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The Employment Implications of Additive Manufacturing

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Abstract

In spite of the fast spread of Additive Manufacturing (AM) in several countries and industries, its impact on employment is still unexplored and theoretically ambiguous. On the one hand, higher product customization and shorter time-to-market entail an expansion of the market, thus fostering labour demand; on the other hand, AM profoundly changes the way goods are produced and little evidence exists regarding the complementarity or substitutability between AM technologies and labour.

In this article, we contribute to fill this gap. Namely, we estimate labour demand functions augmented with a (patent-based) proxy of AM-related innovation in 31 OECD countries, across 21 manufacturing industries, over the 2009–2017 period. Our econometric findings show an overall positive relationship between AM technologies and employment at the industry level, due to both market expansion and complementarity between labour and AM technologies, while no labour-saving effect emerges. The importance of each mechanism, however, is heterogeneous across sectors.

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

JEL classification: J23; O31; O33.

1. Introduction

Since the early stages of industrialization, the question of whether technological progress creates more jobs than it destroys has been at the centre of the academic and policy debates and dates back to the contributions of classical economists, such as the famous chapter 'On Machinery' of Ricardo's Principles ([1821], 1951). More recently, this debate has been fed by important contributions related to the impact of Information and Communication Technology (ICT) on employment initiated by the seminal contribution of Autor et al. (2003). A renewed interest in the effect of technology has emerged with the diffusion of automation, robotics, and artificial intelligence. In particular, in the 1990s and 2000s the diffusion of robots created fear that this new wave of innovations may create technological unemployment. However, extant contributions show employment polarization effects but more mixed findings on total employment (e.g. Graetz and Michels, 2018; Acemoglu and Restrepo, 2020).

Automation and robotization are not the sole technological trends characterizing recent times. Indeed, Additive Manufacturing (or 3D printing; AM hereafter) is taking on an increasingly important role. There has been widespread diffusion of AM technologies in several countries and industries (OECD, 2017; EIB, 2019; Eurostat, 2021[1]) and wide discussion in policy circles where AM receives significant attention from institutional actors and policymakers for its potential impacts on the economy (OECD, 2016; European Commission, 2016, 2017; UNCTAD, 2017, 2020).[2] Despite this, the effects of AM on employment remain unexplored and it is difficult to find quantitative assessments, extant contributions often providing only anecdotal evidence. In this paper, we aim to fill this gap by empirically investigating the relationship between AM and employment at the industry level, thus providing an important contribution to the current debate. In particular, we maintain that AM technology deserves a special focus, given the differences with respect to the other digital production technologies that have been investigated in the literature so far.

[1] See also Table A1 in the Appendix.

[2] AM is becoming one of the main areas of study in the social sciences, from economics to business and management (Mariani and Borghi, 2019).

Specifically, AM embodies a radical process of innovation that reduces the number of production stages but at the same time increases product customization and, therefore, demand. In particular, differently from other capital-embodied process innovations such as robotization, the diffusion of AM technologies is more likely to stem from a market-seeking—rather than a labour-saving—economic incentive.[3]

However, AM also 'activates' all of the channels through which a capital-embodied technological innovation can affect employment. First, the market-driven effect on employment acts both in upstream industries (i.e. a displacing effect on old machines and materials vs a need for new machines and materials) and in downstream industries (i.e. a displacing effect on old products vs the creation of new products). Second, in both the adopting and producing industries, the effect of AM on employment for a given level of production will depend on the degree of complementarity between labour and the other factors of production in AM with respect to the traditional methods of production.

For these reasons, in order to investigate the effect of AM on total employment at the industry level, we need to capture the whole spectrum of innovations related to this new capital-embodied technology, concerning both the adoption and production of AM machines and related products. To this end, we build a proxy based on patents in AM, namely patent family applications (hereafter, patents) to the United States Patent and Trademark Office (USPTO), capturing the whole ecosystem of innovations related to AM. More specifically, the proxy is based on patents related to the production of *AM machines and apparatus*, the production of *materials used in AM*, *pre- and post-processing operations related to AM*, *software for AM*, *products made via AM techniques*. We attribute patents to countries through the inventor's residence and to NACE 2-digit industries by using the concordance methodology, which is also used by PATSTAT. Thus, we match AM innovations to

[3] 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).

those manufacturing industries that are likely to produce and/or adopt AM technology or related products.

Labour demand functions augmented with a proxy capturing the AM-related innovations are estimated across 31 OECD countries and 21 manufacturing industries over the 2009–2017 period. Differently from most of the contributions focusing on the effects of technological progress on employment, we estimate both unconditional (i.e. uncompensated) labour demand functions and conditional (i.e. compensated or constant-output) demand functions, where labour demand is estimated for a given level of output (Ugur et al., 2018) and the market expansion channel is 'switched off'. Estimating the two types of labour demand provides useful insights into the mechanisms through which AM affects employment.

As a second step, since we expect the channels linking AM to employment to work differently depending on industry characteristics, we extend the analysis to allow for industry heterogeneity by considering the Pavitt classification (Pavitt, 1984).

Our analysis demonstrates an overall positive relationship between AM innovations and the level of employment for both conditional and unconditional labour demand estimations, albeit of a larger magnitude in the latter. Conversely, we find no labour-saving effect. Market expansion and complementarity between labour and AM technologies both drive the positive relationship with employment. This relationship holds in all industry groups, but the magnitude is highly heterogeneous across sectors 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 paper is organised as follows. In Section 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 related to AM technology and employment. In Section 3, we describe the data used and the construction of the AM proxy of production and adoption based on patent data. Section 4 introduces the methodology used for the empirical strategy, while Section 5 focuses on the main findings. Section 6 draws conclusions and discusses limitations and future research avenues.

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

Since the contributions of the classical economists, capital-embodied technological progress has been viewed as mainly induced by cost-saving motivations, ultimately being labour-saving. Accordingly, the effect of new production technologies on employment is generally expected to be negative, but possibly counterbalanced by indirect channels. The latter are typically related to market expansion induced by lower prices in the firm/industry where the innovation is used, by the expansion of product demand in upstream firms/industries producing the new machines or complementary inputs (process innovation is a product innovation in upstream industries), and by higher income at the aggregate level (Freeman et al., 1982; Stoneman, 1983; Petit, 1995). Several contributions have also argued that the adoption of new production processes may have an effect on the composition of labour by skill or other dimensions, without affecting the total demand for labour (Acemoglu, 2002). Product innovation, instead, has usually been seen as positively affecting employment by creating new markets. Obviously, this type of innovation can also have counterbalancing forces to the extent that new products displace old ones (Katsoulacos 1984, 1986), i.e. cannibalization or business stealing.[4]

A wide empirical literature investigates the relationship between technological progress and employment at different levels of aggregation (i.e. firm, industry, and country level), using different sources of information to proxy technological progress (i.e. survey data, R&D or investment expenditures, patent data).

Many contributions—mostly those using patents or R&D investments as proxies—look at the innovation–employment nexus, neither distinguishing between type of innovation (product vs process) nor focusing on a specific type of technology/product (for a recent survey, see Ugur et al.,

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

2018). When distinguishing between product and process innovation (usually relying on survey data), scholars find a positive relationship between product innovation and employment. Conversely, results for process innovation (i.e. capital-embodied technological innovation) are more mixed, the relevance and sign depending on the level of aggregation considered, and varying by country and industry group (for comprehensive surveys, see Chennells and Van Reenen, 2002, and Ugur et al., 2018).

A more recent stream of literature has focused on the diffusion of specific capital-embodied innovations such as ICT, automation processes, and industrial robots. The empirical evidence is inconclusive when looking at the effect on total employment, while results are quite robust in showing a labour market polarization effect of these technologies (Autor et al., 2013; Michaels et al., 2014; Dauth et al., 2018; Graetz and Michels, 2018; Acemoglu and Restrepo, 2020).

Differently from other new digital production technologies, AM is not motivated by labour-saving aims. In fact, given its inherent characteristics—in particular, increasing product customization and reducing costs but not primarily labour costs (see below)—AM technologies show novel relationships with employment compared to other types of capital-embodied technological changes. For these reasons, it deserves special attention and an empirical assessment of its effects on employment looking at all of the channels highlighted by the literature. In particular, we expect the effect of AM on the employment level for a given level of output—i.e. the potential substitution of labour—to be less relevant than the effect associated with market seeking, compared to robotization, for instance.

