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Technological interdependencies and employment changes in European industries

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Abstract

This work addresses the role of inter-sectoral innovation flows, which we frame as *technological interdependencies*, in determining sectoral employment dynamics. This purpose is achieved through the construction of an indicator capturing the amount of R&D expenditures embodied in the backward linkages of industries. We aim to find out whether having a more integrated production in terms of requiring more technological inputs is related to a lower demand for workers within the sector. We refer to the literature on innovation-employment nexus, inter-sectoral knowledge spillovers and Global Value Chains, building upon structuralist and evolutionary theoretical considerations. We track the flows of embodied technological change between industries taking advantage of the notion of vertically integrated sectors. The relevance of this vertical technological dimension for determining employment dynamics is then tested on a panel data of European industries over the 2008-2014 period. Results show a statistically significant and negative employment impact of the degree of vertical integration in terms of acquisitions of R&D embodied inputs. Combining the role of demand, the double nature of innovation - as product and as process -, together with inter-sectoral linkages, this work shows that the dependence of a sector from innovation performed by other ones - a proxy for input embodied process innovations - exert a negative effect upon employment.

Keywords: Input-Output, Sectoral Interdependencies, Employment, Embodied Technological Change, Innovation Diffusion

JEL classification: F16, O14, O33

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1 Introduction

Employment loss in developed countries is at the core of nowadays economic investigations. Technology and trade are closely related in this debate: workers can be displaced in industries where labour-saving technologies are adopted or where productive activities are relocated in other branches of the economy or in other countries (Foster-McGregor et al., 2021). Technological progress, making productive process more efficient, and structural change, modifying the proportions of the elements composing economic systems, are both affecting employment dynamics. These two often intertwined phenomena should be both taken into account in assessing labour displacement. The aim of this paper is to pursue this direction of investigation.

The dynamics of job creation and destruction induced by innovation has been a more popular topic in the discipline (Vivarelli and Pianta, 2000; Brynjolfsson and McAfee, 2014; Ford, 2015; Acemoglu and Restrepo, 2018; Dosi and Mohnen, 2019; Pianta, 2020; Dosi et al., 2021b). Large part of the literature focuses on the role of innovation activity and automation while too little emphasis has been devoted to whether the very evolution of the productive structure, with its changes in relative proportions and linkages, can be a determinant of employment dynamics of a sector. We seek to fill this gap by merging three streams of research: the embodied innovation-employment nexus, the analysis of inter-industry knowledge spillovers and the studies on the employment impact of Global Value Chain participation. We will answer to the following research questions: is the degree of vertical technological integration relevant for employment dynamics? That is, is an excessive dependence from technological inputs likely to induce labour displacement? As a result, the study of sectoral employment dynamics is no more enclosed within the boundaries of aggregated sectors considered as distinct bodies, but it is rather linked to the ongoing changes of *technological interdependencies* characterizing the production process. We define *technological interdependencies* as the set of linkages between economic branches combining both a productive and a technological dimension (Rosenberg, 1982; Dosi, 1984a; Los and Verspagen, 2002).[1] We argue that this concept can be represented by measuring the inter-sectoral flows of innovation embodied in intermediary goods and that it is closely related with labour saving process innovations taking place in the user industries.

Bridging an evolutionary attention to the properties of 'the technological background of input-output tables of the economy and their change through time' (Dosi, 1984a, p. 291) with the Pasinettian macro-coordinates in which the process of technical change takes place, our work could be seen as a contribution to the broader assessment of the role played by the structural dynamics of economic systems in generating technological unemployment whenever counter-balancing movements capable of bringing macro-economic conditions towards (non automatic) fulfilment are not in place (Pasinetti, 1981; Vivarelli, 2014). That is, we investigate what Pasinetti (1981, p. 226) defined the 'dynamics of the structure of employment', entailing a 'continuous process of structural

[1] For an historical overview on the importance of technological interdependencies in diffusing technical change and boosting productivity growth in the economy see chapter 3 *Technological interdependence in the American economy* in Rosenberg (1982).

redistribution of employment from one sector to another, in accordance with the pattern shaped by the structural dynamics of technology and demand' - where the heterogeneous nature of technological change is taken into account building upon the evolutionary insights on product *versus* process innovations, with the latter possibly leading to definitive displacement of workers.[2]

WIOD's Input-Output tables, Socio and Economic Account database and ANBERD's R&D expenditures data are used to construct a two-digit industry panel database containing information on employment, value added, R&D expenditures and various indicators of vertical technological integration of an industry, which we label as *Vertical R&D*, to be distinguished from standard horizontal *Sectoral R&D*. Such measures are built exploiting the algorithm of vertically integrated sectors, a methodology proposed in Momigliano and Siniscalco (1982) and nowadays largely used in the literature of inter-industry knowledge diffusion (Marengo and Sterlacchini, 1990; Los and Verspagen, 2002; Montresor and Vittucci Marzetti, 2007a; Hauknes and Knell, 2009; Ciriaci et al., 2015; Taalbi, 2020; Fusillo et al., 2021) and of Global Value Chains (Timmer et al., 2014; Los et al., 2015; Johnson, 2018; Pahl and Timmer, 2019).

Empirically, we test the relationship between employment dynamics and the degree of vertical technological integration of an industry. We implement System-GMM estimations to perform a dynamic panel analysis on 29 two-digit industries for 14 European countries over the 2008-2014 period. We detect a significant and negative employment impact of the level of vertical technological integration of an industry, which represents our proposed original variable that combines R&D dimension, the structure of inter-sectoral linkages and effective final demand. To our knowledge, this work represents the first attempt to exploit the tool of vertical integrated sectors to investigate the dynamics of jobs displacement. This may open various research pathways aimed at analysing the combined effects of technological and structural change on the employment structure of economies, both at sectoral and at supply chain level.

In Section 2 we outline a theoretical framework combining the three aforementioned streams of research. Section 3 shows the methodology used to build the measures of vertical integration of an industry, the data employed and preliminary evidence with descriptive statistics. In Section 4 we present the econometric setting and the results obtained in the baseline specification and in robustness checks. A final section resumes what has been done and discusses the relevance of our results in the current context of globally integrated productive structures.

2 Theoretical background

We rely on a theoretical and methodological framework at the crossroad between three specific streams of research which could be summarised as the following: i) the impact of embodied innovation on employment dynamics; ii) inter-sectoral innovation diffusion; iii) employment impact of Global Value Chains integration. Although the impact of innovation on employment is one of the most studied topic in nowadays economic research, a consensus has not yet emerged and, on

[2] For a theoretical inquiry on the complementarities and similarities between the two intellectual traditions of structural and evolutionary approaches see Scazzieri (2018).

the contrary, empirical investigations reveal a quiet heterogeneous picture varying a lot with the level of analysis, the form of technical change or the compensation mechanism taken into account (Vivarelli, 2014; Barbieri et al., 2019).[3]

R&D expenditure, the most used proxy for innovation activity, is said to be crucial for large firms and advanced sectors and it is too much correlated with labour-friendly product innovation, thus implying an 'optimistic bias' on the resulting employment dynamics. Process innovation, taking place in particular in SMEs and traditional sectors, should be taken into account as well, especially due to its typical labour-saving nature which cannot be left aside by a proper investigation on the innovation-employment nexus. In short, it has been claimed that scholars should address the heterogeneous nature of technical change in terms of how it is generated or adopted, with respect to where (in which sectors) it takes place and not only considering the 'disembodied' component, i.e. own-R&D expenditures (Pianta, 2000; Pellegrino et al., 2019; Dosi et al., 2021b). Process innovation is said to be induced by so-called embodied technological change, namely through innovative investment, such as new machines, components, equipment, or updated scrapping. Broadly speaking, production is made more efficient by acquiring technologically advanced inputs.

From a sectoral point of view, Dosi et al. (2021b) test the employment impact in a vertically integrated two-sector economy composed by 'upstream' industries, where product innovation (i.e. R&D) is more likely to take place, and 'downstream' ones characterized by process innovation distinguished according to the dual dimension of embodied technological change induced by expansionary and replacement investments[4].

[3]A literature review and a summary of the theoretical debate on the different compensation mechanisms at work can be found in Vivarelli (2007, 2014), Calvino and Virgillito (2018), Heijs et al. (2019),Staccioli and Virgillito (2020) and Mondolo (2021). Reviews highlight that R&D expenditures is one of the most common proxies for innovation, that sectoral and firm level analysis are both widely performed and that, concerning the results obtained, there is a general tendency towards a positive effect of R&D innovation on employment, even if it is mainly found with respect to High-Tech sectors (Bogliacino and Vivarelli, 2012). Other works devoted an effort also in disentangling the employment impact of technologies by skills, tasks and occupational groups (Bogliacino et al., 2013; Reijnders and de Vries, 2018; Reljic et al., 2021).

[4]'Upstream' and 'downstream' aggregates are built following the Pavitt Taxonomy, a sectoral classification that allows to collect productive sectors in four classes characterized by different technological attributes, by various internal learning processes and, one could argue, by heterogeneous positioning along value chains. Such taxonomy, revised by Bogliacino and Pianta (2010, 2016) to account for services, is distinguished into:

- Science Based firms (e.g. Pharmaceutical), whose technological progresses are strongly linked to those of basic and applied research.
- Specialised Suppliers (e.g. Machinery and Equipment), which provides capital tools and components to a large spectrum of "downstream" sectors. Learning relies on innovative efforts both through formal expenditures on R&D and through tacit knowledge in the design of artefacts and in the customization.
- Scale and Information Intensive (e.g. Automotive), in which innovation capabilities arise from the technological adoption of capital inputs but also from the ability to develop internally complex products and to manage complex organizations. Learning is cumulative and its effect is amplified by scale economies, also thanks to the production of basic materials and services and consumer durables.
- Suppliers Dominated firms (e.g. Textile), typical of traditional manufacturing industries in which innovation and learning depend from intermediate and capital goods purchased from other sectors.

