms as compared to those who decided to close, coherently with our expectations discussed in Section 2.2. It is also interesting to note that, coherently with what discussed above, the size of the firms involved in closure events is much smaller than that of downsizing firms.

Tables 5 and 6 around here

3.4. Results

3.4.1. Main results

Table 7 reports the main results of the regression analysis testing our hypotheses. Results of the probit model describing the first stage selection problem are presented in column (1), exploring the relationship between firm and industry characteristics and firm's propensity to restructure by resorting to collective employee layoffs. The AMT adoption variable indicates that firms featuring a higher level of adoption are, on average, less likely to restructure ($p = 0.067$).[45] This result supports the view that AMTs can represent a source of competitive advantage and that adopting firms enjoy benefits in terms of efficiency, flexibility and productivity, making them more likely to face challenging economic conditions and macroeconomic shocks without experiencing pressure to restructure by laying-off workers. These findings lend support for Hypothesis 1a, while the competing Hypothesis 1b suggesting that AMT adoption would lead to more job-destructing restructuring events is not supported.

[45] Although this finding shows statistical significance only at the 10% level, we note that the p-value is not far from the 5% threshold. Furthermore, the robustness checks on the first-stage model reported in the following Section all highlight statistical significance at the 5% level, making us confident on the goodness of our main findings.

Like most studies in the literature, we also find evidence that restructuring firms are on average bigger and less profitable. However, we also find that restructuring firms are less leveraged as compared to non-restructuring ones, suggesting that the presence of a high debt is not *per se* indicative of a higher propensity to restructure. This result highlights a more proactive approach, suggesting that restructuring firms are likely to do so pushed by performance-increasing aims (Reynaud, 2013). Besides, such managerial decision may be conditional on the market's perception of the firm's health status and profitability (Atkins and Favreau, 2022), but also to other context-specific factors like the level of liquidity available on the market and borrowed by firms. As highlighted by Berg et al. (2021), over the last decades and especially after the 2008 financial crisis, European firms have been accumulating relatively more debt as compared to US companies, also due to a significantly lower cost of debt.

Table 7 around here

While we find no significant difference between restructuring and non-restructuring firms when looking at firm's age and capital intensity, our results suggest that restructuring firms are, on average, more productive than their counterfactual ($p < 0.001$, i.e. passing test of relevance as exclusion restriction, according to Wolfolds and Siegel (2019)).[46] Similarly, innovation (as measured by firms having an active patent) is associated with an higher probability of restructuring. Several empirical studies (most recently, Grazzi et al., 2022) highlight that more innovative and productive firms are likely to survive while less productive firms may be pushed to restructure in order to improve operational efficiency or to exit the market (Coucke and Sleuwaegen, 2008). Thus, several authors highlight how *ex ante* more productive and innovative firms are more likely to proactively undertake restructuring decisions, especially through downsizing and offshoring (e.g.

[46] This result supports our choice of using labour productivity as main exclusion restriction in our model.

Bandick, 2016; Barba Navaretti et al., 2010; Yoo and Mody, 2000). Furthermore, on average, we find that firms which are part of a corporate group are less likely to restructure through employee layoffs.

Concurrently with the extant literature (e.g. Coucke et al., 2007), we find that companies who have recently invested in physical assets are less likely to pursue collective layoffs; this emphasises 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 FEs in our specification well captures the underlying sectoral and country-specific trends, in particular, relatedly to technological and investment intensity.

Columns (2) and (3) present the results of the multinomial logit model describing the second stage choice problem. The IMR from the first stage is either weakly significant (in column (2)) or not (in column (3)), suggesting that a weak self-selection mechanism only identifies restructuring firms opting for downsizing.[47] The estimated coefficient for the AMT adoption variable is positive and statistically significant ($p < 0.001$) in column (2), supporting Hypothesis 2 and highlighting that restructuring firms which also adopt AMTs are more likely to downsize and layoff a portion of the workforce rather than close an entire plant or, in the worst case, terminate all activities. Likewise, the AMT adoption coefficient is statistically significant in column (3) ($p = 0.036$), suggesting Hypothesis 3 is also supported and meaning that AMT adoption affect firm's propensity to restructure by pushing them towards preferring the offshoring option as compared to closure.

To further dig into the mechanisms behind these results, columns (4) to (6) present the marginal effect of adopting AMTs on the probability to pursue each specific restructuring mode. Hypotheses 2 and 3 argued that AMTs can influence the firm's propensity to prefer downsizing and

[47] Beside highlighting that our exclusion restriction (i.e. labour productivity) passes the test of relevance in the first stage being highly significant, we further check robustness our result on the presence of a weak self-selection by checking for multicollinearity between the IMR and other explanatory variables (variance inflation factors (VIFs) never above 5) and by testing the robustness of our main results on the AMT adoption variable in a model without IMR, and including the labour productivity variable and the two additional sectoral controls. Results for this last check are in line with those shown in Table 7.

offshoring over closure as a result of a double mechanism, since adoption-related benefits and implications may act on the one hand by creating incentives to downsize or offshore activities (e.g. increasing efficiency, flexibility, and productivity; lowering coordination costs), and on the other hand by creating barriers to closure (e.g. rising sunk costs). We find evidence that these hypothesised mechanisms behind firm's observed behaviour are partially in place: on average, a 1% increase in the level of AMT adoption is associated with a 0.0038 drop in the probability of closure ($p < 0.001$, column (4)), to a 0.004 increase in the probability of downsizing ($p = 0.002$, column (5)), but to no significant effect on the probability of offshoring. This insight suggests that the observed effect of AMT adoption in column (2) results from the simultaneous positive effect of AMT-related benefits in terms of flexibility, efficiency and productivity on the probability of downsizing, associated with a process of automation deepening, and the negative effect of resources committed to investments in AMTs, resulting in higher sunk costs. Conversely, the positive effect observed in column (3) only spurs from the latter mechanism, as our results shows that AMTs exert no influence on the likelihood of the offshoring decision.

Finally, column (7) presents the results of our analysis on the relationship between AMT adoption and the magnitude of collective layoffs associated with the restructuring modes discussed above. On average, we find a negative relationship between AMT adoption and the size of collective layoffs, small in magnitude but statistically significant ($p = 0.009$), thus indicating that higher AMT adoption is associated with layoffs involving fewer workers. Overall, these findings point at the existence of a less explored side of the effects of AMTs on employment: while extensive evidence in the literature suggests these new digital automation technologies of the 4IR displace jobs, we uncover a secondary effect which works in the opposite direction, by affecting firm's operational performance and strategic decisions, and resulting in a lower likelihood of pursuing restructuring decisions involving a high number of laid-off employees.

3.4.2. Robustness checks

Alternative FEs specification: Column (2) of Table 7 shows that, beyond firm's AMT adoption, also the level of sectoral AMT investments is related to the propensity to downsize and shut down business activities. In Table 8 we conduct a further robustness check including country-sector dummies, that is a more demanding combination of FEs. Through this test, we aim at excluding the possibility that our results for the firm-level AMT adoption variable could be conditional to the significance of the sectoral AMT investments control. On the contrary, the latter variable could capture unobserved trends which are simultaneously country- and sector-specific. This robustness test implies a reduction in our sample due to the lack of sufficient variability in our data at the country-sector level, leading to exact outcome predictions.

Table 8 around here

The results, reported in Table 8, are highly similar to our main findings shown in Table 7. Notably, including country-sector FEs implies a consistent reduction in our sample making it shrink by 8% or around 20.000 observation referring to almost 3.000 firms in column (1) (i.e. the probit model for the first stage selection problem), but it also results in several explanatory variables of the probit model (including AMT adoption, our main explanatory) being estimated with higher precision. Even controlling for country-sector FE, AMT adoption reduces the likelihood of restructuring. As for the estimates for the multinomial logit model describing the second stage choice problem, in columns (2) and (3), our findings concerning the role of AMT adoption are consistent with the corresponding estimates in Table 7, showing an even larger probability of offshoring relative to closure (column 3). The coefficients for the sectoral AMT investment intensity variable are now no longer significant, as most of their variation is picked up by the country-sector fixed effects. The marginal effects in columns (4) to (7) are qualitatively and quantitatively unchanged as compared to the same specifications in Table 7.

First-stage logit model: The standard Heckman (1979) two-step correction method assumes that the error terms both in the model describing the selection equation (1) – usually estimated using a probit model – and in the main model describing the outcome generation process – usually estimated *via* OLS – are normally distributed (Wolfolds and Siegel, 2019). This is not the case in our model, since the multinomial logit used in the second stage describing the determinants of a firm's restructuring choice among different alternatives is based on a different set of assumptions, specifically, the independence of irrelevant alternatives (IIA). Hence, we test the robustness of our main results by estimating an alternative specification of the first-stage model using a logit model, which only requires the random component of the underlying utility function to be independent and identically distributed (IID). The estimated coefficients are shown in Table 9. Also in this case, our main results are qualitatively and quantitatively unchanged.

Table 9 around here

Multinomial logit model with control group: As final robustness check, we explore specifications of the multinomial logit model describing the relationship between AMT adoption and other explanatories, and the probability of choosing alternative restructuring options using a group of non-restructuring firms as reference category. This test can be thought as an alternative of the Heckman-type two-step correction model discussed above, where the selection mechanism is embedded in the multinomial logit model describing the choice problem, including the main exclusion restriction (i.e. labour productivity) and the other additional sectoral controls. Yet, since our counterfactual used in the first-stage probit model include more than 75.000 observations (i.e. more than 75.000 non-restructuring events), in order to reduce computational complexity and facilitate the convergence of the maximisation algorithm, we use a subsample of non-restructuring firms as reference group.

Figure 2 around here

In order to define the counterfactual group of non-restructuring firms, we relied on the nearest neighbour matching algorithm using the seven[48] closest neighbours (i.e. resorting to oversampling) with replacement (i.e. a non-restructuring firm-year observation can be used more than once as a match for a restructuring one). The idea is to define a control group of non-restructuring firms that are sufficiently similar to firms that have engaged in restructuring events. We performed the propensity score matching using all firm-level variables, sectoral controls and FEs used in the main analysis. Observations for restructuring and control firms falling outside of the region of common support have been discarded. Overall, we have identified 2,552 firms in the counterfactual control group. Diagnostic tests suggest our matching procedure performs well: Rosenbaum and Rubin's (1985) standardised bias falls below 5% (i.e. mean bias is 3.3% and median bias is 2.6% for matched firms), and t-test on differences in sample means in observable characteristics between restructuring and control firms (matched firms) are always statistically equal to zero (i.e. no significant difference between restructuring and non-restructuring firms after matching). Figure 2 reports standardised percentage bias reduction across firm-level explanatory variables and sectoral controls, ordered by decreasing bias reduction. Furthermore, following Sianesi (2004), we also check for $pseudo\text{-}R^2$ the likelihood ratio (LR) test on the joint significance of regressors from a probit model[49] re-estimated on the matched sample: the $pseudo\text{-}R^2$ is very small and the LR test is

[48] We also tested alternative specifications using control groups defined using alternative matching procedures, by allowing for a smaller and larger number of nearest neighbours (i.e. three, five and nine). We report estimates using seven nearest neighbours since this matching allows obtaining the highest bias reduction. Results obtained using three, five and nine nearest neighbours are in line with those reported in Table 10 and available upon request.
[49] The dependent variable equals 1 if the firm is a restructuring one, 0 otherwise.

rejected (i.e. $pseudo\text{-}R^2 = 0.021$ and LR $p = 0.958$), further suggesting the validity of our matching strategy.[50]

Table 10 around here

Table 10 reports results of our robustness check using the identified counterfactual as reference group for the multinomial logit model, additionally including a full set of country-sector and year FEs. Column (1) reports estimated coefficients for the probability of choosing closure over non-restructuring: the AMT adoption coefficient is negative and statistically significant ($p = 0.002$). Together with the estimated marginal effect reported in column (4), this results further confirm the previous insight on the hypothesised role that sunk costs and high specificity associated with AMTs have in making firms less likely to close, but rather to continue operations by opting for alternative restructuring modes. However, looking at the estimated coefficient for AMT adoption in columns (2)-(3) and at the related marginal effect in column (5)-(6), we find that the adoption of AMTs has a positive, but not significant, impact on the probability of downsizing and offshoring. This result might highlight that AMT adoption has similar implications for non-restructuring firms and downsizing/offshoring firms (e.g. improved resource usage, efficiency and productivity), hence implying no statistically significant difference between these categories.

3.5. Discussion and conclusions

The management decision to lay-off employees and restructure business activities results from the interplay of several diverse strategic considerations around the firm's level of performance, its financial status and competitive position on the market. At the same time, such decision responds to

[50] We used STATA's psmatch2 and pstest routines to compute the nearest neighbour matching algorithm and to check the diagnostics.

the stimuli that comes from the external environment, as a result of changing macroeconomic conditions, new global challenges and investment opportunities across the world, as well as to sudden and unforeseen shocks. As such, research (e.g. Bandick, 2016; Brauer and Zimmermann, 2017; Coucke et al., 2007; Coucke and Sleuwaegen, 2008; O'Brien and Folta, 2009; Powell and Yawson, 2012; Reynaud, 2013) has largely focussed so far on understanding the organisational and contextual features that influence the strategic decision process involving the restructuring of business activities, in the attempt of providing clear and meaningful policy recommendations helping to mitigate the negative consequences of collective employee layoffs.

In this context, we focus on the role of advanced technology, specifically looking at advanced manufacturing technologies (AMTs) of the Industry 4.0 (I4.0) wave. We take stock of prior research in the operations and technology management literature (e.g. Bogers et al., 2016; Dalenogare et al., 2018; Frank et al., 2019; Marcucci et al., 2021; Müller et al., 2018; Porter and Heppelmann, 2014; 2015; Rayna and Striukova, 2016) on the implications associated with the adoption of these technologies for firms, industries and markets. in doing so, we propose a conceptual framework accounting for the adoption-related benefits, barriers and implications, and highlighting the main features that come into play when the adoption of AMTs interplays with the strategic decision-making process ending with a restructuring decision involving a collective layoff. To the best of our knowledge, such relationship has been largely neglected to date and represents a research gap deserving further investigation.

We test our hypotheses by addressing a multilevel problem, first by analysing the role of AMT adoption in the decision to restructure or not, and secondly by analysing its effect on the likelihood of opting for a specific type of restructuring once the firm has decided to restructure. Our findings suggest that AMTs influence the firm's propensity to restructure *via* employee layoffs by reducing the likelihood of such events. The observed overall effect comes as a combination of multiple mechanisms: a lower probability of permanently closing a firm's plant or even terminating activities and a higher probability of pursuing downsizing, instead. The former behaviour is coherent with the established theoretical and empirical background (e.g. Coucke et al., 2007; O'Brien and Folta, 2009) arguing that investments in highly specialised, capital-intensive technologies create a 'lock-in' effect by rising sunk costs associated with both physical and intangible assets, and lower the firm's ability to reuse – by either redeploy or sell – previously acquired assets. The latter is instead coherent with the extensive research on the benefits spurring from the adoption of new advanced digital technologies of the fourth industrial revolution (4IR), which provide firms with higher efficiency and flexibility, increase the level of productivity and enable a deeper digital integration within and across organisations (e.g. Dalenogare et al., 2018; Frank et al., 2019; Kagermann et al., 2013; Müller et al., 2018; Schuh et al., 2014; Weller et al., 2015). In addition, such research stream also highlights that the adoption of these technologies entail a process of automation deepening (Cascio, 2012; Coucke et al., 2007; Freeman and Ehrhardt, 2012), resulting in a reduced and/or changed need for human labour.

Prior research on the nexus of new automation technologies of the 4IR and employment has been devoting much attention on the compositional dynamics of such relationship, investigating the exposure of jobs to automation by digging into the differences across tasks and skills (e.g. Acemoglu and Autor, 2011; Acemoglu and Restrepo, 2018; 2019; 2020; Frey and Osborne, 2017), resulting in the widespread agreement that, so far, these technologies have displaced more jobs than they have contributed to create, especially in manufacturing. However, only few works have made a first move into the intersection between the adoption of these technologies and collective layoff resulting from restructuring events, whilst looking at the implications for displaced workers (Beer et al., 2019; Blien et al., 2021; Goos et al., 2021; Olsson and Tåg, 2017). Thus, this research presents fresh evidence that investments in AMTs of the I4.0 wave and the associated benefits may also trigger additional side effects, providing new tools and opportunities for managers to sustain competition and increase chances of success, as well as creating incentives for firms to avoid restructuring decisions implying a heavy toll on the workforce. To this end, while assessing the role of the industrial and innovation policies launched by virtually every EU country over the last decade (Mariani and Borghi, 2019) and promoting the adoption of new digital technologies of the I4.0 wave, our work stresses prior findings on the efficiency and productivity gains brough by AMTs, and further highlights a secondary positive effect acting as a countervailing force and reducing the number of jobs lost through corporate restructuring.

We acknowledge that while benefits for adopting firms are well documented in the literature, the observed employment effect on adopting firms might not be as large as expected. On the one hand, our results suggest this empirical behaviour to be related to the role of AMTs of the I4.0 wave in creating the conditions for firms to avoid restructuring events implying employment layoffs. On the other hand, we might not exclude that the automation-related displacement of workers documented in sectoral and aggregate studies are largely happening to non-adopting firms, as a result of business stealing (see, for instance, Acemoglu et al., 2020). Unfortunately, our empirical framework and the data used does not allow to disentangle such potential issue, hence leaving it for future research.

While we believe this study is a first step in exploring this yet unexplored relationship, we acknowledge the limitations of our research. First and foremost, 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 like the one used in this study. Besides, while focusing on an extensive sample of restructuring events allow us to better understand the phenomenon of interest, we acknowledge that restructuring data provided in the ERM database presents some limitations. In particular, since the database relies on a list of major media titles active in each EU country to collect information on each restructuring events, its coverage of restructuring activity cannot be considered representative of the whole population (Eurofound, 2022). Furthermore, as already noted above, since ERM only reports on restructuring events in medium-sized and large establishment (as discussed in Section 3.3) a size bias is likely to arise, potentially leading to either over- or under-representation of some countries and/or sectors. Finally, ERM data only reports the number of workers displaced and/or hired because of a restructuring event, unfortunately it does not provide information on the type of workers affected by such events. This makes it impossible to establish a detailed analysis of the compositional and/or inequality-enhancing employment effects associated with restructuring events.

Despite its limitation, ERM's data also provide a rich set of unstructured information. Further research could dig into such richness, for instance, by understanding the locations of offshoring decisions, tracking firm's movement across countries, analysing the compositional effects of restructuring events over the affected workforce, disentangling the net effect on hirings and layoffs, as well as monitoring with a higher degree of accuracy specific mention to the role of AMTs and other technologies of the 4IR. To this end, machine learning techniques and advanced data analysis tools could prove to be helpful methodologies to extract value from the available unstructured information and make them available for both economics and management research.

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3.7. Tables and Figures

Table 1. Distribution of restructuring events by year

Year	Closure		Downsizing		Offshoring		Control		Total
	N	%	N	%	N	%	N	%	N
2013	13	2.77	73	15.57	10	2.13	373	79.53	469
2014	19	4.55	60	14.35	7	1.67	332	79.43	418
2015	11	3.22	58	16.96	6	1.75	267	78.07	342
2016	9	2.59	57	16.38	7	2.01	275	79.02	348
2017	17	4.64	58	15.85	7	1.91	284	77.60	366
2018	16	5.13	42	13.46	5	1.60	249	79.81	312
2019	20	4.55	75	17.05	4	0.91	341	77.50	440
2020	21	3.58	123	20.95	12	2.04	431	73.42	587
Total	126	3.84	546	16.64	58	1.77	2552	77.76	3282

Notes: Authors' own computations based on ERM and Amadeus data.

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

NACE 2-digit code	Closure		Downsizing		Offshoring		Control		Total
	N	%	N	%	N	%	N	%	N
10 – Man. of food prod.	26	6.21	49	11.69	7	1.67	337	80.43	419
11 – Man. of beverages	6	7.06	9	10.59	2	2.35	68	80.00	85
12 – Man. of tobacco prod.	1	3.70	3	11.11	1	3.70	22	81.48	27
13 – Man. of textiles	1	1.72	7	12.07	1	1.72	49	84.48	58
14 – Man. of wearing apparel	3	6.25	5	10.42	0	0.00	40	83.33	48
15 – Man. of leather and related prod.	1	7.69	2	15.38	0	0.00	10	76.92	13
16 – Man. of wood and of prod. of wood and cork	2	3.39	7	11.86	1	1.69	49	83.05	59
17 – Man. of paper and paper prod.	9	6.82	21	15.91	1	0.76	101	76.52	132
18 – Printing and reproduction of recorded media	1	3.13	5	15.63	0	0.00	26	81.25	32
19 – Man. of coke and refined petroleum prod.	1	3.13	7	21.88	0	0.00	24	75.00	32
20 – Man. of chemicals and chemical prod.	3	1.91	29	18.47	4	2.55	121	77.07	157
21 – Man. of basic pharmaceutical prod. and pharmaceutical preparations	4	3.51	20	17.54	3	2.63	87	76.32	114
22 – Man. of rubber and plastic prod.	6	5.26	14	12.28	3	2.63	91	79.82	114
23 – Man. of other non-metallic mineral prod.	6	5.22	15	13.04	1	0.87	93	80.87	115
24 – Man. of basic metals	4	2.25	34	19.10	2	1.12	138	77.53	178
25 – Man. of fabricated metal prod., except machinery and equipment	4	3.25	18	14.63	2	1.63	99	80.49	123
26 – Man. of computer, electronic and optical prod.	5	2.50	34	17.00	2	1.00	159	79.50	200
27 – Man. of electrical equipment	9	4.62	31	15.90	10	5.13	145	74.36	195
28 – Man. of machinery and equipment n.e.c.	13	3.09	73	17.34	5	1.19	330	78.38	421
29 – Man. of motor vehicles, trailers and semi-trailers	15	3.75	90	22.50	8	2.00	287	71.75	400
30 – Man. of other transport equipment	0	0.00	54	31.03	0	0.00	120	68.97	174
31 – Man. of furniture	1	1.96	7	13.73	2	3.92	41	80.39	51
32 – Other manufacturing	2	3.17	4	6.35	3	4.76	54	85.71	63
33 – Repair and installation of machinery and equipment	3	4.17	8	11.11	0	0.00	61	84.72	72
Total	126		546		58		2552		3282

Notes: Authors' own computations based on ERM and Amadeus data.