2.1. AM and changes in production and organization processes

AM is an innovative manufacturing technique used in both prototyping and in the production phase of tools and final products (Mellor et al., 2014). This technology works in a rather simple way: a digital model of the object to be printed is transferred to an AM machine and the model is decomposed into a series of 2D layers, which one or more printing heads physically reproduce and juxtapose, recreating the whole. Depending on the input, different fabrication processes exist.[5]

Two main characteristics distinguish AM production techniques from previous technologies: the reduction in the number of production stages and the potential to customise products, creating potential advantages for adopting firms (Attaran, 2017; see also Weller et al., 2015, for a theoretical analysis of the economic aspects of AM).

Traditional manufacturing techniques can generally produce only simple components, requiring assembly procedures to build articulated products. Instead, AM allows for the production of functional articulated assemblies in a single or a few steps, thus strongly reducing or completely eliminating the need for post-manufacturing assembly (Weller et al., 2015; Cuellar et al., 2018; Singamneni et al., 2019).

Furthermore, by shortening the duration to market, AM allows reducing inventory stocks and therefore logistic, transport, and communication costs—i.e. overall supply chain simplification (Holmström et al., 2010; Liu et al., 2014; Delic and Eyers, 2020). As for other production costs, the effect of adopting AM is more ambiguous: costs can decrease thanks to lower waste but more costly materials might be required (Tuck et al., 2008; Atzeni and Salmi, 2012; Achillas et al., 2015; Weller et al., 2015; Baumers et al., 2016).

At the same time, AM enhances the manufacturability of highly complex products (Diegel et al., 2010; Schniederjans, 2017). As AM creates the product without the need for tools and moulds, it offers designers and engineers complete freedom, high flexibility in manufacturing and prototyping and, therefore, ample room for customization (Rosen, 2014), better satisfying customer demand. Such capability comes at a minimal cost while also achieving enhanced technical and physical product characteristics (Atzeni and Salmi, 2012; Petrick and Simpson, 2013), thus enabling new business opportunities and applications in several industries (Mellor et al., 2014; Bogers et al., 2016; Attaran,

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

2017). A few examples are prosthetics and dental implants (Chen et al., 2016), hearing aid apparatuses, (Petrovic et al., 2011) and the aerospace industry (Singamneni et al., 2019).

AM also allows shortening the time-to-market for new products (Petrovic et al., 2011, Petrick and Simpson, 2013; Achillas et al., 2015), speeding up the design process and boosting product innovation and the overall production cycle (Leal et al., 2017).

Together, greater product customization and faster delivery times increase consumers' willingness to pay for additively manufactured goods (Bogers et al., 2016; Rayna and Striukova, 2016), reducing demand shrinkage and potentially increasing mark-ups for adopting firms (Weller et al., 2015).

These advantages over traditional manufacturing techniques emerge in the low-volume production of complex design products for which traditional manufacturing techniques would be too expensive, requiring high volumes to exploit scale economies (Ruffo and Hague, 2007; Baumer et al., 2016). Hence, customization motives prevail over scale-seeking ones. Conversely, applying AM to the mass production of standardized goods requires a complete re-design of the product (Kianian et al., 2015), making the cost advantages less clear. Therefore, in principle AM brings higher benefits in markets with strong demand for customization and flexible parts, allowing for the acquisition of broader customer domains (Weller et al., 2015). Yet, in recent years AM techniques have been adopted in the production of mass-consumption products, such as Adidas shoes (Cheng, 2018), signalling technological maturity and a shift from a primary use in rapid prototyping to direct manufacturing in a growing number of industries (Laplume et al., 2016; Attaran, 2017). Finally, AM is likely to reduce the cost advantages of producing in low-wage countries, potentially inducing some reshoring in the long run (Weller et al., 2015; UNCTAD, 2020).

2.2. AM and employment: conceptual framework and hypotheses

In order to investigate the relationship between AM and employment and to distinguish the main channels at work, we estimate both unconditional and conditional labour demand functions (Hamermesh, 1986; Lichter et al., 2015; Ugur et al., 2018). In the former, innovation can affect sectoral employment through all possible channels, i.e. both by affecting firm product demand and therefore the level of production and employment, and by changing the relative intensity of the factors used in production. Conversely, in conditional labour demand the market expansion channel is 'switched off'.

With some notable exceptions (see Van Reenen, 1997, and Michels et al., 2014), most of the literature on the employment effects of innovation 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 the unconditional demand (Dauth et al., 2018; Graetz and Michaels, 2018). In our opinion, this distinction is instead relevant for disentangling the mechanisms through which AM affects employment, especially given the main goal of AM technologies.

On the one hand, AM increases the opportunities for product innovation and customization, potentially having a market expansion effect that could nonetheless be mitigated to the extent that new products might substitute older ones and make the marginal contribution of AM to innovation negligible. The overall market expansion effect will therefore depend on the relative magnitude of these contrasting forces.

On the other hand, AM is a radical capital-embodied technological innovation that entails the production of new machines specifically requiring new specific intermediate inputs (e.g. materials and software) and represents a wave of product innovations for the upstream industries. AM innovations are likely to open new market segments. Thus, the employment effect at the industry level depends on the extent to which these new machines and inputs substitute the old ones, something that is to be assessed empirically.

The effect of AM on total employment for a given level of output—i.e. the 'classical' potential substitution of labour with capital-embodied technological progress—in the adopting industries depends on the degree of complementarity between labour and capital (or other production inputs) and on whether and how this complementarity itself is affected by the innovation.[6] The direct effect on total labour demand also depends on how technology affects different types of labour (e.g. skilled vs unskilled, male vs female, old vs young) and their substitutability with the other factors of production.

Several recent contributions focus on the effect of technological progress on employment composition, pointing out that investment in new technologies, such as ICT, can change 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 labour demand.

By increasing efficiency in the production of customized goods (e.g. by eliminating the assembly stages), AM requires more highly specialized workers in both design and operations activities as compared to traditional manufacturing techniques. Thus, AM is a production process that is typically skill-biased (Kianian et al., 2015). As for industries producing these technologies or complementary inputs, nothing suggests that labour demand should decrease, while again, its composition is likely to be affected in favour of higher-skilled workers.

As a second step to further explore the channels affecting the relationship between AM technologies and employment we take into account sectoral heterogeneity using industry groups (see also Van Reenen, 1997; Greenhalg et al., 2001; Bogliacino et al., 2012; Dachs et al., 2017; Van Roy et al., 2018). We rely on the Pavitt taxonomy (Pavitt, 1984) in the revised version of Bogliacino and Pianta (2016) (see Table A2 in the Appendix). The Pavitt taxonomy is widely employed, from theoretical and empirical investigation to policy analysis. It is useful also for our purposes since it groups industries with different degrees of product differentiation, different sources of innovation (industries producing and adopting the new technology), and different degrees of economies of scale, all factors that should affect their exposure to AM technologies and the effect of the latter.

[6] An innovation can be *labour-augmenting* (i.e. increasing labour productivity) and at the same time *labour-biased* (requiring more labour) if the elasticity of substitution between labour and other factors in production is low enough (Acemoglu, 2009, pp. 500–503).

Specifically, Science Based (SB) and Specialized Supplier (SS) sectors include industries producing AM machinery and equipment as well as sectors producing the chemical materials used in AM production and those high-tech sectors adopting the AM technology (e.g. manufacture of computer, electronic, and optical products and the manufacture of other transport equipment). Additionally, these are also highly specialized and innovative sectors (many small innovative firms populate SS industries). On the one hand, in highly differentiated sectors producing specialty goods the adoption of AM could increase a firm's ability to meet sophisticated needs, with a strong market expansion effect since in these sectors demand for customization is higher. On the other hand, this market expansion could nonetheless be mitigated by the fact that in these industries products are already highly customized and competition occurs largely through product innovation and quality improvement. Therefore, new AM-related machines, materials, and products could substitute older ones, either by the same firm or by competitors belonging to the same sector.[7] AM technologies might help firms survive competition instead of increasing market shares. Generally speaking, these industries are already at the innovation frontier, implying that the marginal contribution of AM is possibly limited.

Conversely, Supplier Dominated (SD) industries include traditional sectors, generally adopting outside-generated innovations. Industries such as fabricated metal product manufacturing, furniture, and other manufacturing have been shown to increasingly adopt AM production techniques. A large share of the employment in sectors belonging to the SD class produces standardized goods by employing scale-intensive techniques. In standardized industries, the new AM techniques allow for the potential customization of previously standardized products. On the one hand, the adoption of AM techniques could be too costly and therefore too limited to have a large impact in increasing demand. On the other hand, when adopting AM technologies in these industries, AM customized goods are likely to create new market niches instead of substituting existing standardized products.