Upstream classes (Science Based and Specialised Suppliers) perform R&D activity and trigger product innovation, which includes the technologically advanced inputs (i.e. machinery, tools, software) then adopted, in the form of embodied technological change, by downstream classes (Scale and Information Intensive and Suppliers Dominated) mainly characterized by process innovation. We follow Dosi et al. (2021b) in taking advantage of this classification

Even if sharing the aforementioned criticisms and Dosi et al. (2021b)'s attempt to take into account a detailed assessment of embodied technological change, the literature on the innovation-employment nexus might still fall short of a true inter-sectoral dimension. Indeed, in Dosi et al. (2021b) there is a separation between upstream and downstream sectors, seeking to represent the theoretical distinction according to which 'product innovation of one sector are often process innovation for other sectors which are using them' (Dosi, 1984b, p.104). The assumption of a dual economy is obviously grounded in literature and the distinction is justified on the basis of the well known Pavitt Taxonomy (Pavitt, 1984; Bogliacino and Pianta, 2010, 2016). However, these features of what can be called *vertical technological integration* could be addressed without assuming any *a priori* relationship among sectors.

We thus aim to integrate these analyses with insights from the literature on inter-industry innovation diffusion, which is useful to better frame the concept of *technological interdependencies* and then to build a measure of *vertical technological integration*. The key idea of this stream of research is that an initial amount of innovation produced by R&D efforts of a generic industry might be embodied in the commodities such industry produces, likely increasing its quality, i.e. increasing the amount of innovation they incorporate.[5] This amount of innovation then flows to those other industries that have bought those goods as intermediate inputs or as capital goods necessary to produce their final commodity (Dietzenbacher and Los, 2002). As a result, 'R&D spent in one sector can have repercussions in other sectors of the economy' (Mohnen, 1997, p.4). Moreover, industries differ not only in terms of amount of R&D expenditures (or R&D intensity), but also in terms of the use they do of the technology embodied in the intermediate inputs, i.e. in the goods they purchase from other industries, thus highlighting inter-sectoral linkages, i.e. technological interdependencies, as important sources of knowledge creation. The idea goes back to Schmookler (1966)'s observation that the best way for an industry to innovate is to improve the inputs it buys from other industries (Hauknes and Knell, 2009). However, it must be pointed out that the mechanism at work here depends crucially on the nature of innovation and on the positioning in terms of supplier or buyer of technological inputs. As a result, technological interdependencies can be relevant for knowledge creation especially in those 'downstream' industries where process innovations are induced as a consequence of the acquisition of advanced inputs, which in turn may be the output of product innovations originally performed in 'upstream' industries (Dosi et al., 2021b).

The literature has attempted to measure inter-industry innovation diffusion often building upon the 'analysis of industrial interdependencies'. The latter represents an approach developed by authors such as Leontief (1951) and Pasinetti (1981) but that can be traced back, in the basic idea of

to define the two aggregates avoiding arbitrary choices or more standard OECD high/medium/low R&D industry classification.

[5] We are obviously aware that other mechanisms are in place and that R&D activity may also not yield any invention or it may involve a completely new commodity or may simply be not related at all with the goods produced. Moreover, R&D can be embodied both in intermediate and in capital inputs but, given the lack of reliable industry-by-industry capital stock tables, they are generally omitted in literature, exploiting instead the increasingly rich data from I-O tables that include (without distinction) both intermediate and capital goods deliveries. The conceptual reasoning we are putting forward is by necessity bounded by simplifying assumptions on the effect of innovations spurred by R&D expenditure.

measuring inter-industry relationships, to the pioneering works of the french school of physiocrats, as Francois Quesnay (1894)'s *Tableau économique* (see Pasinetti, 1977). Since the 60s, the traditional Input-Output (hereafter, I-O) analysis, dealing exclusively with commodity flows, has been enriched by new lines of research seeking to map the inter-sectoral flows of technological knowledge, considering industrial interdependencies as important sources of knowledge creation and diffusion (see DeBresson, 1996). Moreover, as highlighted by Castellacci (2008), one crucial aspect of the evolutionary studies of sectoral patterns of innovation is the focus on vertical linkages among sectors, hence on the set of interactions, cooperation, exchanges between producers, suppliers and users of technologies (more in Dosi, 1982, 1984a; Pavitt, 1984; Breschi and Malerba, 1997). In short: the set of I-O relationships in terms of advanced knowledge, or - methodologically - an innovation I-O table along the insights by Lundvall (1988) and DeBresson (1996), among others.

Schmookler (1966) provided the first systematic approach for measuring industrial technology flows extending the idea of Leontief (1951), then followed by many other authors (e.g. see Terleckyj, 1974; Scherer, 1982; Momigliano and Siniscalco, 1982; Marengo and Sterlacchini, 1990; Verspagen, 1997; Papaconstantinou et al., 1998; Drejer, 1999).[6] The measures proposed by these works were then used to provide detailed evidence on the network structure of technology flows, examining single country's experience or comparing production systems of different economies, showing those industries essential for production, diffusion and use of innovation (Montresor and Vittucci Marzetti, 2007b; Hauknes and Knell, 2009; Ciriaci et al., 2015; Taalbi, 2020; Fusillo et al., 2021).

We take advantage of this approach in the way extramural R&D expenditures, namely that part of performed R&D which is assumed to get embodied in the intermediaries sold to other industries, is measured. Marengo and Sterlacchini (1990), building upon the methodology developed by Momigliano and Siniscalco (1982), proposed an approach based on the concept of vertically integrated sectors, previously formalized by Pasinetti (1973). A vertically integrated sector can be defined as the set of all the economic activities required in the production process of a final commodity (both for consumption and investment purposes). It is obtained by partitioning the whole economic system into subsets (called 'subsystems'), each producing a final good and including all the inputs requirements directly and indirectly activated by its final demand.[7] The algorithm of vertical integration allows to move from a *circular* (or *horizontal*) industry-by-industry representation of the production process, common to standard I-O analysis developed by Leontief (1951), to a *vertical* industry-by-subsystem configuration, revealing the whole interconnections through forward and backward linkages activated in the sequential rounds of production. Therefore, the focus shifts from single 'industry producing a certain commodity, intermediate or final, as it may be' to

[6]A building block of the literature aimed at measuring inter-sectoral innovation diffusion is represented by the work by Marengo and Sterlacchini (1990), in which the authors review the previous studies and stress the need for an integrated framework merging the two main approaches: the method using I-O tables and focused on embodied transfer of technologically improved goods (Siniscalco, 1982; Momigliano and Siniscalco, 1984), and the so called Scherer's one focused on disembodied transfers of knowledge (Scherer, 1982). In this way, the authors argue, it is possible to take into account at the same time embodied and disembodied technological change, considering them as two connected phenomena in the process of innovation diffusion.

[7]Throughout the paper 'subsystems' and 'vertically integrated sectors' must be read as interchangeable terms. We also make the simplifying assumption that they represent a proxy of 'supply chains' for given final productions.

'the process of production of a final commodity', while the problem evolves from assessing for each industry 'where its inputs come from and where its outputs go to', to 'build *conceptually* behind each final commodity a vertically integrated sector which, by passing through all the intermediate commodities, goes right back to the original inputs.' (Pasinetti, 1981, p. 113). In this way the study of structural change in the economy overcomes single inter-industry transactions to focus on two categories: primary (direct and indirect) inputs provided by industries and final demands activated by subsystems. Consumption (and investment) then appears as the final aim of production (Pasinetti, 1973, 1981; Scazzieri, 1990; Landesmann and Scazzieri, 1993, 1996; Di Berardino, 2017; Cardinale, 2018). As a consequence, this logical device is useful in assessing the parallel dynamics of technology and demand, originally put forward by Pasinetti (1981), bringing together an evolutionary attention to the heterogeneous nature of technical change and the 'structural' emphasis on the role of demand (Pianta, 2001; Antonucci and Pianta, 2002; Crespi and Pianta, 2007).

As recently highlighted by Di Berardino (2017) and Antonioli et al. (2020), it can be seen as a powerful tool to complement the traditional "horizontal" sector-based perspective of production systems, which considers sectors as separate from one another, thus neglecting user-producer interactions. In short, the configuration of the productive structure emerging from this approach hints to Andreoni (2018, p.1614)'s argument that '[t]echnological change, technology system integration and the scaling up and diffusion of emerging technologies (robotisation and digitalisation in particular) have also led to the 'genetic mutation' of traditionally defined sectors'. Rosenberg (1982, p.76) too claimed already in the 80s that 'technology flows have radically reshaped industrial boundary lines, and that we still talk of "interindustry" flows because we are working with an outmoded concept of an industry'.[8] Taking into account this perspective enables us to propose a novel way for assessing innovation-employment nexus.

Vertically integrated sectors can be calculated from I-O data and be used to reclassify a sector variable (as R&D expenditure) into a industry-by-subsystem matrix representation. As a result, we are able to relate changes in the occupation levels of industry i not only to variation of its sectoral characteristics (i.e. its R&D activity), but also on the changes taking place in the productive structure triggered by inter-sectoral linkages and final demand and thus on its 'position' in terms of vertical integration. We build upon the aforementioned approaches in order to compute a measure of what we call vertical technological integration of an industry and then test its relationship with sectoral employment changes.

Furthermore, I-O linkages, at the core of the concept of technological interdependencies and of the indicator we propose, are international and change over time. It could be said that we are evaluating the employment impact of an industry's *technological* participation to Global Value Chains (GVCs from now on) year by year. Indeed, we are close to Reijnders and de Vries (2018, p.413)'s view of GVCs as 'compelling unit of aggregation to study how technology and trade interact and shape the demand for labour'. Hence, we find useful to make an additional bridge with the not

[8]An overview of the criticisms pointed out in the literature on the traditional definition of sectors, together with insights on how to address its limitations, can be found in Andreoni (2020).

too extensive literature on GVCs specifically assessing the employment impact of offshoring and related indicators (Rodrik, 2018; Szymczak et al., 2018; Reijnders et al., 2021; Bramucci et al., 2021). In short, after the seminal works by Feenstra and Hanson (1996, 1999) a series of scholars investigated the link between GVCs participation, often by looking at offshoring (i.e. backward linkages) indicators, and labour demand shift. A substantial effort has been devoted in distinguishing between skilled and unskilled labour (OECD, 2007; Gonzalez et al., 2015; López González et al., 2019), while more recently the focus has been shifted to tasks (Marcolin et al., 2016; Reijnders and de Vries, 2018; Bontadini et al., 2019) and occupations (Bramucci et al., 2021).[9] Recent reviews by Bontadini et al. (2020, 2021b) and Bramucci et al. (2021) stress that this literature is far from providing converging results due to the difficulties in effectively measuring offshoring activities and in disentangling the heterogeneous nature of this process as well as in taking into account the multiple dimensions that play a role, as institutions, technology and power relations in GVCs (see also Milberg and Winkler, 2013; Celi et al., 2018).[10]

Besides these considerations, we are close to Bramucci et al. (2021)'s view of the dynamics of offshoring and employment as part of the broader process of structural change. However, our approach takes a slightly different route: we do not aim at assessing skill, task or occupational aspects of offshoring impact and we do not stay within the sole *productive* or *material* dimension. In fact, we want to measure the broader degree of vertical integration from a technological dimension. We do not make use of offshoring indicators, but rather and simply compute the amount of R&D expenditures in the supply chain of every sector, thus combining outsourcing and offshoring phenomena. The final aim is to investigate the relationships between such measure and employment dynamics, enriching the literature on innovation-employment nexus, which is lacking this 'structural interdependencies' dimension as it is relying only on standard sectoral boundaries of analysis. Hence, it is a perfect field to apply the aforementioned methodology to track the amount of innovation that doesn't remain within the sectoral boundaries (and therefore does not only impact on the sector that generates it) but spreads throughout the productive structure following the physical flows of intermediate products required by final goods production.