Table 3. Distribution of restructuring events by country

ISO	Closure		Downsizing		Offshoring		Control		Total
	N	%	N	%	N	%	N	%	N
AUT	5	4.76	13	12.38	5	4.76	82	78.10	105
BEL	9	10.23	27	30.68	7	7.95	45	51.14	88
CZE	2	2.38	11	13.10	1	1.19	70	83.33	84
DEU	24	3.83	131	20.89	10	1.59	462	73.68	627
DNK	1	1.85	8	14.81	1	1.85	44	81.48	54
EST	0	0.00	4	13.33	0	0.00	26	86.67	30
FIN	7	1.93	58	15.98	3	0.83	295	81.27	363
FRA	20	5.10	109	27.81	13	3.32	250	63.78	392
GBR	29	5.13	59	10.44	5	0.88	472	83.54	565
GRC	1	14.29	1	14.29	0	0.00	5	71.43	7
HUN	4	7.14	4	7.14	1	1.79	47	83.93	56
IRL	2	11.11	0	0.00	0	0.00	16	88.89	18
LTU	0	0.00	7	14.58	0	0.00	41	85.42	48
LVA	0	0.00	2	12.50	1	6.25	13	81.25	16
NLD	1	1.28	10	12.82	3	3.85	64	82.05	78
POL	12	4.11	34	11.64	0	0.00	246	84.25	292
SVK	4	5.48	8	10.96	2	2.74	59	80.82	73
SVN	2	2.15	14	15.05	1	1.08	76	81.72	93
SWE	3	1.02	46	15.70	5	1.71	239	81.57	293
Total	126		546		58		2552		3282

Notes: Authors' own computations based on ERM and Amadeus data.

Table 4. Descriptive statistics: summary statistics of employee layoffs

	Closure		Downsizing		Offshoring		Total	
	Normalised	log	Normalised	log	Normalised	log	Normalised	log
Mean	0.764	5.393	0.678	5.351	0.705	5.193	0.694	5.346
SD	0.148	0.689	0.127	1.014	0.171	0.616	0.138	0.939
p10	0.554	4.625	0.508	4.277	0.449	4.564	0.507	4.394
p25	0.662	4.883	0.592	4.644	0.578	4.736	0.596	4.710
Median	0.782	5.250	0.680	5.142	0.723	5.075	0.694	5.176
p75	0.890	5.861	0.762	5.861	0.835	5.525	0.786	5.832
p90	0.964	6.293	0.834	6.553	0.920	6.256	0.884	6.399

Notes: Authors own computations based on ERM and Orbis data. Observations: 126 closures; 546 downsizing; 58 offshoring. Normalised 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).

Table 5. Descriptive statistics: summary statistics and correlation matrix

Variable	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]
Firm-level variables													
[1] AMT adoption													
[2] Size	0.349												
	0.337												
[3] Age	0.114	0.275											
	0.190	*0.214*											
[4] ROA	0.189	0.133	0.128										
	0.122	*0.104*	*0.058*										
[5] Leverage	0.195	0.160	0.070	-0.043									
	0.132	*0.116*	*-0.012*	*-0.125*									
[6] Capital intensity	0.828	0.276	0.091	0.151	0.185								
	0.883	*0.257*	*0.157*	*0.109*	*0.120*								
[7] Labour productivity	0.227	-0.057	0.035	0.048	0.019	0.308							
	0.311	*-0.033*	*0.077*	*0.051*	*-0.073*	*0.340*							
[8] MNE dummy	0.247	0.371	0.266	-0.008	0.169	0.193	0.117						
	0.240	*0.388*	*0.227*	*0.014*	*0.146*	*0.184*	*0.105*						
[9] Innovator dummy	0.222	0.371	0.232	-0.059	0.141	0.194	0.029	0.402					
	0.174	*0.237*	*0.279*	*-0.004*	*0.042*	*0.109*	*0.072*	*0.266*					
[10] Recent investments dummy	0.209	0.186	0.030	0.127	0.038	0.048	0.065	0.120	0.115				
	0.186	*0.233*	*0.035*	*0.063*	*0.028*	*0.056*	*0.029*	*0.129*	*0.092*				
Sectoral variables													
[11] AMT investment intensity	0.101	0.275	0.107	-0.047	-0.009	-0.134	0.081	0.180	0.207	0.128			
	0.149	*0.206*	*0.150*	*-0.031*	*0.034*	*-0.105*	*0.107*	*0.203*	*0.276*	*0.104*			
[12] Investment intensity	-0.001	0.053	-0.001	0.014	-0.059	-0.034	0.073	-0.039	-0.045	0.053	0.160		
	0.042	*0.025*	*0.001*	*0.002*	*-0.037*	*0.028*	*0.079*	*-0.053*	*0.028*	*0.046*	*0.099*		
[13] Product differentiation	-0.130	-0.161	-0.014	-0.019	-0.035	-0.135	0.042	-0.099	-0.152	-0.102	0.040	0.144	
	0.007	*-0.034*	*0.054*	*-0.005*	*0.003*	*-0.017*	*-0.010*	*-0.023*	*0.026*	*0.016*	*0.102*	*0.186*	
N	730	730	730	730	730	730	730	730	730	730	730	730	730
	3282	*3282*	*3282*	*3282*	*3282*	*3282*	*3282*	*3282*	*3282*	*3282*	*3282*	*3282*	*3282*
Mean	73.508	7.726	3.532	-0.006	0.081	3.646	5.636	0.766	0.701	0.374	20.590	22.500	0.795
	71.388	*7.054*	*3.386*	*0.010*	*0.076*	*3.549*	*5.576*	*0.722*	*0.645*	*0.365*	*20.368*	*21.491*	*0.795*
SD	28.660	2.098	0.909	0.196	0.120	1.236	0.915	0.424	0.458	0.484	1.895	11.509	0.163
	26.779	*1.736*	*0.879*	*0.293*	*0.121*	*1.265*	*0.908*	*0.448*	*0.478*	*0.482*	*2.003*	*12.219*	*0.163*
Min	-143.354	1.792	0.000	-2.498	-0.315	-1.375	2.066	0.000	0.000	0.000	13.637	3.740	0.150
	-172.197	*1.792*	*0.000*	*-8.683*	*-0.773*	*-10.404*	*1.607*	*0.000*	*0.000*	*0.000*	*13.323*	*3.260*	*0.136*
Max	223.975	13.393	5.606	0.514	0.701	11.077	12.651	1.000	1.000	1.000	25.263	81.400	1.000
	223.975	*13.393*	*5.606*	*0.938*	*1.818*	*11.077*	*12.651*	*1.000*	*1.000*	*1.000*	*25.263*	*119.550*	*1.000*

Notes: Statistics in italic refer to the robustness analysis including the control group. All statistics refer to 1-year lagged variables.

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

Variable	Closure		Downsizing		Offshoring		Closure vs Downsizing	Closure vs Offshoring
	Mean	SD	Mean	SD	Mean	SD	T-test (*p*-value)	T-test (*p*-value)
Firm-level variables								
AMT adoption	62.378	36.927	76.243	26.010	71.943	26.429	0.000	0.047
Size	6.850	1.852	7.924	2.097	7.765	2.152	0.000	0.006
Age	3.304	0.968	3.575	0.876	3.626	1.024	0.005	0.046
ROA	-0.037	0.259	0.001	0.185	-0.003	0.128	0.127	0.235
Leverage	0.069	0.114	0.081	0.116	0.100	0.159	0.302	0.195
Capital intensity	3.369	1.190	3.714	1.256	3.610	1.059	0.004	0.171
Labour productivity	5.595	0.935	5.637	0.902	5.712	0.998	0.648	0.454
MNE dummy	0.643	0.481	0.795	0.404	0.759	0.432	0.001	0.106
Innovator dummy	0.579	0.496	0.727	0.496	0.724	0.451	0.003	0.052
Recent investments dummy	0.302	0.461	0.396	0.489	0.328	0.473	0.043	0.728
Sectoral variables								
AMT investment intensity	20.538	1.740	20.611	1.936	20.506	1.852	0.678	0.912
Investment intensity	20.170	10.234	23.030	11.998	22.566	8.571	0.007	0.100
Product differentiation	0.785	0.176	0.794	0.161	0.831	0.154	0.573	0.070

Notes: Observations: 126 closures; 546 downsizing; 58 offshoring. All statistics refer to 1-year lagged variables.

Table 7. Main results

	First stage (selection problem): Probit model	Second stage (choice problem): Multinomial Logit model					Second stage: OLS
	H1	H2	H3	Marginal Effects			Layoff size
		Downsizing vs Closure	Offshoring vs Closure	Closure	Downsizing	Offshoring	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Firm-level variables							
AMT adoption	-0.005*	0.0357***	0.0260**	-0.0038***	0.0040***	-0.0002	-0.006***
	(0.003)	(0.010)	(0.012)	(0.001)	(0.001)	(0.001)	(0.002)
Size	0.440***	-0.2887	-0.2137	0.0305	-0.0320	0.0015	0.281***
	(0.027)	(0.326)	(0.356)	(0.035)	(0.039)	(0.017)	(0.070)
Age	0.015	0.2575*	0.3370	-0.0289*	0.0208	0.0081	0.012
	(0.036)	(0.150)	(0.232)	(0.016)	(0.019)	(0.013)	(0.040)
ROA	-0.636***	1.4621	1.1360	-0.1552	0.1591	-0.0040	-0.434**
	(0.125)	(1.022)	(1.153)	(0.111)	(0.112)	(0.045)	(0.186)
Leverage	-0.524**	0.6377	1.0922	-0.0746	0.0379	0.0367	-0.684***
	(0.233)	(1.028)	(1.673)	(0.111)	(0.134)	(0.093)	(0.258)
Capital intensity	0.012	-0.5333***	-0.4037*	0.0565***	-0.0586**	0.0021	0.075
	(0.060)	(0.182)	(0.232)	(0.019)	(0.024)	(0.014)	(0.054)
Labour productivity	0.213***						
	(0.038)						
Corporate group dummy	-0.110*	0.3604	0.0204	-0.0352	0.0529	-0.0177	0.034
	(0.057)	(0.343)	(0.551)	(0.037)	(0.045)	(0.031)	(0.086)
Innovator dummy	0.139**	-0.0260	0.3039	-0.0010	-0.0199	0.0209	-0.016
	(0.060)	(0.312)	(0.514)	(0.033)	(0.042)	(0.029)	(0.076)
Recent investments dummy	-0.371***	0.3735	0.2345	-0.0390	0.0436	-0.0046	-0.067
	(0.049)	(0.400)	(0.525)	(0.043)	(0.047)	(0.025)	(0.086)
Sectoral variables							
AMT investment intensity	-0.037	-0.8805***	-0.7157	0.0938***	-0.0942***	0.0004	-0.039
	(0.053)	(0.284)	(0.461)	(0.030)	(0.035)	(0.025)	(0.056)
Investment intensity	-0.000						
	(0.003)						
Product differentiation	-0.107						
	(0.215)						
First-stage IMR		-1.6020*	-1.6636	0.1749*	-0.1523	-0.0226	0.280
		(0.944)	(1.164)	(0.102)	(0.114)	(0.058)	(0.208)
Observations	77.556	730		730			730
Firms	12.162	565		565			565
(pseudo) R^2	0.464	0.225		-			0.373
Log-likelihood	-2214	-408.0		-			-

Notes: All regressions include 18 country dummies, 23 sector dummies and 7 year dummies. Coefficients and standard errors for the intercept and for FEs dummies have been omitted due to space constraints. All variables are 1-year lagged. The *Labour productivity* variable is used as exclusion restriction in the first-stage model, the *Investment intensity* and *Product differentiation* variables are included as additional controls in the first-stage model. Robust standard errors in brackets are clustered at the firm level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 8. Robustness of main results: Country-Sector FEs

	First stage (selection problem): Probit model	Second stage (choice problem): Multinomial Logit model					Second stage: OLS
	H1	H2	H3	Marginal Effects			Layoff size
		Downsizing vs Closure	Offshoring vs Closure	Closure	Downsizing	Offshoring	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Firm-level variables							
AMT adoption	-0.006**	0.0399***	0.0550***	-0.0029***	0.0021**	0.0008	-0.007**
	(0.003)	(0.011)	(0.018)	(0.001)	(0.001)	(0.001)	(0.003)
Size	0.520***	0.1647	-0.4568	-0.0081	0.0317	-0.0236	0.305***
	(0.032)	(0.354)	(0.483)	(0.025)	(0.027)	(0.015)	(0.082)
Age	-0.016	0.2956	0.5717*	-0.0227	0.0101	0.0127	0.022
	(0.040)	(0.206)	(0.336)	(0.014)	(0.017)	(0.011)	(0.051)
ROA	-0.693***	0.5277	1.7758	-0.0450	-0.0074	0.0524	-0.531**
	(0.142)	(0.997)	(1.376)	(0.071)	(0.077)	(0.041)	(0.243)
Leverage	-0.667**	0.2678	3.3491	-0.0373	-0.0860	0.1233	-0.729**
	(0.267)	(1.473)	(2.302)	(0.104)	(0.128)	(0.080)	(0.316)
Capital intensity	0.012	-0.7698***	-0.9327***	0.0559***	-0.0449**	-0.0110	0.135*
	(0.065)	(0.245)	(0.341)	(0.016)	(0.023)	(0.013)	(0.070)
Labour productivity	0.240***						
	(0.043)						
Corporate group dummy	-0.142**	0.6180	0.3985	-0.0428	0.0478	-0.0050	0.054
	(0.066)	(0.456)	(0.789)	(0.032)	(0.040)	(0.027)	(0.112)
Innovator dummy	0.267***	0.6140	0.5353	-0.0433	0.0428	0.0005	-0.008
	(0.072)	(0.460)	(0.723)	(0.032)	(0.039)	(0.025)	(0.112)
Recent investments dummy	-0.410***	-0.2893	-0.1860	0.0200	-0.0224	0.0024	-0.067
	(0.052)	(0.464)	(0.743)	(0.033)	(0.039)	(0.025)	(0.100)
Sectoral variables							
AMT investment intensity	0.440	-5.5882	-2.9502	0.3831	-0.4542	0.0712	0.320
	(0.329)	(5.471)	(6.129)	(0.385)	(0.385)	(0.137)	(0.802)
Investment intensity	-0.006						
	(0.004)						
Product differentiation	0.418						
	(0.512)						
First-stage IMR		-0.2111	-1.9795	0.0255	0.0456	-0.0711	0.372
		(0.975)	(1.594)	(0.069)	(0.082)	(0.053)	(0.228)
Observations	57.212	671		671			671
Firms	9246	515		515			515
(pseudo) R^2	0.495	0.509		-			0.513
Log-likelihood	-1844	-230.0		-			-

Notes: All regressions include 263 country-sector dummies and 7 year dummies. Coefficients and standard errors for the intercept and for FEs dummies have been omitted due to space constraints. All variables are 1-year lagged. The *Labour productivity* variable is used as exclusion restriction in the first-stage model, the *Investment intensity* and *Product differentiation* variables are included as additional controls in the first-stage model. Robust standard errors in brackets are clustered at the firm level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 9. Robustness of main results: First-stage logit model

	First stage (selection problem): Logit model	Second stage (choice problem): Multinomial Logit model					
	H1	H2	H3		Marginal Effects		
		Downsizing vs Closure	Offshoring vs Closure		Closure	Downsizing	Offshoring
	(1)	(2)	(3)		(4)	(5)	(6)
Firm-level variables							
AMT adoption	-0.014**	0.0346***	0.0256**		-0.0037***	0.0038***	-0.0002
	(0.007)	(0.009)	(0.012)		(0.001)	(0.001)	(0.001)
Size	0.951***	-0.1335	-0.0795		0.0139	-0.0158	0.0019
	(0.061)	(0.227)	(0.239)		(0.024)	(0.027)	(0.011)
Age	0.053	0.2511*	0.3274		-0.0282*	0.0203	0.0078
	(0.091)	(0.151)	(0.232)		(0.016)	(0.019)	(0.013)
ROA	-1.347***	1.2294	0.9526		-0.1304	0.1339	-0.0035
	(0.417)	(0.938)	(1.035)		(0.102)	(0.101)	(0.039)
Leverage	-1.118*	0.4391	0.9356		-0.0535	0.0164	0.0371
	(0.602)	(0.985)	(1.636)		(0.107)	(0.129)	(0.092)
Capital intensity	0.022	-0.5168***	-0.3999*		0.0548***	-0.0563**	0.0015
	(0.145)	(0.179)	(0.231)		(0.018)	(0.024)	(0.013)
Labour productivity	0.552***						
	(0.092)						
Corporate group dummy	-0.304**	0.3481	0.0168		-0.0340	0.0513	-0.0173
	(0.145)	(0.342)	(0.552)		(0.037)	(0.045)	(0.031)
Innovator dummy	0.269*	0.0249	0.3504		-0.0065	-0.0148	0.0212
	(0.159)	(0.310)	(0.511)		(0.033)	(0.041)	(0.029)
Recent investments dummy	-0.902***	0.2932	0.1842		-0.0306	0.0342	-0.0036
	(0.121)	(0.356)	(0.473)		(0.038)	(0.042)	(0.024)
Sectoral variables							
AMT investment intensity	-0.110	-0.8859***	-0.7190		0.0943***	-0.0948***	0.0004
	(0.143)	(0.284)	(0.462)		(0.030)	(0.035)	(0.025)
Investment intensity	0.003						
	(0.007)						
Product differentiation	-0.242						
	(0.561)						
First-stage IMR		-0.5254*	-0.5962	0.0579*	-0.0472	-0.0107	-0.0226
		(0.296)	(0.367)	(0.032)	(0.036)	(0.019)	(0.058)
Observations	77.556	730			730		
Firms	12.162	565			565		
(pseudo) R^2	0.454	0.226			-		
Log-likelihood	-2255	-407.9			-		

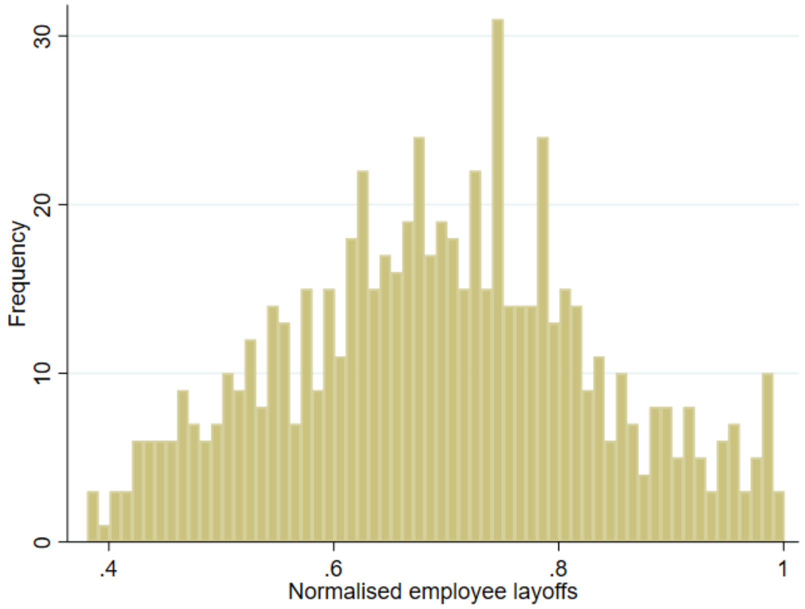
Notes: All regressions include 18 country dummies, 23 sector dummies and 7 year dummies. Coefficients and standard errors for the intercept and for FEs dummies have been omitted due to space constraints. All variables are 1-year lagged. The *Labour productivity* variable is used as exclusion restriction in the first-stage model, the *Investment intensity* and *Product differentiation* variables are included as additional controls in the first-stage model. Robust standard errors in brackets are clustered at the firm level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 10. Robustness of main results: Multinomial logit model with control group as reference category

	Closure vs Control	Downsizing vs Control	Offshoring vs Control	Marginal Effects		
				Closure	Downsizing	Offshoring
	(1)	(2)	(3)	(4)	(5)	(6)
Firm-level variables						
AMT adoption	-0.0297***	0.0009	0.0022	-0.0011***	0.0003	0.0001
	(0.009)	(0.005)	(0.009)	(0.000)	(0.001)	(0.000)
Size	0.0737	0.2699***	0.1839	0.0005	0.0326***	0.0023
	(0.089)	(0.060)	(0.113)	(0.003)	(0.007)	(0.002)
Age	-0.0988	0.0413	0.1022	-0.0042	0.0055	0.0020
	(0.136)	(0.092)	(0.210)	(0.005)	(0.011)	(0.004)
ROA	-0.3115	-0.2977*	-0.2403	-0.0092	-0.0339*	-0.0030
	(0.216)	(0.163)	(0.239)	(0.008)	(0.019)	(0.005)
Leverage	-0.7618	-0.3197	0.0601	-0.0265	-0.0348	0.0038
	(0.776)	(0.571)	(1.313)	(0.029)	(0.070)	(0.027)
Capital intensity	0.4806**	-0.0476	-0.1068	0.0188**	-0.0092	-0.0025
	(0.208)	(0.111)	(0.183)	(0.008)	(0.014)	(0.004)
Labour productivity	0.1003	0.1114	0.1650	0.0027	0.0124	0.0027
	(0.124)	(0.103)	(0.197)	(0.005)	(0.013)	(0.004)
Corporate group dummy	-0.1958	-0.1603	-0.2987	-0.0058	-0.0172	-0.0051
	(0.240)	(0.168)	(0.342)	(0.009)	(0.021)	(0.007)
Innovator dummy	0.0183	0.1300	0.1210	-0.0005	0.0157	0.0018
	(0.240)	(0.174)	(0.355)	(0.009)	(0.021)	(0.007)
Recent investments dummy	-0.0244	-0.1424	-0.1969	0.0004	-0.0168	-0.0033
	(0.194)	(0.118)	(0.273)	(0.007)	(0.015)	(0.006)
Sectoral variables						
AMT investment intensity	0.8110	-0.2143	1.4149	0.0307	-0.0406	0.0293
	(1.594)	(0.778)	(1.696)	(0.061)	(0.100)	(0.036)
Investment intensity	0.0049	-0.0095	-0.0087	0.0003	-0.0012	-0.0001
	(0.016)	(0.008)	(0.019)	(0.001)	(0.001)	(0.000)
Product differentiation	2.7388	0.2409	0.1037	0.1020	0.0087	-0.0025
	(1.969)	(1.109)	(2.772)	(0.075)	(0.139)	(0.057)
Observations		3.282			3.282	
Firms		1.762			1.762	
(pseudo) R^2		0.267			-	
Log-likelihood		-1660			-	

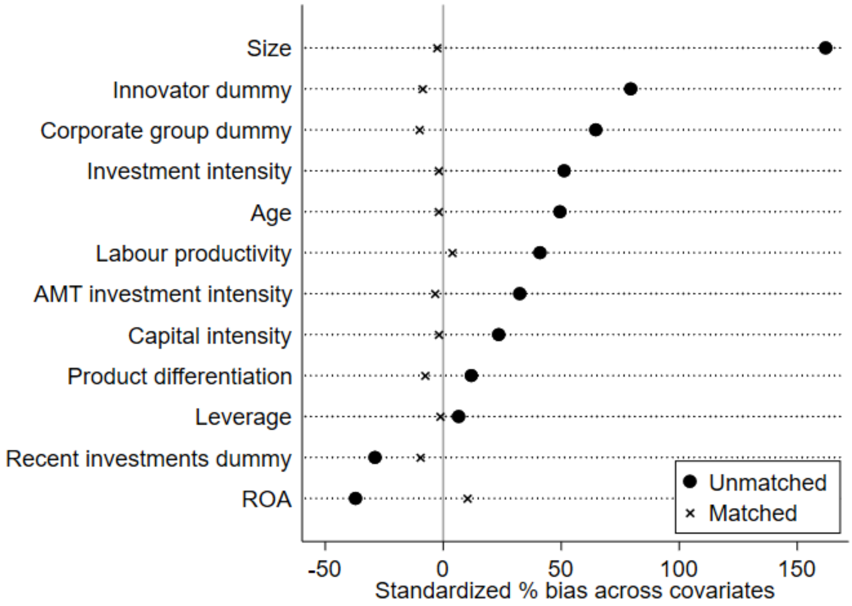
Notes: All regressions include 495 country-sector dummies and 7 year dummies. Coefficients and standard errors for the intercept and for FEs dummies have been omitted due to space constraints. All variables are 1-year lagged. Robust standard errors in brackets are clustered at the firm level. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Figure 1. Frequency distribution of normalised employee layoffs



Notes: Authors' own computations based on ERM and Amadeus data. Employee layoffs have been normalised using the firm's number of workers in the year preceding the restructuring event.