[7] Several studies analysing the effect of product innovation report evidence on business stealing and cannibalization (recently, Harrison et al., 2014).

Hence, AM could be a relevant source of innovation also in traditional industries, where product customization for an increasingly sophisticated demand has started playing a relevant role in surviving competition.

Finally, the Scale and Information Intensive (SII) category includes both adopting industries such as manufacturers of motor vehicles, trailers, and semi-trailers and industries producing some of the materials used in AM methods (i.e. manufacture of rubber and plastic products and manufacture of basic metals). These industries are characterized by large economies of scale, this possibly reducing the incentives to adopt AM technologies.

As for the effect at a given level of product demand, AM is likely to play a positive or nil role on employment in SB and SS classes; in these industries the complementarity between skilled labour and capital is already high but AM technologies may further increase it. As for SII and SD industries, AM technologies show more skilled labour complementarities than mature production techniques typically employed in these sectors; therefore, the effect could be positive and larger than in SB and SS classes.

Building on the above discussion, our main hypotheses on the relationship between AM innovation and employment are summarized below.

H1. *AM technologies will have, on average, a positive effect on employment in both uncompensated and compensated demand estimations* since the primary goal of AM is not saving on labour costs.

H2. *AM technologies will have, on average, a higher positive effect in uncompensated than in compensated demand estimations*, driven by large and positive market-creation effects.

What we claim should hold for the whole economic system on average may, however, apply with different degrees to the different industries (according to the Pavitt classification). Indeed, as we have argued above, the classical contrasting forces at play operate differently across industry classes. Assessing what effect prevails in each industry is therefore a question that must be addressed empirically.

3. Main variable construction and data

3.1. AM patents and construction of the AM innovation proxy

Despite their limitations, patent data are widely accepted and used as a measure of technological innovation in studies investigating the relationship between innovation and employment (see, for instance, Van Reenen, 1997, and more recently, Mann and Puttman, 2020).

A proxy suitable for investigating the effect of AM innovation on total employment should be correlated with both production and adoption of the technology and related inputs, in order to capture all of the channels through which the new technology can affect labour demand. AM technologies are indeed new products for the producers of both the capital goods and the complementary goods used in production (e.g. materials, software). At the same time, AM also changes the production process and/or the organization of production of the using firms/sectors. Thus, we build our proxy relying on patent data, with the aim of capturing both production and adoption of the new technology.[8] In order to build our proxy, we identified AM-related patents and matched them to industries and countries following the methodology described below in this Section. By using patent data at the sectoral level, we can capture the effects of AM on employment that are external to the firm and we can consider heterogeneous effects in the AM–employment nexus. This strategy has limitations, however. Our industry-level analysis does not allow us to capture the effects of AM external to the sector/country and general equilibrium effects. Moreover, a patent-based proxy computed at the industry–level entails that we are likely to capture the adoption of AM technologies only partially, and, in any case, it does not allow differentiating between adoption and production of the capital-embedded technological innovation. Although disentangling the two is not strictly required to answer the core question of this work, i.e. whether technological innovations related to AM produce more

[8] The pros and cons of different innovation proxies are well known, being extensively stressed in the literature (Archibugi and Pianta, 1996; Hagedoorn and Cloodt, 2003).

jobs than they destroy, a distinction between the two would provide relevant insights. Alternative approaches followed in the literature share similar limitations.[9] Namely, survey data—collected ad hoc to include separate information on the production and adoption of AM—could help distinguish between the different channels. Yet, existing surveys on AM do not include information on the production of the new technologies and materials.[10] Beyond that, due to their cross-sectional dimension existing surveys on AM are not suitable to capture long-run technological trends. The majority of the recent contributions investigating the impact of ICT or industrial robots on employment use survey data regarding adoption since their aim is to gauge the substitutability vs complementarity of new machines with different types of labour/tasks. This legitimises their focus on adopting sectors only since the relationship between the new machine and the use of different types of labour takes place where the machine is used.[11]

We collected information on AM patents at the USPTO[12] from the PATSTAT data set.[13] Specifically, our SQL query[14] includes a list of selected keywords (see Table A3.1 in the Appendix), identified using several sources (i.e. engineering literature, product catalogues of AM producers). In addition, we included patents belonging to the International Patent Classification (IPC) class B33Y, specifically created in 2015 by the World Intellectual Property Organisation (WIPO) to cover all innovations associated with *AM processes, apparatuses, materials, ancillary equipment and software,*

[9] For instance, survey data from the International Federation of Robotics (used by several contributions cited above) do not allow disentangling manufacturing users of robots from integrators, i.e. the firms 'integrating' the robot into the manufacturing process. This challenges a correct attribution of robots to the sector/country adopting it.

[10] Including a proxy for either adoption or production alone would imply a serious omitted-variable problem when dealing with the total employment effect at the industry level of the introduction of a new technology, since each of them taken alone overlooks one important part of the employment implications of a specific technology.

[11] Nonetheless, the use of data on adoption of the new technology is more questionable whenever the research question regards total employment, and therefore, the results are reported in terms of the 'effect of ICT/robots on employment'. Indeed, by using proxies of pure adoption at the industry level, they capture the effect of ICT/robot 'adoption' on employment, i.e. not taking into account the effect on employment in industries producing the new machines and the related goods (e.g. software). The related bias can be more or less relevant depending on the type of technology under investigation, i.e. its relative impact in adopting and producing industries. For instance, while the impact of ICT has been radical in both producing and adopting industries, opening up entirely new markets (e.g. personal computers and mobile phones), the impact of industrial robots in producing industries is probably much more limited.

[12] We focus on applications to the USPTO as it is considered the reference patent office when seeking protection for innovative technologies (Cantwell, 1995).

[13] The version of PATSTAT used is PATSTAT Online (2019 Autumn edition) V5.14, accessed between September and October 2019.

[14] We followed guidelines from Pasimeni (2019) to improve the effectiveness of our SQL query in PATSTAT.

as well as *products made via 3D printing*, i.e. all aspects of the technology not covered elsewhere in the IPC classification (WIPO, 2019). This selection includes patents protecting AM innovations related to both adoption and production of the technology, as emerges from the terminology used by WIPO for the subcategories of the patents belonging to the IPC B33Y class.

3.1.1. Sectoral attribution of AM patents

PATSTAT data include several aspects of information on inventors, applicants, IPC classes, and probability scores for 2-digit NACE Rev.2 sectors in which each patent is more likely to be used. 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 and NACE Rev.2 by identifying the NACE 2-digit sector with the highest occurrence rate amongst those of firms applying for a patent classified under a specific IPC code. This is very useful for us in case the applicant is, for instance, a group of firms, but also in case it is a large firm operating in a value chain (and patents are more likely to be introduced by large firms). In these cases, the potential effect of the patent on employment would emerge in the sector to which the supplier (or controlled firm) using the patent belongs to. In fact, in the case of large firms, multinationals, or conglomerate firms, it would be misleading to attribute the patent to the applicant's NACE sector, a possible alternative strategy.

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 AM patents we collected also capture the adoption of AM for production purposes—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 adopt 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 patents relating to either adoption or production. Further details on the case shown in Table 1 and other examples of our sectoral attribution are provided and discussed in Appendix A3.

Table 1 around here

Mann and Putmann (2020) 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 Rev.2 industrial classification, being also widely appreciated for its user-friendliness and international comparability thanks to the correspondence between NACE Rev.2 and ISIC Rev.4 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.

3.1.2. Geographical attribution of AM patents

Although we focus on applications made at a single patent office—the USPTO—since the same invention can be filed more than once in the same jurisdiction, to avoid double-counting issues we used patent families instead of overall patent applications in our data set. We then allocated patents to the year in which their priority filing (i.e. the earliest filing) occurred, and to the country of residence of their inventors using fractional counting, a diffused principle to assign patents to the country of invention, used, among the others, by Eurostat and the OECD (2009). The resulting structure of our AM data is then the patent fraction by inventor country and by related sector in each year.

The underlying assumption we make by attributing patents to the country of residence of the inventor(s) is that countries not patenting (either AM or related innovations) are likely to display a lower level of adoption than those developing the innovation, i.e. countries producing the technology. An alternative strategy would be to attribute the patent on the basis of the jurisdiction, i.e. where the patent provides protection, or to attribute it to the applicants' country. While recognising the limitations of our strategy, we argue in Appendix A3 that alternative approaches would result in a proxy less appropriate for our purposes.