3 Methodology, data and preliminary evidence

As anticipated, in constructing our measure of vertical technological integration we refer to the galaxy of offshoring measures and to the indicators of inter-sectoral knowledge spillovers. In par-

[9]Still on skill-bias effect of offshoring and specifically using World Input-Output Database (Timmer et al., 2015) some challenging evidence emerge from the works by Foster-McGregor et al. (2013, 2016) and Reijnders et al. (2021).

[10]As it is hopefully clear by now, by measuring the amount of R&D embodied in the flow of intermediaries we add the technological dimensions to standard offshoring analysis providing fresh evidence. Indeed, as stressed by Fusillo et al. (2021) in their network analysis exercise, the world I-O network (WION) commonly assessed in literature, does not coincide with the global R&D network. Indeed, 'while the former can be taken to represent the production substratum of the latter, the configuration and properties of the global R&D network at stake depends also on how R&D expenditures are distributed across countries and industries. Because of this, the global R&D network does not necessarily mimic the properties of the WION and its analysis allows us to explore important additional issues'. (Fusillo et al., 2021, p.3)

ticular, we adopt the methodology originally developed by Momigliano and Siniscalco (Momigliano and Siniscalco, 1982; Siniscalco, 1982; Momigliano and Siniscalco, 1984). It is based on connecting a vector of sectoral R&D expenditure (used as proxy for innovative capability) to physical inter-industry transactions after having transformed I-O tables into vertically integrated sectors. As a result, we obtain information on the flows of R&D expenditure between sectors and subsystems (i.e. along supply chains), implicitly assuming that technology flows are embodied in physical deliveries of intermediaries. The methodology used by Momigliano and Siniscalco (1982) and enriched by Marengo and Sterlacchini (1990) has been reviewed and accurately described in a book by Leoncini and Montresor (2003). The procedure leads to the construction of an *inter-sectoral embodied innovation flows matrix* to track the amount of innovation flowing from every primary good sector i to every final good sector j.[11] The theoretical notion of vertically integrated sectors (Pasinetti, 1973) enables us to include all the production flows (and thus innovation flows) activated by effective components of final demand. Then the interconnections of a productive structure can be captured in terms of forward and backward linkages building upon I-O analysis. The industry-subsystem matrix of inter-sectoral embodied innovation flows is obtained in the following way.

The starting point is the generic I-O matrix $\boldsymbol{Z}$ of intermediate deliveries, from which we compute matrix $\boldsymbol{A}$ of direct inter-industry coefficients, post-multiplying $\boldsymbol{Z}$ by the inverse of the diagonal matrix of sectoral gross output $\hat{x}$:[12]

$$\boldsymbol{A} = \boldsymbol{Z}\hat{x}^{-1} \tag{1}$$

The crucial tool common to the majority of works in I-O literature is represented by the so-called Leontief Inverse matrix, which is given by:

$$\boldsymbol{L} = (\boldsymbol{I} - \boldsymbol{A})^{-1} \tag{2}$$

with $\boldsymbol{I}$ representing the identity matrix and assuming that the inverse of $(\boldsymbol{I} - \boldsymbol{A})$ exists.[13] Considering n industries with $i, j = 1, ..., n$, every $l_{i,j}$ element of matrix $\boldsymbol{L}$ captures the combination of *direct* and *indirect* requirements of increased output of industry i needed to produce one additional unit of final good in industry j. *Direct* component refers to the flow of intermediaries from

[11] As already said, this amount is going to be proportional to the goods that j directly and indirectly requires from i to produce given amount of its output.

[12] The hat over variables stands for the transformation from vector to diagonal matrix.

[13] The Leontief Inverse matrix ($(\boldsymbol{I} - \boldsymbol{A})^{-1}$), or 'total requirements matrix', derives from the solution of economic system described by the accounting equations put forward by Leontief (1951) where n industries are represented as a vector of output x, intermediate demand $\boldsymbol{A}x$ and final demand d:

$$x = \boldsymbol{A}x + d$$

Solving by x yields:

$$(\boldsymbol{I} - \boldsymbol{A})x = d$$
$$x = (\boldsymbol{I} - \boldsymbol{A})^{-1}d$$

Hence, in order to have a unique solution, $(\boldsymbol{I} - \boldsymbol{A})$ needs to be singular, i.e. it depends whether or not $(\boldsymbol{I} - \boldsymbol{A})^{-1}$ exists. (Pasinetti, 1977; Miller and Blair, 2009) sector i to subsystem j, while *indirect* contribution stands for the amount of inputs which from sector i flows to all the other sectors that require them in order to produce the intermediaries to be eventually delivered to subsystem j. Therefore, Leontief Inverse matrix enables researchers to take into account not only the *direct* intermediate transactions between each two sectors observed in standard I-O table, but also all the stages of production processes underlying those deliveries and that entail a larger number of economic branches as providers of further inputs. In this way it is possible to measure the true whole contribution of sector i for the final production of commodity j (i.e. directed to subsystem j).

From here we build the linear algebra 'operator' (Momigliano and Siniscalco, 1982) that is used to decompose every vector expressing a variable classified in sectoral branches into a square matrix in which such variable is re-mapped from an industry to a subsystem perspective:

$$\boldsymbol{B} = \hat{x}^{-1}\boldsymbol{L}\hat{d} \tag{3}$$

where $\hat{x}$ is the diagonal matrix of total sectoral output, $\hat{d}$ is the diagonal matrix of sectoral final demand (i.e. the output destined for the final uses of consumption and investment) and $\boldsymbol{L}$ is the Leontief Inverse matrix. $\boldsymbol{L}$ times $\hat{d}$ yields the matrix of inter-sectoral production flows activated directly and indirectly by effective final demand. Pre-multiplying it by $\hat{x}^{-1}$ leads to a transformation into shares of the production requisites. $\boldsymbol{B}$ can be seen as an industry-by-subsystem matrix where every row represents the proportion of the activity of each industrial branch required by the different subsystems (directly and indirectly activated by the final demand of the various commodities). Every column stands instead for the proportion of activities of the different branches occurring in each subsystem. In this square matrix each subsystem (i.e. each vertically integrated or final-good sector) is represented as a column vector. The main diagonal shows how much of each industry's activity is activated by the final demand of the commodity such industry produces. It is often the case that this share is limited, thus pointing out that their production activity is directed more towards the final production of other sectors' goods (Marengo and Sterlacchini, 1990). Multiplying the operator $\boldsymbol{B}$ by the diagonal matrix of sectoral R&D expenditures, $\hat{r}$, we obtain the *inter-sectoral embodied innovation flows matrix* $\boldsymbol{R}$ (Leoncini and Montresor, 2003):

$$\boldsymbol{R} = \hat{r}\boldsymbol{B} \tag{4}$$

Since we deal with global tables (n industries for each of the m countries), every element $r_{ic,jk}$ of $\boldsymbol{R}$ measures the R&D expenditures of sector i in country c which is embodied in the production of the final good j in country k, i.e. that is integrated in subsystem j, k.[14] We argue that this matrix can be used to assess the technological interdependencies arising in the global productive structure under consideration in a given year. Such interdependencies can be summarised by a variable of

[14]More in detail, $r_{ic,jk}$ measures the innovation made by sector i in country c which sector j in country k acquires from it *directly*, as a direct use in (j, k)'s final production, and *indirectly*, that is, embodied in the intermediate goods (still produced by sector (i, c)) used to produce those inputs sector (j, k) gets from other sectors. As stressed by Montresor and Marzetti (2008), although "intermediated" by the production of the other sectors, the innovation sector (j, k) receives via $r_{ic,jk}$ is "produced" by sector (i, c) only.

vertical technological integration, computed essentially as a measure of backward linkages - i.e. by summing up the row values for any column, after we have removed the main diagonal elements representing the part of technological inputs required by each sector itself. That is, we rule out the amount of innovation generated internally, focusing on the part coming from other branches of the domestic and global economy.[15] We call this indicator of vertical technological integration *Vertical* R&D expenditures (VRD) - to be distinguished from horizontal *Sectoral* R&D expenditures (SRD) - which for every subsystem j in country k it is given by:

$$VRD_{jk} = \sum_{i=1,c=1}^{n,m} r_{ic,jk} \tag{5}$$

Although it is a more standard measure in comparison to the various offshoring indicators proposed in Global Value Chains literature, we are proposing alternative ways to compute this indicator.[16] On one hand we highlight the technological intensity of inputs in a similar vein with what has been done elsewhere in the literature (Reljic et al., 2021; Bramucci et al., 2021):

$$VRD_{jk}^{UP} = \sum_{i=1,c=1}^{n,m} r_{ic,jk} \tag{6}$$

where i belongs to the group of industries that we identify as the two 'upstream' classes following the Pavitt Taxonomy: Science Based and Specialised Suppliers (Pavitt, 1984; Bogliacino and Pianta, 2010, 2016). On the other by weighting the measure by a proxy of size of the industry, as proposed in Foster-McGregor et al. (2016):

$$VRD_{jk}^{W} = \frac{\sum_{i=1,c=1}^{n,m} r_{ic,jk}}{VA_{jk}} \tag{7}$$

where VA_{jk} stands for the value added of sector j in country k.