Figure 2. Robustness check: % bias reduction across explanatory variables in the matched and unmatched sample of non-restructuring firms



Notes: Authors' own estimates. % bias reductions for FEs have been omitted due to space constraints.

Chapter 4

The Employment Implications of Additive Manufacturing[†][*]

Abstract

Despite the fast pace at which Additive Manufacturing (AM) has been spreading across several countries and industries, its impact on employment is still theoretically ambiguous and vastly unexplored from an empirical standpoint. On the one hand, these technologies bring higher product customization and shorter time-to-market, entailing market expansion effects which, in turn, foster labour demand. On the other hand, AM innovations imply profound changes in the way goods are manufactured. Yet, little empirical evidence exists on the complementarity or substitutability between AM and labour. We contribute to the literature filling this gap by estimating labour demand functions augmented with a measure of diffusion of AM-related innovations, based on patent data from the USPTO. Our analysis spans across 31 OECD countries, 21 manufacturing industries, over the 2009–2017 period. Our econometric results highlight an average positive relationship between AM technologies and employment at the industry level, resulting from both market expansion and complementarity between AM and labour; at the same time, no labour-saving effect emerges. However, the quantitative importance of each mechanism is heterogeneous across sectors.

Keywords: Additive manufacturing; 3D printing; employment; technological change; industry-level analysis.

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[*] This Chapter is co-authored with Giulia Felice (DIG, Politecnico di Milano, IT) and Lucia Piscitello (DIG, Politecnico di Milano, IT). Contributions: Fabio Lamperti 55% (Conceptualisation, Methodology, Investigation, Data curation, Formal analysis, Writing – Original draft, Visualisation); Giulia Felice 35% (Conceptualisation, Methodology, Formal analysis, Validation, Writing – Review/editing, Visualisation, Supervision); Lucia Piscitello 10% (Conceptualisation, Writing – Review/editing, Supervision).

4.1. Introduction

The question of whether technological change creates more jobs than it destroys has been at the core of the academic and policy debates since the early stages of industrialization, dating back to the contributions of classical economists (e.g. Ricardo, 1951). More recently, important contributions related to the impact of Information and Communication Technology (ICT) on employment initiated by the seminal contribution of Autor and colleagues (2003) pushed forward this debate. Recently, the diffusion of automation, artificial intelligence and, in general, advanced manufacturing technologies of the Industry 4.0 (I4.0) wave – or fourth industrial revolution (4IR) – fostered a renewed interest in the effect of technology (Brynjolfsson and McAfee, 2014; Schwab, 2016). For instance, the diffusion of industrial robots in the 1990s and 2000s has created fear that this new wave of innovations may foster technological unemployment: although existing contributions show employment polarization effects, evidence is more mixed when looking at total employment (e.g. Graetz and Michels, 2018; Dauth et al., 2021; Acemoglu and Restrepo, 2020). Similarly, while new technologies of the 4IR are suggested to create a displacement effect in manufacturing (e.g. Acemoglu and Restrepo, 2020; Dauth et al., 2021), they also bring benefits and set incentives that may help sustaining manufacturing firms' activities, avoiding their closure (as discussed in Chapter 3).

The rising industrial automation and the rapid diffusion of industrial robots are not the sole technological trends characterizing the advent of the I4.0 wave (Kagermann et al., 2013; Davies, 2015). Indeed, additive manufacturing (or 3D printing; AM hereafter) is assuming an increasingly important role due to its diffusion in several countries and industries (OECD, 2017; EIB, 2019; Eurostat, 2021[51]), being widely discussed and receiving great attention from institutional actors and policymakers for its potential economic impacts (OECD, 2016; European Commission, 2016, 2017;

[51] See also Table A1 in Appendix A.

UNCTAD, 2017, 2020).[52] Yet, the effects of AM on employment remain unexplored from a quantitative standpoint, extant contributions providing only anecdotal evidence.

This Chapter contributes to the established literature analysing the employment-technology nexus and to the growing literature looking at the economic implications of advanced manufacturing technologies of the I4.0 wave by empirically investigating the relationship between AM innovations and employment at the industry level, thus providing an important contribution to these current debates. Specifically, we argue that AM technologies deserve a special focus, since they differ consistently from other digital production technologies so far investigated in the literature.

AM embodies a radical process innovation that reduces the number of production stages, at the same time increasing product customization and, ultimately, demand. Contrary to other forms of capital-embodied process innovations such as industrial robots, the diffusion of AM innovations is more likely to follow market seeking – rather than a labour-saving – economic incentive.[53] At the same time, AM '*activates*' all those channels through which capital-embodied technological innovations can affect employment. On the one hand, AM triggers market-driven employment effects both in upstream and downstream industries: in the former, happening as a displacement of jobs from the production of old machines and materials to that of new machines and materials; in the latter, moving jobs from the production of old products to that of new ones. On the other hand, in both the innovation-using and innovation-producing industries, the effect of AM on employment – for a given level of production – depends on their level of complementarity with labour and other production factors, as compared to traditional manufacturing methods.

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[52] AM is becoming one of the main areas of study in the social sciences, from economics to business and management (Mariani and Borghi, 2019).
[53] Indeed, this revolutionary manufacturing perspective, which involves adding and instantly joining layers of various materials in specific locations and creating objects from digital 3D data (ASTM International, 2013), has progressively gained attention in several fields, being used either as a complementary or mainstream manufacturing technology (Laplume et al., 2016).

Building on these theoretical arguments, in order to investigate the effect of AM innovations on total employment at the industry level, we build a patent-based proxy – namely patent family applications (hereafter, patents) – to the United States Patent and Trademark Office (USPTO), capturing the whole ecosystem of innovations relating to AM. Specifically, since the goal of this Chapter is to look at the overall diffusion of AM innovations, we rely on patent information, as they provide a deeper and more detailed insight on both AM-related product and process innovations. Our measure is built using patents protecting innovations for *AM processes, AM machines and apparatus, materials used in AM, pre- and post-processing operations related to AM, software for AM, products made via AM techniques* (WIPO, 2019). We attribute AM patents to countries through the inventor's residence and to NACE 2-digit manufacturing industries that are likely to feature higher diffusion of AM innovations leveraging on a widely used concordance methodology.

We estimate standard labour demand functions, which are augmented with our measure of AM innovations across 31 OECD countries and 21 manufacturing industries over the 2009–2017 period. As opposed to most research looking at the effects of technological change on employment, we estimate both unconditional and conditional labour demand functions: in the former, labour demand is uncompensated and we control for labour cost and technical progress, whereas in the latter labour demand is compensated – i.e. we control for the level of output – (Ugur et al., 2018) and the market expansion channel is '*switched off*'. Estimating both types of labour demand provides useful insight into the mechanisms characterising the AM-employment nexus. Yet, given the way AM affects industrial operations, we expect the channels linking these technological innovations to employment to work differently depending on the industry characteristics. Thus, we further extend our analysis to account for industrial heterogeneities, leveraging on the Pavitt classification (Pavitt, 1984).

We find an average positive relationship between AM innovations and the level of employment in both conditional and unconditional labour demand estimations, albeit of a larger magnitude in the latter. At the same time, our results show no labour-saving mechanisms to be in place with AM. Indeed, both market expansion and complementarity between labour and AM technologies drive the positive relationship we uncover with employment. Despite this average positive relationship holds across all manufacturing industries, its magnitude is highly heterogeneous across sectoral groups depending on the main source of innovation, the level of product differentiation, the degree of economies of scale, the related magnitude of market expansion, and factor complementarity effects.

The remainder of the Chapter is organised as follows. In Section 4.2, after shortly reviewing the main theories and empirical evidence on the relationship between technological change and employment, we develop our conceptual framework and hypotheses on the employment effects of AM. In Section 4.3, we describe the data used and the construction of our diffusion measure for AM innovations. Section 4.4 introduces the methodology used for the empirical strategy, while Section 4.5 focuses on the main findings. Section 4.6 draws conclusions and discusses limitations and future research avenues.

4.2. Technological change, employment, and the case of AM

The economic theory views capital-embodied technological change as driven mainly by cost-saving motivations, ultimately being labour-saving. As a result, the implications resulting from the introduction of process innovations are generally expected to be negative for employment. Yet, indirect channels possibly counterbalance these negative effects. These compensation mechanisms typically relate to market expansion effects induced by lower prices set by firms using the innovation, by the expansion of product demand for firms operating in upstream industries producing the new machines or complementary inputs – since process innovations are also product innovations in upstream sectors – and by higher income at the aggregate level (Freeman et al., 1982; Stoneman, 1983; Petit, 1995). At the same time, several contributions also argue that technological change associated with the introduction of new production technologies may result in uneven effects on the composition of labour (i.e. by the level of education and skills, occupation, age and gender) without affecting the total labour demand (Acemoglu, 2002). Conversely, product innovations are usually seen as positively affecting employment by creating new markets. Still, also this type of innovation can have negative counterbalancing forces, mainly related to the displacement of old products occurring when new ones are introduced, i.e. business stealing or cannibalization effects (Katsoulacos 1984, 1986).[54]

The relationship between technological change and employment has been subject to extensive analysis in the empirical literature, by looking at different aggregation levels – firms, industries and countries – and using different sources of information to measure technological innovations (i.e. R&D or investment expenditures, patents, survey data looking at process and/or product innovations or the adoption of specific technologies).

Several works – particularly, those using R&D expenditure or patent data as proxies – look at the effects of technological change on employment without distinguishing between types of innovation (product vs process) nor addressing a specific technology or product (Ugur et al., 2018). Conversely, those studies distinguishing between process and product innovations usually rely on survey data. On the one hand, these works mainly find a positive relationship between product innovation and employment; on the other hand, results for (capital-embodied) process innovation are heterogeneous depending on the aggregation level considered, vary by country and industry group (Chennells and Van Reenen, 2002, and Ugur et al., 2018).

More recently, a stream of literature has focused on the employment implications resulting from the diffusion of specific capital-embodied innovations like ICT, automation in general or industrial robots. While empirical evidence highlights the emergence of polarization effects in the labour market associated with the adoption of these technologies, results are still inconclusive when looking at the implications for total employment (Autor and Dorn, 2013; Michaels et al., 2014;

[54] For recent surveys, see Pianta (2006) and Vivarelli (2014).

Graetz and Michels, 2018; Mann and Püttmann, 2021; Acemoglu and Restrepo, 2020; Dauth et al., 2021).

As opposed to these technologies, the use of AM is not driven by labour-saving aims. The inherent characteristics of AM – specifically, higher potential for product customization and overall cost reduction – open space for new and different links with employment, as compared to other capital-embodied technological innovations. Hence, AM deserves particular attention when being assessed empirically, addressing all potential channels – highlighted in the literature – through which it could affect employment. For instance, compared to industrial robots, the effect of AM on the level of employment at constant output – the potential labour substitution effect – is likely to be less relevant than market-related effects.

4.2.1. AM and changes in industrial processes

AM is an innovative manufacturing process used in both prototyping and in the production of tools and final products (Mellor et al., 2014). More precisely, the term AM groups together seven distinct technologies and related production processes working in different ways and using different input materials, although all following the same production logic (ASTM International, 2013). The way these technologies work is rather simple: the AM machine receives the digital three-dimensional model of the object to be manufactured, the model is broken down into a set of bi-dimensional models, which are subsequently reproduced one-by-one by one or more printing heads physically juxtaposing the material and recreating the whole object.[55]

AM distinguishes itself from traditional manufacturing technologies for two main characteristics: it allows for a reduction in the number of production stages, while increasing the potential for product customization (Attaran, 2017). These two peculiar features of AM create several potential economic advantages for adopting firms (Weller et al., 2015).

[55] See ASTM International (2013) for a detailed description of processes and specificities.

Commonly, traditional manufacturing techniques produce rather simple objects or components, which subsequently require some assembly procedure to build the final articulated product desired. Conversely, AM enables the production of functional articulated assemblies in a few or even in a single step, in turn completely offsetting or strongly reducing post-manufacturing assembly operations (Weller et al., 2015; Cuellar et al., 2018; Singamneni et al., 2019). On the one hand, the lower number of production steps implied by AM also results in an overall shorter time needed to get the final product to the market. This results in the opportunity for firms to achieve an overall supply chain simplification by reducing inventory stocks and therefore logistic, transport, and communication costs (Holmström et al., 2010; Liu et al., 2014; Delic and Eyers, 2020). On the other hand, as far as other production costs are concerned, the implications of adopting AM either as main or as complementary production mode are more ambiguous: potential cost reductions may arise relatedly to the waste cut introduced by AM, but at the same time the process may require more costly input materials (Tuck et al., 2008; Atzeni and Salmi, 2012; Achillas et al., 2015; Weller et al., 2015; Baumers et al., 2016).

The second main characteristic of AM – higher potential for product customization – results from the underlying production logic behind these technologies. As AM methods build the final object without needing tools or moulds, at the same time enhancing the manufacturability of highly complex products (Diegel et al., 2010; Schniederjans, 2017), these technologies provide engineers with higher flexibility in manufacturing and prototyping, and designers with complete freedom and considerable scope for customization (Rosen, 2014), in turn better satisfying customer demands. Relatedly, AM further reduces the time-to-market of new products (Petrovic et al., 2011, Petrick and Simpson, 2013; Achillas et al., 2015), speeding up the whole design process and increasing product innovation (Leal et al., 2017). Notwithstanding, these opportunities come at a minimum cost, while also opening space for enhanced technical and physical product characteristics (Atzeni and Salmi, 2012; Petrick and Simpson, 2013), and creating new business opportunities and rising AM diffusion across several industries (Mellor et al., 2014; Bogers et al., 2016; Attaran, 2017). In fact, these benefits associated with AM have been the main driver of adoption in sectors producing, for instance, prosthetics and dental implants (Chen et al., 2016), hearing aid apparatuses, (Petrovic et al., 2011) and in the aerospace industry (Singamneni et al., 2019).

As a result, faster delivery times – enabled by the boost in the overall production cycle – and greater product customization increase consumers' willingness to pay for goods produced via AM techniques (Bogers et al., 2016; Rayna and Striukova, 2016) and benefit adopting firms by mitigating demand shrinkage and potentially rising mark-ups (Weller et al., 2015).

The advantages which AM brings over other traditional manufacturing methods stand out in the production of goods usually featuring complex designs and characterised by low volumes for which mainstream techniques would be too expensive, requiring high volumes to exploit economies of scale in production (Ruffo and Hague, 2007; Baumer et al., 2016). Conversely, applying AM to the mass production of standardized products requires a substantial re-design of both the product and the production process (Mellor et al., 2014; Kianian et al., 2015), making the economic advantages related to cost optimisation more uncertain.

From a conceptual standpoint, customization motives prevail over scale-seeking ones. Therefore, AM brings higher gains in markets showing strong demand for product customization, flexibility and freedom in design, allowing for the acquisition of broader customer base (Weller et al., 2015). Nonetheless, recent years have witnessed the diffusion of AM technologies in the production of several mass-consumption products – for instance, Adidas shoes (Cheng, 2018) – thus signalling technological maturity and a major shift from a primary use for rapid prototyping applications to direct manufacturing ones in a growing number of sectors (Laplume et al., 2016; Attaran, 2017).

4.2.2. AM and employment

The distinct characteristics of AM are likely to affect the channels through which these technologies may have an impact on employment. Thus, in order to investigate such relationship and to disentangle the main links at work, we distinguish between – and estimate both – unconditional and conditional labour demand functions (Hamermesh, 1986; Lichter et al., 2015; Ugur et al., 2018). Unconditional (i.e. uncompensated) labour demand allows technological innovations to affect employment via all potential channels: by affecting firms' product demand and, in turn, production and employment levels, and by altering the relative intensity of the production factors used in the process. By contrast, in conditional (i.e. compensated) labour demand the market expansion channel is 'switched off'.

Most of the empirical literature looking at the employment effects associated with technological change does not compare the two types of labour demand, focusing either on the conditional (e.g. Bogliacino and Pianta, 2010¸ Bogliacino et al., 2012; Dachs et al., 2017; Pantea et al., 2017; Van Roy et al., 2018; Acemoglu and Restrepo, 2020) or on the unconditional demand (Graetz and Michaels, 2018; Mann and Püttmann, 2021; Dauth et al., 2021). Only few works represent notable exceptions to this common research practice, where both types of labour demand functions are estimated and compared, gaining deeper understanding of the underlying mechanisms driving the relationship between technological innovations and employment (Van Reenen, 1997; Michels et al., 2014). Similarly, given the peculiarities of AM technologies presented in the previous Section, this distinction seems relevant for disentangling the mechanisms through which AM innovations may affect employment.

AM opens up space for product innovation and customization that potentially result in market expansions, which could nonetheless be mitigated depending on the substitution effect between new and old products, potentially making the marginal contribution of AM innovations to employment less relevant. In turn, at the sector level, the total market expansion effect associated with AM will depend on the relative magnitude of these contrasting forces. At the same time, AM is a technological innovation embodied in new machines – hence, a capital-embodied form of technological change – which also requires new specific intermediate inputs, like different and non-standard raw materials and software. Coherently, AM machines represent a new wave of product innovation in upstream sectors producing such machinery, this making such innovation likely to open new market segments. As a result, at the sector level, the employment effect will reflect the extent to which new AM machines and inputs substitute for old ones.

When these market-related effects are taken into account – i.e. when labour demand is estimated at a given level of output – the relationship between AM and employment will depend solely on its level of complementarity with or substitution between labour, capital and other production factors. In addition, the way this potential complementarity is affected by AM will shape its link with employment (e.g. labour-augmenting vs labour-biased innovations),[56] as the direct effect technological change on labour demand also depends on how a technology impacts on different types of labour (e.g. by gender, age or skill composition) and their degree of substitutability with other production factors. Indeed, several recent works have looked at the implications of technological change for the composition of employment, highlighting that adopting innovations like ICT potentially alters the relative demand for high-skilled, medium-skilled, and unskilled workers (Michaels et al. 2014) or between different tasks (Autor et al., 2013; Graetz and Michaels, 2017), although not necessarily affecting the total level of employment.

Similarly, AM innovations are likely to trigger potential composition effects, too. in AM-using sectors, given the high customization component and the increased production efficiency – for instance, resulting from the strong reduction of the assembly stages – brought by AM, more highly specialized workers are likely to be required in both design and operations activities relatively to traditional manufacturing methods, making AM processes skill-biased (Kianian et al., 2015). In AM-producing sectors (i.e. machines and complementary inputs), instead, the overall demand of labour is likely to remain unchanged, although its composition is again likely to shift in favour of higher-skilled workers given the advanced technological characteristics of these machines.[57]

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[56] See also Acemoglu (2009, pp. 500–503) for a detailed discussion.