Geographical or sectoral proximity and path dependence are fundamental in driving technology diffusion (Farinha et al., 2019; Baumgartinger-Seiringer et al., 2020), and the adoption of new technological innovations tends to be dumped by geographical distance to their locations of origin (Gertler, 1995; Baptista, 2001). The rich technological leaders are usually those innovating and adopting new technologies the earliest. After the initial adoption by the leading countries, the laggards follow and partially catch up with the leaders. As documented empirically for most technologies by Comin and Hobijn (2004), this catching up can take a long time, depending on many factors at the country level such as human capital endowment, quality of institutions, degree of openness to trade, and adoption of predecessor technologies.[15]

This is confirmed also for AM by the latest empirical evidence, finding AM innovations to be highly concentrated geographically due to the role played by spatial proximity, knowledge relatedness and cumulativeness in their diffusion (Corradini et al., 2021).

The persistence in the observed cross-country differences in the technology used can be explained on the basis of the arguments of the Evolutionary Economic Geography literature, according to which history and path dependence are core in shaping economic structure (Boschma and Martin, 2010), of the National Innovation Systems literature (Lundvall (ed.), 1992; Patel and Pavitt, 1994; Nelson, 2002; Malerba, 2004) stressing the role of country-sector-specific institutional factors, as well as those of the literature on demand pull factors of innovation, underlining that innovations are often spurred by the needs of specialized users, typically in upstream–downstream relationships (Von Hippel, 1988; Baldwin and Von Hippel, 2011).

All of these arguments support the assumption that even if a capital-embodied innovation is a tradable good and can therefore be imported, its use in the countries developing the new technology is likely to be persistently higher than in a country accessing the technology through imports, i.e. international diffusion in the use of a technology is far from being instantaneous. For all of these reasons, we think that patents in country A are more strongly correlated with higher adoption in country A than with adoption in other countries. This may not necessarily be true for similar and geographically close countries. In this case, inter-country and inter-sectoral exchanges might occur, challenging our assumption. This caveat is investigated in Section 5.1.1.

[15] See Cappelli et al. (2018) on the relationship between economic resilience, measured by unemployment rate, and technological resilience after the 2008 crisis in 248 EU regions, highlighting the role of institutions and policies at the country level in affecting the interaction between the two and their dynamics.

3.1.3. Descriptive evidence on AM diffusion

Our analysis focuses on 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.[16] Before 2009, activity was instead quite limited (Laplume et al., 2016). In total, over our investigation period we count about 3,500 AM patents.

Figure 1 shows the distribution of AM patents at the USPTO between 2009 and 2017. As the distribution for our AM patents is highly skewed across years, 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.

Figure 1 around here

Figure 2 presents the breakdown of AM patents by country (panel A) and by sector in our sample (panel B), while Figure 3 shows the distribution of AM patents across countries and years, by each of the four sectoral groups included in the Pavitt classification. Here, we also report data on a logarithmic scale. 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.

[16] 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.

Figures 2 and 3 around here

3.2. Data and variables

Our dependent variable is the natural logarithm of the number of people employed in each sector–country pair in each year.

For our main explanatory variable, i.e. AM innovations, we use the three-year-lagged natural logarithm of the AM-related stock of patents applied for at the USPTO.[17] For each country-sector-year observation, our stock of AM patents is computed through the perpetual inventory method as $AM_{ijt} = F_{ijt}^{AM} + (1-\delta)\ AM_{ijt-1}$, where F_{ijt}^{AM} represents the patent count (i.e. the flow).[18] We assume a depreciation rate of 15%, similarly to Venturini (2019).

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 of the NACE Rev.2 classification. Specifically, 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.

We further include a control for the stock of non-AM patents filed at the USPTO at the industry level, i.e. the complement to our main explanatory variable. 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

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

[18] 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 patent families 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} as F_{ijt}^{AM} drops in absolute value after that year. This does not depend on declining interest in the technology *per se*, as explained above.

patents following the perpetual inventory method, with the same assumption regarding the depreciation rate as for our main explanatory variable.

All nominal variables are reported in local currency units in the OECD data sets. As industry-specific deflators are not available for all countries considered here, 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 (see the list of countries in Appendix A2) and 21 2-digit manufacturing industries (see Table A2 in the Appendix). 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 the Appendix reports the related summary statistics and the correlation matrix.

Table 2 around here

Figure 4 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.[19]

Similarly, panel B in Figure 4 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

[19] Panel A in Figure 4 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.

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.

Figure 4 around here
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4. Empirical strategy

To investigate the relationship between employment and AM, we estimate an industry-level labour demand function augmented with a variable specifically capturing the AM-related innovations (see also Van Reenen, 1997, for a similar approach). We estimate both unconditional labour demand functions and conditional demand functions, where labour demand is estimated conditional on the level of output (Hamermesh, 1986; Lichter et al., 2015; Ugur et al., 2018).

We start from the following baseline specification:

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

where AM_{ijt-3} indicates our measure of AM innovations, $nonAM_{ijt-3}$ indicates our measure of non-AM innovations, $\boldsymbol{X}_{i,j,t-1}$ is a vector of sectoral control variables, namely, 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. Including all non-AM patented innovations, we control for all (patented) output of innovation different from AM. We do not include controls for input of innovation at the sectoral level, such as sectoral R&D, since they are supposed to affect employment by affecting the output of innovation, i.e. they are correlated with non-AM patents, which we cannot exclude since we would end up with a serious omitted-variable problem.

We include FEs in order to account for potential unobserved heterogeneity. In particular, we include country FEs to capture all country-specific institutional factors that may affect the level of employment, such as labour market institutions and union activity, and which might not be captured by sectoral FEs (Graetz and Michaels, 2017; 2018).

Sector FEs are instead meant to capture the characteristics of technology and production that are industry-specific and common to all countries, such as the level of efficiency, the degree of standardization and economies of scale, the use of natural resources, the weight of intermediate inputs in production, and the degree of competition of the market.

Year FEs should capture the cost of capital, which we do not have in the data and is usually assumed to be common to all firms in an industry, as well as time-varying, but neither sectoral- nor country-specific (Van Reenen, 1997; Onaran, 2008). Year FEs also capture the component of technological progress that evolves in time, affecting all countries and sectors.

However, in our preferred specifications instead of year, industry, and country FEs we include country-year (γ_{it}) and sector-year (γ_{jt}) FEs. These combinations allow us to control for time patterns or unobservables that may characterize employment at the country and industry level, such as those produced by the dynamics of technological progress or aggregate stock of R&D specific to some countries, or such as the robotisation process or the use of ICT, which are specific to some sectors. Country-year FEs should also capture the country-specific dynamics of income, population, demographic structure, and other macroeconomic factors potentially affecting the employment level. It is worth noting that country-year and sector-year FEs also represent a robustness check of the assumption in the main specification that the cost of capital is common to all countries and sectors. Country-year FEs also capture the fact that (especially in some countries) labour cost is partially determined at the national level and not at the industry level (Michaels et al., 2014). Our alternative combination of FEs should also control for the dynamics of prices of other factors of production, such as capital goods incorporating other innovations.

All of our models are estimated using the pooled OLS estimator. The main reason is that our panel is quite short and we do not have enough time variation to use the within estimator (i.e. to include country-industry (γ_{ij}) FEs). Indeed, the country-sector FEs capture almost all of the variation in our employment data (the R^2 of the regression of employment on country-industry and year FEs is above 0.99).

All explanatory variables are included with a one-year lag to offset potential contemporaneity issues (e.g. reverse causation), while our main explanatory variable is included in the model with a three-year lag in order to account for the delay in the potential impact of the new technology on employment. Indeed, 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 (see Figure 1 in Section 3) and the average time needed to receive the grant (USPTO, 2019) and use the patent in production.

After the analysis of the average relationship between employment and AM innovation (i.e. across all countries and sectors), as a second step we estimate the same specifications described above but allowing for heterogeneity across sectoral classes, as suggested by the literature on the characteristics of this technology (discussed in Section 2). We rely on the updated version (Bogliacino and Pianta, 2016) of Pavitt's sectoral taxonomy (see Table A2 in the Appendix). We therefore estimate the following specification:

$$\begin{aligned} L_{ijt} = \alpha_0 + \alpha_1 AM_{ijt-3} + \alpha_2 AM_{ijt-3} \times SB + \alpha_3 AM_{ijt-3} \times SS + \alpha_4 AM_{ijt-3} \times SII \\ + \alpha_5 nonAM_{ijt-3} + \boldsymbol{\alpha}_6 \boldsymbol{X}_{ijt-1} + \gamma_i + \gamma_j + \gamma_t + u_{ijt}, \end{aligned} \quad (2)$$

where SB, $SS,$ and SII are dummies for Science Based, Specialized Suppliers, and Scale- and Information- Intensive, respectively, and all other terms are defined as in equation (1). In this specification, the coefficient of our AM proxy captures the AM–employment relationship for the omitted class of Supplier Dominated industries.[20] Results are reported in Tables 3 and 4 in the following Section.