Concerning the data, symmetric industry-by-industry I-O tables provided by World Input-Output Database (Timmer et al., 2015) and ANBERD's R&D expenditures data at a two-digit level of aggregation (NACE Rev. 2 classification) have been used to construct $\boldsymbol{R}$, a 406x406 matrix

[15] Here there is a crucial conceptual reasoning to be pointed out. As we already stressed, in the exercises adopting Pavitt Taxonomy there is an artificial separation between industries performing as suppliers of technological inputs and industries that are users of them, on the basis of sectoral characteristics on learning and sources of innovation. The configuration by means of vertically integrated sectors displays a distinction between upstream and downstream industries that emerges directly from the intermediate deliveries of I-O data. One could say that since all the row-industries are suppliers and the column ones are users, the result is a 'natural' upstream *versus* downstream separation. However, as we will show, having an *a priori* classification of upstream suppliers is useful in better addressing those industries really producing technologically advanced inputs which are more likely to displace workers. To sum up, in the following pages we will keep the term 'upstream' and 'downstream' to identify the aggregates composing the Pavitt Taxonomy and use them to enrich the distinction between suppliers and users of technological inputs that we obtained directly from the data.

[16] Offshoring indicators are often computed as a share on the total inputs required in final production, or by considering only export component in final demand, or distinguishing between domestic and foreign production. However the main difference is that usually these measures are computed out of a standard Z matrix or out of a matrix of value added embodied in production flows, the so-called Trade-in-Value-Added (TiVA) set of measures (see Johnson, 2018). As such, they remain bounded to a material productive dimension. We add the technological one.

(29 sectors for 14 European countries), for each period from 2008 to 2014.[17] This is the best that can be done in terms of temporal and cross-sectional dimensions given data availability constraints and trying to avoid missing values as much as possible. Indeed, WIOD data (2016 Release) are available from 2000 to 2014, while ANBERD's R&D expenditures data (ISIC Rev. 4 version) are often missing for crucial country-sector observations before 2008. The impossibility of having a perfect coherence between the two database generates a bias that must be highlighted for the sake of clarity. WIOD's I-O tables include 43 countries (plus one Rest of the World) and 56 sectors. In order to distribute the diagonalized vector of sectoral R&D $\hat{r}$ we need the operator $\boldsymbol{B}$ to have the row dimension equal to the column one of $\hat{r}$. That is, we necessarily need to remove rows that are not matching the availability of ANBERD dataset both in terms of industries and countries. This forces us to focus on European industries for which information on R&D is largely provided. As a result, we compute backward linkages that take into account only flows within the European productive structure. Hence, we measure vertical technological integration within the boundaries of European supply chains. Moreover, we select rows matching only manufacturing industries. This choice, together with the aforementioned lack of R&D data common also to services, is led by conceptual motivations too. Our assumption is that innovation spurred by R&D activity gets embodied in the intermediate goods an industry is producing. This "embodiment" assumption is way more credible with respect to manufactures than services. Hence, our measure of vertical technological integration is implicitly considering only innovation embodied in manufacturing goods.[18]

We then build the Vertical R&D set of variables and we add them to a two-digit industry-level balanced panel dataset of 7 years, 14 European countries and 29 sectors together with SEA's variables (value added and number of persons engaged) and standard Sectoral R&D expenditures data.[19] Standard descriptive statistics can be found in Appendix A. In the following section we provide evidences of the heterogeneous nature of our proposed indicator for the year 2014, before we move to the econometric estimation.[20]

3.1 *Vertical R&D*: Preliminary evidence from descriptive statistics

VRD (Vertical R&D) and SRD (Sectoral R&D) vary a lot with respect to the sector and country of belonging. Differences may stem from the size of the sector and of the supply chain, i.e. in terms of R&D performed by the industries supplying inputs or purely in terms of amount of inputs required. In addition, Vertical R&D can also vary with respect to the effective components of final demand

[17] Final demand has been computed considering the consumption side (by household, government and organizations) and the investment one (capital formation and changes in inventories).

[18] Among manufacturing we omit only two sectors: 'Manufacture of coke and refined petroleum products' (C19), as we work with current prices I-O tables and this industry is largely subject to price dynamics; 'Repair and installation of machinery and equipment' (C33), due to its nature more close to service activity than manufacturing one.

[19] Countries included are: Austria, Belgium, Czech Republic, Finland, France, Germany, Hungary, Italy, Lithuania, Poland, Portugal, Slovenia, Spain and The Netherlands. The list of sectors can be found in Table 3 in Appendix A. 18 manufacturing sectors, the construction sector and 10 services sectors are included. All variables are expressed in nominal terms in US dollars.

[20] Given the short length of the panel, due to aforementioned data constraints, time dynamics is left aside of the descriptive statistics in favour of cross-sectional investigations. 2014 has been preferred as it is the most recent year.

which activate production of each subsystem and, as a consequence, all the activated intermediate productions too. What is worth highlighting is the heterogeneity displayed by these indicators. Figure 1 shows the top 10 ranking in country-industry terms in 2014, by their amount of standard Sectoral R&D expenditures in millions of US dollars. The predominance of German industries is highlighted (followed by French ones), with Automotive ranking first, and then other manufacturing R&D intensive activities following. So far nothing new. The picture becomes more heterogeneous in country and sector dimensions if we rank by Vertical R&D, still in 2014 (Figure 2). German Automotive is still leading the ranking, but Construction sector for three main countries is now included. The main novelty is that in the top 10 country-industry there is a strong heterogeneity in terms of what we call vertical technological integration, that is the amount of R&D embodied in the supply chain. Furthermore, this can be relevant both for upstream activities and for downstream industries which especially depend on technologically advanced inputs acquired from more upstream branches of the economy in order to develop innovation capacity.

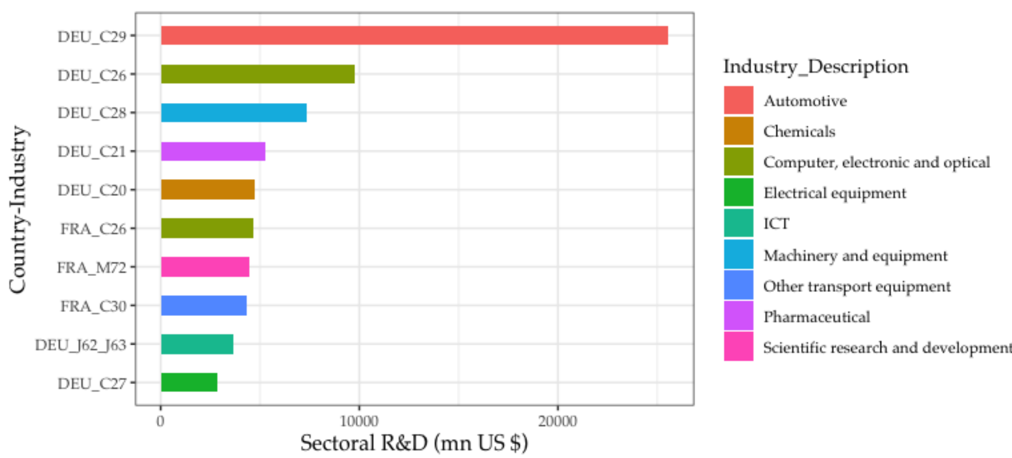

Figure 1: Sectoral R&D expenditures by country-industry in 2014

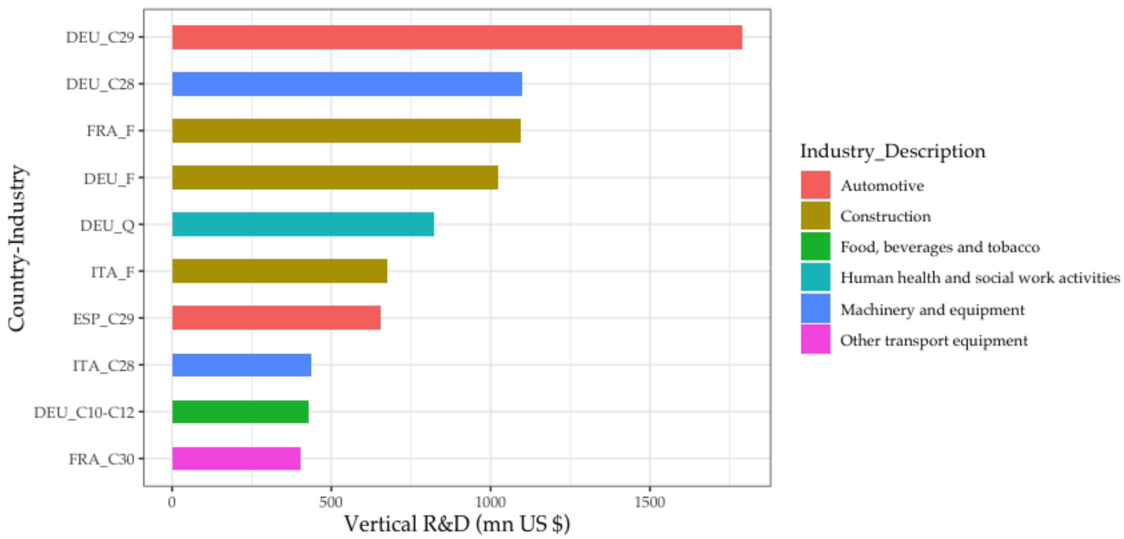

Figure 2: Vertical R&D expenditures by country-industry in 2014

However, the previous two evidences suffer from the same bias: the size of the sector, considering Sectoral R&D, and the size of the supply chain, considering Vertical R&D. Focusing on the second, which will represent our main explanatory variable in the econometric investigation, we must recognize that the amount of R&D embodied in the supply chain includes first the amount of pure productive flows between sectors upon which R&D expenditures are then distributed proportionally. That is to say, that a more informative and accurate measure on the degree of dependence from technological inputs could be obtained simply by scaling VRD by the value added of the sector, as it is done sometimes in the literature (see for instance Foster-McGregor et al., 2016). In this way we seek to rule out the size effect of the supply chain. Plotting the top 10 ranking in 2014 of Vertical R&D scaled by value added (Figure 3) results in having the prevalence of Automotive and Computer, electronic and optical industries, but from a various range of countries belonging mainly to southern and eastern periphery. This evidence might confirm that this two sectors are deeply involved in technological integrations, but we could state that the way you are more or less dependent on technological inputs depends on the country of origin. Automotive in Germany is likely to provide more technological components for European car productions, while Poland Automotive industries may be more keen on requiring advanced inputs to produce components with a lower content of innovation. In this sense, Polish or Hungarian industries are more dependent on technological inputs than, e.g., German ones.