[57] Unfortunately, sectoral data on the composition of employment (i.e. by educational level, age and gender) are not available for the sample of countries we investigate here. EU KLEMS provides such data, yet at the aggregate level, for EU27 countries and the UK. In Appendix C we preliminary explore how AM innovations affect the composition of

Building on the specific characteristics of AM reviewed in the previous Section and on the above discussion, we hypothesise that:

H1. *AM innovations have a positive effect on employment in both unconditional (i.e. uncompensated) and conditional (i.e. compensated) demand estimations since its primary goal is not saving on labour costs*.

H2. *AM innovations have a higher positive effect in unconditional (i.e. uncompensated) than in conditional (i.e. compensated) demand estimations, driven by large and positive market-creation effects*.

Another important strand of the literature investigates the existing differential effects that various forms of technological change have on employment across individual sectors or sectoral groups (Van Reenen, 1997; Greenhalg et al., 2001; Bogliacino et al., 2012; Dachs et al., 2017; Van Roy et al., 2018). As discussed in the previous Section, the diffusion of AM technologies is likely to affect differently some industries as compared to others because of its characteristics. Thus, we further explore the differential links characterising the relationship between AM and employment in order to account for such heterogeneity. We rely on the Pavitt taxonomy[58] (Pavitt, 1984), which is widely used for both theoretical and empirical investigation, as well as for policy analysis. This classification groups together sectors with different levels of product differentiation, diverse sources of innovation (sectors producing and adopting the innovation), and varying relevance of scale economies into four sectoral groups: Science Based (SB) industries, Specialized Supplier (SS)

employment for the whole economy across EU27+1 countries. Results are reported in Table C7 and confirms that that while workers with lower educational levels are not affected by AM innovations, these are found to boost demand for both highly educated and middle educated workers, thus confirming AM to be a skill-biased but not a displacing technology. Clearly, such findings are to be further investigated at a finer level of sectoral disaggregation depending on future data availability.

[58] More specifically, we use the revised version form Bogliacino and Pianta (2016).

industries, Supplier Dominated (SD) industries and Scale and Information Intensive (SII) industries.[59] As the factors driving diversity across these sectoral groups coincide with most of the factors that should affect their exposure to AM, this taxonomy is particularly suitable to study the heterogeneity of its industry-level implications for employment.

The SB and the SS groups include those sectors featuring the highest diffusion of AM: industries producing AM machinery and equipment, industries producing the chemicals used in AM processes, as well as some high-tech sectors adopting the AM technology (i.e. manufacture of computer, electronic, and optical products and manufacture of other transport equipment). These are also specialized and highly innovative industries where many firms lead technological progress (Pavitt, 1984; Bogliacino and Pianta, 2010, 2016), thus implying the marginal contribution of AM innovations to be possibly limited. In fact, the growing diffusion of AM in highly differentiated sectors producing specialized goods has the potential to enhance firms' ability to meet sophisticated needs and the demand for customization, resulting in consistent employment effects related to market expansion. Yet, in these sectors, the magnitude of such market expansion will depend on the extent to which products already bears high levels of customization and on the playfield on which competition occurs (i.e. mostly around product innovation and quality improvement). In turn, new AM machines, equipment, materials, and additively manufactured products could substitute older ones,[60] helping firms to survive competition instead of increasing market shares.

The SD category includes industries which generally adopts outside-generated innovations. As shown in Table A1 in Appendix A, AM diffusion is now consistent in sectors like manufacture of fabricated metal products, as well as furniture and other manufacturing, while also growing in industries like the manufacture of textiles, wearing apparel, leather and related products (Eurostat, 2021). Nonetheless, SD industries generally manufacture standardized goods by using scale-

[59] See Table A2 in Appendix A for further details.
[60] Several works looking at product innovations show evidence of business stealing effects by competing firms and of cannibalization effects by the same firm (recently, Harrison et al., 2014).

intensive processes. Here, new AM methods open space for new ways of customizing previously standardized products, although AM could represent a costly alternative to mainstream technologies and therefore followed by too few firms in order to result in a large impact on demand. Yet, differently from other sectoral groups already seen, in SD sectors, the diffusion of AM technologies is likely to create new market niches instead of substituting for the existing standardized products and – given the rising level of product sophistication needed to survive competition – AM likely becomes a relevant source of innovation also in traditional industries.

Finally, the SII group includes both adopting sectors (e.g. manufacture of motor vehicles, trailers, and semi-trailers) and industries producing some of the input materials used in AM methods (e.g. manufacture of rubber, plastic products, and basic metals), thus featuring some diffusion. However, these industries traditionally feature consistent scale economies, thus strongly limiting the incentives to switch from traditional production methods to AM.

Similarly to when looking at the average industry-level effect on employment, at a constant level of output, AM diffusion is likely to have a positive or null impact on labour demand in SB and SS categories, as these sectors are characterised by already high levels of complementarity between skilled labour and capital but AM may further increase it. At the same time, given that AM methods bear higher complementarity with skilled labour with respect to traditional production technologies typically adopted in SII and SD sectors, the effect there is likely to be again positive but larger than in the SB and SS groups.

In turn, our hypotheses on the prevailing average relationship between AM innovations and employment across all manufacturing industries may hold with varying degrees to the different sectoral groups outlined in the Pavitt taxonomy. Indeed, as discussed above, the mechanisms highlighted in the compensation theory are likely to work differently across the four categories. Hence, we leave a further exploration of the prevailing effects in each industry to the empirical assessment.

4.3. Data and descriptive evidence

4.3.1. AM patents and innovation measure

Patent data are used extensively to measure technological change and innovation (recently, Van Roy et al., 2018, Mann and Püttmann, 2021, Venturini, 2022). Following the discussion in Section 4.2.2, in order to investigate properly the effect of AM innovations on total employment, our measure should capture the overall diffusion of AM innovations, i.e. it should capture both AM-related product innovations in both upstream and downstream industries and AM-related process innovations affecting downstream industries. In this way, we can capture all of the channels through which these innovations can affect the demand of labour.[61] Indeed, AM innovations include both machinery, equipment and complementary goods used in manufacturing processes, like materials and software – i.e. new products for technology producers, which also represent process innovations for firms in using industries – and products made via AM techniques by firms in adopting sectors.

We build our AM diffusion proxy by identifying AM-related patents and by matching them to sectors and countries using the methodology described in the following Sections. Our strategy bears pros and cons. On the one hand, using industry-level patent data allow us to capture the effects that AM innovations might have on sectoral employment, that are external to the firm, and we can gain insight on the sectoral heterogeneity potentially characterising the AM-employment nexus. On the other hand, our level of analysis does not allow us to capture the effects of AM technologies, that are external to the industry and to the country in which AM innovations occur, as well as general equilibrium effects.[62] As discussed later in this Section and in Appendix B, measuring AM diffusion using a patent-based measure built at the sector level poses that we are not able to unambiguously disentangle between the product and the process nature of AM innovations.

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[61] The pros and cons of different innovation proxies are widely analysed in the literature (see, for instance, Archibugi and Pianta, 1996; Hagedoorn and Cloodt, 2003).
[62] In Section 4.5.1.1 we discuss a robustness check aimed at accounting for the role of 'external' AM innovations.

Yet, distinguishing the two does not represent a strict requirement in order to test our hypotheses – i.e. whether AM-related innovations produce more jobs than they destroy – and to provide insight of the potential sectoral heterogeneity of such mechanisms.

We collected data on AM patents at the USPTO[63] from the PATSTAT data set.[64] First, we identified a list of keywords (see Table A3 in Appendix A) using several sources such as the international standard-regulating organisation for AM technologies (ASTM International, 2013), the engineering literature, as well as product catalogues from manufacturers of AM machines.[65] Then, we considered patents classified under the International Patent Classification (IPC) code B33Y, specifically created in 2015 by the World Intellectual Property Organisation (WIPO) to group all AM innovations related with *processes, apparatuses, materials, ancillary equipment and software,* and *products made via 3D printing* – namely, all the aspects of AM innovations not covered elsewhere in the IPC classification (WIPO, 2019).

Our analysis covers the 2009–2017 period, since between 2009 and 2014 core patents protecting AM technologies – such as fused deposition modelling (FDM) and selective laser sintering (SLS) – expired, thus boosting patenting activity[66] and before 2009 AM-related patenting activity was indeed rather limited (Laplume et al., 2016; EPO, 2017). In total, we collected data on around 3,500 AM patents over the period we investigate.

4.3.1.1. Sectoral attribution of AM patents

PATSTAT data include several information on inventors, applicants, IPC classes, and the probability of use by NACE Rev.2 2-digit sectors (NACE sectors, hereafter) – i.e. the sector in

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[63] We focus on applications to the USPTO as it is considered the reference patent office when seeking protection for innovative technologies (Cantwell, 1995).
[64] The version of PATSTAT used is PATSTAT Online (2019 Autumn edition) V5.14, accessed between September and October 2019. We followed guidelines from Pasimeni (2019) to improve the effectiveness of our SQL query in PATSTAT.
[65] We looked at product catalogues from three main manufacturers of AM machinery, equipment and materials worldwide: Stratasys Ltd., 3D Systems Inc. and EOS GmbH.
[66] FDM and SLS were invented and their patent applications first filed at the USPTO in 1989 and 1986, respectively. Patents were granted in 1992 and 1997. The core patent for FDM expired in 2009 and SLS's one in 2014.

which operating firms are more likely to use the innovation protected by each specific patent. To match patents to industries, we rely on the DG Concordance Table constructed by Schmoch et al. (2003) and subsequently updated in more recent years (Van Looy et al., 2014; 2015). This attribution strategy – included in PATSTAT data – is commonly accepted and particularly appropriate for our purposes. The matching exploits a statistical approach building the concordance between IPC codes and NACE sectors by identifying the NACE sector with the highest occurrence rate amongst NACE sectors of the firms applying for a patent classified under a specific IPC code. This turns out to be particularly useful in cases where the applicant is, for instance, the holding of a conglomerate, or a large firm operating in a value chain (and large firms are more likely to apply for patents), as the matching approach even out the potential bias in the sectoral matching introduced such 'extreme' cases. Using the DG Concordance Table implies that the potential effect a patent might have on employment would then emerge in the sector to which the firm – or the controlled firm/subsidiary – actually exploiting the patent belongs to. In fact, attributing the patent to the applicant's NACE sector – a possible alternative strategy – would be misleading in our AM case as well since we find several large firms, multinationals, and conglomerates – like Boeing, Airbus, General Electric and Siemens – amongst AM patent applicants.

To show how the sectoral attribution method we adopted works, Table 1 illustrates two examples of AM patents in our data, their focus/content, applicants, and matched sectors. These examples suggest that the patents we collected capture both AM (product and process) innovations – in this specific case, of footwear and other apparel products by Nike and Adidas. As shown in Table 1, the larger sectoral weight of the patent describes its probability-of-use in NACE sector 15 (manufacturing of leather and related products), indicating that the applicants employ AM methods to produce specific and customised products for commercialisation. Nonetheless, minority shares of the first patent link to other sectors. Patents pertaining to additively manufactured products may also relate to other aspects of the described AM innovation – e.g. the AM production technique or the materials. Specifically, as sports footwear and equipment are mostly plastic products, the patent shows some probability-of-use in NACE sector 22 (manufacturing of rubber and plastic products); furthermore, since it describes possible production techniques it also features a lower probability-of-use in NACE sector 28 (manufacturing of machinery and equipment). This stems from the characteristic of patents of usually featuring more than one IPC code and hence being cross-matched to multiple industries according to different proportions. In general, depending on the inner nature of an AM innovation, the probabilistic matching between patents and sectors in the DG Concordance Table allows us to gain insight into the distribution of AM innovations across industries. Yet, as in the example in Table 1, the correspondence between patents and sectors is not unique, the subject of a patent being potentially relevant to multiple industries. This makes it almost impossible to unambiguously disentangle AM patents relating to either product or process innovations. Further details on the case shown in Table 1 and other examples of our sectoral attribution are reported and discussed in Appendix B.

Table 1 around here

Mann and Püttmann (2021) adopt a similar sectoral attribution strategy – the Yale Technology Concordance (Kortum and Putnam, 1997) – to investigate the effect of automation on employment across US commuting zones, using patent data selected through text analysis to proxy for automation. Our choice of the PATSTAT concordance method is motivated by its fit to the current NACE classification, being also widely appreciated for its user-friendliness and international comparability thanks to the correspondence between the latest versions of NACE and ISIC classifications. Hence, we discarded other matching methodologies as they are used less frequently or provide matching for older or different industrial classifications (see Dorner and Harhoff, 2018). Similarly, we decided to rely on the DG Concordance Table and not on newer ones such as those provided by Lybbert and Zolas (2014) and Dorner and Harhoff (2018), given the lack of empirical testing for these new concordances. More importantly, as shown in Dorner and Harhoff (2018) the three concordance methodologies lead to a highly similar matching of patents to sectors in manufacturing.

4.3.1.2. Geographical attribution of AM patents

As discussed above, we collect information on patent applications filed at the USPTO alone; yet, as patent applications can be filed more than once in the same jurisdiction, there might be potential double-counting issues if considering overall patent applications in our data set. Thus, in order to avoid such issue, we used AM patent family applications and allocated patents to the year of the priority filing – i.e. the earliest filing. We then matched AM patents to the countries of residence of their inventors using fractional counting, a diffused principle used for instance by Eurostat and the OECD (2009). In turn, in each year, our AM data are structured as the patent fraction by inventor country and by sector.

By attributing AM patents to the country of residence of the inventor(s), we assume that countries featuring a high patent count in AM are likely to have high diffusion rates. Conversely, countries showing no or a low number of AM patents, by being scarcely innovative in AM, are also likely to have a lower level of diffusion of these technologies relatively to those countries being active AM innovators.[67] Alternative strategies attribute patents based on the jurisdiction – i.e. where the patent provides protection – or to the applicants' country. While recognising the limitations of our attribution strategy, in Appendix B we discuss alternative approaches and argue why they would result in a less appropriate AM measure for the purpose of our analysis.

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[67] We acknowledge that local innovation does not represent the only source of diffusion of a technology. Specifically, as shown in Chapter 1, AM devices may become known and available in a country even without the presence of local innovators thanks to imports of such machinery from abroad. Across EU countries, this seems to be the case of, for instance, Latvia and Hungary, who feature zero or very few patents, no local production (coherently), but high import growth rates over our observation period. Furthermore, also in cases characterised by a relatively low innovation (patenting) activity in AM, such as that of Denmark, our measure could underestimate actual diffusion, since in Chapter 1 we acknowledge a high growth rate of our net consumption measure (i.e. considering both imports, local production and exports). This highlights a growing level of adoption, but also growing local production, hence overall diffusion. Unfortunately, this is a limitation of our work exploiting patent data, which further emphasize the need for analysing a more complete picture by looking at different sources of information such as those used here (patents) and in Chapter 1 (trade and production data).

4.3.1.3. Descriptive evidence on AM diffusion

Figure 1 shows the distribution of AM patents at the USPTO between 2009 and 2017. Notably, the distribution for our AM patents is highly skewed across years, thus we transformed the data into natural logarithms to increase comparability across years (we also report the actual value of the AM patent count at the end of each bar in Figure 1). The pattern shows a steep increase between 2009 and 2015, moving from an initial patent count of around 70 to a peak of more than 900 AM patents. More recent years instead witnessed a decline in the number of applications filed. However, this pattern is not related to a decline in innovation activity in AM *per se*, but rather relates to bureaucratic delays affecting the filing of an application at the patent office due to screening and checking procedures, corrections, and resubmission requests. Depending on the regulation of the specific patent office considered, such time lag might vary, resulting in applications being published around 18 months after the actual filing date (EPO, 2019; USPTO, 2019).

Figure 1 around here

Figure 2 presents the breakdown of AM patents by country (panel A) and by sector in our sample (panel B). The US, Japan and Germany together have the highest patent counts in AM, with the US alone making up the 57.2% of all AM patents at the USPTO and reaching about 80% of the total all together. The sectoral distribution of AM patents presents a similar pattern, with the highest share of AM patents (42.5%) concentrated in the sector manufacturing machinery and equipment.

Figure 3 shows the distribution of AM patents across countries and years, by each of the four sectoral groups included in the Pavitt classification. Furthermore, it is worth noting that these are absolute numbers, i.e. they are not normalized by country population or by industry employment. This must be taken into account when looking at the distribution by country and industry. In particular, the four industry classes have very different weights in terms of total employment.

Figures 2 and 3 around here

4.3.2. Data and variables

For our main explanatory variable measuring the diffusion of AM innovations, we use the three-year-lagged natural logarithm of the stock of AM-related patents at the USPTO.[68] For each country-sector-year observation, we compute the stock of AM patents using the perpetual inventory method as $AM_{ijt} = F_{ijt}^{AM} + (1 - \delta)\ AM_{ijt-1}$, where F_{ijt}^{AM} represents the count, or flow, of AM patents.[69] We assume a depreciation rate of 15%, as commonly done in the literature on I4.0/4IR technologies (e.g. Graetz and Michaels, 2018; Corradini et al., 2021; Venturini, 2022).

All other explanatory variables in our models derive from a standard labour demand equation (Hamermesh, 1986; Van Reenen, 1997). We use sectoral data on employment, labour cost, and output from the Statistical Analysis (STAN) database of the OECD for 2-digit manufacturing industries in the NACE classification. Specifically, our dependent variable is the natural logarithm of the number of people employed in each country-sector pair in each year, sectoral labour cost is measured by the natural logarithm of labour cost per thousand employees and gross output through the natural logarithm of gross sectoral output produced.

Using data from PATSTAT data set, we build a variable to control for the stock of non-AM patents filed at the USPTO at the industry level, the complement to our main explanatory variable.

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[68] Since the variables include zeros, we added 1 before taking natural logarithms.

[69] According to the perpetual inventory method, the initial stock is given by $F_{ij0}^{AM}/(\delta + GR_{ij})$, with GR_{ij} representing the average growth rate in AM patents between 1989 and 2015. Having collected patent information over the 1989–2017 period, we build the stock using additional information on pre-sample years. We use 2015 as the last year to compute GR_{ij} in order to avoid the drop in the absolute value of F_{ijt}^{AM} in following years, as explained above.

This control allows us to isolate the effect of AM-related innovations from other types of innovation. We compute the sectoral stock of non-AM patents following the same methodology and assumptions as for our main explanatory variable.

STAN data set reports all nominal variables in local currency units. As industry-specific deflators are not available for all countries considered in this work, in order to compare sectoral variables across OECD members we convert them into Purchasing Power Parity (PPP) constant 2011 US dollars using country-wide PPP conversion factors from the World Development Indicators (WDI) data set of the World Bank.

Our sample includes 31 OECD countries[70] and 21 2-digit manufacturing industries (see Table A2 in Appendix A). The resulting dataset is an unbalanced panel of 5,741 country-sector observations between 2009 and 2017. Table 2 presents a summary description of the variables used in our empirical analysis, while Table A4 in Appendix A reports the related summary statistics and the correlation matrix.

Table 2 around here

Figure 4 reports the overall stock of AM patents for all 31 OECD countries in our sample (on the right vertical axis), together with the share of AM patent stock in the total stock of patents at the USPTO (on the left vertical axis), between 2009 and 2017. Both figures have been rising steadily over our observation period, experiencing a strong increase especially around 2014 – most probably, following the expiration of the yet cited core patents. The total AM patent stock experienced about a 6-fold increase, rising from around 400 in 2009 to around 2500 in 2017.

[70] Country list: Australia (AUS), Austria (AUT), Belgium (BEL), Canada (CAN), Czech Republic (CZE), Denmark (DNK), Estonia (EST), Finland (FIN), France (FRA), Germany (DEU), Greece (GRC), Hungary (HUN), Ireland (IRL), Israel (ISR), Italy (ITA), Japan (JPN), Korea (KOR), Latvia (LVA), Lithuania (LTU), Luxembourg (LUX), Mexico (MEX), Netherlands (NLD), Norway (NOR), New Zealand (NZL), Portugal (POR), Slovakia (SVK), Slovenia (SVN), Spain (ESP), Sweden (SWE), United Kingdom (GBR), and the United States (USA).

Similarly, the share of AM patent stock in the total stock of patents moved from 0.05% to 0.22% over the observed period.

Figure 5 illustrates the correlation between the level of employment and the stock of AM innovations, measured at the average levels of logged variables over the 2009–2017 period. Panel A shows the cross-country variation in the relationship, on average, across 21 manufacturing industries. Looking at the simple OLS cross-sectional linear regression fit line, there appears to be a positive relationship between our measure of AM-related patents and employment.[71] Similarly, panel B in Figure 5 plots sectoral employment against AM innovation stock, expressed as the average across 31 OECD countries, between 2009 and 2017. Although this suggestive evidence goes in the same direction as our model's predictions (as the slope is positive), it does not account for potential confounders that might influence the relationship at the country and industry level. In general, several factors might influence the link between labour demand and AM. Hence, our econometric strategy in the following analysis aims to account for country and industry factors that might confound the relation under investigation.

Figures 4 and 5 around here

4.4. Empirical strategy

Our aim is to investigate the relationship between AM innovations and employment. As a first step, we estimate both unconditional and conditional, industry-level, labour demand functions augmented

[71] Panel A in Figure 5 shows a higher number of countries presenting no patenting activity as compared to panel A in Figure 2. This is due to constraints in the computation of the stock measure used in our estimations because of countries showing single or few patent applications, hence making it impossible to compute an average growth rate $GR_{i,j} \geq 0$. The same holds for similar sectoral cases reported in panel B.

with our variable measuring the diffusion of AM innovations (for a similar approach, see Van Reenen, 1997). Our baseline specification is:

$$L_{ijt} = \alpha_0 + \alpha_1 AM_{ijt-3} + \alpha_2 nonAM_{ijt-3} + \boldsymbol{\alpha}_3 \boldsymbol{X}_{ijt-1} + \gamma_i + \gamma_j + \gamma_t + u_{ijt}, \tag{1}$$

where AM_{ijt-3} is our measure of AM innovations, $nonAM_{ijt-3}$ is our measure of non-AM innovations, $\boldsymbol{X}_{i,j,t-1}$ is a vector of sectoral control variables. $\boldsymbol{X}_{i,j,t-1}$ includes labour cost per thousand workers (LC_{ijt-1}), in the unconditional demand specification and both labour cost per thousand workers and gross output (Y_{ijt-1}) in the conditional demand specification. γ_i, γ_j, and γ_t are country, industry, and year fixed effects (FEs, hereafter), respectively, and $u_{i,j,t}$ is the idiosyncratic error term. By including a variable capturing all non-AM innovations, we control for all the innovation output different from AM. We do not include controls for input of innovation at the sectoral level, such as sectoral R&D, as they should affect employment by affecting the innovation output – i.e. they are correlated with non-AM patents. Clearly, we cannot exclude $nonAM_{ijt-3}$ as this would result in a serious omitted-variable problem in our model.