We undertake several robustness checks, which are described in Section 5.1.1 and Appendix A5, and an analysis using instrumental variables, reported in Section 5.2.1.

5. Econometric results

5.1. Main results

Table 3 shows the results of the estimations of equation (1), where we look at the average relationship (across all sectors) between employment and AM innovation.

In the first model in column (1), a positive relationship emerges between AM and employment. In columns (2) and (3) we estimate the unconditional demand functions, including labour cost per worker and the stock of non-AM patents and controlling for sector-year and country-year FEs (columns (2) and (3), respectively). In all models, the coefficient of AM is positive and statistically significant at the 1% level, dropping from 0.2 to 0.09 with the inclusion of labour cost per worker and innovations other than AM. The elasticity of employment to AM is 0.095 in our favourite specification, i.e. column (3), where we control for the more demanding combination of FEs. Thus, a one-percent increase in the AM patent stock at the industry level is associated with about a 0.1 percent increase in sector-level employment, on average.

In columns (4) and (5), we estimate the conditional demand function by including the level of gross output, with the combination of FEs as in columns (2) and (3), respectively. The relationship between employment and AM is still positive and statistically significant at the 1% level, but the coefficient is slightly smaller than in the unconditional models. A one-percent increase in the AM patent stock is associated with an increase of 0.065 percent in employment. This is in line with

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

theoretical expectations, since in our interpretation the conditional demand estimation 'switches off' the market-driven channel through which AM innovation is likely to have an important effect on employment due to its very nature. The fact that we are left with a positive average relationship in the conditional demand estimations suggests a certain degree of complementarity between capital and (total) labour.

Interestingly enough, the difference in the conditional vs unconditional demand coefficients is much larger in the case of non-AM patents, suggesting a larger role of market expansion for the bundle including all patents other than AM. This is reasonable since non-AM patents include all patented innovations, thus typically—even if not only—product innovations, while AM patents are a process innovation for downstream industries. Instead, the coefficient of non-AM patents is smaller in conditional demand estimations, showing that AM technologies have a higher degree of complementarity with labour than the bundle of all other innovations. The signs of the other variables included in our specifications, i.e. labour costs and gross output, are in line with what is predicted by the theory. In the conditional demand estimation of columns (4) and (5), where they are both included, labour cost and gross output are negatively and positively associated with the level of employment, respectively.

Table 3 around here

Summarizing, we can claim that our findings confirm hypotheses H1 and H2. In both uncompensated and compensated demand estimations, AM and employment are positively associated: AM technologies are not labour-saving, both overall and for a constant level of output. The elasticity of employment to AM is slightly larger in uncompensated than in compensated demand (H2), confirming a market-creation effect of AM. However, the magnitude of the effect is smaller than expected. This might be explained by the market creation and by the AM–labour complementarity being different across industries, as we argued in Section 2.2. For this reason, in Section 5.2 we analyse industry heterogeneity, while hereafter we discuss potential caveats for the main results and discuss some robustness checks.

5.1.1. Robustness checks

Exploring an alternative proxy of AM and inter-sectoral/inter-country AM effects

Our analysis is subject to some caveats. By carrying out the analysis at the industry level and including only the industry's own-AM proxy—i.e. the stock of AM patents belonging to each industry—we miss inter-sectoral linkages through which AM technologies may affect an industry's employment, i.e. general equilibrium effects going through production linkages along the supply chain. In the same way, we miss the role of inter-country linkages. For instance, AM in other sectors/countries may impact a country's sectoral employment through the acquisition of intermediate goods that have some AM content, e.g. which were produced through AM technologies. The intermediate goods incorporating the AM content can entail different labour requirements in the assembly stages or they can change the competitiveness of the sector using it, by changing the quality content of the good incorporating it or reducing its costs.[21] Reshoring induced by the adoption of AM technologies in a country could also affect sectoral employment in countries where production was offshored.

Another caveat is that the proxy used in our baseline analysis might in some cases miss the adoption of AM. In Section 3.1 and Appendix A3, describing in detail how we selected the AM patents and our strategy in attributing patents by industry and country, we argued why we think this proxy captures both the production and adoption of AM innovations, and we also discuss the weaknesses of other alternative strategies. We are nonetheless aware that in some cases an industry

[21] In order to capture potential between-sector interactions and general equilibrium effects, we also carried out the analysis at the macro level. Moreover, using macro data allows us to also undertake a preliminary exploration of the potential heterogeneous effects of AM on employment by education level. Results are reported in Table A6.1 in the Appendix and details of the analysis are reported in the table's notes. On average, the elasticity of employment to AM is about 0.12 and 0.06 in unconditional and conditional demand estimations, respectively, and both are statistically significant at the 1% level. The elasticity is larger for middle-educated workers compared to highly educated workers; it is very small and not significant for low-educated workers.

could use AM machines (i.e. adoption) produced by other sectors/countries without this always showing up in ‘its own’ AM patenting activity.

For both of these reasons (between-sector/country effects and external AM adoption), in this Section we develop a robustness analysis building another proxy for sectoral AM that better accounts for ‘external AM’ patenting activity, i.e. for AM patents from other sectors and countries, and which is included as an additional variable in the regression models. By using world input-output tables from the WIOD data set (Timmer et al., 2015), we build an AM variable by country, sector, year, which is the weighted sum of all industries and countries’ AM patent stocks.

The index is built as follows:

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

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 construction of this ‘external AM’ proxy is based on the assumption that the more a sector buys from sectors/countries with a large AM patent stock, the larger the AM content of its upstream relationships. This additional proxy of AM should capture at least in part those inter-sectoral and inter-country effects mentioned above. Moreover, it should capture part of the ‘adoption’ not emerging in a sector-own AM patent stock.

We estimate the models in Table 3 by including this new variable together with three new control variables: a similar ‘external non-AM’ variable built for all non-AM innovation, a measure of domestic vertical fragmentation, and a measure of foreign exposure. The latter is done since the new AM proxy could otherwise capture both of these industry-country-specific characteristics.

The details of the construction of the variables, the estimated model, and the results are reported in Appendix A5. Our results in Table A5.1 are robust to the inclusion of the new proxy and the additional 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, and both are statistically significant at the 1% level. In contrast, 'external AM' is not statistically significant in the unconditional demand estimations; for conditional demand, it is positive and statistically significant (0.07 and significant at the 5% level in the most demanding specification in terms of fixed effects). All in all, these results confirm the positive relationship between labour and AM technologies.

Countries and sectors

Figure 2 in Section 3 (Panel a) highlights that the distribution of AM patents is very skewed. To check that our results are not driven by major AM producers, we estimate specifications 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 A5.2 in the Appendix, confirm our main findings.

Similarly, Figure 2 in Section 3 (Panel b) highlights that a larger share of AM patents belongs to NACE sector 28 (manufacturing of machinery and equipment), which is also the sector producing the AM machines. We therefore estimate specifications excluding this sector. The results, reported in Table A5.3 in the Appendix, show that the findings of the main analysis are robust and unlikely to be solely driven by producers of AM technology.[22]

[22] Our sample includes a few countries (i.e. Estonia, Greece, Latvia, and Portugal) and sectors (i.e. 19–Coke and refined petroleum products; 33–Repair and installation of machinery and equipment) that do not have AM patents at the USPTO over the period considered in our sample. 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 A5.4) are robust.

Other robustness checks: alternative patent offices and lag structures

We further conduct several robustness checks by employing 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 patent applications and lag structures in the regression analysis, the details of which are reported in Appendix A5. As can be seen in Tables A5.5 and A5.6, our results are robust to these additional checks.

5.2. Sectoral heterogeneity by industry class

The average positive relationship could hide heterogeneous effects at the industry level, as argued in Section 2. We therefore turn our attention to the results reported in Table 4, where we allow for heterogeneous effects across Pavitt classes, estimating equation (2).

In models (1) and (2), we estimate the unconditional labour demand by including the labour cost per worker and controlling for the stock of non-AM patents, with the two combinations of Fes as before. In columns (3) and (4), we estimate the conditional labour demand by including the level of production. Panel A reports the coefficients of the baseline class (SD) and the interaction coefficients; panel B reports the sum of the two coefficients and the standard error, i.e. the coefficients of the classes SB, SS, and SII.