The country dimension fades away if we aggregate at industry level (Figure 4). We also adopt the Pavitt Taxonomy (Pavitt, 1984; Bogliacino and Pianta, 2010) to distinguish betweeen four classes: Specialised Suppliers (SS), Science Based (SB), Suppliers Dominated (SD), Scale and Information Intensive (SII).[21] Automotive sector clearly appears as the dominant one in terms of

[21] Please notice that we include in the analysis also few industries not belonging to any Pavitt class, hence we frame this groups as NA (not available) class. Among these industries what we call ICT stands for the merge between

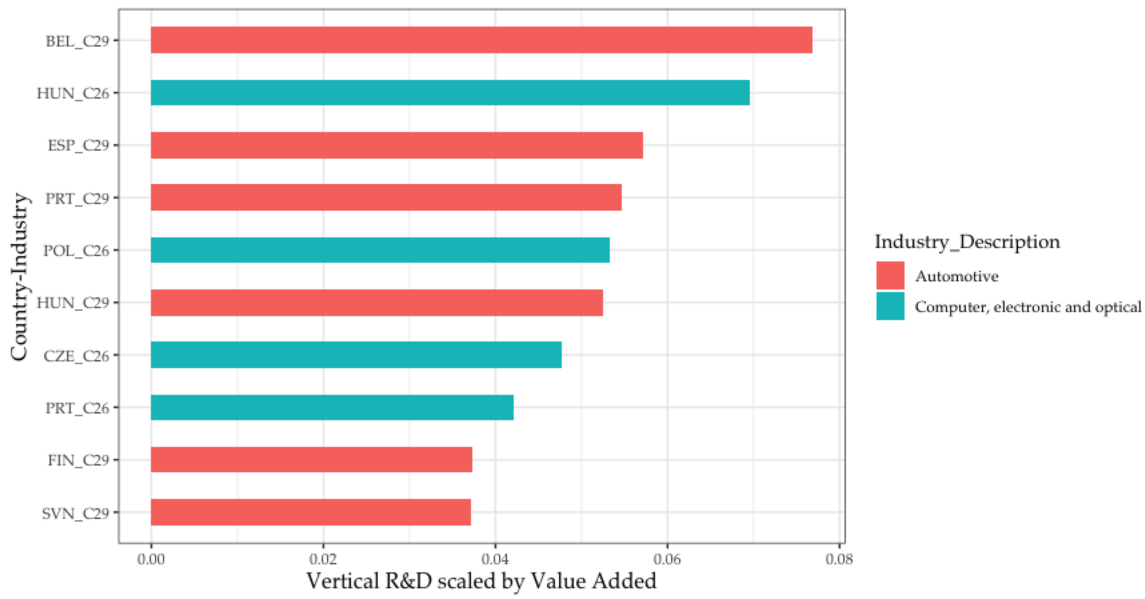

Figure 3: Vertical R&D expenditures scaled by Value Added by country-industry in 2014

technological inputs needed in the production process, followed by other manufacturing industries belonging to Science Based and Specialised Suppliers, which represents the upstream classes in Pavitt Taxonomy, displaying a high technological intensity in their supply chain. At the bottom of the ranking we find those industries which scarcely rely on technologically advanced inputs to produce their final commodities, such as Wood and cork, Real estate activities, Basic metals, Recorded media and so on.

We have shown that the degree of vertical technological integration is highly heterogeneous among sectors. However, Vertical R&D is still a rough measure as we include every kind of manufacturing inputs. Hence, a sequential step in addressing this technological dependence necessarily entails disentangling this indicator. We do this in two ways: first, in Figure 5, we account for the share of upstream inputs over the total, that is we compute the ratio of an indicator of Vertical R&D coming from upstream industries in the supply chain (Science Based and Specialised Suppliers classes) over the standard measure of Vertical R&D. In this new ranking we denote a clear dominance of Science Based and Specialised Suppliers activities, together with two industries belonging to the NA class (not registered in any Pavitt class), Human health and ICT, and two Scale and Information Intensive industries (Rubber and plastic and Video and music). As a result we learn that the major dependence on technological inputs is among the very more technological industries. A possible explanation we put forward is that we are forced to make this analysis at two-digit level of aggregation and hence we may argue that large part of inter-sectoral transactions in many industries take place with other sectors of the same 2-digit classification. For instance, it

"Computer programming, consultancy and related activities" - belonging to Science Based - and "Information service activities" - belonging to Scale and Information Intensive. The merge was necessary to match ANBERD and WIOD data, but then we were forced to leave the industry without a Pavitt affiliation.

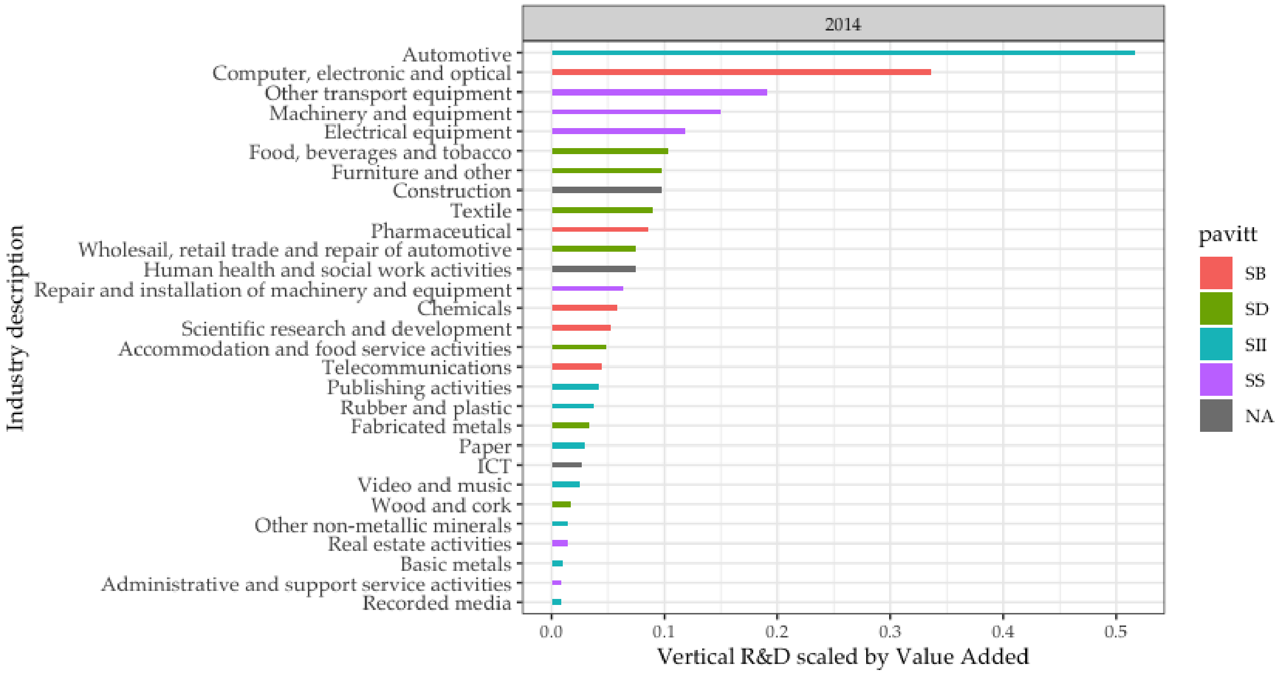

Figure 4: Vertical R&D expenditures scaled by Value Added in 2014 aggregated by industry and by Pavitt class: Science Based (SB) in red, Specialised Suppliers (SS) in violet, Scale and Information Intensive (SII) in light blue, Suppliers Dominated (SD) in green, Not Available (NA) in grey.

could be that Computer, electronic and optical in Italy is largely requiring advanced inputs from other activities of the same classification in other countries.

Is this holding for all industries? This issue can be addressed by disentangling Vertical R&D between what Feenstra and Hanson (1996) and Foster-McGregor et al. (2016) call *Broad* and *Narrow* indicators. Broad Vertical R&D for a sector stands for the amount of technological inputs coming from different branches of the economy (thus including domestic and foreign industries), while Narrow Vertical R&D takes into account inputs coming from industries of the same classification (hence only foreign industries). Figure 6 displays heterogeneous behaviour of the European subsystems. Automotive seems to be quite split in the two components, while sectors like Food, beverages and tobacco, Machinery and equipment, Furniture and other are definitively more dependent from broad kind of inputs. The opposite holds for activities as Computer, electronic and optical largely requiring technological inputs from sectors of the same kind in other countries. An implication arising from this evidence is that firms in macro-sectors like Automotive and Computer, electronic and optical are largely trading with firms belonging to the same category of activity, meaning that at this 2-digit level of aggregation we are in a way loosing track of all these *intra*-sectoral interdependencies. That is, for instance, we are neglecting the technological flows between a firm producing engines for vehicles and the car company requiring them to assemble the final good, the car. This is obviously an issue of data availability, mainly due to current I-O tables.