All the explanatory variables enter our model with a one-year lag in order to avoid potential contemporaneity issues, while our main explanatory variable (AM_{ijt-3}) and the other innovation variable ($nonAM_{ijt-3}$) enter our model with a three-year lag in order to account for the delay in the potential impact of the new technology on employment. Following the discussion in Section 4.3 (see Figure 1), we argue that in our case a three-year time window is the proper lag as it accounts for pendency following the application process at the USPTO, the average time needed to receive the grant (USPTO, 2019) and use the patent in production.

Equation (1) includes a set of FEs in order to account for potential unobserved heterogeneity. Specifically, country FEs should capture all country-specific institutional factors, which may affect the level of employment (e.g. labour market institutions and union activity), although being common across sectors (Graetz and Michaels, 2017; 2018). Sector FEs should instead capture all those characteristics related to technology and production processes that are industry-specific and common across countries (e.g. the level of efficiency, standardization and economies of scale, use of natural resources, relevance of intermediate inputs in production and the level of market competition). Finally, year FEs should capture all those time trends evolving commonly across all countries and sectors (e.g. the general trajectory of technological progress and the cost of capital).[72]

In addition, in our preferred specifications, we consider a stricter FEs strategy by including country-year (γ_{it}) and sector-year (γ_{jt}) FEs.[73] These combinations allow us to control for those unobservables that might affect employment and are characterised by time trends specific to either the geographical or the sectoral dimension. This set of FEs should control for the dynamics of technological progress – for instance, related to the use of industrial robots or ICT – as well as the dynamics of income, population, and other macroeconomic factors.[74]

All of our model specifications are estimated using the pooled OLS estimator. Since our panel is quite short (i.e. 9 years) we do not have sufficient time variation to use the within estimator, thus including country-sector (γ_{ij}) FEs. Indeed, the country-sector FEs alone capture almost all of the variation in our employment data (i.e. the R^2 of the regression with sectoral employment as dependent variable and country-industry and year FEs alone as independent variables is above 0.99).

As a second step in our analysis, we estimate specifications similar to those described above, but also allowing for potential heterogeneity across sectoral groups, following the literature on AM

[72] In particular, the cost of capital is not usually measured and available in the data, and it is traditionally assumed to be common across firms, but neither sectoral- nor country-specific (Van Reenen, 1997; Onaran, 2008).
[73] We used STATA's reghdfe command to estimate OLS regressions including either unit-specific FEs and linear trends. We also test additional specifications including unit-specific FEs (country, sector, year) and linear trends (country-year, sector-year) simultaneously. Results (available upon request) are qualitatively unchanged in both unconditional and conditional specifications (we only witness a drop in significance for the coefficient of our AM variable to the 10% level in the unconditional specification). When looking at the sectoral heterogeneity in the effect of AM innovations, our main results are qualitatively confirmed, although the coefficient for the SS category is no longer significant in the unconditional specification and the coefficient for the SII category is no longer significant in the conditional specification.
[74] For instance, country-year FEs should also capture the fact that, in some cases, labour cost is partially determined at the national level and not at the industry level (Michaels et al., 2014).

discussed in Section 4.2. As further discussed in Section 4.2, we rely upon the revised version (Bogliacino and Pianta, 2016) of the Pavitt taxonomy (see Table A2 in Appendix A) and we estimate the specifications of the type:

$$L_{ijt} = \alpha_0 + \alpha_1 AM_{ijt-3} + \alpha_2 AM_{ijt-3} \times SB + \alpha_3 AM_{ijt-3} \times SS + \alpha_4 AM_{ijt-3} \times SII \\ + \alpha_5 nonAM_{ijt-3} + \boldsymbol{\alpha_6 X}_{ijt-1} + \gamma_i + \gamma_j + \gamma_t + u_{ijt}, \quad (2)$$

where SB, SS, and SII are dummies for Science Based, Specialized Suppliers, and Scale and Information Intensive industry groups, respectively. All other terms in equation (2) are defined as in equation (1). In this specification, the coefficient of our measure of AM innovations captures the potential relationship between AM and employment for the omitted sectoral category of Supplier Dominated industries.[75] We report results of specifications estimated following equations (1) and (2) respectively in Tables 3 and 4, in the following Section. In addition, we perform different robustness checks to our main results, which are described in Section 4.5.1.1 and in Appendix C, together with a further robustness using instrumental variables estimation, reported in Section 4.5.2.2.

4.5. Results

4.5.1. Main results

Table 3 reports our first set of results where we look at the average relationship between AM innovations and employment across sectors and countries. We start our analysis by looking at the simple relationship between our dependent and main explanatory variables in column (1), where a positive relationship emerges between AM innovations and employment. In columns (2) and (3) we estimate the unconditional demand functions, including labour cost per worker and the stock of

[75] We omit the terms SB, SS, and SII in equation (2) as they are collinear with the sector FEs included in all specifications.

non-AM patents, as well as our baseline and stricter set of Fes (in columns (2) and (3), respectively). In all three models, the coefficient of AM is positive and statistically significant at the 1% level, dropping from 0.19 to 0.09 when shifting from the simple relationship (column (1)) to the augmented unconditional labour demand function (column (2)). In column (3) – our preferred specification where we adopt a stricter Fes strategy – the elasticity of employment to AM is 0.095, meaning that a one-percent increase in the industry-level stock of AM patents associates with, on average, almost 0.1 percent rise in the level of sectoral employment.

In columns (4) and (5) of Table 3, we show estimates of the augmented conditional labour demand functions – including the level of gross output – again including the different combinations of Fes as in columns (2) and (3), respectively. Results highlight the relationship between AM and employment to be again positive and statistically significant at the 1% level, although the elasticity coefficients feature a slight drop as compared to those in the unconditional specifications. In our preferred conditional specification in column (5), a one-percent increase in the AM patent stock relates with an increase of about 0.07 percent in employment.

The difference we find in the magnitude of the coefficients for AM between unconditional and conditional specifications – a 30% drop in the elasticity, decreasing from about 0.1 to around 0.07 – seems to be in line with our theoretical expectations. In our interpretation, the conditional demand estimation switches off the market-related channels through which AM innovations, due to the characteristics described in Section 4.2, can possibly have an effect on employment. According to our estimates, across all countries and sectors in our data, such link would account for 30% of the overall relationship between AM an employment. Furthermore, we still witness a positive average relationship in the conditional labour demand estimations, suggesting that AM also features a certain level of capital-labour complementarity.

Notably, the difference between the elasticities of employment to the stock of non-AM patents in the unconditional and conditional labour demand specifications is much larger than in the case of AM (columns (3) and (5)). This suggests that market-related channels have a more relevant role for all other innovations together as compared to AM alone.[76] At the same time, we find the coefficient of the non-AM patent stock variable to be smaller in conditional labour demand specifications relatively to that for AM patent stock, suggesting that AM innovations have a comparatively higher level of complementarity with labour than the bulk of all other innovations.

To conclude, the sign of the other variables included in our specifications – labour costs and gross output – is in line with the type of relationship predicted by the theory, i.e. labour cost (in both unconditional and conditional specifications) and gross output (in conditional specifications) are negatively and positively associated with the level of employment, respectively.

Table 3 around here

Relatively to the predictions discussed in Section 4.2, our findings seem to support hypotheses H1 and H2. Indeed, in the estimates of both uncompensated and compensated labour demand functions, AM innovations and employment are positively associated (H1), thus AM technologies appear not to be labour-saving in nature. At the same time, the elasticity of employment to AM is larger in uncompensated than in compensated specifications (H2), confirming a role of AM in creating market-expansion effects. Nonetheless, the magnitude of such effects is smaller than expected (in turn, being much larger for other innovations altogether). This latter finding might result from compositional effects across industries, with the market-creation and the AM-labour complementarity mechanisms having different relevance across sectors, as we argued in Section 4.2. In Section 4.5.2, we further analyse industry heterogeneity to explore the potential presence of such effects, while hereafter we discuss the robustness checks for our main results.

[76] Indeed, this finding is coherent with the literature, which traditionally assumes patents to proxy primarily product innovations, while in this case AM patents capture the diffusion of both process (capital-embodied) and product innovations.

4.5.1.1. Robustness checks

Alternative AM innovation proxy and inter-sectoral/inter-country relationships: As discussed in Section 4.3.1, our baseline industry-level analysis of the relationship between AM diffusion and employment only accounts for the industry's own AM patent stock to proxy AM innovations. In turn, we do not capture inter-sectoral linkages through which AM innovations developed in a specific sector may affect employment in other industries, i.e. general equilibrium effects propagating along (within-country) supply chain links.[77] Similarly, our main AM diffusion proxy does not capture inter-country linkages, i.e. AM innovations created in sectors of another country may affect the level of a country's sectoral employment via intermediates featuring some AM content (e.g. AM devices or goods produced using AM technologies).[78] Hence, we are cautious in the interpretation of our results since the diffusion of AM innovations in a sector of a country might spur from AM machinery or products generated in other industries and/or countries, this eventually not showing up in the sector's own stock of AM patents.

For these reasons, hereafter we introduce a robustness test conducted by creating a proxy for the inter-country and inter-sectoral effect of AM innovations using the world input-output tables from the WIOD data set (Timmer et al., 2015):

$$extAM_{ijt} = \sum_{c}\sum_{s} AM_{cst} \times \left(\frac{int_{ij2008}^{cs}}{int_{ij2008}}\right) \tag{3}$$

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[77] As further robustness check, we carried out a country-level analysis in order to capture potential inter-sectoral interactions and general equilibrium effects. Using country-level data, we also undertook a preliminary exploration of the heterogeneous links that AM innovations may have on employment by education level. We report results in Table C7 in Appendix C together with the details of the analysis (in the Table's notes). We found the elasticity of employment to AM to be, on average, about 0.12 and 0.06 in unconditional and conditional labour demand specifications, respectively (both statistically significant at the 1% level). Such elasticity appears to be larger for middle-educated workers compared to highly educated workers, while it is rather small (and not significant) in the case of low-educated workers.

[78] In such case, intermediate goods incorporating some AM content would entail potentially different labour requirements during assembly operations or they would potentially change competitive dynamics of the downstream using sector (e.g. by increasing the quality or reducing the cost of the good incorporating it). Furthermore, potential reshoring induced by the adoption of AM technologies in a country could also affect sectoral employment in countries where production was offshored, a mechanism widely discussed in the literature that we further address in the concluding Section.

for each country i, sector j and year t, $extAM_{ijt}$ variable is then the weighted sum of the AM patent stock of each country and industry, where the weights are built as the ratio of intermediate goods bought by sector j of country i from sector $s \neq j$ in country i and from all industries in country $c \neq i$ (i.e. all sectoral domestic intermediates bought from all sectors excluding owns, plus all foreign intermediates bought from all sectors) over total intermediate goods used by sector j in country i (int_{ij}). We take predetermined weights in order to minimize potential endogeneity concerns and avoid biases induced by reverse causality.

The baseline assumption we make while building this external AM innovations proxy is that the higher the amount of intermediates purchased by one sector from sectors/countries with a high stock of AM patents, the larger the AM content of its upstream relationships. This additional AM innovations proxy should (at least partially) capture the inter-sectoral and inter-country transfers of technological content described above. Similarly, it should measure the diffusion of outside-generated AM innovations not captured by our baseline AM variable. We investigate specifications like those in Table 3 by including this additional AM variable, together with three additional controls: a variable built in the same way but for all non-AM innovations, a variable capturing the degree of domestic vertical fragmentation and a variable capturing the level of foreign exposure. These three further controls are included as the new additional AM innovation proxy could otherwise capture all other inter-sectoral and inter-country mechanisms, yet not related to AM.

The details of the construction of the new variables and the results of this robustness analysis are reported in Appendix C. Our results – reported in Table C1 – are robust to the inclusion of the new AM variable and the three additional controls: the elasticity of employment to the original AM innovations proxy ranges between 0.075 and 0.079 in unconditional labour demand specifications and around 0.045 in the conditional labour demand specifications, always statistically significant at the 1% level. In contrast, the new variable for external AM innovations is not statistically significant in models estimating the unconditional labour demand, while being positive and statistically significant in conditional labour demand models (the elasticity coefficient is 0.07

and significant at the 5% level in our preferred specification with more demanding Fes). Overall, these results confirm our main findings, uncovering a positive relationship between AM technologies and employment.

Countries and sectors: Figure 2 in Section 4.3 highlights that the distribution of AM patents is very skewed, both across countries (panel A) and across industries (panel B). We conduct further robustness tests to control that major innovators in AM do not drive our main results. Specifically, we investigate models in which we exclude the top six countries producing AM-related patents (US, Japan, Germany, UK, France, and Korea) from our estimation sample. Results, reported in Table C2 in Appendix C, confirm our main findings. Similarly, we test for the presence of biases in our results due to the role of the leading sector in AM innovations by excluding NACE sector 28 – i.e. manufacturing of machinery and equipment, which is also the sector producing the AM machines. The results, reported in Table C3 in Appendix C, show that the findings of the main analysis are robust and unlikely to be solely driven by producers of AM innovations.

As discussed in the notes of Figure 2, our sample includes a few countries (i.e. Estonia, Greece, Latvia, and Portugal) and sectors (i.e. NACE sector 19 - manufacture of coke and refined petroleum products; NACE sector 33 - repair and installation of machinery and equipment) that do not have AM patents at the USPTO. Thus, we further control for the robustness of our main results when we drop observations related to these countries and sectors. Similarly, the results (reported in Table C4) are robust.

Other robustness checks: alternative patent offices and lag structures: We further conduct different robustness tests by using data on patent applications to other major patent authorities (i.e. the European Patent Office and the Patent Cooperation Treaty) to check for the presence of home bias resulting from the usage of USPTO data. In addition, we explore specifications of our regression analysis using alternative lag structures for our AM innovations variable. The details of these further robustness checks are reported in Appendix C. Results reported in Tables C5 and C6 suggest robustness to these additional checks.

4.5.2. Sectoral heterogeneity

As we suggest in Section 4.2, the average positive relationship between AM innovations and employment emerging from our main analysis could hide heterogeneous effects taking place at the industry level. Therefore, in Table 4 we explore the presence of heterogeneous effects across groups of the revised Pavitt taxonomy by estimating equation (2).

As in our main analysis, we explore unconditional labour demand specifications in models (1) and (2) – including the labour cost and the non-AM patent stock control variable, and testing for different combinations of FEs – whereas we estimate conditional labour demand specifications in models (3) and (4) – also including the level of gross output. Panel A reports the coefficients of the baseline group (SD) and the interaction coefficients, while panel B reports the sum of the baseline and the interaction coefficients together with the related standard errors – i.e. coefficients for the SB, SS, and SII categories.

Table 4 around here

Results reported in Table 4 confirm the average relationship emerged in Table 3: the diffusion of AM innovations positively relates with employment in both unconditional and conditional demand estimations. Nonetheless, our results highlight the presence of some interesting sectoral heterogeneity, as two Pavitt's categories, SB and SD, seem to drive the average relationship shown in Table 3 while, in both unconditional and conditional models, the coefficients for SS and SII groups are much smaller. At the same time, the difference in the coefficients between unconditional and conditional specifications found in our main analysis – the market-expansion effects – appears to be driven almost entirely by SD industries. In the other sectoral categories, the differences between the coefficients for the two types of model are not statistically significant – or we even find a larger coefficient in conditional labour demand models, as in the case of SII industries. This means that the expansion of the market emerges as relevant for the SD class only. Overall, results reported in Table 4 suggest that, in all sectoral groups, there is a certain degree of complementarity between AM and labour (i.e. positive coefficients in conditional specifications), although such complementarity is suggested to be higher for SD and SB industries where elasticities are about 0.08 and 0.12, respectively (statistically significant at the 1% level).

The role of market expansion mechanisms clearly emerges in SD sectors – the coefficient of our AM variable drops from 0.23 in the unconditional specification in model (2) to 0.08 in the conditional specification in model (4) (both statistically significant at the 1% level) – and is in line with that found for non-AM innovations (dropping from 0.28 to 0.035). Yet, there is still evidence of higher AM-labour complementarity than in the case of non-AM innovations, as the coefficient of the AM variable in model (4) is still positive and larger than that for the non-AM control. Indeed, the SD category includes traditional industries using outside-generated technologies (Bogliacino and Pianta, 2010, 2016). Therefore, here our findings are likely to reflect the market-seeking aim of firms who introduce AM technologies in order to innovate on new products without necessarily substituting older ones (e.g. Nike, Adidas and other shoes manufacturers introducing new AM-based product lines). In turn, SD industries are those more likely to experience the higher marginal contribution of AM to the overall innovation rate.

In SB industries, the estimated elasticities are quite similar in both conditional and unconditional labour demand specifications – around 0.12, statistically significant at the 1% level. The SB group traditionally includes large R&D-intensive firms (Bogliacino and Pianta, 2010, 2016), some of which are producers of input materials for AM processes and others are adopters (e.g. manufacturers of computer, electronic and optical products), as discussed earlier in Section 4.2.2. Being highly innovative, SB industries already lies at the innovation frontier, thus limiting the potential role of AM innovations to create further market expansions. Nonetheless, the magnitude of the estimated elasticity – particularly in model (4) estimating conditional labour demand –

suggests AM to have some role in further enhancing capital-labour complementarities in these skill-intensive industries.

Across sectors of the SS group, our estimates in panel B of Table 4 highlight the elasticity of employment to AM to drop from about 0.06 in unconditional labour demand specifications to about 0.04 in conditional models – both statistically significant at the 1% level, although the difference between the coefficients is not statistically significant. SS industries generally include small and highly specialized firms producing new process innovations then employed by buying sectors (Bogliacino and Pianta, 2010, 2016), such as the case of AM machinery. Although we expected market expansion to be a relevant factor relevant in these sectors, our results instead suggest that new AM machines and related products may, to a certain extent, be substituting older ones.

Finally, sectors of the SII category seem to less affected by AM innovations than all other Pavitt groups, probably due to the innovation patterns characterising these industries. In models investigating the unconditional labour demand, results are not statistically significant and coefficients are rather small, while in conditional specifications some complementarity between AM and labour emerges (the elasticity coefficient is 0.04, statistically significant at the 1% level).

4.5.2.1. AM and the role of demand

As discussed in Section 4.5.2, the larger elasticity coefficient we uncover in unconditional labour demand models as compared to that found in conditional specifications might be a consequence of new products introduced by firms thanks to the technical features of AM. These new products might either erode market shares of competitors in the same sector or erode sales of existing products by the same firm. For instance, in the case of SII sectors, these are mainly producing input materials used in AM processes and the use of AM techniques is probably still very limited – due to the role played by scale economies – thus explaining the low coefficient reported in Table 4 for our estimates of the compensated labour demand model, as compared to SD industries.

To further investigate the heterogeneity in the market-creation channel, we explore models in which we regress sectoral gross output on our AM innovations proxy, by groups of the revised Pavitt taxonomy and controlling for all other innovations and FEs. Results are reported in Table 5 and clearly highlight that AM innovations seem to have a strong role in affecting demand in SD industries, while it does not show up in SB and SS sectors and it is actually detrimental in the case of SII industries. In turn, these results point to AM innovations creating markets for completely new products primarily in sectors of the SD group, while in other sectoral categories its role may be limited to a substitution one between new and old products, potentially helping to survive competition also through the opportunity for firms to rise mark-ups.

Table 5 around here

4.5.2.2. Instrumental variables estimations

Our model assumes the diffusion of AM innovations to be predetermined to employment decisions. Yet, there may be endogeneity issues in presence of unobservable factors correlated with the error term and simultaneously affecting employment and AM innovations (e.g. demand shocks). Similarly, we might incur in reverse-causality issues if the level of sectoral employment drives the pattern of technological change, and specifically the choice of developing or adopting AM innovations. Hence, given that our main results highlight a strong correlation between our main explanatory variable and employment, we need to be cautious in the interpretation of such a result as causal.

To address these concerns, we employ an instrumental variables (IV) approach using the Two-Stage Least Squares (2SLS) estimator. We instrument the current stock of AM patent stock with past values. Following Van Reenen (1997), we assume that past patenting activity should be a good predictor of current patenting activity since innovation activity is usually path-dependent and firms operating in the sectors introducing a technological innovation are likely to be the same ones subsequently updating the new technology. In addition to this, since our focus is a single specific technology and our AM proxy variable already enters all our models with sufficient lags, it is unlikely that past AM innovations directly affects employment, unless through its subsequent upgrades. In practice, we use longer-lagged values of the AM patents' flow (i.e. F_{ijt-4}^{AM}, F_{ijt-5}^{AM}) as instruments for our AM patent stock variable (AM_{ijt-3}). Similarly, in models analysing industry-level heterogeneity, we use lags of the interacted variables as instruments for the interaction terms between AM innovations variable and dummies for the Pavitt categories. At the same time, as we cannot exclude sources of endogeneity simultaneously affecting sectoral employment and all other explanatory variables in our model, we also instrument all the control variables following the same strategy.

Table 6 reports 2SLS estimates for unconditional and conditional labour demand models augmented with our variables capturing AM and non-AM innovations. We first present the analysis on average across all sectors in column (1) and then by sectoral groups in column (2) for unconditional models; columns (3) and (4) replicate the analysis for conditional specifications. Overall, estimates reported in Table 6 the main findings presented in Tables 3 and 4 to be robust to endogeneity problems, with only minor differences emerging in the magnitudes of the coefficients.

