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ABSTRACT

New Technologies and Employment: The State of the Art*

The relationship between technology and employment has long been a topic of debate. This issue is even more pertinent today as the global economy undergoes a technological revolution driven by automation and the widespread adoption of Artificial Intelligence. The primary objective of this paper is to provide insights into the relationship between innovation and employment by proposing a conceptual framework and by discussing the state of the art of the debates and analyses surrounding this topic.

JEL Classification: O33
Keywords: technology, employment, compensation theory, AI, robot

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1. Introduction

The relationship between technology and employment has always been a "hot" topic both for social scientists and policy makers, at least since the first industrial revolution. Indeed, claims of technologically caused unemployment tend to re-emerge at times of radical technological change such as countries are currently experiencing, facing the arrival of automation and artificial intelligence (AI) technologies.

Today, debate focuses on three main questions: What are the roles of technology and innovation in explaining the long-term declining trend of manufacturing as a share of the modern economy? Are new technologies, such as robots and artificial intelligence, replacing humans? Are job losses due to the advent of robots and AI structural and therefore inevitable?

Contextualizing, McKinsey (2017) forecasts that nearly 50% of work activities could be automated by 2055. Specific sectors, such as "Accommodation and Food Services" (66%), "Manufacturing" (64%), and "Transportation and Warehousing" (60%), are particularly susceptible to automation (Figure 1).

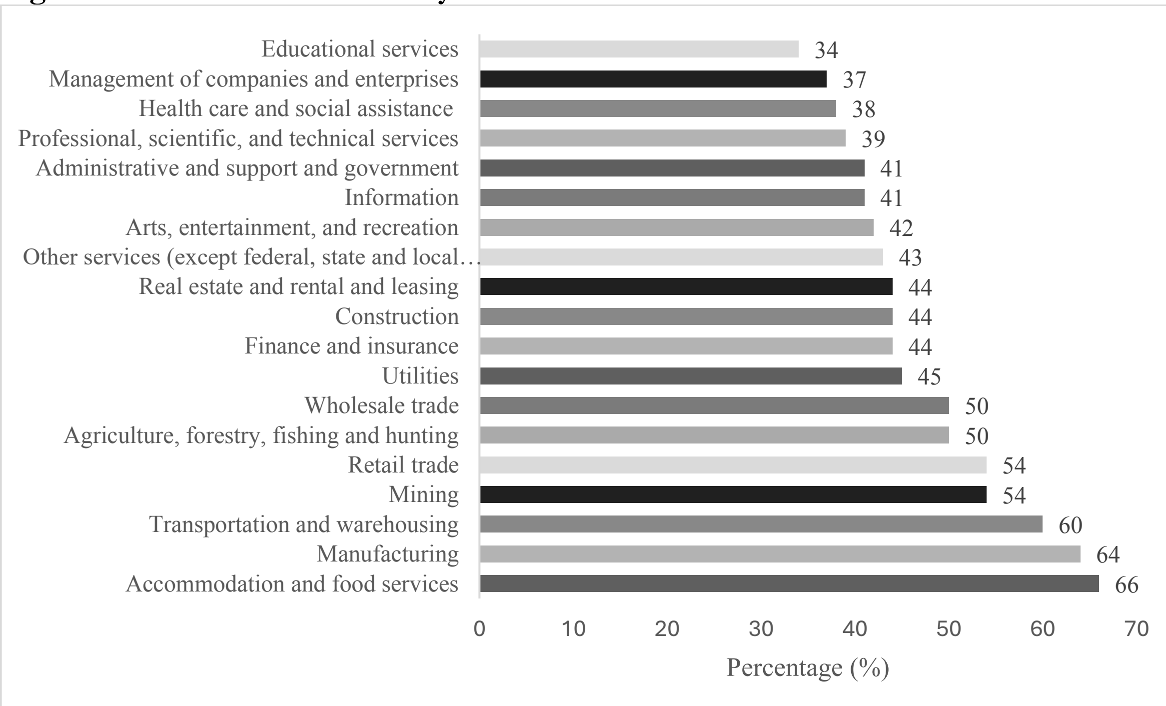
A more recent report from Goldman Sachs (2023) estimates that 25% of current jobs in the United States and 24% in the European Union could be automated. In the U.S., industries most exposed to AI include "Office and Administrative Support" (46%), "Legal" (44%), and "Architecture and Engineering" (37%), while sectors such as "Building and Grounds Cleaning and Maintenance" (1%), "Installation, Maintenance, and Repair" (4%), and "Construction and Extraction" (6%) are among the least exposed (Figure 2).