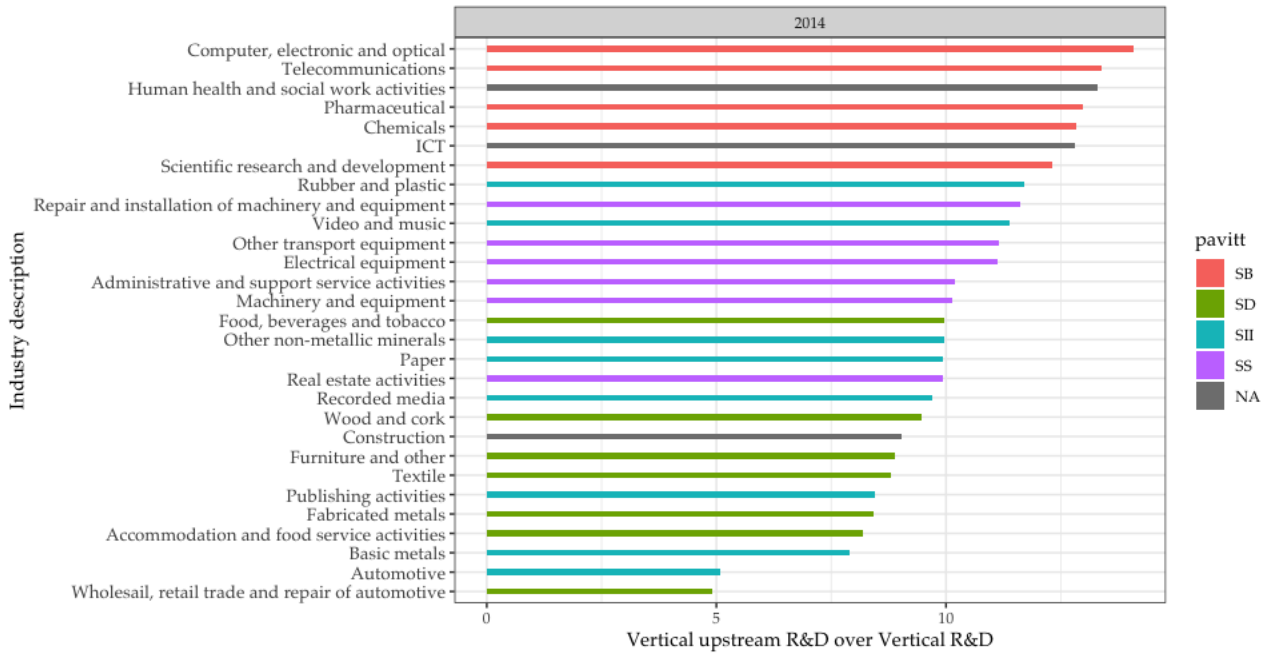

Figure 5: Vertical R&D expenditures from upstream industries over the total Vertical R&D in 2014, by industry and by Pavitt class: Science Based (SB) in red, Specialised Suppliers (SS) in violet, Scale and Information Intensive (SII) in light blue, Suppliers Dominated (SD) in green, Not Available (NA) in grey.

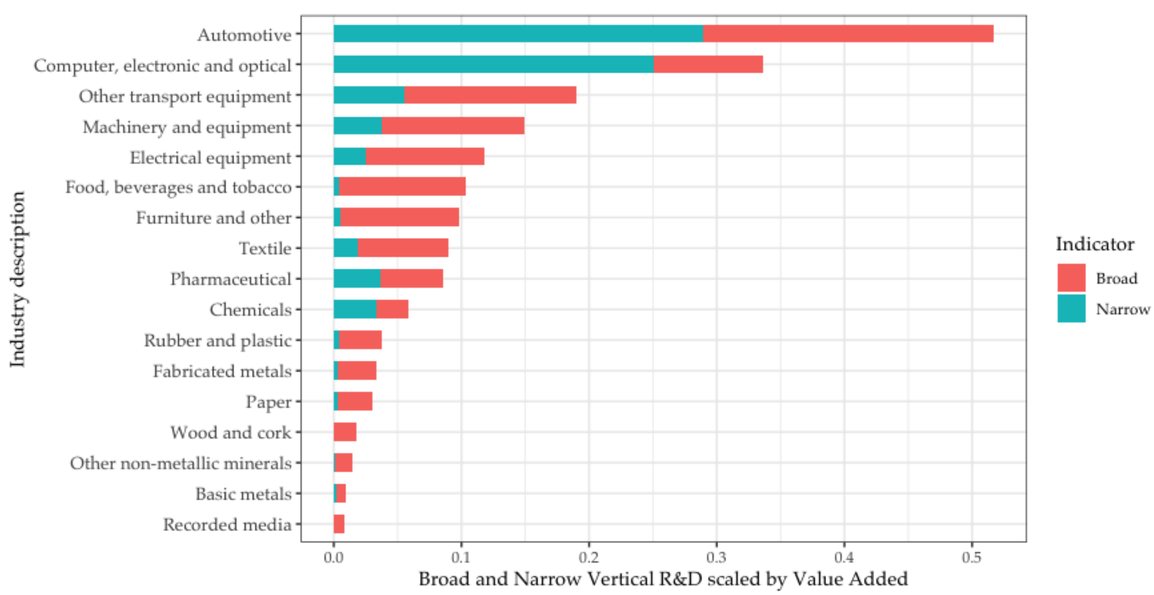

Figure 6: Vertical R&D expenditures in 2014 by industry distinguished by broad and narrow indicators and scaled by Value Added.

One last evidence we provide seeks to merge the sectoral and country dimensions, selecting three countries, Germany (DEU), Italy (ITA) and Poland (POL), and keeping Pavitt Taxonomy highlighted.[22] Moreover, we focus here only on the *foreign* component of technological inputs thus proposing an indicator of Foreign Vertical R&D, again scaled by Value Added, in order to better highlight which are the sectors, within each country, for which the greatest dependence on technological inputs from abroad is detected. For instance, Pharmaceutical industry (in Science Based class) is largely dependent on those inputs in Italy, while way less in the other two countries, which can be explained, for Poland in terms of lower integration and lower size, while for Germany in a different kind of integration, being specialized in more advanced parts of production processes, thus being less demanding on technological inputs. Similarly, Computer, electronic and optical is one of the most demanding on technological inputs both in Italy and in Poland, among the sectors of each country, but the same does not hold for Germany. On the contrary, Automotive is requiring technological inputs at the same intensity in the three countries. Italy and Germany seem to be more similar with regards to Specialised Suppliers (violet industries), while Poland generally displays a very skewed distribution, having only Automotive and Computer, electronic and optical requiring huge amount of technological inputs with respect to the other national activities. Adopting the Pavitt Taxonomy for this country-sector dimension is extremely useful as it allows us to advance conjectures on the productive specialization of countries in terms of *technological* participation to GVCs. Broadly speaking, we could argue that having Science Based (red bars) industries as the more demanding in terms of technologically advanced inputs might denote a weak technological specialization.

Having better understood what these indicators are about, we can move to investigate how technological integration at subsystem level relates with employment dynamics of the respective industry. That is, for instance, if the Italian Automotive industry increases the amount of R&D emobodied inputs required to produce its final goods (i.e. if $VerticalRD_{automotive,Italy}$ increases), we want to see whether this is associated with variation in employment in the Italian automotive industry itself or not.

[22] We select these countries as they well represent the three different economic areas we have in our sample: Core European countries, South Periphery and East Periphery.

Figure 7: Foreign Vertical R&D expenditures scaled by Value Added in 2014 by industry in three countries: Germany (DEU), Italy (ITA) and Poland (POL). Values are normalized between 0 and 1 for each country.

4 Econometric analysis

In this second part of the article we propose an empirical estimation to contribute to the literature on innovation-employment nexus by proposing our set of novel process innovation indicators taking into account vertical integration of sectors. We thus propose a slightly different specification from the one usually adopted in common sectoral investigations of employment dynamics (Van Reenen, 1997; Piva and Vivarelli, 2005; Lachenmaier and Rottmann, 2011; Bogliacino and Vivarelli, 2012; Dosi et al., 2021b) adding the dimension of technological interdependencies. Namely, instead of having only Sectoral R&D expenditures as proxy for innovation activity, we include an indicator of the degree of vertical technological integration, Vertical R&D. As a result, variation in the occupation of country-sector i may end up to be related not only to properties of country-sector i itself (R&D expenditures, value added) but also related to its role in the productive structure in terms of backward linkages of extramural R&D.[23] The econometric specification follows:

$$\begin{aligned} E_{i,t} &= \alpha E_{i,t-1} + \beta_1 SRD_{i,t-1} + \beta_2 VA_{i,t} + \beta_3 VRD_{i,t-1} + \varepsilon_i + \delta_t + \mu_{i,t}, \\ &\text{where } t = 2008,...,2014,\ i = 1,...,406 \end{aligned} \tag{8}$$

Where E is employment, VA value added (to control for size and demand of the industry), SRD R&D expenditures at industry level, with one-period lag following the idea, common in this literature, that innovation takes some time to impact on employment dynamics. VRD is Vertical R&D, our variable of interest (lagged one period too): the amount of extramural R&D expenditures at the subsystem level (i.e. of the supply chain), proxing the degree of vertical technological integration. All variables are expressed in logs. Finally ε_i represents the individual and time-invariant fixed effect, δ_t the time fixed effect and $\mu_{i,t}$ the usual error term.

The empirical question comes as follows: is there a relationship between employment of an industry and the degree of its vertical technological integration in terms of innovative inputs? Our conjecture is that being more vertically integrated in terms of acquisitions of embodied R&D might result in lower labour requirements, other things being equal, because an industry, in order to produce its commodity for whatever final purposes, is crucially dependent on other industries in terms of input-embodied process innovations. Furthermore, the foregoing analytical apparatus aims at assessing the technological effects involved in the product *versus* process dichotomy as distinct from the more generic impact of the outsourcing and offshoring tendencies.

In this sense, having both Sectoral and Vertical measures of R&D-led innovation efforts results in capturing both product and process innovation respectively. As aforementioned, while product innovation is proxied by Sectoral R&D as it is commonly done in literature (Calvino and Virgillito, 2018; Dosi et al., 2021b), we aim to represent features of process innovation with our proposed indicator of Vertical R&D, instead of standard variable seeking to measure investments in capital formation. As said, we aim to detect a negative relationship between Vertical R&D and Employment

[23] In the econometric specification the subscript i stands for country-industry identifier. Hence we end up with 406 observations (14 countries times 29 industries) observed over 7 periods. As a result we have a panel of 2842 observations that then collapse to 2221 due to the adopted estimation techniques.

level.[24]

4.1 The estimation technique

We test employment-innovation nexus by means of dynamic panel model estimated through System-GMM estimation (hereafter, GMM-SYS), largely used in this literature (Heijs et al., 2019). It is designed for short, wide panels ('small T, large N') and to fit linear models with one dynamic dependent variable, additional controls and fixed effects (Roodman, 2009b). GMM-SYS is useful also to address possible endogeneity problems due to the inclusion of the lagged dependent variable. Moreover, endogeneity may arise from other covariates in the model, hence as suggested by Dosi et al. (2021b), all the explanatory variables can be considered as potentially endogenous to labour demand and instrumented when necessary.[25] Finally, GMM-SYS is also preferred when there is strong persistence in the data and when cross-section dimension and variability are larger that the temporal ones, as in our case.[26] The idea to use GMM-SYS in innovation-employment studies was strongly recommended by Piva and Vivarelli (2005) and the overall proposed strategy, common also to the recent work by Dosi et al. (2021b), is in line with what is suggested by Blundell and Bond (1998), Bond et al. (2001) and Roodman (2009a,b). We take advantage of all these suggestions and adopt as preferred estimation method the System-GMM.[27]