Diagnostic tests for our 2SLS models show no sign of under identification issues (the Kleibergen–Paap rk LM test whether the instruments are correlated with the endogenous regressors): under the null hypothesis, the estimated equation is underidentified; our tests always reject the null hypothesis (*p*-values are always below 0.05). Furthermore, the chosen instruments (i.e. lags) perform well in all IV specifications, presenting no sign of weak identification (the Kleibergen–Paap rk Wald F-statistics are always well above the Stock–Yogo critical values for maximal bias). Furthermore, the null hypothesis of valid instruments is never rejected by the Hansen J-statistics, confirming that the set of chosen instruments is valid and uncorrelated with the error term u_{ijt}.

Table 6 around here

4.6. Conclusions

This Chapter addresses the relationship between AM and employment using data on patent applications filed at the USPTO as a proxy for the whole ecosystem of AM innovations, in the attempt of capturing the overall employment effect resulting from the growing diffusion of this technologies. We explore this relationship estimating labour demand functions using data on 31 OECD countries and on 21 manufacturing sectors over the period 2009–2017.

We have shown that a statistically significant positive relationship between AM innovations and overall employment emerges in both our unconditional and conditional labour demand models, the latter featuring a smaller coefficient of elasticity. On the one hand, this evidence supports our intuition – rooted in the very nature of AM technologies – that market-related (job-creating) compensation mechanisms have a particularly important role when looking at the employment implications of AM innovations. On the other hand, our results from compensated labour demand models highlight a certain level of AM-labour complementarity.

At the same time, our exploratory analysis of the potential sectoral heterogeneity in the relationship between AM and employment – considering categories of the Pavitt taxonomy – suggests the positive effect we uncover across all manufacturing industries is substantially driven by the SD and SB groups. Specifically, the market-expansion mechanisms strongly emerge in the former category, whereas the latter shows the highest level of complementarity between AM innovations and labour. By contrast, our findings suggest that AM innovations are not developed and used following labour-saving aims.

Our results are robust various checks ranging from testing for different combinations of FEs, the use of an alternative AM innovations proxy controlling for inter-sectoral and inter-country transfers, various tests on restricted samples, to the use of IV estimations. Our sectoral analysis allows us to capture inter-firm employment effects, as opposed to works looking at the firm level, like those related with competitive mechanisms. At the same time, we are able to explore sectoral heterogeneity, as opposed to country-level studies.

Our findings provide valuable insight for policymakers aiming to foster the diffusion of welfare-enhancing innovations and job creation, providing indication of the sectors more likely to experience employment-related gains from AM innovations. To the best of our knowledge, our study is the first one addressing specifically the employment implications of AM technologies and related innovations. With this respect, the evidence we provide adds to and complement the existing one on latest forms of technological change associated with new digital technologies of the I4.0 wave (e.g. Graetz and Michaels, 2018; Mann and Püttmann, 2021; Acemoglu and Restrepo, 2020). Yet, we conceptualise and highlight the specificities of AM technologies, in our opinion fundamental in understanding the existing differences with other technologies of the 4IR like industrial robots, internet of things or artificial intelligence. Indeed, studies already cited above usually found these technologies to be labour displacing at different levels (particularly so in manufacturing and for lesser educated or skilled workers). However, recent firm-level evidence suggests the aggregate effect of automation technologies of the 4IR to be labour-friendly (e.g. Domini et al., 2021). Our industry-level results for AM go in the same direction, although positive employment effects at the firm-level do not necessarily translate into employment gains at the sectoral or at the aggregate level (Acemoglu et al., 2020).

Our study is not exempt from limitations. First, the use of patent data at the sectoral level bears some shortcomings: although the methodology we implement to identify AM-related patents and their geographical and sectoral attribution is, in our opinion, the best possible to capture the diffusion of AM innovations, a portion of their sectoral diffusion may not be captured by our main explanatory variable. Secondly, our main industry-level analysis could miss some relevant inter-sectoral and inter-country effects associated with transfer of AM innovations and related technological content. With respect to the latter concern, we nonetheless provide some reassuring evidence through our robustness tests, as discussed above. Finally, we have shown that our relatively short panel exhibit too little time variation in employment, within country and industry, preventing us from adopting a more precise econometric strategy (i.e. using the within estimator). Although we control for different FEs specifications in our models, our source of identification remains mainly cross-sectional; hence, exploiting additional sources of within-sector or within-firm variation in the data would help to further analyse the AM-employment nexus.

As our work only represents a first attempt to dig into such relationship, future research could take different directions. Depending on the data availability, a firm-level analysis exploiting on survey data could further explore the role played by AM adoption in affecting employment and its composition – e.g. differential effects due to the skill composition of the workforce, tasks and occupations. As we could not address this issue, mainly due to the lack of employment data by skill and task composition for disaggregated industries, a deeper investigation of the relationship between AM and employment focusing on these compositional mechanisms would provide further evidence on the AM-labour complementarity. At the same time, a country-level study, possibly exploiting data on longer time series, could shed more light on potential general equilibrium effects triggered by the diffusion of AM.

In addition, a further promising avenue for future research would also consist in the exploration of the role of inter-country effects associated with AM technologies; specifically, those related to AM diffusion in other countries due to the reshoring and/or the relocation of production across countries. Indeed, AM is increasingly diffusing across a growing number of countries and sectors, while also a growing number of mass-consumption products are partially or completely manufactured using AM processes. As a result, the cost advantage of producing in low-wage countries is also likely to be eroded if not to vanish completely, this potentially inducing some reshoring in the long-run (Weller et al., 2015; Laplume et al., 2016; UNCTAD, 2020).

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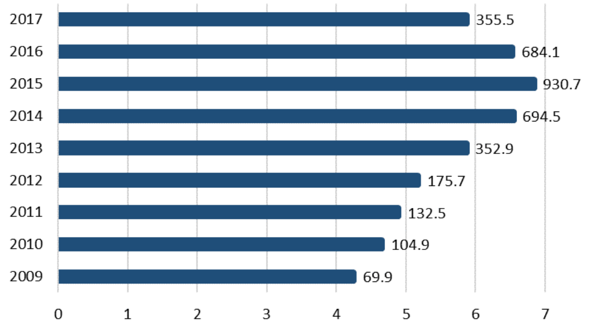
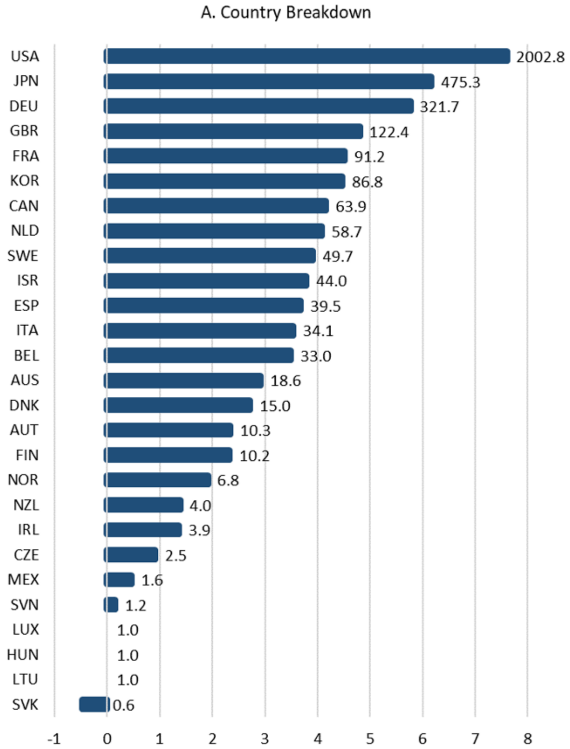
4.8. Figures and Tables

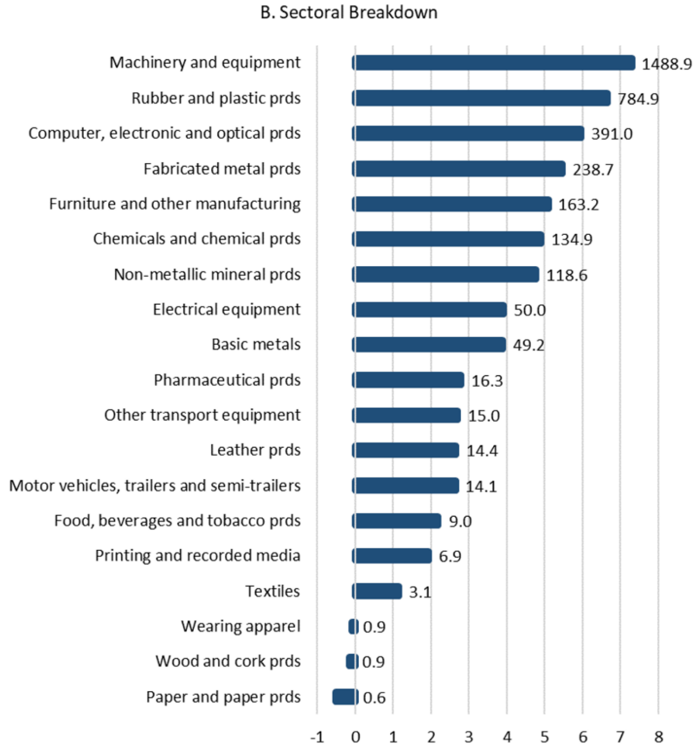
Figure 1. Distribution of AM patents, 2009–2017 period



Notes: Authors' own computations based on USPTO data extracted from PATSTAT database. Data reported on a natural logarithmic scale. Numbers reported at the edge of each bar are actual AM patent counts. The total number of AM patents is 3,500.6.

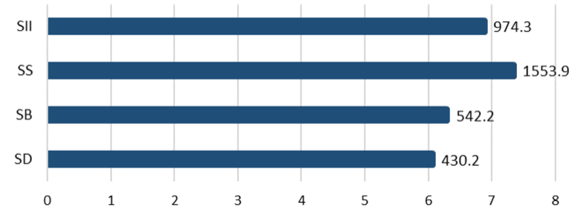
Figure 2. Distribution of AM patents by country and sector, 2009–2017 period





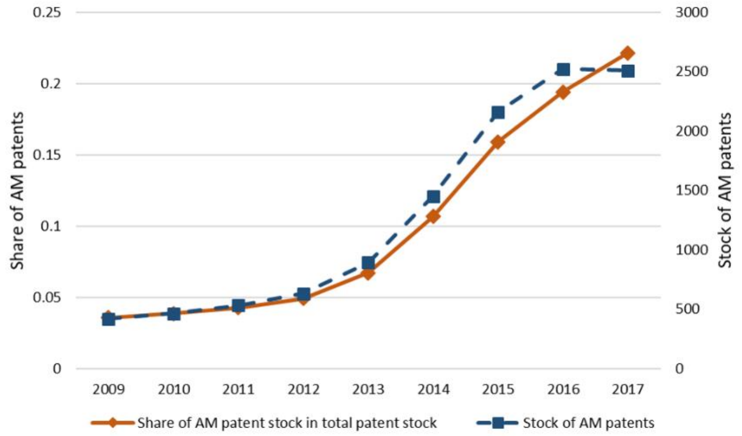
Notes: Authors' own computations based on USPTO data extracted from PATSTAT database. Data reported on a natural logarithmic scale. Numbers reported at the edge of each bar are actual AM patent counts. We omit Estonia, Greece, Latvia, and Portugal from panel A and sectors 19 (Coke and refined petroleum products) and 33 (Repair and installation of machinery and equipment) from panel B as they feature zero AM patents. The total number of AM patents is 3,500.6.

Figure 3. Distribution of AM patents by Pavitt taxonomy class, 2009–2017 period



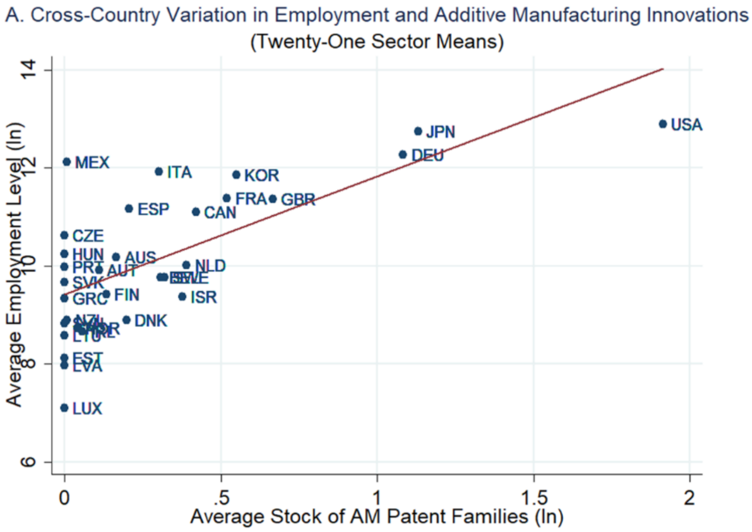
Notes: Authors' own computations based on USPTO data extracted from PATSTAT database. Data reported on a natural logarithmic scale. Numbers reported at the edge of each bar are actual AM patent counts. The total number of AM patents is 3,500.6.

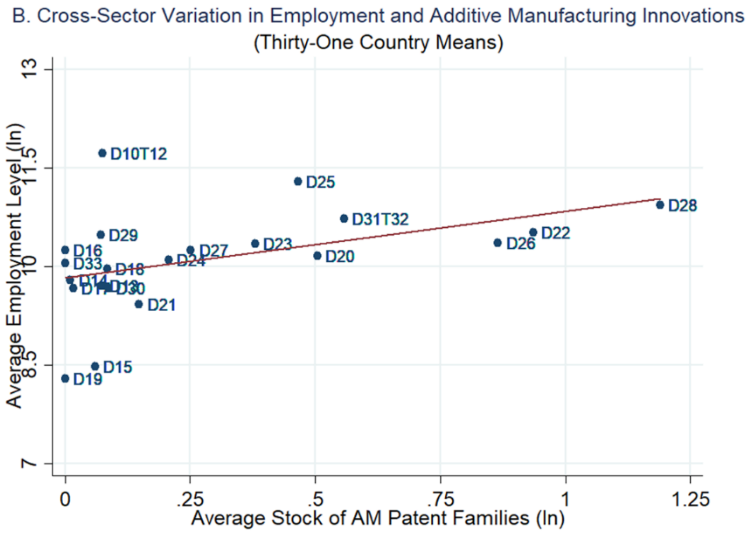
Figure 4. AM patent stock and share of AM patent stock in total patent stock, 2009–2017 period



Notes: Authors' own computations based on USPTO data extracted from PATSTAT database.

Figure 5. Cross-country and cross-sector variation in employment and AM patent stock, average values, 2009–2017 period





Notes: Authors' own estimates. Panel A plots the average employment level between 2009 and 2017 against the average stock of AM patents at the USPTO (both expressed as their natural logarithms) by country, averaged across industries. Panel B repeats the exercise by sector and averaging across countries.

Table 1. Examples of the link between AM patents and NACE Rev.2 sectors

Title	Abstract	Applicant	NACE 2 Sectors	Sectoral Weights
Articles and methods of manufacture of articles	Various articles, such as footwear, apparel, athletic equipment, watchbands, and the like, and methods of forming those articles are presented. The articles are generally formed, in whole or in part, using rapid manufacturing techniques, such as laser sintering, stereolithography, solid deposition modelling, and the like. The use of rapid manufacturing allows for relatively economical and time efficient manufacture of customized articles. [...] The methods may also include performing a scan of an appropriate body part of a user, such as a foot, in order to create a customized article of footwear for the user.	Nike International Ltd., US	22 15 28.9	0.25 0.5 0.25
Additive manufactured metal sports performance footwear components	The present invention relates to a sole for a shoe, in particular for a cycling shoe, comprising: (a.) a three-dimensionally shaped rim; and (b.) a plurality of first reinforcing struts, wherein (c.) at least two of the plurality of first reinforcing struts extend from a heel region of the rim of the sole to a toe region of the rim of the sole, and wherein (d.) the rim of the sole and the plurality of first reinforcing struts are integrally manufactured as a single piece in an additive manufacturing process.	Adidas AG., DE	15	1.0

Source: PATSTAT database.

Table 2. Descriptions of the variables used

Variable Name	Variable Description	Variable Label
Employment	Natural logarithm of the number of people employed, by sector	L_{ijt}
AM patent stock	Natural logarithm of the stock of AM patents at the USPTO, by sector, 3-y lagged	AM_{ijt-3}
Non-AM patent stock	Natural logarithm of the stock of non-AM patents at the USPTO (in thousands), by sector, 3-y lagged	$nonAM_{ijt-3}$
Labour cost	Natural logarithm of the cost of labour per thousand employees, by sector, 1-y lagged	LC_{ijt-1}
Gross output	Natural logarithm of gross output, by sector, 1-y lagged	Y_{ijt-1}

Notes: Data on sectoral variables comes from OECD's STAN data set; data on AM and non-AM patents collected from PATSTAT database.

Table 3. Relationship between AM patent stock and average employment, 2009–2017 period

	Unconditional			Conditional	
Employment (L_{ijt})	(1)	(2)	(3)	(4)	(5)
AM patent stock (AM_{ijt-3})	0.190***	0.090***	0.095***	0.065***	0.069***
	(0.019)	(0.017)	(0.019)	(0.008)	(0.008)
Non-AM patent stock ($nonAM_{ijt-3}$)		0.270***	0.270***	0.036***	0.034***
		(0.011)	(0.011)	(0.005)	(0.005)
Labour cost (LC_{ijt-1})		-0.186***	-0.202***	-0.793***	-0.806***
		(0.065)	(0.065)	(0.040)	(0.039)
Gross output (Y_{ijt-1})				0.782***	0.788***
				(0.011)	(0.011)
Observations	5,741	5,741	5,741	5,741	5,741
R^2	0.865	0.881	0.883	0.974	0.975
Country, Sector, Year FEs	✓	✓		✓	
Country-Year, Sector-Year FEs			✓		✓

Notes: Coefficients estimated by OLS with robust standard errors in parentheses. All variables are expressed in natural logarithms and measure elasticities. The dependent variable is sectoral employment (L_{ijt}). Coefficients for the constant term, for 59 countries, for sector and year dummies (columns (1), (2), and (4)), and for 459 country-year and sector-year dummies (columns (3) and (5)) are omitted due to space limitations. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 4. Relationship between AM patent stock and employment by Pavitt class, 2009–2017 period

	Unconditional		Conditional	
Employment (L_{ijt})	(1)	(2)	(3)	(4)
Panel A. OLS estimates				
AM patent stock (AM_{ijt-3})	0.219***	0.228***	0.080***	0.080***
	(0.043)	(0.045)	(0.011)	(0.012)
($AM_{ijt-3} \times SB$)	-0.102**	-0.104**	0.034**	0.036**
	(0.044)	(0.046)	(0.017)	(0.018)
($AM_{ijt-3} \times SS$)	-0.164***	-0.171***	-0.046***	-0.044***
	(0.045)	(0.047)	(0.012)	(0.012)
($AM_{ijt-3} \times SII$)	-0.214***	-0.225***	-0.047***	-0.043***
	(0.043)	(0.045)	(0.012)	(0.013)
Non-AM patent stock ($nonAM_{ijt-3}$)	0.280***	0.281***	0.037***	0.035***
	(0.011)	(0.011)	(0.005)	(0.005)
Labour cost (LC_{ijt-1})	-0.193***	-0.210***	-0.798***	-0.811***
	(0.065)	(0.065)	(0.040)	(0.039)
Gross output (Y_{ijt-1})			0.782***	0.787***
			(0.011)	(0.011)
Observations	5,741	5,741	5,741	5,741
R^2	0.882	0.883	0.974	0.975
Country, Sector, Year FEs	✓		✓	
Country-Year, Sector-Year FEs		✓		✓
Panel B. Baseline + sectoral interaction coefficients				
$(AM_{ijt-3}) + (AM_{ijt-3} \times SB)$	0.117***	0.124***	0.114***	0.116***
	(0.022)	(0.022)	(0.015)	(0.016)
$(AM_{ijt-3}) + (AM_{ijt-3} \times SS)$	0.055***	0.057***	0.034***	0.036***
	(0.020)	(0.021)	(0.008)	(0.008)
$(AM_{ijt-3}) + (AM_{ijt-3} \times SII)$	0.005	0.003	0.033***	0.037***
	(0.020)	(0.022)	(0.009)	(0.011)

Notes: Coefficients estimated by OLS with robust standard errors in parentheses. All variables are expressed in natural logarithms and measure elasticities. The dependent variable is sectoral employment (L_{ijt}). Dummies for SB, SS, and SII classes are omitted due to collinearity with sector FEs. The excluded class captured by the coefficient of the main variable is SD. Coefficients for the constant term, for 59 countries, for sector and year dummies (columns (1) and (3)), and for 459 country-year and sector-year dummies (columns (2) and (4)) are omitted due to space limitations. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 5. Relationship between AM patent stock and gross output by Pavitt class, 2009–2017 period

Gross output (Y_{ijt})	(1)	(2)
Panel A. OLS estimates		
AM patent stock (AM_{ijt-3})	0.164***	0.170***
	(0.055)	(0.058)
$(AM_{ijt-3} \times SB)$	-0.127**	-0.128**
	(0.057)	(0.059)
$(AM_{ijt-3} \times SS)$	-0.152***	-0.160***
	(0.056)	(0.059)
$(AM_{ijt-3} \times SII)$	-0.260***	-0.279***
	(0.055)	(0.058)
Non-AM patent stock ($nonAM_{ijt-3}$)	0.319***	0.321***
	(0.012)	(0.013)
Observations	5,741	5,741
R-squared	0.866	0.868
Country, Sector, Year FEs	✓	
Country-Year, Sector-Year FEs		✓
Panel B. Baseline + Pavitt interaction coefficients		
$(AM_{ijt-3}) + (AM_{ijt-3} \times SB)$	0.037	0.042
	(0.027)	(0.028)
$(AM_{ijt-3}) + (AM_{ijt-3} \times SS)$	0.011	0.011
	(0.024)	(0.025)
$(AM_{ijt-3}) + (AM_{ijt-3} \times SII)$	-0.096***	-0.109***
	(0.025)	(0.028)