This somewhat pessimistic outlook has gained significant attention among scholars to explore the potential impacts of new technologies on the labor market. New statistical tools and machine learning methods are enabling researchers to analyze more granularly which technologies affect specific jobs and tasks. For instance, Felten et al. (2018) and Felten et al. (2021) found that white-collar workers in the U.S. are more exposed to AI-driven automation.

Conversely, Webb (2020) shows that robots primarily affect low-wage occupations, software alters medium-wage occupations, and high-wage occupations are most vulnerable to AI. More recently, Montobbio et al. (2023) found that low-wage jobs concentrated in production are particularly exposed to robotic labor-saving technologies, especially in installation and maintenance roles. Their study also notes that service-based activities, such as those performed by logistic and healthcare workers, are increasingly exposed to robotic technologies.

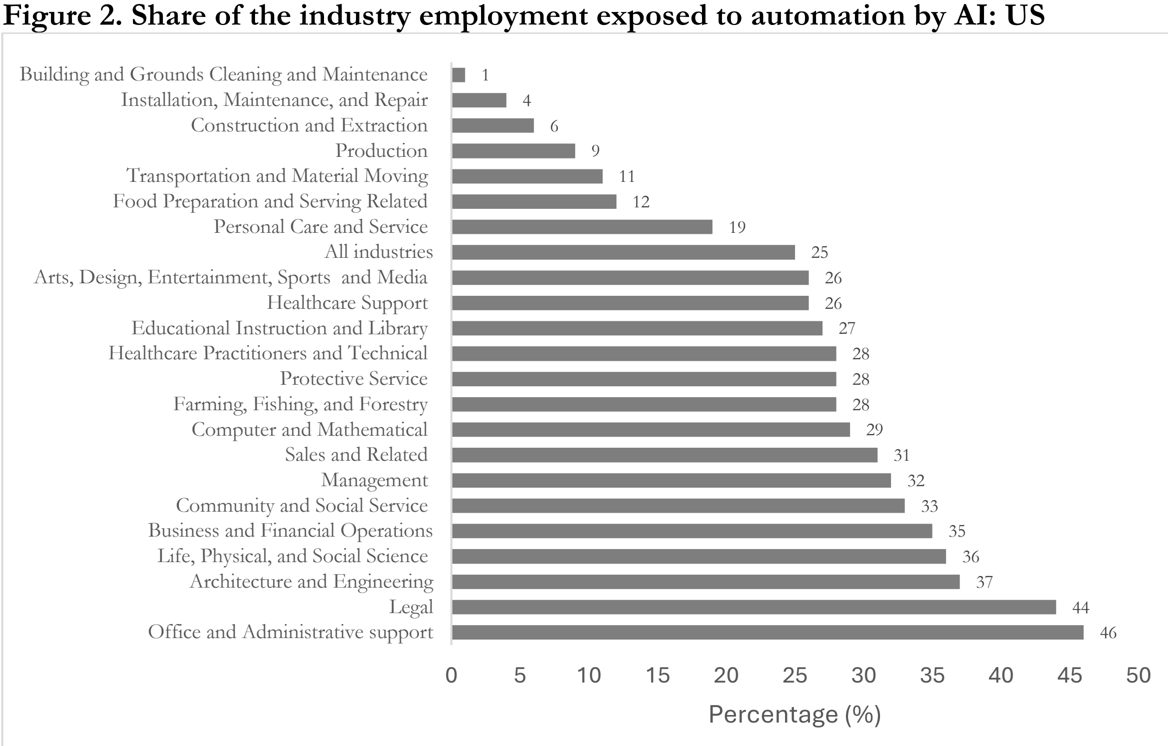
However, the impact of innovation on employment is not trivial, and it requires understanding the all-possible theoretical mechanisms involved in this relationship: labor-creating (mainly from product innovation), labor-saving (mainly from process innovation), and the so-called market compensation mechanisms, potentially able to counterbalance the initial labor-saving impact of innovation (see Section 2.2).