Together with lagged employment, we consider all regressors as potentially endogenous variables, thus instrumented with Arellano-Bond logic, using multiple lags. We follow Roodman (2009b,a) in the choice of valid instruments also taking into account the Arellano-Bond test for serial correlation of the error term and the Hansen test for overidentified restrictions. Respecting the diagnostic tests lead us to a parsimonious choice of lags of instruments from (t-3) to (t-4). Moreover, we implement a Pooled OLS (POLS) and a Fixed Effect (FE) estimations, both with robust standard errors clustered by country-industry, as a further check to establish a plausible range in which the autoregressive coefficient of the GMM-SYS estimation should lie in, as suggested by Arellano and Bond (1991) and Bond (2002). In the two-step GMM-SYS estimates the Windmeijer (2005) finite sample correction for standard errors is employed. Results are reported in Table 1 and show five different estimations: Pooled OLS, Fixed Effect and three GMM-SYS varying the indicator of

[24] One could correctly argue that a greater effect in magnitude could be found by focusing on the embodied innovation flowing specifically from upstream industries towards downstream ones, as conjectured by the model proposed in Dosi et al. (2021b). However, we will limit this kind of extension only by selecting upstream industries in the rows of matrix R, while avoiding selecting columns too. This is motivated by two reasons: first, for the sake of comparing two regression coefficients, we believe it is better to keep the same number of observations, that is by assessing the impact of process innovation on the employment of both upstream and downstream industries; secondly, since we are forced to work at two-digit level of aggregation, we argue that a large part of embodied innovation flows are intra-sectoral and as such we would fall short in capturing them. This is especially true for specific sectors as shown in Figure 6.

[25] The endogeneity problem in measuring the effect on innovation on employment is a largely recognised issue in this literature and it has been addressed, by the inclusion of instrumental variables, by adopting two main estimators: the General Moment Method models (GMM) and the two-stage least squares estimator (2SLS). Heijs et al. (2019) in their review of the literature devote lots of attention in describing the different methods of instrumental variables scholars adopted.

[26] For a concise overview on the motivations for adopting GMM-SYS please refer also to Heid et al. (2012).

[27] GMM-SYS estimations are carried out using the `xtabond2` package in Stata (see Roodman, 2009a)

vertical technological integration.

As a first step, the reliability of baseline GMM-SYS estimations (columns 3 to 5) is confirmed by the fact that the coefficients of lagged employment are always within the range established by the upper bound of FE estimation (0.993) and the lower bound of the POLS one (0.517). The validity of the instruments, and hence the consistency of the estimation, is confirmed by the Hansen test and by the Arellano-Bond test. The row for the Hansen test reports the p-values for the null hypothesis of the validity of overidentifying restrictions that we do not reject. The rows for AR(1) and AR(2) show the p-values for the first and second order autocorrelations. As normally detected in literature, there is evidence for strong first-order autocorrelations and none for second-order one. These diagnostic tests confirm the reliability of our specification.

4.2 Results and robustness checks

GMM-SYS1, column (3), represents our baseline econometric specification. Coefficient of lagged number of employees is significative, positive and of sizeable magnitude, confirming the highly persistent nature of employment variables. Value added coefficient is significative and positively related to employment, as it is commonly found in the literature. It must be pointed out that value added is not meant just to control for the size of the industry but also to take into account the Keynesian role of demand, always positive and relevant in boosting employment. The coefficient of Sectoral R&D is positive, as the majority of evidence suggests, but it is not significative and rather small in magnitude. This can be explained by the fact that we are including together so-called upstream and downstream industries, while R&D is actually relevant in spurring product innovation and hence in increasing the demand for labour mainly in upstream R&D intensive industries (Bogliacino and Vivarelli, 2012; Dosi et al., 2021b). Coming to our variable of interest, lagged Vertical R&D, we clearly detect a significant and negative relationship with employment at time t with an elasticity (as both variables are in log terms) of -0.108%. That is, if the industries in European countries that we consider become 10% more technologically integrated at time t-1 (i.e. the amount of Vertical R&D increases by 10%), then their employment level, or demand for labour, at time t will decrease on average by 1%. For instance, if Automotive in Italy absorbs 150 thousands workers at time t-1 but requires a 10% more of technological inputs, the following year it will get rid of 1500 workers. This may be due to the labour-saving tendency of expanding vertical integration through increasing acquisitions of new technologically advanced inputs, likely shutting down previous internal activities and thus requiring less workers in favour of more advanced inputs produced elsewhere. It must be specified that requiring more technological inputs at t-1 may be due to two interrelated phenomena: the industries providing inputs have increased the amount of R&D expenditures that subsequentially get embodied in the good produced, or the final production simply increases the amount of inputs required externally in the supply chain.

Columns 4 (GMM-SYS2) and 5 (GMM-SYS3) represent robustness checks of our results against using two measures explored in the descriptive statistics of section 3.1. In GMM-SYS2 (4) we substitute the variable of interest by selecting the industries in the chain related to upstream activities, that is Science Based and Specialised Suppliers Pavitt classes. We call this indicator *Vertical UP R&D* and we detect a more pronounced relationship with employment, both in terms of magnitude and significance (at 1% level). This can be explained by the fact that such upstream industries are the ones producing the more technological inputs, which are more likely to displace workers activities. This result is important as it reports that our attempt to capture the dependence from technologically advanced inputs is in a way substantiated by the evidence. To be on the safe side, GMM-SYS3 (5) instead considers Vertical R&D scaled by Value Added in order to control for the size of the supply chain, as explained in section 3.1. The statistical significance is slightly lower but the magnitude is greater and the sign is confirmed. Moreover, in this check we also scale Sectoral R&D by Value Added, again resulting in positive but not significant coefficient.

In Table 2 we present three robustness checks in addition to those shown in Table 1. In GMM-SYS SS1 and GMM-SYS SS2 we implement a sub-sampling with respect to sectors and countries respectively. In regression (1) we omit services sectors absorbing huge amount of workforce and whose data on R&D are missing for some countries.[28] In (2) we remove three big countries belonging to three commonly identified economic areas of Europe: Germany for core countries, Italy for south periphery and Poland for eastern periphery. In (3) we increase the range of lags available for the instruments of the System-GMM, thus imposing no restrictions. All outcomes confirm our previous results with the only weakness of the Hansen test in regression (3) which might cast some doubt on the validity of instruments. However, magnitude, sign and significance of our main variable are confirmed, which makes us confident of the overall goodness of the result.

The economic intuition behind these findings is that the amount of innovation embodied in the inter-sectoral flows of intermediaries, which we label as technological interdependencies (and measure with Vertical R&D indicators), is a driver of sectoral employment dynamics. In particular, the more technological inputs are required, the less workers are absorbed by the sector. This can be due to the very processes of outsourcing and offshoring lying behind the increase in technological integration and/or by the technological content of inputs we have highlighted with our methodology. In this framework, the improvements in productive efficiency characterizing a given production process (i.e. the making of a given commodity within each subsystem) entails a labour saving effect of process innovations by means of substituting labour with advanced technological inputs. It must be stressed that the acquisition of such inputs is originally activated by the effective components of final demand (consumption and investments) to produce a given commodity. In this sense, the process innovation spurred by Vertical R&D is induced by the effective demand for the goods produced by the industry adopting the technological inputs. Hence, demand can have two crucial counteracting effects: on one hand, by boosting production it leads to higher labour requirements (see the value added proxy for this effect); on the other, the larger the final demand, the higher is in turn the amount of technological inputs demanded that are likely inducing job displacements, as our results suggest. Therefore, technological interdependencies, visualized with vertically integrated

[28]These sectors are: Accommodation and food service activities (I), Administrative and support service activities (N), Human health and social work activities (Q).

Table 1: Baseline results

	Pooled OLS (1)	FE OLS (2)	GMM-SYS1 (3)	GMM-SYS2 (4)	GMM-SYS3 (5)
Log(Employees)$_{t-1}$	0.993***	0.517***	0.897***	0.880***	0.829***
	(0.00255)	(0.0519)	(0.0544)	(0.0577)	(0.0884)
Log(Sectoral R&D)$_{t-1}$	-0.0000249	0.0183***	0.00985	0.0153	
	(0.00110)	(0.00593)	(0.0173)	(0.0185)	
Log(Sectoral R&D / VA) $_{t-1}$					0.0172
					(0.0204)
Log(Value Added)	0.0114***	0.201***	0.199***	0.233***	0.157***
	(0.00254)	(0.0278)	(0.0641)	(0.0631)	(0.0588)
Log(Vertical R&D)$_{t-1}$	-0.00134	0.00713	-0.108**		
	(0.00171)	(0.00858)	(0.0500)		
Log(Vertical UP R&D)$_{t-1}$				-0.122***	
				(0.0450)	
Log(Vertical R&D / VA)$_{t-1}$					-0.129**
					(0.0560)
Observations	2221	2221	2221	2221	2221
Number of groups			388	388	388
Number of instruments			36	36	36
Hansen test (p-value)			[0.085]	[0.117]	[0.155]
Diff-in-Hansen test			[0.161]	[0.220]	[0.146]
AR(1) (p-value)			[0.000]	[0.000]	[0.000]
AR(2) (p-value)			[0.135]	[0.116]	[0.143]

Notes: Dependent variable is employment level in all specifications (Log(Employees)$_t$). Standard errors in parentheses, p-values in brackets. Pooled and Fixed Effect OLS adopt robust standard errors clustered by country-industry. GMM-SYS regressions (columns 3 to 5) implement two-step estimations and use Windmeijer (2005) finite sample correction for standard errors. In the Arellano-Bond test we do not reject the null hypothesis of second order correlation. This allows us to start from (t-2) lags in instrumenting variables but in order to fulfil the Hansen test too, not rejecting the null hypothesis of the validity of the moment conditions used in instrumenting the variables, we end up with a minimum lags of (t-3) for all endogenous variables. A parsimonious choice of the lags led us to a time span ranging from (t-3) to (t-4). Following Roodman (2009b) we report also the Diff-in-Hansen test for GMM level instruments for the validity of the additional moment restrictions. In a further robustness check in Table 2 we allow the lags to go from (t-3) until the end of the period. Yearly time dummies and the constant are included in the regressions but omitted from the output table.*, ** and *** denote significance level of 10%, 5% and 1%.