Notes: Coefficients estimated by OLS with robust standard errors in parentheses. All variables are expressed in natural logarithms. The dependent variable is sectoral gross output (Y_{ijt}). Dummies for SB, SS, and SII Pavitt categories are omitted due to collinearity with sector FEs. The excluded Pavitt category captured by the coefficient of the main variable is SD. Coefficients for the constant term, for 59 countries, for sector and year dummies (column (1)), and for 459 country-year and sector-year dummies (column (2)) are omitted due to space limitations. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 6. Effect of AM patent stock on employment, on average and by Pavitt class, 2009–2017 period

	Unconditional		Conditional	
Employment (L_{ijt})	(1)	(2)	(3)	(4)
Panel A. 2SLS estimates				
AM patent stock (AM_{ijt-3})	0.098***	0.300***	0.059***	0.082***
	(0.021)	(0.053)	(0.010)	(0.014)
$(AM_{ijt-3} \times SB)$		-0.164***		0.037*
		(0.053)		(0.020)
$(AM_{ijt-3} \times SS)$		-0.250***		-0.058***
		(0.053)		(0.014)
$(AM_{ijt-3} \times SII)$		-0.303***		-0.058***
		(0.052)		(0.015)
Non-AM patent stock ($nonAM_{ijt-3}$)	0.286***	0.301***	0.050***	0.050***
	(0.012)	(0.012)	(0.006)	(0.006)
Labour cost (LC_{ijt-1})	-0.204***	-0.213***	-0.838***	-0.845***
	(0.065)	(0.065)	(0.039)	(0.039)
Gross output (Y_{ijt-1})			0.785***	0.785***
			(0.011)	(0.011)
Observations	5,741	5,741	5,741	5,741
R^2	0.883	0.883	0.975	0.975
Country-Year, Sector-Year FEs	✓	✓	✓	✓
Underidentification test	300.347***	289.375***	296.481***	307.178***
Weak identification test	419.958	203.236	427.203	215.442
Hansen J statistic (*p*-value)	0.635	0.809	0.439	0.628
Panel B. Baseline + Pavitt interaction coefficients				
$(AM_{ijt-3}) + (AM_{ijt-3} \times SB)$		0.136***		0.119***
		(0.022)		(0.017)
$(AM_{ijt-3}) + (AM_{ijt-3} \times SS)$		0.050**		0.023***
		(0.020)		(0.008)
$(AM_{ijt-3}) + (AM_{ijt-3} \times SII)$		-0.003		0.024**
		(0.022)		(0.010)

Notes: Coefficients estimated by 2SLS with robust standard errors in parentheses. All variables are expressed in natural logarithms. The dependent variable is sectoral employment (L_{ijt}). In columns (2) and (4), dummies for SB, SS, and SII sectoral classes are omitted due to collinearity with sector FEs. The excluded class captured by the coefficient of the main variable is SD. Coefficients for the constant term and for 459 country-year and sector-year dummies are omitted due to space limitations. All right-hand-variables are considered as endogenous and instrumented with their lagged values (see Section 4.5.2.2). The underidentification test is the Kleibergen–Paap rk LM test; weak identification test based on Kleibergen–Paap rk Wald F statistics, to be compared with Stock–Yogo critical values. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

4.9. Appendix A: Additional Tables

Table A1. AM usage by 2-digit sector of the NACE Rev.2 classification, % of enterprises with 10+ employees, 2018

	10–12	13–15	16–18	19–23	24–25	26	27–28	29–30	31–33	10–33
Austria	3		2							14
Belgium	6	5	<1	16						
Czech Republic	1	4	3	9	5	27	13	20	6	8
Denmark	1	<1	8	19	16	58	26	17	10	17
Estonia	<1	1	2	5	1	13	9	9	3	3
Finland				20	12					17
France	1	4	4	18	11	37	16	29	16	11
Germany	1	4	6	14	14	34	20	22	14	13
Greece	2	3	2	6	3		8		9	
Hungary	<1	3	1	7	5	13	13	10	7	5
Ireland	2	<1	1	11	11	17	18	<1	9	8
Italy	2	2	2	9	9	30	16	25	14	9
Latvia	<1	1	1	3	1	19	9	11	5	3
Lithuania	4	6	6	7	6	35	18	19	11	8
Luxembourg				9	7					9
Netherlands	2	6	3	16	10	27	14	19	13	11
Norway	<1	2	6	2	9	63	20	41	6	10
Poland	1	2	1	6	6	27	12	16	5	5
Portugal	<1	1	10	14	11	35	14	16	14	7
Slovakia	1	1	1	4	3	4	7	17	7	4
Slovenia		<1	2	15	8	25	18	29	11	10
Spain				8	7					7
Sweden	<1	7	3	14	10	45	16	12	9	10
United Kingdom	8	5	13	7	8			24	20	14

Notes: Sectors: 10–12 - Manufacture of beverages, food, and tobacco products; 13–15 - Manufacture of textiles, wearing apparel, leather, and related products; 16–18 - Manufacture of wood and products of wood and cork, except furniture; articles of straw and plaiting materials; paper and paper products; printing and reproduction of recorded media; 19–23 - Manufacture of coke, refined petroleum, chemical and basic pharmaceutical products, rubber and plastics, other non-metallic mineral products; 24–25 - Manufacture of basic metals and fabricated metal products excluding machines and equipment; 26 - Manufacture of computer, electronic, and optical products; 27–28 - Manufacture of electrical equipment, machinery and equipment n.e.c.; 29–30 - Manufacture of motor vehicles, trailers and semi-trailers, other transport equipment; 31–33 - Manufacture of furniture and other manufacturing; repair and installation of machinery and equipment; 10–33 - Total manufacturing. Usage includes use to produce goods for both external sale and internal use and prototyping for both external sale and internal use.
Source: Eurostat's European ICT usage survey.

Table A2. 2-digit manufacturing sectors of the NACE Rev.2 classification, by group of the Pavitt taxonomy

Science Based	
Manufacture of chemicals and chemical products	20
Manufacture of basic pharmaceutical products and pharmaceutical prep.	21
Manufacture of computer, electronic, and optical products	26
Specialised Suppliers	
Manufacture of electrical equipment	27
Manufacture of machinery and equipment n.e.c.	28
Manufacture of other transport equipment	30
Repair and installation of machinery and equipment	33
Scale and Information Intensive	
Manufacture of paper and paper products	17
Printing and reproduction of recorded media	18
Manufacture of coke and refined petroleum products	19
Manufacture of rubber and plastic products	22
Manufacture of other non-metallic mineral products	23
Manufacture of basic metals	24
Manufacture of motor vehicles, trailers, and semi-trailers	29
Supplier Dominated	
Manufacture of food products, beverages, and tobacco products	10-12
Manufacture of textiles	13
Manufacture of wearing apparel	14
Manufacture of leather and related products	15
Manufacture of wood and of products of wood and cork, except furniture	16
Manufacture of fabricated metal products, except machinery and equipment	25
Manufacture of furniture and other manufacturing	31-32

Notes: By considering the sources and patterns of innovation, firm characteristics, and market structure, the Pavitt taxonomy identifies similarities among industries. It allows to distinguish four sectoral groups: (a) Science Based industries, where innovation is based on R&D and there is high propensity towards product innovation and patenting; (b) Specialized Supplier industries, where the source of innovation is only partially R&D and most of the innovation occurs through tacit knowledge and skills embodied in the labour force; average firm size is small and buyer-supplier relationships and exchange of knowledge are a fundamental source of innovation; the products of these industries are new processes for other industries; (c) Scale and Information Intensive industries, typically characterized by large economies of scale and a concentrated industrial structure, where technological change is in general incremental and new products and new processes coexist; (d) Supplier Dominated industries mainly include traditional sectors, where technological change is introduced mainly through the adoption of new inputs and machinery produced in other sectors and where internal innovation activities are low.
Source: Bogliacino and Pianta (2016).

Table A3. List of keywords related to AM

First-tier keywords (General terminology, processes, technologies)		
Additive manufacturing	Additive process	3d printing
3-d printing	3-dimensional printing	3d manufacturing
3-d manufacturing	3-dimensional manufacturing	Three-d printing
Three-dimensional printing	Three-d manufacturing	Three-dimensional manufacturing
Binder jetting	Direct energy deposition	Material extrusion
Material Jetting	Powder bed fusion	Sheet lamination
Vat photopolymerization	Fused deposition modelling	Fused filament fabrication
Laser sintering	Laser melting	Direct metal laser deposition
Laser metal deposition	Electron beam melting	Laser engineering net shaping
Stereolithography	Poly-jet matrix	Multi-jet modelling
Continuous liquid interface production		
Second-tier keywords (Specific IPC codes)		
B33		

Notes: Keywords' selection based on the engineering literature, terminology from ruling bodies, and product catalogues on AM.

Table A4. Summary statistics for OECD countries and manufacturing industries, 2009–2017 period

	[1]	[2]	[3]	[4]	[5]
[1] Employment (L_{ijt})	1.000				
[2] AM patent stock (AM_{ijt-3})	0.444	1.000			
[3] Non-AM patent stock ($nonAM_{ijt-3}$)	0.524	0.529	1.000		
[4] Labour cost (LC_{ijt-1})	0.054	0.251	0.516	1.000	
[5] Gross output (Y_{ijt-1})	0.889	0.430	0.628	0.383	1.000
N. of Countries	31	31	31	31	31
N. of Sectors	21	21	21	21	21
N. of Obs.	5,741	5,741	5,741	5,741	5,741
Mean	10.114	0.215	3.524	17.537	8.729
SD	1.771	0.581	2.785	0.564	1.969
Min.	0.000	0.000	0.000	15.065	0.233
p25	8.939	0.000	1.064	17.193	7.337
Median	10.074	0.000	3.209	17.590	8.828
p75	11.370	0.009	5.431	17.906	10.103
Max.	14.458	5.627	12.604	20.347	13.737

Notes: Statistics reported here refer to cross-sectional variation across all country-sector-year cells.

4.10. Appendix B: On the AM proxy: keywords, industries, and countries

4.10.B1. On the sectoral attribution of AM patents

Hereafter, we provide a few examples on how the DG Concordance Table (Schmoch et al., 2003; Van Looy et al., 2014; 2015) used in PATSTAT database to match patents to sectors relatedly to their probability of being used in a specific industry. We argue that our measure of AM innovations captures the overall diffusion of AM innovations (i.e. both product and process innovations). To show this, we first provide an example of a patent capturing an AM-related product innovations for an upstream industry, becoming a process innovation for downstream sectors. Table B1 reports an AM patent filed at the USPTO, representative of a patent family describing an AM system and the related production process. The largest share of the patent links to NACE sector 28 (manufacture of machinery and equipment) as most of the information included in the patent deals with the specifics of the AM device. In addition, as the process described is specifically suited for the production of airfoils (i.e. metallic components used in engines/aerospace industries), a minor share of the patent is attributed to NACE sector 25 (manufacture of fabricated metal products).

The example illustrates the way in which patents are matched with sectors in our data: the weights allocated to NACE sector 28 measure the probability of the AM invention described in the patent being used in NACE sector 28, i.e. in producing the AM machinery in question. On the other hand, it also shows that to a lesser extent the patent is likely to be related to the usage of the described AM device to produce airfoils, i.e. by using the AM machine for production purposes.

Furthermore, and quite interestingly, the identity of the applicant (i.e. General Electric) provides additional insight into the nature of the AM innovation process itself. In recent years, advancements in AM technologies have not been developed solely by established 3D printer producers (e.g. Stratasys, 3D Systems, EOS, among others). Firms like General Electric, Rolls-Royce, and several others (who traditionally are both producers of other types of equipment and users of other types of machinery, produced in upstream sectors) have been developing their own AM processes and machines, leveraging partnerships (Colyer, 2019) or acquisitions of other machinery producers (Kellner, 2018a; 2018b), allowing them to internalise core competencies.

Table B1. Example 1 on the link between AM patents and NACE Rev.2 sectors

Title	Abstract	Applicant	NACE 2 Sectors	Sectoral Weights
A high temperature additive manufacturing system for making near net shape airfoil leading edge protection with a cladded mandrel	A high temperature additive manufacturing system comprising a high temperature additive manufacturing device for providing a metallic deposit; and a tooling system comprising a mandrel for receiving and providing shape to, the metallic deposit, a metallic cladding applied to the mandrel for reducing contamination of the metallic deposit, and at least one cooling channel associated with the mandrel for removing heat from the system.	General Electric Company, US	28.9 28.4 25.5	0.143* 0.714* 0.143

Source: PATSTAT database. * Since our analysis focuses on the 2-digit level of sectoral aggregation, sectoral weights such as those reported in the example (at the 3-digit level) were summed to reach the 2-digit level.

Similarly, we now provide key examples suggesting that AM innovations in our data also relate to the product innovations in downstream (using) industries, i.e. suggesting adoption of AM innovations for production purposes. Table B2 presents two examples of patent applications describing 3D-printed products, i.e. footwear and other apparel products, and the method for producing such products. In these examples, the larger sectoral weight of the patent describes its probability-of-use in NACE sector 15 (manufacture of leather and related products), suggesting that the applicants, i.e. Nike and Adidas (also like Reebok) adopt AM techniques to produce specific and customised products suitable for commercialisation. In fact, Nike's Zoom Vaporfly Elite Flyprint (Nike, 2018), Vapor Laser Talon, and Vapor Hyper Agility (Del Nibletto, 2017), and Adidas' Futurecraft 3D (Nelson, 2015) and Alphaedge 4D (Adidas, 2019) are just some of the 3D printed footwear currently sold by these two firms. Specifically, Nike and Adidas developed these new products in partnership with firms like Materialise for the design phase (Materialise, 2019), then started production by setting up dedicated plants with machines supplied by the 3D-printer producer Carbon (Cheng, 2018).

Like in the previous example, here minority shares of the patent also link to other sectors differently related to the AM innovation described. Specifically, as sports footwear and equipment are mostly plastic products, the patent also shows some probability-of-use in NACE sector 22 (manufacture of rubber and plastic products); furthermore, since it also describes possible production techniques, it also features a lower probability-of-use in NACE sector 28.

Table B2. Examples 2 and 3 on the link between AM patents and NACE Rev.2 sectors (Table 1 in Section 4.3.1.1)

Title	Abstract	Applicant	NACE 2 Sectors	Sectoral Weights
Articles and methods of manufacture of articles	Various articles, such as footwear, apparel, athletic equipment, watchbands, and the like, and methods of forming those articles are presented. The articles are generally formed, in whole or in part, using rapid manufacturing techniques, such as laser sintering, stereolithography, solid deposition 244odelling, and the like. The use of rapid manufacturing allows for relatively economical and time efficient manufacture of customized articles. [...] The methods may also include performing a scan of an appropriate body part of a user, such as a foot, in order to create a customized article of footwear for the user.	Nike International Ltd., US	22 15 28.9	0.25 0.5 0.25
Additive manufactured metal sports performance footwear components	The present invention relates to a sole for a shoe, in particular for a cycling shoe, comprising: (a.) a three-dimensionally shaped rim; and (b.) a plurality of first reinforcing struts, wherein (c.) at least two of the plurality of first reinforcing struts extend from a heel region of the rim of the sole to a toe region of the rim of the sole, and wherein (d.) the rim of the sole and the plurality of first reinforcing struts are integrally manufactured as a single piece in an additive manufacturing process.	Adidas AG., DE	15	1.0

Source: PATSTAT database.

Another example we present shows an AM patent pertaining a product innovation, featuring a one-to-one correspondence to NACE sector 25 (manufacture of fabricated metal products), again suggesting AM processes are adopted in this specific industry. The metallic product described in Table B3 is specifically designed to be manufactured using additive techniques. In fact, over the last few years companies like General Electric, Airbus, and Rolls-Royce have directly used AM techniques in the production of parts and components installed in their turbine engines (Kellner, 2018b; Kingsbury, 2019).

Table B3. Example 4 on the link between AM patents and NACE Rev.2 sectors

Title	Abstract	Applicant	NACE 2 Sectors	Sectoral Weights
Article produced by additive manufacturing	An article includes at least one first portion, wherein the at least one first portion is additively manufactured by depositing successive layers of one or more materials upon a surface such that a three dimensional structure is obtained; at least one second portion […]; and at least one third portion, wherein the at least one third portion is additively manufactured by depositing successive layers of one or more materials upon the at least one top surface such that a three dimensional structure is obtained.	General Electric Company, US	25.5	1.0

Source: PATSTAT database.

Finally, in addition to these examples, and as extensively analysed in the literature on AM, other industry applications deal with the production of medical devices (e.g. prostheses, surgical and dental implants, hearing aids), luxury goods (i.e. jewellery), and musical instruments and toys (Laplume et al., 2016). Several patents dealing with these types of products in our data present majority shares relating to sectors 26 (manufacture of computer, electronic, and optical products), 32 (other manufacturing, including the manufacturing of medical devices), and 22 (manufacture of rubber and plastic products). These industries witnessed the diffusion of AM innovations well before others (Sandström, 2016), and direct manufacturing via AM is now an established manufacturing method, especially due to the high potential for customization (Laplume et al., 2016; Sandström, 2016). We provide some examples in Table B4.

Table B4. Example 5 and 6 on the link between AM patents and NACE Rev.2 sectors

Title	Abstract	Applicant	NACE 2 Sectors	Sectoral Weights
3-D printing of bone grafts	Computer implemented methods of producing a bone graft are provided. These methods include obtaining a 3-D image of an intended bone graft site; generating a 3-D digital model of the bone graft based on the 3-D image of the intended bone graft site, the 3-D digital model of the bone graft being configured to fit within a 3-D digital model of the intended bone graft site; [..]. A layered 3-D printed bone graft prepared by the computer implemented method is also provided.	Warsaw Orthopedic, Inc., US	32.5	1.0
A method for fabricating a hearing device	A method for fabricating a hearing aid using a self contained hearing aid production laboratory employing three dimensional printing technology. The method comprises the steps of conducting audiometric testing of an individual with a hearing impairment; selecting and customizing a product design for the hearing aid to be produced; producing the selected and customized hearing aid; and performing final adjustments to the produced hearing aid.	Siemens Hearing Instruments, Inc., US	26.3	1.0

Source: PATSTAT database.

In turn, the examples just presented also highlight that in the alternative case of attributing AM patents only to the sector of the applicant we would have potentially incurred in strong misallocations. Obviously, given the lack of information on licencing agreements, both attribution strategies have drawbacks. The size of the misattribution basically depends on the number of multiproduct firms, conglomerates, or firms involved in complex value chains and therefore possibly patenting but not directly using the patent (except through firms in other sectors) that are in the sample as applicants, as already pointed out by Dorner and Harhoff (2018).

4.10.B2. On the geographical attribution

In Section 4.3.1.2 we explain how we allocated patents to the country of residence of their inventors using fractional counting. An alternative strategy would be to attribute patents on the basis of the jurisdiction, i.e. where the patent provides protection. In our opinion, this strategy would result in a worse proxy for several reasons. First, this way would be more likely to capture defensive or strategic patenting. Second, firms may extend the number of countries where they apply for protection for reasons different from the real 'economic' rationale for protection. In fact, many patent authorities, e.g. the European Patent Office (EPO) or Patent Cooperation Treaty (PCT), provide the opportunity to protect patent families for which an application is filed in all or a selection of member states (i.e. contracting states) with just one application (EPO, 2019). This may induce applicants to extend the countries where they seek protection somehow automatically, because the cost is negligible. In turn, this would lead to a measure highly skewed towards, for instance, EPO member states, and thus not reflecting the real diffusion of AM innovations.

Furthermore, in the alternative scenario where, for instance, protection is sought to slow-down competitors in the market where the applicant firm wants to sell the capital-embodied innovation, even if we capture partially the diffusion of these innovations in the importing country, such proxy would most likely overestimate the level of local innovation activity in the field of AM. It is also worth noting that the resulting skewed distribution, in particular for our sample of countries, would not allow for enough variation in the data to carry out the econometric analysis.

Finally, the alternative strategy of assigning patent families to the country of the applicant would not be exempt from some pitfalls as well. For example, if the applicant is a small-medium firm – as often is the case in the AM field – this would not be an issue since the country of the applicant and the inventor would be the same. On the contrary, if the applicant is a large multinational, for instance, we would end up in assigning it to the country where the multinational enterprise (MNE) has its (legal) headquarters, which in many cases is not the place (or sector) where the production or the adoption occurs. Clearly, in view of the lack of direct information on where the patent is used, either alternative could be considered a second best rather than a first best choice.

4.11. Appendix C: Details on the robustness checks

4.11.C1. Alternative AM innovation proxy and inter-sectoral/inter-country relationships

In Section 4.5.1.1, we explain that our main analysis could miss inter-sectoral and inter-country linkages through which the diffusion of AM innovations may affect industry-level employment. These mechanisms represent general equilibrium effects acting through the existing links along supply chains. Moreover, firms in an industry may use AM machines that are produced by firms in other sectors or countries, this not showing up in the sectoral own patenting activity, i.e. in our main proxy for AM diffusion. To check for potential bias in our results arising from these relationships, we build a measure that should be able to capture also AM innovations generated outside of the focal industry, which still may have an effect on the employment of the focal sector via transfer of AM-related technological content embodied in the imported intermediate inputs. Hereafter, we illustrate in more detail the data used, the technical caveats of building these measures, and the results of the related analysis.

We use the world input–output tables from the 2016 release of the WIOD data set (Timmer et al., 2015). The use of these data results in a slight reduction of the sample used in our main investigation. Specifically, we lose two countries (Israel and New Zealand) and the detailed disaggregated information for two industries, namely NACE sectors 13 to 15 (manufacturing of textiles, wearing apparel, leather, and related products), which is provided as a unique aggregate.