Table 4 around here

At first glance, the results in Table 4 confirm what emerged in Table 3 for the average relationship. AM is positively associated with employment in both unconditional and conditional demand estimations. On the other hand, an interesting sectoral heterogeneity emerges. The average effect shown in Table 3 is mainly driven by two classes, SB and SD. The effect, both in unconditional and in conditional estimations, is much smaller in the SS and SII classes. On the other hand, the difference in the unconditional and conditional estimations reported in Table 3, i.e. the role of market expansion, is driven entirely by the SD class since in the other classes the differences in the two coefficients are not statistically significant (or, as in the SII class, the conditional demand shows a larger coefficient). This means that the expansion of the market emerges as relevant for the SD class only. Overall, in all classes a complementarity between AM and labour emerges, with positive coefficients in conditional demand estimations in all classes; nonetheless, the complementarity is higher in the SD and SB classes (elasticities of 0.08 and 0.12, respectively, and statistically significant at the 1% level).

As we have stressed, the role of market expansion clearly emerges in the SD class, where the difference in the coefficients between unconditional and conditional demand estimations is the largest (0.23 vs 0.08, respectively; all statistically significant at the 1% level) and is almost aligned with that of non-AM patents (0.28 vs 0.035). Still, the level of complementarity between AM and labour is higher than for other non-AM innovations. The SD class includes traditional industries adopting AM technologies; therefore, the role of the market is likely to reflect the market-seeking aim of the adopting firms, where new products do not substitute old ones and where the marginal contribution of AM to the overall innovation rate of the sectors is likely to be higher.

On the other hand, the SS class shows an elasticity of 0.06 in unconditional demand estimations, while the estimation for a given level of output shows an elasticity of about 0.04; both are statistically significant at the 1% level. Nonetheless, the difference in the coefficients is not statistically significant. The SS class includes sectors producing AM devices and adopting industries; on average, firms are small and highly specialized. Market expansion was expected to possibly play a large role in these sectors. However, these results suggest that new AM machines and products may, to a certain extent, be substituting older ones.

In the SB class the effect in both conditional and unconditional estimations is of a similar magnitude (around 0.12 and statistically significant at the 1% level). SB industries generally include large R&D-intensive firms, among which feature producers of materials related to AM technologies. Here, the adoption of AM is probably limited to prototyping while the use of AM to produce final goods is negligible. Moreover, SB industries are already operating at the innovation frontier, limiting the space for AM innovations to expand the market. The magnitude of the elasticity in conditional demand estimations suggests that AM increases capital–labour complementarities in already highly skilled industries, like SB industries.

As expected, SII industries seem to be far less responsive to AM technologies than the other classes. In unconditional demand estimations, the results are not statistically significant and are very small (0.003), while estimation for a constant level of output confirms a complementarity between AM and labour (0.04, statistically significant at the 1% level) of the same magnitude as in SS industries.

The larger coefficient of compensated demand estimates might be a consequence of the new products produced by a firm via AM either eroding the market shares of the competitors belonging to the same sector or eroding its sales of existing products. The SII class includes some sectors producing the materials used in AM production processes, but the adoption of AM techniques is probably still very limited due to the role played by scale economies in these sectors. This probably also explains the lower elasticity in the compensated demand estimation compared to SD industries.

To further single out the heterogeneity in the market-creation channel, we regress the total output on our AM proxy by Pavitt class. The results, shown in Table 5, clearly highlight that the market-expansion channel strongly emerges in the SD class, while it does not show up in the SS class and is actually negative in the SII class.

To summarize, market expansion is a channel through which AM affects employment only in SD industries. In the other industry classes, AM technologies seem to help survive competition or increase mark-ups more than expand the market. This can be explained by the level of substitution for old products in both upstream and downstream industries, which is higher in the SS class and even more so in the SB and SII classes. Moreover, the results confirm that the marginal contribution of AM technologies in increasing product innovation—and in this way, market shares—is likely to be more relevant in traditional sectors (SD) than in already highly innovative sectors (SB, SS).

As for conditional demand estimations, a complementarity between AM and labour emerges in all industries and is particularly large in SB and SD industries.

Table 5 around here

5.2.1. Instrumental variables estimations

Although our model assumes AM innovations to be predetermined to employment decisions, we still may have endogeneity issues if unobservable factors entering the error term affect both the production and/or the adoption of AM technologies and labour demand (e.g. shocks to product demand). Similarly, we might have reverse-causality issues as, for instance, the level of sectoral employment might drive the choice of the technology, and in particular the introduction of AM technologies.

Thus, although our main results show a strong correlation between our proxy of AM innovation and employment, the interpretation of such a result as causal requires cautiousness. To address these potential concerns, as a robustness check we implement an instrumental variables (IV) approach using the Two-Stage Least Squares (2SLS) estimator. Specifically, we instrument the current stock of AM innovations with past patenting activity. The idea is that past patenting activity should be a good predictor of current activity since innovation activity is usually path-dependent and industries introducing a new technology are likely to be the ones updating the technology in subsequent years. At the same time, as we focus on a specific technology and use sufficient lags, it is unlikely that past patenting in AM directly affects employment, unless through its updates. Specifically, we use longer-lagged values of AM innovation flow (i.e. F_{ijt-4}^{AM}, F_{ijt-5}^{AM}) as instruments for the stock of AM patents (AM_{ijt-3}). In specifications investigating sectoral heterogeneity, we use lags of the interacted variables as instruments for the interaction terms between AM patents and Pavitt classes.

Similarly, 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. The results are reported in Table 6. Specifically, Table 6 reports 2SLS estimates for the unconditional (uncompensated) labour demand equation augmented with the proxies capturing AM and non-AM innovations, on average across all sectors and by sectoral class, in column (1) and column (2), respectively. Columns (3) and (4) replicate the analysis by focusing on the conditional (compensated) labour demand function, i.e. controlling for total output. Estimates in Table 6 confirm the findings of our main specifications; only small differences in the magnitudes of the elasticities emerge.

As for relevance, all our IV estimates 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
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6. Conclusions

In this paper, we investigate the relationship between AM and employment by relying on patents filed at the USPTO in order to proxy for the whole innovation ecosystem around AM, i.e. aiming to capture both the production and adoption of these technologies. To this end, we labour demand functions augmented with AM patent stock in a panel of 31 OECD countries and across 21 manufacturing industries over the period of 2009 to 2017.

Our analysis demonstrates a statistically significant positive relationship between AM and overall employment in both conditional and unconditional labour demand estimations, with a smaller elasticity in the former. This result on the one hand supports our intuition, suggested by the very nature of this technology, that the market-driven channel is particularly important for AM; on the other hand, it suggests a certain level of complementarity between AM and labour for a given level of output since the estimated conditional demand elasticities are positive.

Exploring industry heterogeneity through the Pavitt sectoral classification, we find that the positive effect is substantially driven by the relationship in Supplier-Dominated and in Science-Based industries. In particular, the role of market expansion emerges in the former, while the latter group exhibits the highest complementarity between AM technology and labour. Overall, these findings suggest that AM technologies are associated with market-seeking and mark-up-increasing rather than labour-saving aims.

Our estimates are robust to the inclusion of different combinations of fixed effects and to an instrumental variables approach. They are also robust to using an alternative AM innovation proxy that aims to control for the role of inter-sectoral and inter-country effects, to controlling for other innovation output, and to excluding top AM patenting countries and industries producing AM machines.

We believe that our results, showing a labour-increasing effect of AM, are particularly relevant for policymakers aiming to foster the diffusion of welfare-enhancing innovations and job creation, providing insights into the type of industries that are more likely to gain from AM in terms of employment. Furthermore, our findings add new and complement existing evidence from the emerging strain of research focusing on the latest forms of technological change brought by new digital technologies (e.g. Acemoglu and Restrepo, 2020)—showing the specificities of AM, however.

By conducting the analysis at the sectoral level, we capture inter-firm employment effects such as competition effects (as opposed to firm-level analyses) and we are able to analyse industry heterogeneity (as opposed to country-level analyses). Both of these aspects are shown to be relevant in our results.

However, our study is not exempt from limitations. The use of patent data at the sectoral level has some relevant shortcomings. The methodology we adopted to select AM-related patents (i.e. patents related to the production of *AM machines and apparatus*, production of *materials used in AM*, *pre-*

and post-processing operations related to AM, *software for AM*, and *products made via AM techniques*) and their geographical and sectoral attribution is, in our opinion, suitable to correctly capture both the adoption and production of AM innovations. Yet, a portion of the adoption of AM devices may not show up in an industry's patent stock. Secondly, in our industry-level analysis we might miss some relevant inter-sectoral and inter-country AM effects.