Figure 1. Potential automation by 2055 in different sectors



Source: Oxford Economic Forecasting; US Bureau of Labor Statistics; McKinsey analysis (2017)

Figure 2. Share of the industry employment exposed to automation by AI: US



Source: taking from Goldman Sachs' report (2023). Goldman Sachs Global Investment Research

In more detail, while process innovation can be job-destroying, product innovation can imply the emergence of new firms, new sectors, and thus new jobs. But even for process innovation, the final impact on labor demand is shaped by market mechanisms that can compensate for the direct job- destroying impact, if market and institutional rigidities do not impede them.

Furthermore, a Schumpeterian vision is essential for better understanding the relationship between innovation and employment. Schumpeter (1939, 1947) argues that technical unemployment arises from disparities between the skills and abilities of workers displaced from old sectors and those required by emerging ones. This view - focusing on "creative destruction" - emphasizes that while some jobs disappear, new roles are simultaneously created (Díaz, Guerrero, et al., 2024).

Additionally, as highlighted by Dosi et al. (2021), innovation should not be viewed as an exogenous or isolated phenomenon. Instead, it influences the entire socio-economic system. In other words, innovation not only impacts the firms or sectors that introduces it, but also might affect related firms and industries. For instance, a robot might serve as a process innovation for downstream sectors while simultaneously functioning as a product innovation for upstream sectors (Díaz, Barge-Gil, et al., 2024; Dosi et al., 2021).

Drawing on the previous literature, the main objective of this study is to analyze the relationship between innovation and employment through a comprehensive conceptual framework, considering on the one hand the possible labor-saving impact of technological change, the scope for job creation on the other hand and focusing in particular on the market and institutional mechanisms that can shape the final labor demand outcomes. To achieve this, we first put forward an interpretative theoretical framework and then we critically discuss the key empirical studies that have explored this relationship (including studies that focus on new technologies, such as robotics and artificial intelligence, to provide a comprehensive understanding of how these recent innovations impact employment).

The remainder of the paper is structured as follows: in Section 2 we discuss the main theoretical mechanisms determining the relationship between innovation and employment. Section 3 discusses the empirical literature through a selection of previous studies. In Section 4 we summarize the main findings, while Section 5 concludes.

2. A theoretical framework

2.1 A comprehensive conceptualization

One of the main drivers of the long-term deindustrialization trend in developed countries is the productivity gap between manufacturing and services. Indeed, technological change is singled out as the main determinant of the productivity improvements that entail job losses in manufacturing and that therefore lead to the declining share of industrial employees in total employment. However, more recently, automation and AI diffusion have made possible a similar labor-saving prospect in service industries ranging from the financial sectors to trade and retail.

Referring to the theory put forward by the economists of innovation, there are two basic innovation inputs: research and development (R&D), which may lead to product innovation, and embodied technological change, which may lead to process innovation. R&D investments are the key innovation input in the approach originally proposed in 1979 by Zvi Griliches, who identified the concept of the "knowledge production function" (Griliches, 1979).

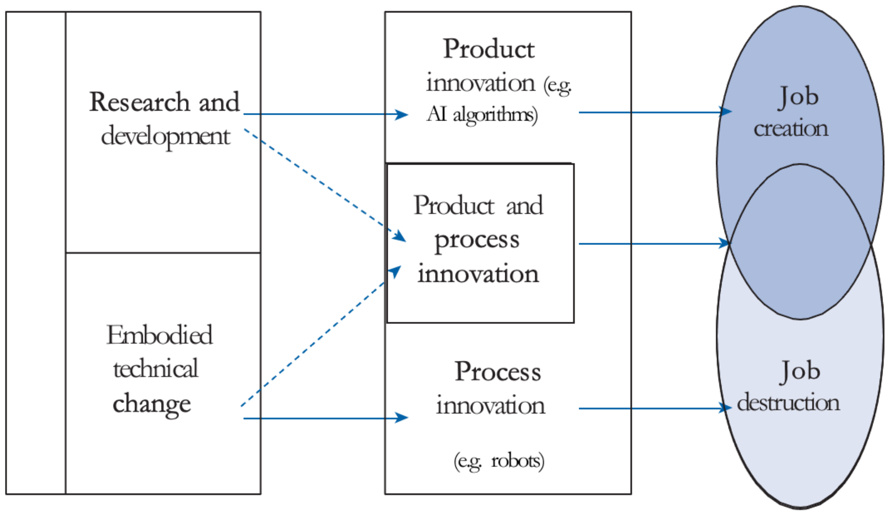
In this functional relationship linking innovative inputs to innovative outputs, firms pursue new economic knowledge as an input into generating innovative activities. Indeed, a vast literature has identified a strong significant link between R&D investment, innovation, and productivity gains, demonstrating that R&D is a main driver of technological progress at macroeconomic, sectoral, and microeconomic levels (Crepon et al., 1998). Meanwhile, embodied technological change involves process innovation, or innovation that is incorporated in investments in capital goods (machinery and equipment, for instance robots and other automation devices) (Freeman & Soete, 1987).