Table 2: Robustness checks

	GMM-SYS SS1 (1)	GMM-SYS SS2 (2)	GMM-SYS NR (3)
Log(Employees)$_{t-1}$	0.944***	0.889***	0.952***
	(0.0451)	(0.0429)	(0.0450)
Log(Sectoral R&D)$_{t-1}$	0.0206	0.00549	0.0135
	(0.0251)	(0.0132)	(0.0186)
Log(Value Added)	0.149**	0.192***	0.164***
	(0.0617)	(0.0473)	(0.0595)
Log(Vertical R&D)$_{t-1}$	-0.0984*	-0.0879***	-0.114*
	(0.0568)	(0.0233)	(0.0583)
Observations	2027	1758	2221
Number of groups	351	306	388
Number of instruments	37	39	43
Hansen test (p-value)	[0.113]	[0.119]	[0.0240]
Diff-in-Hansen test	[0.202]	[0.397]	[0.317]
AR(1) (p-value)	[0.000]	[0.000]	[0.000]
AR(2) (p-value)	[0.157]	[0.162]	[0.130]

Notes: Dependent variable is employment level in all specifications (Log(Employees)$_t$). Standard errors in parentheses, p-values in brackets. Yearly time dummies and the constant are included in the regressions but omitted from the output table.

*, ** and *** denote significance level of 10%, 5% and 1%.

sectors algorithm, represent the relationships between suppliers and users of technology embodied in intermediaries and these linkages can broadly represent the effective bridge between product innovations in upstream industries with process innovations in downstream ones with the initial trigger given by final demand. Moreover, such linkages are international and thus intermediate and final demand become international too. In this configuration, labour-saving technical progress is 'an unavoidable process' (Pasinetti, 1981, p. 227) related to the evolution of productive structure and its interdependencies, with cross-sector and cross-country effects fueled by the increasing global fragmentation of production that brings about a larger diffusion of innovation and a consequent impact on employment.

To sum up, what we learn, at least focusing on the European production system, is that employment changes within sectors are inevitably linked with process innovations that originally were the product innovations taking place in all the upstream activities providing them inputs. The effect on employment, however, depends on the magnitudes of the technological interdependencies conncecting the inter-sectoral dynamics of product *versus* process innovations with the *primum movens* of final demand.

5 Discussion and concluding remarks

This work develops the concept of technological interdependencies and aims at testing their role on determining sectoral employment dynamics, contributing to the literature on the innovation-employment nexus but linking it with the streams of research on inter-sectoral knowledge diffusion and GVCs participation. The main novelty comes from the use of an indicator of vertical technological integration, our proxy of technological interdependencies, which measures the amount of R&D expenditures embodied in the supply chain of an industry, the so-called subsystem dimension. Such measure, which we labeled Vertical R&D, has been obtained out of the matrix of inter-sectoral embodied innovation flows, constructed with a specific methodology aimed at using the notion of vertically integrated sectors to transform industry-by-industry into industry-by-subsystem I-O tables. This algorithm enabled us to capture the role of each industry in providing the technology embodied in inputs for the production of final commodities, and inversely the role of each subsystem (final good sector) in acquiring them (Siniscalco, 1982; Marengo and Sterlacchini, 1990; Leoncini and Montresor, 2003).

Vertical R&D and related alternative measures have been used to collect descriptive evidence on the vertical feature of dependence from technological inputs, highlighting heterogeneity in terms of sector and country cross-sectional characteristics. Afterwards, we took advantage of these variables to make a contribution to the innovation-employment literature, by testing whether Vertical R&D, as an original proxy for process innovation, matters in determining the dynamics of employment. Results show a statistically significant and negative relationship. In words familiar to I-O analysis, we detect an important role for backward linkages, within a technological dimension, in affecting employment dynamics. In line with recent findings by Dosi et al. (2021b), the often optimistic labour-friendly effect of technological change is questioned in this work, but from a so far unexplored dimension entailing the concept of technological interdependencies. Our findings are robust to a series of checks, both in terms of econometric specification and in terms of adopting alternative indicators of vertical integration.

These results suggest that technological change affecting employment dyanamics is a phenomenon that overcomes national and sectoral boundaries and that it is closely linked to the on-going mutations of the weights of economic branches. Economic systems, as European countries considered in this work, are nowadays deeply intertwined also in technological terms and their structural dynamics constantly affect the employment structure. In particular, the more you get integrated, likely externalizing part of your economic activities or performing process innovation by acquiring technologically advanced inputs, the less labour you require internally. This hints to a technological dimension of Global Value Chain which has been poorly addressed so far, notwithstanding a well established methodology that allows to take it into account. Innovation cannot be seen as enclosed within the boundaries of the firm or the industry which spurs it, but rather spreads through the domestic and international productive structure and its effect on employment dynamics might show up also in activities distant from the ones where the initial innovation effort has been made. In addition, product innovation in the suppliers of technological inputs is activated by the final demand for the commodity produced in the sector where such inputs induce process kind of innovation. As such, technological interdependencies are the channels through which demand in one industry stimulates innovation in another which in turn displaces workers in the former.

There are limitations for the analysis we put forward. First of all, data restrictions, mainly on R&D data, forced us to focus only on European supply chains. Hence a natural extension of this work must entail an effort to re-gain a global dimension, starting from the inclusion of other OECD countries. Related to this is the need to better address the role innovation embodied in services, which was not possible to be included in this work, but that deserves a specific focus. Secondly, we have claimed throughout the paper that two-digit level of aggregation is preventing us to capture a relevant part of productive and technological interdependencies, as in some sector (as Automotive), firms are demanding inputs and technological components from other firms within the same industry. This is a limit deriving from current data availability, but firm-level or case studies could be seen as good alternatives to shed light on this missing element of analysis, the *intra*-sectoral flows of technology. A further natural extension could be to disentangle employment by occupations, as it has been done elsewhere (Bogliacino et al., 2013; Reljic et al., 2021; Bramucci et al., 2021; Bontadini et al., 2021a). This goes together with further efforts in investigating the flow of jobs in value chains triggered by structural change and technological progress as it is clear that labour can be displaced, but also shifted and activated in other branches of the domestic and global economy. Lastly, in future works an effort should be devoted in better distinguishing process innovation from outsourcing and offshoring of technological inputs, which is somehow related with aforementioned extensions.

In conclusion, the analytical and empirical framework proposed in this article can be seen as providing a broad picture on the mechanisms at work in nowadays globally integrated productive structures, where the production of a final commodity in one country stimulates R&D investments in various branches of other countries. Conversely, these innovation efforts might get embodied in intermediaries then adopted by other sectors of the supply chain to improve productive process with possible detrimental outcomes for the workers engaged. It goes without saying that these insights imply that the management of final demand, innovation spillovers and employment dynamics should be at the core of any industrial and innovation strategy, focusing on the balance between demand creation and labour displacement which defines the general conditions of macroeconomic stability and utilization of the labour force (more in Dosi, 1984b; Dosi et al., 2021a).

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A Data and descriptive statistics

Code	Industry descriptions	Pavitt Class
	Manufacturing	
C10-C12	Manufacture of food products, beverages and tobacco products	SD
C13-C15	Manufacture of textiles, wearing apparel and leather products	SD
C16	Manufacture of wood and of products of wood and cork, except furniture	SD
C17	Manufacture of paper and paper products	SII
C18	Printing and reproduction of recorded media	SII
C20	Manufacture of chemicals and chemical products	SB
C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations	SB
C22	Manufacture of rubber and plastic products	SII
C23	Manufacture of other non-metallic mineral products	SII
C24	Manufacture of basic metals	SII
C25	Manufacture of fabricated metal products, except machinery and equipment	SD
C26	Manufacture of computer, electronic and optical products	SB
C27	Manufacture of electrical equipment	SS
C28	Manufacture of machinery and equipment n.e.c.	SS
C29	Manufacture of motor vehicles, trailers and semi-trailers	SII
C30	Manufacture of other transport equipment	SS
C31-C32	Manufacture of furniture; other manufacturing	SD
C33	Repair and installation of machinery and equipment	SS
F	**Construction**	
	Services	
G45	Wholesale and retail trade and repair of motor vehicles and motorcycles	SD
I	Accommodation and food service activities	SD
J58	Publishing activities	SII
J59-J60	Video, music and broadcasting activities	SII
J61	Telecommunications	SB
J62-J63	Computer programming, consultancy and related activities; information service activities	
L68	Real estate activities	SS
M72	Scientific research and development	SB
N	Administrative and service activities	SS
Q	Human health and social work activities	

Table 3: List of sectors in 2-digit NACE Rev. 2 classification. Pavitt classes are: Science Based (SB), Specialised Suppliers (SS), Scale and Information Intensive (SII) and Suppliers Dominated (SD)

Code	Description	
SB	Science Based	upstream
SS	Specialised Suppliers	upstream
SII	Scale and Information Intensive	downstream
SD	Suppliers Dominated	downstream

Table 4: Pavitt Taxonomy

Country	Code
Austria	AUT
Belgium	BEL
Czech Republic	CZE
Finland	FIN
France	FRA
Germany	DEU
Hungary	HUN
Italy	ITA
Lithuania	LTU
The Netherlands	NLD
Poland	POL
Portugal	PRT
Slovenia	SVN
Spain	ESP

Table 5: List of countries

Variable	Obs	Mean	Std. Dev.	Min	Max
Employees	3248	180.842	430.627	.4	5264
Vertical R&D	3248	50.482	131.708	-1.942	1790.435
Sectoral R&D	2949	361.687	1276.64	0.0003	25577.919
Value Added	3248	14925.519	36631.545	26.615	398636.81

Table 6: Descriptive statistics. While Employees are expressed in thousands of persons engaged, Vertical R&D, Sectoral R&D and Value Added are expressed in millions of US dollars.

Variables	Employees	Indirect R&D	Sectoral R&D	Value Added
Employees	1.000			
Vertical R&D	0.726	1.000		
Sectoral R&D	0.307	0.543	1.000	
Value Added	0.873	0.796	0.481	1.000
Spearman rho = 0.481				

Table 7: Spearman correlation coefficients