We made an attempt to address these issues by using a second patent-based proxy of AM innovation capturing AM innovations external to the industry/country but potentially affecting it through (input–output) production linkages.

Future work could develop along different lines, depending mostly on data availability. Analyses based on survey data—in particular at the firm level—may further investigate the different role played by adoption versus production of AM technologies in affecting the employment level and composition. Analyses at the country level, with possibly longer time series, would better capture all potential general equilibrium effects following the diffusion of AM innovations. In particular, the literature suggests that AM technologies may differently impact skilled and unskilled labour as well as different tasks (e.g. manual and non-manual work); unfortunately, we could not address this issue, due to lack of data on employment skill and task composition disaggregated by industry. A deeper investigation of the relationship between AM and employment by skill level and task composition would be very important to explain the complementarity between AM and labour, and it certainly ranks high in our future research agenda. A promising avenue for future research would also be to further explore the role of inter-country effects, i.e. the employment effects of AM diffusion in other countries due to reshoring and/or the relocation of production across countries.

Finally, we have shown that in our relatively short panel data employment levels exhibit too little time variation within country and industry, preventing us from including fixed effects at this level (country-industry) in the empirical specifications. In other words, although we separately control for country and industry fixed effects, and in some specifications for country-year and industry-year fixed effects, our source of identification of the relationship of interest is mainly cross-sectional, i.e. it leverages the different production and adoption of AM across countries and industries. In this regard, it would be important to exploit additional sources of within-sector or within-firm variation in the data to shed light on the employment effects of AM.

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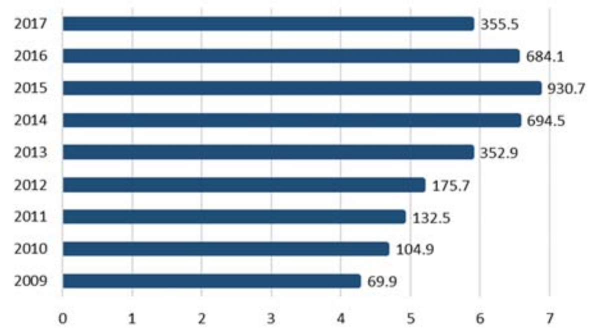
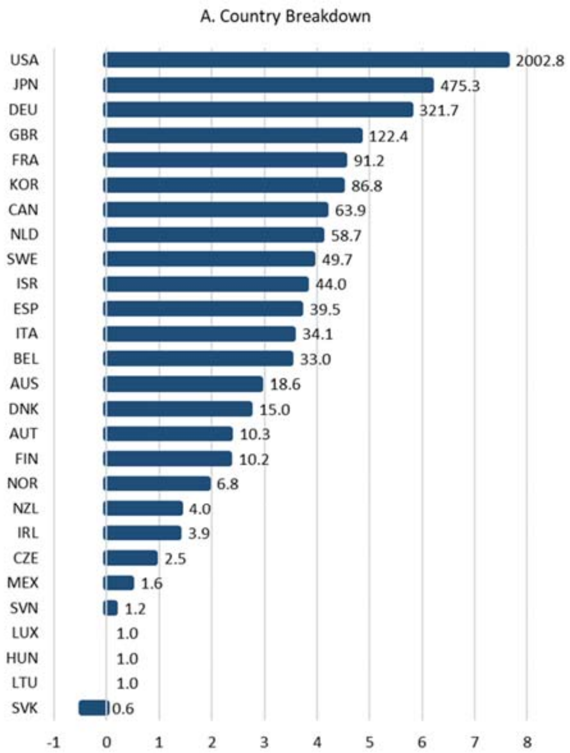
Figures and Tables

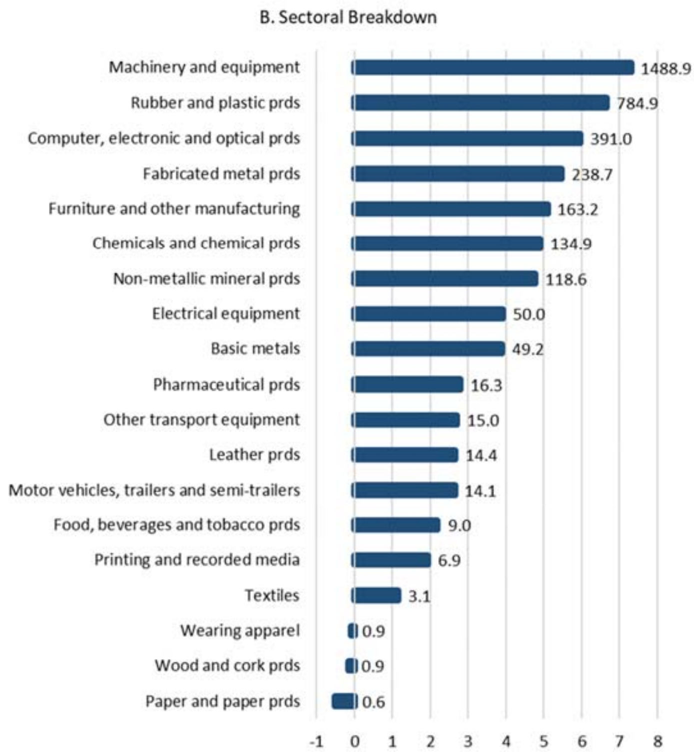
Figure 1. Distribution of AM patents between 2009 and 2017



Notes: Authors' own computations based on USPTO data. 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.

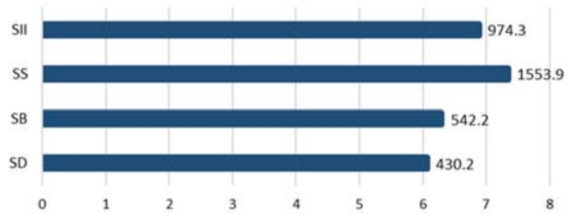
Figure 2. Distribution of AM patents by country and sector, 2009–2017 period





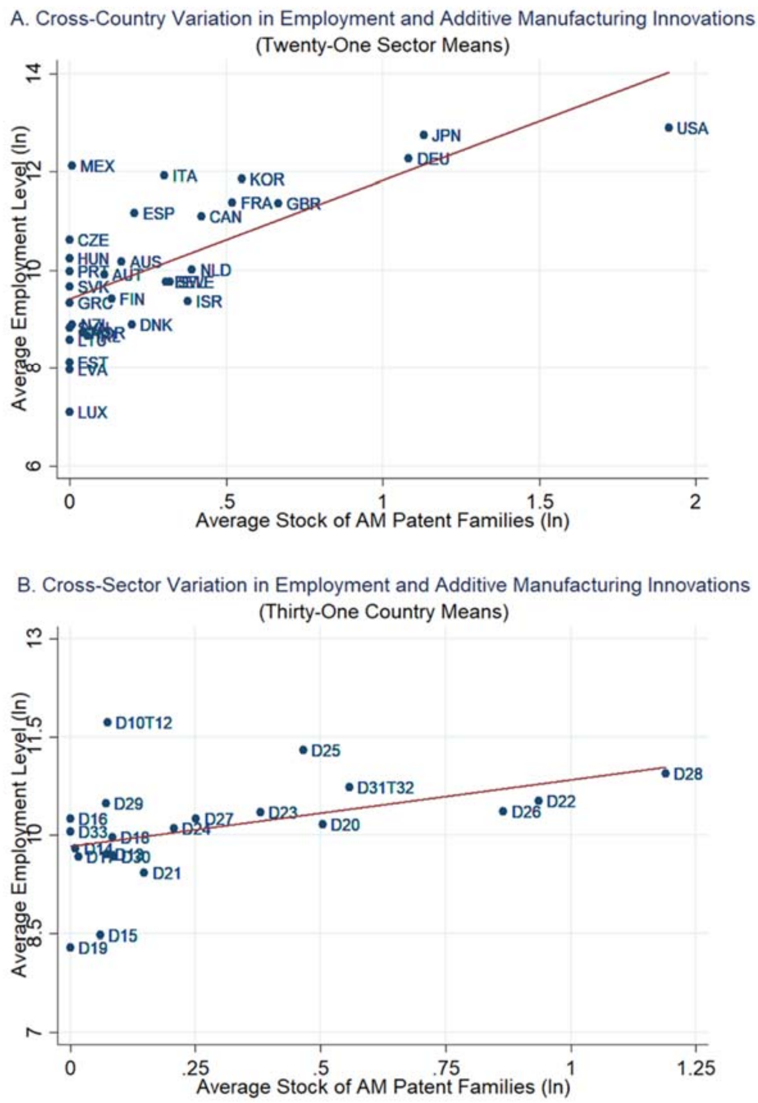
Notes: Authors' own computations based on USPTO data. Data reported on a natural logarithmic scale. Numbers reported at the edge of each bar are actual AM patent counts. We omit Estonia, Greece, Latvia, and Portugal from panel A and sectors 19 (Coke and refined petroleum products) and 33 (Repair and 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. 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. Cross-country and cross-sector variation in employment and AM patent stock, average values, 2009–2017 period



Notes: 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 modeling, 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

Notes: Data source is PATSTAT data set.