We build an index of AM innovations capturing both potential inter-sectoral and inter-country transfers of AM innovations going through value-chain relationships as follows:

$$extAM_{ijt} = \sum_{c}\sum_{s} AM_{cst} \times \left(\frac{int_{ij2008}^{cs}}{int_{ij2008}}\right) \qquad \text{(A1)}$$

for each country i, sector j, and year t. The $extAM_{ijt}$ variable is then the weighted sum of the AM patent stock in each country and industry, where the weights are built as the ratio of intermediate inputs bought by sector j of country i from sector $s \neq j$ in country i and from all industries in country $c \neq i$, i.e. all sectoral domestic intermediates bought from all sectors excluding one's own, plus all foreign intermediates bought from all sectors, over the total intermediate goods used by sector j in country i (int_{ij}). Weights int_{ij}^{cs}/int_{ij} are constant over time and predetermined with respect to our observation period, as they refer to year 2008. We take predetermined weights in order to minimize potential endogeneity concerns and avoid biases induced by reverse causality. We estimate the following specification:

$$L_{ijt} = \alpha_0 + \alpha_1 AM_{ijt-3} + \alpha_2 nonAM_{ijt-3} + \alpha_3 extAM_{ijt-3} + \alpha_4 extnonAM_{ijt-3} \\ + \alpha_5 DVF_{ij2008} + \alpha_6 FE_{ij2008} + \boldsymbol{\alpha}_7 \boldsymbol{X}_{ijt-1} + \gamma_i + \gamma_j + \gamma_t + u_{ijt}, \tag{A2}$$

Where, in addition to the measure of AM innovations used in the main analysis and all other controls, we include the new $extAM_{ijt-3}$ variable, a similar variable – built following equation (A1) – capturing inter-sectoral and inter-country technology transfers associated with non-AM patents ($extnonAM_{ijt-3}$), two controls for foreign exposure (FE_{ij2008}, in the spirit of the offshoring index originally introduced by Feenstra and Hanson, 1996), and a measure of domestic vertical fragmentation (DVF_{ij2008}). The numerator of the foreign-exposure variable is the sum of the value of all intermediate inputs imported by sector j of country i from all sectors of all partner countries, while the denominator is the total value of all intermediate inputs used in production in sector j of country i. The numerator of the domestic vertical fragmentation variable is the sum of the value of all intermediate inputs bought by sector j of country i from all sectors $s \neq j$ of country i, while the denominator is the total value of all intermediate inputs used in production by sector j. Both variables are time-invariant as they refer to the year 2008, again to avoid reverse-causality issues. They both play a similar role to country-sector Fes (γ_{ij}), which as explained in Section 4.4 cannot be included in the analysis due to the short time span of our series and the scarce variation over time left along the country-sector dimension. We therefore underline that the inclusion of the two control variables also works as a relevant robustness check per se.

As can be seen from Table C1, our results are robust to the inclusion of the new proxy and control variables. The employment elasticity to the original AM proxy is about 0.075 in unconditional demand estimations and 0.045 in the conditional demand estimations, both being statistically significant at the 1% level. In contrast, the newly added external AM innovations variable is not statistically significant in the unconditional demand estimations; for conditional demand it is positive and statistically significant (0.07, statistically significant at the 5% level in the most demanding specification in terms of FEs). Thus, the results confirm the complementarity between AM technologies and labour. The new variable capturing technology transfer for all non-AM innovations is also positive and statistically significant at the 1% level in all specifications, with an elasticity again much larger in unconditional demand estimations (about 0.5) than in conditional ones (about 0.05), as in our baseline model. The domestic vertical fragmentation control is negatively and significantly (at the 1% level) correlated with employment in the unconditional demand estimation, potentially capturing an outsourcing effect. It is positively and significantly correlated with sectoral employment (significant at the 10% level) in conditional estimations and is probably capturing a composition effect since most labour-intensive tasks/activities are less likely to be outsourced, both at the bottom and at the top of the skill distribution. The foreign-exposure variable correlates negatively with employment in all specifications, but the elasticity is smaller (about 0.2) and not statistically significant in the unconditional demand estimations while it is about 0.7 and statistically significant at the 1% level in the conditional demand estimations. This is in line with the theoretical literature, suggesting that offshoring has pro-competitive effects and increases production and sales, but also a large labour-saving effect (at constant output).

Table C1. Relationship between AM patent stock and average employment, 2009–2017 period, inter-sectoral/inter-country AM relationships

	Unconditional		Conditional	
Employment (L_{ijt})	(1)	(2)	(3)	(4)
AM patent stock (AM_{ijt-3})	0.075***	0.079***	0.045***	0.046***
	(0.017)	(0.018)	(0.008)	(0.009)
Non-AM patent stock ($nonAM_{ijt-3}$)	0.175***	0.176***	0.023***	0.021***
	(0.009)	(0.009)	(0.005)	(0.005)
External AM patent stock ($extAM_{ijt-3}$)	-0.004	-0.001	0.044*	0.074**
	(0.048)	(0.059)	(0.023)	(0.029)
External non-AM patent stock ($extnonAM_{ijt-3}$)	0.512***	0.513***	0.051***	0.041***
	(0.015)	(0.016)	(0.013)	(0.014)
Domestic vertical fragmentation (DVF_{ij2008})	-1.304***	-1.318***	0.126*	0.124*
	(0.122)	(0.126)	(0.068)	(0.070)
Foreign exposure (FE_{ij2008})	-0.118	-0.117	-0.698***	-0.689***
	(0.216)	(0.222)	(0.101)	(0.104)
Labour cost (LC_{ijt-1})	-0.107	-0.133*	-0.641***	-0.667***
	(0.069)	(0.068)	(0.029)	(0.028)
Gross output (Y_{ijt-1})			0.716***	0.725***
			(0.016)	(0.015)
Observations	4,854	4,854	4,854	4,854
R-squared	0.936	0.937	0.980	0.981
Country, Sector, Year FEs	✓		✓	
Country-Year, Sector-Year FEs		✓		✓

Notes: Coefficients estimated by OLS with robust standard errors in parentheses. All variables are expressed in natural logarithms. The dependent variable is sectoral employment (L_{ijt}). Coefficients for the constant term, for 55 countries, sector and year dummies (columns (1) and (3)), and for 423 country-year and sector-year dummies (columns (2) and (4)) are omitted due to space limitations. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

4.11.C2. Countries and sectors

Hereafter, we provide results for the robustness checks described in Section 4.5.1.1 pertaining to the exclusion of the top six AM-patenting countries and of NACE sector 28 (manufacturing of machinery and equipment), which produce AM machines. As can be seen from Tables C2 and C3 below, our findings are robust to these checks. Similarly, Table C4 present results related to the further robustness test we conduct to test our results to the exclusion of country and sector, which have no AM patents in our data; also in this case, results are robust.

Table C2. Relationship between AM patent stock and average employment, 2009–2017 period, excluding the top six AM-patenting countries

	Unconditional		Conditional	
Employment (L_{ijt})	(1)	(2)	(3)	(4)
AM patent stock (AM_{ijt-3})	0.112***	0.130***	0.093***	0.109***
	(0.036)	(0.041)	(0.018)	(0.021)
Non-AM patent stock ($nonAM_{ijt-3}$)	0.308***	0.310***	0.043***	0.041***
	(0.013)	(0.014)	(0.007)	(0.007)
Labour cost (LC_{ijt-1})	-0.225***	-0.245***	-0.833***	-0.849***
	(0.077)	(0.079)	(0.048)	(0.046)
Gross output (Y_{ijt-1})			0.785***	0.791***
			(0.012)	(0.012)
Observations	4,625	4,625	4,625	4,625
R-squared	0.829	0.832	0.962	0.964
Country, Sector, Year FEs	✓		✓	
Country-Year, Sector-Year FEs		✓		✓

Notes: Coefficients estimated by OLS with robust standard errors in parentheses. All variables are expressed in natural logarithms. The dependent variable is sectoral employment (L_{ijt}). Coefficients for the constant term, for 53 countries, sector and year dummies (columns (1) and (3)), and for 405 country-year and sector-year dummies (columns (2) and (4)) are omitted due to space limitations. The top six AM-patenting countries excluded are the US, Japan, Germany, UK, France, and Korea. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table C3. Relationship between AM patent stock and average employment, 2009–2017 period, excluding AM machinery-producing sector

	Unconditional		Conditional	
Employment (L_{ijt})	(1)	(2)	(3)	(4)
AM patent stock (AM_{ijt-3})	0.100***	0.106***	0.081***	0.086***
	(0.020)	(0.022)	(0.009)	(0.010)
Non-AM patent stock ($nonAM_{ijt-3}$)	0.265***	0.266***	0.036***	0.034***
	(0.011)	(0.012)	(0.005)	(0.005)
Labour cost (LC_{ijt-1})	-0.189***	-0.204***	-0.792***	-0.805***
	(0.066)	(0.066)	(0.041)	(0.039)
Gross output (Y_{ijt-1})			0.781***	0.787***
			(0.011)	(0.011)
Observations	5,462	5,462	5,462	5,462
R-squared	0.878	0.879	0.973	0.974
Country, Sector, Year FEs	✓		✓	
Country-Year, Sector-Year FEs		✓		✓

Notes: Coefficients estimated by OLS with robust standard errors in parentheses. All variables are expressed in natural logarithms. The dependent variable is sectoral employment (L_{ijt}). Coefficients for the constant term, for 58 countries, sector and year dummies (columns (1) and (3)), and for 450 country-year and sector-year dummies (columns (2) and (4)) are omitted due to space limitations. The sector producing AM machinery is sector NACE 28 - Manufacture of machinery and equipment. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table C4. Relationship between AM stock and average employment, 2009–2017 period, excluding countries and sectors with no AM patents

	Unconditional		Conditional	
Employment (L_{ijt})	(1)	(2)	(3)	(4)
AM patent stock (AM_{ijt-3})	0.054***	0.056***	0.039***	0.041***
	(0.017)	(0.019)	(0.008)	(0.009)
Non-AM patent stock ($nonAM_{ijt-3}$)	0.306***	0.308***	0.045***	0.043***
	(0.015)	(0.016)	(0.005)	(0.006)
Labour cost (LC_{ijt-1})	-0.233***	-0.245***	-0.847***	-0.857***
	(0.059)	(0.062)	(0.022)	(0.022)
Gross output (Y_{ijt-1})			0.780***	0.784***
			(0.009)	(0.009)
Observations	4,545	4,545	4,545	4,545
R-squared	0.904	0.905	0.980	0.981
Country, Sector, Year FEs	✓		✓	
Country-Year, Sector-Year FEs		✓		✓

Notes: Coefficients estimated by OLS with robust standard errors in parentheses. All variables are expressed in natural logarithms. The dependent variable is sectoral employment (L_{ijt}). Coefficients for the constant term, for 53 countries, sector and year dummies (columns (1) and (3)), and for 405 country-year and sector-year dummies (columns (2) and (4)) are omitted due to space limitations. This estimation only exploits the intensive margin of AM (i.e. it excludes observations for which the AM stock is zero). Countries with no AM patents are Estonia, Greece, Latvia and Portugal. Sectors with no AM patents are: sector NACE 19 - Manufacture of coke and refined petroleum products; sector NACE 33 - Repair and installation of machinery and equipment. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

4.11.C3. Alternative patent data

In order to test the robustness of our main results, we perform a battery of additional checks. First, in our main analysis we focus on AM patent families applied for at the USPTO. Although the USPTO represents the reference patent office where inventors and applicants worldwide tend to file their new inventions to seek IP protection, being a large and highly innovative market, it is not the only important patent authority worldwide. Thus, we collected information on AM patent families filed at the European Patent Office (EPO) and at the Patent Cooperation Treaty (PCT), which allow inventors and applicants to seek protection for their invention in a large number of countries simultaneously (European countries in the case of the EPO, internationally in the case of the PCT). We build AM patent stock measures following the methodology described in Section 4.3 using both EPO and PCT applications, which we test alternatives to our main AM measure based on USPTO data. As shown in Table C5 below, our results are robust to these checks.

Table C5. Relationship between AM patent stock and average employment, period 2009-2017, AM patents at alternative patent authorities

	EPO				PCT			
	Unconditional		Conditional		Unconditional		Conditional	
Employment (L_{ijt})	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AM patent stock (AM^{EPO}_{ijt-3})	0.120***	0.121***	0.061***	0.062***				
	(0.019)	(0.020)	(0.010)	(0.010)				
AM patent stock (AM^{PCT}_{ijt-3})					0.090***	0.093***	0.069***	0.073***
					(0.017)	(0.019)	(0.008)	(0.009)
Non-AM patent stock ($nonAM_{ijt-3}$)	0.270***	0.271***	0.038***	0.036***	0.269***	0.270***	0.035***	0.033***
	(0.011)	(0.012)	(0.005)	(0.005)	(0.011)	(0.012)	(0.005)	(0.005)
Labour cost (LC_{ijt-1})	-0.187***	-0.203***	-0.794***	-0.807***	-0.186***	-0.201***	-0.793***	-0.806***
	(0.065)	(0.065)	(0.040)	(0.039)	(0.065)	(0.065)	(0.040)	(0.039)
Gross output (Y_{ijt-1})			0.782***	0.788***			0.782***	0.788***
			(0.011)	(0.011)			(0.011)	(0.011)
Observations	5,741	5,741	5,741	5,741	5,741	5,741	5,741	5,741
R-squared	0.881	0.883	0.974	0.975	0.881	0.883	0.974	0.975
Country, Sector, Year FEs	✓		✓		✓		✓	
Country-Year, Sector-Year FEs		✓		✓		✓		✓

Notes: Coefficients estimated by OLS with robust standard errors in parentheses. All variables are expressed in natural logarithms. The dependent variable is sectoral employment (L_{ijt}). Coefficients for the constant term, for 59 countries, sector and year dummies (odd columns), and for 459 country-year and sector-year dummies (even columns) are omitted due to space limitations. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

4.11.C4. Alternative lag structures

A further check we conduct concerns the lag structure that we assume for our main variable of interest. As described in Sections 4.3.2 and 4.4, our assumption regarding the three-year lag is based on both practical considerations related to the time required to get from the application of a patent to the moment at which the innovation it seeks to protect is actually brought to the market and on econometric practices in the related literature. Nonetheless, depending on the specificity of the innovation this time window could vary; alternatively, this rule of thumb may not be appropriate in the case of very narrow categories of innovation, as in the case of AM. Hence, we also explore specifications in which we allow for different lag structures for both our patent-based variables (i.e. the AM patent stock and the non-AM patent stock). Specifically, we test models in which these variables may have a relationship with employment over a shorter period, i.e. including these variables with a one-year ($AM_{ijt-1}, nonAM_{ijt-1}$) and a two-year lag ($AM_{ijt-2}, nonAM_{ijt-2}$). Alternatively, we allow the AM–employment relationship to be in place with longer lags ($AM_{ijt-4}, nonAM_{ijt-4}, AM_{ijt-5}, nonAM_{ijt-5}$). These results are reported in Table C6 below and again show that our findings are robust.

Notably, as presented in columns (1) to (8), assuming a shorter lag structure for our AM patent stock variable – thus, assuming the effect of AM on employment happens almost synchronously with the filing of the related innovation – turns out to still highlight a positive relationship, but one predominantly driven by existing complementarities between AM and labour. Conversely, market-related channels appear negligible for shorter lags as we observe almost no (for AM_{ijt-1}) and little (for AM_{ijt-2}) change in the coefficient when comparing unconditional and conditional specifications.

However, and coherently with our main assumption on the appropriate lag structure to assume in order to properly and fully gauge the effects of AM on employment, specifications testing longer lag structures (columns (9) to (16)) show a positive impact of AM, highlighting both an important role of the market channel as well as complementarities between the technology and labour.

Table C6. Relationship between AM patent stock and average employment, 2009–2017 period, alternative lag structures for AM and non-AM patent stocks

	1-year lag				2-year lag				4-year lag				5-year lag			
	Unconditional		Conditional		Unconditional		Conditional		Unconditional		Conditional		Unconditional		Conditional	
Employment (L_{ijt})	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
AM patent stock (AM_{ijt-1})	0.059***	0.062***	0.056***	0.061***												
	(0.015)	(0.017)	(0.007)	(0.007)												
Non-AM patent stock ($nonAM_{ijt-1}$)	0.279***	0.280***	0.035***	0.033***												
	(0.011)	(0.012)	(0.005)	(0.005)												
AM patent stock (AM_{ijt-2})					0.071***	0.076***	0.060***	0.065***								
					(0.016)	(0.018)	(0.007)	(0.008)								
Non-AM patent stock ($nonAM_{ijt-2}$)					0.275***	0.275***	0.035***	0.033***								
					(0.011)	(0.012)	(0.005)	(0.005)								
AM patent stock (AM_{ijt-4})									0.109***	0.113***	0.070***	0.072***				
									(0.019)	(0.020)	(0.009)	(0.009)				
Non-AM patent stock ($nonAM_{ijt-4}$)									0.264***	0.265***	0.036***	0.034***				
									(0.011)	(0.011)	(0.005)	(0.005)				
AM patent stock (AM_{ijt-5})													0.119***	0.122***	0.072***	0.072***
													(0.019)	(0.020)	(0.009)	(0.009)
Non-AM patent stock ($nonAM_{ijt-5}$)													0.260***	0.262***	0.037***	0.035***
													(0.011)	(0.011)	(0.005)	(0.005)
Labour cost (LC_{ijt-1})	-0.188***	-0.203***	-0.793***	-0.806***	-0.188***	-0.202***	-0.793***	-0.806***	-0.185***	-0.201***	-0.793***	-0.806***	-0.183***	-0.199***	-0.793***	-0.806***
	(0.064)	(0.065)	(0.040)	(0.038)	(0.064)	(0.065)	(0.040)	(0.038)	(0.065)	(0.065)	(0.040)	(0.039)	(0.065)	(0.066)	(0.040)	(0.039)
Gross output (Y_{ijt-1})			0.782***	0.788***			0.782***	0.788***			0.782***	0.788***			0.782***	0.788***
			(0.011)	(0.011)			(0.011)	(0.011)			(0.011)	(0.011)			(0.011)	(0.011)
Observations	5,741	5,741	5,741	5,741	5,741	5,741	5,741	5,741	5,741	5,741	5,741	5,741	5,741	5,741	5,741	5,741
R-squared	0.882	0.883	0.974	0.975	0.882	0.883	0.974	0.975	0.881	0.883	0.974	0.975	0.881	0.882	0.974	0.975
Country, Sector, Year FEs	✓		✓		✓		✓		✓		✓		✓		✓	
Country-Year, Sector-Year FEs		✓		✓		✓		✓		✓		✓		✓		✓

Notes: Coefficients estimated by OLS with robust standard errors in parentheses. All variables are expressed in natural logarithms. The dependent variable is sectoral employment (L_{ijt}). Coefficients for the constant term, for 59 countries, sector and year dummies (odd columns), and for 459 country-year and sector-year dummies (even columns) are omitted due to space limitations. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table C7. Relationship between AM patent stock and average employment, 2009–2017 period, country-level analysis

	Full sample		European sample		High education		Middle education		Low education	
Employment	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
AM patent stock (AM_{it-3})	0.154***	0.063***	0.122***	0.064***	0.176***	0.102***	0.243***	0.177***	0.082	-0.005
	(0.034)	(0.008)	(0.040)	(0.013)	(0.038)	(0.024)	(0.040)	(0.026)	(0.069)	(0.057)
Non-AM patent stock ($nonAM_{it-3}$)	0.645***	-0.026	0.583***	-0.019	0.541***	0.045	0.616***	0.168***	0.552***	-0.034
	(0.031)	(0.019)	(0.035)	(0.021)	(0.027)	(0.035)	(0.029)	(0.042)	(0.048)	(0.086)
Labour cost (LC_{it-1})	-1.329***	-0.626***	-0.443**	-0.763***	-0.512**	-0.714***	-1.698***	-1.880***	0.862***	0.624**
	(0.121)	(0.032)	(0.197)	(0.082)	(0.221)	(0.145)	(0.179)	(0.099)	(0.306)	(0.281)
Gross output (Y_{it-1})		0.936***		0.933***		0.801***		0.722***		0.946***
		(0.019)		(0.021)		(0.047)		(0.054)		(0.111)
Observations	270	270	205	205	205	205	205	205	205	205
R-squared	0.949	0.996	0.951	0.995	0.956	0.984	0.964	0.986	0.926	0.950

Notes: Coefficients estimated by OLS with robust standard errors in parentheses. All variables are expressed in natural logarithms. All specifications include time FEs; country FEs are not included since our panel is short in T, not providing enough time variation in the data (the R^2 of a regression of the dependent variable on country FEs is 0.99). Coefficients for the constant term, 9 year dummies, and all additional country-level controls are not reported in the table due to space limitations (full results are available upon request).The dependent variable is country-level employment (L_{it}) in columns (1) to (4); the dependent variable is country-level employment by education category (L_{it}^{EDU}) in columns (5) to (10). Data on employment by education category comes from the EU KLEMS database (2019 release). Specifications in columns (1) and (2) include 31 OECD countries in our original sample; specifications in columns (3) to (10) include 23 countries included in the EU KLEMS database (Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Latvia, Lithuania, Luxembourg, Netherlands, Portugal, Slovakia, Slovenia, Spain, Sweden, United Kingdom). Variables for AM patent stock and non-AM patent stock are included in all specifications with a three-year lag; all other explanatory variables are included with a one-year lag. All specifications include additional country-level controls (data comes from the World Development Indicators database of the World Bank): R&D expenditure (as share of GDP), trade openness (the sum of import and export as share of GDP), labour force share of workers with at least post-secondary education (age 25+), share of working-age (age 15–64) population. Specifications reported in columns (5) to (10) further include additional country-level controls (data comes from the EU KLEMS database): employment share of female workers, employment share of workers aged 30–49, employment share of workers aged 50+.
Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

4.12. References (Appendix only)

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DECLARATION OF ORIGINAL AUTHORSHIP

Declaration: I confirm that this is my own work and the use of all material from other sources has been properly and fully acknowledged.

Fabio Lamperti

DECLARATION OF CANDIDATE'S CONTRIBUTION

Declaration: I confirm that my contribution to each single Chapter of this Thesis, as well as that of my co-authors, relate to the forms, tasks and components highlighted at the beginning of each Chapter, and they can be quantified in the indicated percentages.

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