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 the Section 5.2.1). 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.

Appendix (Online Supplemental Material)

A1. AM in European countries from Eurostat survey data

Table A1. AM usage by NACE 2-digit sector, % 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: Data from Eurostat's European ICT usage survey. 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.

A2. List of industries (according to Pavitt taxonomy and NACE Rev.2 classification) and list of countries

Industries

Table A2. Sectors in 2-digit NACE Rev.2 classification, by Pavitt taxonomy class

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: Sectors in this table refer to a simplified version of the revised Pavitt taxonomy by Bogliacino and Pianta (2016) considering only manufacturing sectors.

By considering the sources and patterns of innovation, firm characteristics, and market structure, the taxonomy identifies similarities among industries, allowing to distinguish four classes: (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, and; (d) Supplier Dominated industries, 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. These are mainly traditional sectors.

Countries

Australia, Austria, Belgium, Canada, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, Norway, New Zealand, Portugal, Slovakia, Slovenia, Spain, Sweden, United Kingdom, and the United States.

A3. On the AM proxy: keywords, industries, and countries

AM keywords

Table A3.1. 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: Authors' own selection based on the engineering literature, terminology from ruling bodies, and product catalogues on AM.

Examples of 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 by PATSTAT matches patents to industries on the basis of their probability of being used in a specific sector. First, we provide an example of a patent capturing production in our AM innovations, by describing what clearly is a product innovation for an upstream industry becoming a process innovation for downstream (adopting) sectors. Table A3.2 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 is linked 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 link to sectors in our data: the weights allocated to sector 28 measure the probability of the AM invention described in the patent being used in sector

28, i.e. in producing the AM device 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 adopting the AM machine for production purposes.

Furthermore, and quite interestingly, the identity of the applicant—General Electric—provides further 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). Adopting firms like General Electric, Rolls-Royce, and several others 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 A3.2. 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

Notes: Data source is the PATSTAT data set.

Similarly, we now provide key examples suggesting that AM innovations in our data also relate to the adoption of AM technology for production purposes, i.e. the use of process innovations in downstream sectors. Table A3.3 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 A3.3. Examples 2 and 3 on the link between AM patents and NACE Rev.2 sectors (Table 1 in Section 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 modeling, 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

Notes: Data source is the PATSTAT data set.

We also report the example of an AM patent featuring a one-to-one correspondence to NACE sector 25 (manufacture of fabricated metal products), again suggesting adoption of the technology in this specific industry. The metallic product described in Table A3.4 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 A3.4. 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

Notes: Data source is the PATSTAT data set.

Table 3.5. 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

Notes: Data source is the PATSTAT data set.

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 were widely affected by the technologies 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 A3.5.

The examples just presented also highlight that in the alternative case of attributing AM patents to the sector of the applicant only, we would have ended up with potentially strong misallocations.

Obviously, with 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).

On geographical attribution

As explained in Section 3.1, we allocated patent families to the country of residence of their inventors using fractional counting.

An alternative strategy would be to attribute the patent family on the basis of the jurisdiction, i.e. where the patent provides protection. This strategy would result in a worse proxy for several reasons. Defensive or strategic patenting would be more likely to be captured this way. Beyond that, firms may extend the number of countries where they apply for protection for reasons different from the real 'economic' rationale for protection. 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 there is no cost for doing it. This would lead to a measure highly skewed towards, for instance, EPO member states, not reflecting the real diffusion of the technology. On the other hand, even in better cases, i.e. protection is sought for protection from competitors where the applicant firm wants to sell the (capital-embodied) innovation, even if we capture the real diffusion of the technology in the importing country the proxy would capture adoption only (something we would not like, as explained in Section 2). 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.

The other possible alternative strategy of assigning patent families to the country of the applicant would have other pitfalls. 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. However, 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 production/adoption occurs. We assume that it is more likely that the inventor's residence is closer to where the patent is produced or adopted than the applicant's. But of course, this is in any case a second-best option in view of the lack of direct information on where the patent is used.

A4. Summary statistics

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

	[1]	[2]	[3]	[4]	[5]
[1] *Employment*	1.000				
[2] *AM patent stock*	0.444	1.000			
[3] *Non-AM patent stock*	0.524	0.529	1.000		
[4] *Labour cost*	0.054	0.251	0.516	1.000	
[5] *Gross output*	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.

A5. Details on the robustness checks

An alternative AM proxy and inter-sectoral/inter-country AM effects

As explained in Section 5.1.1, our main analysis could miss inter-sectoral and inter-country linkages through which AM technologies may affect industry-level employment. These mechanisms represent general equilibrium effects materializing through the existing links along supply chains. Moreover, an industry could adopt AM devices that are produced by other sectors/countries without this showing up in its own patent activity, i.e. our main AM innovation proxy. To check for potential bias in our results stemming from these mechanisms, we build measures for 'external AM'. 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 drop two countries (Israel and New Zealand) and the details for two industries, namely NACE sectors 13 to 15 (manufacturing of textiles, wearing apparel, leather, and related products) is provided as a unique aggregate.

We build an index of AM technology capturing both potential inter-sectoral and inter-country effects of AM innovations going through value-chain relationships. The index is built as follows:

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

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 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 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; specifically, they refer to 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 our main AM innovation proxy 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 effects for the 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 goods 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 goods 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 since they are built for the year 2008, again to avoid reverse-causality issues. They both play a similar role to country-industry FEs (γ_{ij}), which as explained in Section 4 cannot be included in the analysis due to the short time span of our series and the small time variation left along the country–industry 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 A5.1, 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 ‘external AM’ 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 labour and AM technologies. The ‘external non-AM’ 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, while 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 is negatively correlated 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. In line with the theoretical literature, this suggests that offshoring has pro-competitive effects and increases production and sales, but also a large labour-saving effect for a given level of output.

Table A5.1. Relationship between AM patent stock and average employment, 2009–2017 period, inter-sectoral/inter-country AM effects

	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, for 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.

Countries and sectors

Hereafter, we provide results for the robustness checks described in Section 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 devices. As can be seen from Tables A5.2 and A5.3 below, our findings are robust to these checks.

Table A5.2. 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)	(5)
AM patent stock (AM_{ijt-3})	0.238***	0.112***	0.130***	0.093***	0.109***
	(0.040)	(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	4,625
R-squared	0.808	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, for sector and year dummies (columns (1), (2) and (4)), and for 405 country-year and sector-year dummies (columns (3) and (5)) 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 A5.3. 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, for 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 A5.4. 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)	(5)
AM patent stock (AM_{ijt-3})	0.104***	0.054***	0.056***	0.039***	0.041***
	(0.016)	(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	4,545
R-squared	0.887	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, for sector and year dummies (columns (1), (2) and (4)), and for 405 country-year and sector-year dummies (columns (3) and (5)) 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.

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 3 using both EPO and PCT applications, which we test alternatives to our main AM measure based on USPTO data. As shown in Table A5.5 below, our results are robust to these checks.

Table A5.5. 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_{ijt-3}^{EPO})	0.120***	0.121***	0.061***	0.062***				
	(0.019)	(0.020)	(0.010)	(0.010)				
AM patent stock (AM_{ijt-3}^{PCT})					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, for 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.

Alternative lag structures

A further check we conduct concerns the lag structure that we assume for our main variable of interest, i.e. AM technological innovation. As described in Sections 3.2 and 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 A5.6 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 technologies 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 A5.6. 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, for 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.

A6. Country-level explorative analysis

Table A6.1. 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_{ijt-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 ($nonAM_{ijt-3}$)	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_{ijt-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_{ijt-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_{ijt}) in columns (1) to (4); the dependent variable is country-level employment by education category (L_{ijt}^{EDU}) in columns (5) to (10). Data on employment by education category comes from the EU KLEMS database. 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.

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