Moreover, the innovation literature suggests that it is mainly large high-tech firms that rely on formal R&D to drive complex product innovation, while embodied technological change plays a key role in small- and medium-size firms in more traditional industries (Pavitt, 1984).

As mentioned above, of the two main drivers of technological change, R&D is mainly related to product innovation, and embodied technological change is more closely related to process innovation. However, in some circumstances, the distinction between product innovation and process innovation is ambiguous from an empirical point of view (consider, for instance, the diffusion of ICT in the past decades, and artificial intelligence nowadays), and in many cases the two forms of innovation are interrelated. Moreover, both R&D and embodied technological change participate in mixed innovative activities that entail both product and process innovation. Figure 3 illustrates the main links between innovative inputs, innovative outputs and their eventual impact on the labor market.

Obviously enough, process innovation and product innovation involve different employment impacts (as shown in the right panel of Figure 3). Process innovation results in a direct labor-saving (job-destroying) effect, related mainly to the introduction of machinery and equipment that can substitute for labor and allow the production of the same amount of output with fewer inputs (generally workers). On the one hand, product innovation can entail a job-creating effect through the emergence of new industries and new markets. However, on the other hand, the same innovation can play the role of product innovation in a given sector (supply side) and the role of process innovation in another industry (demand/adoption side). For example, the design and implementation of a new AI algorithm is a product innovation in the supplier industries and may entail job creation (e.g. an increase in the demand for data scientists). However, the same algorithm may imply job losses when is adopted in the user sectors as a process innovation (e.g. a drop in the demand for bank clerks).

Figure 3. The two faces of innovation: how product and process innovation affect employment



Source: Author's own illustration.

2.2 The labor market implications of process innovation and the compensation mechanisms

Since by definition process innovation means producing the same amount of output with less labor (and sometimes other) inputs, the direct impact of process innovation is job destruction when output is fixed. However, economic analysis has demonstrated the existence of countervailing economic forces that can compensate for the reduction in employment arising from technological progress. Indeed, the classical economists put forward a theory that Marx later called the "compensation theory"(Pianta, 2005; Vivarelli, 1995, 2013, 2014). These compensation mechanisms include new machinery, lower prices, new investments, and lower wages.

2.2.1 The compensation mechanism via new machinery

The effect of the introduction of new machinery (for instance robots) is ambiguous. On the one hand, process innovations displace workers in downstream industries that introduce the embodied technological change incorporated in the new capital goods. On the other hand, additional workers are needed in the upstream industries that produce the new machinery.

However, there are at least three arguments against the efficacy of this compensation mechanism. First, for the introduction of the new machinery to be profitable, the cost of labor associated with the construction of the new machinery has to be lower than the cost of labor displaced by the new capital goods. Second, labor-saving technologies spread to the capital goods sector as well as to the product sector, so this compensation can be an endlessly repeating story, with only partial labor compensation. Third, and most important, the new machinery can be implemented through either new investments or by the replacement of obsolete machinery (scrapping). In the case of scrapping of obsolete machinery, which is the most common case, there is no compensation at all for the resulting job losses (Vivarelli, 1995, 2014).

2.2.2 The compensation mechanism via lower prices

While process innovations destroy jobs, the changes that they introduce lead to declining average costs. Assuming perfect competition, this effect is translated into lower prices, which in turn imply rising demand and therefore additional production and employment (Vivarelli, 1995 and 2013).

However, this line of reasoning does not take into account possible demand rigidities. For instance, pessimistic expectations by firms may delay expenditure decisions, resulting in lower demand elasticity. In that case, the compensation mechanism of lower prices fails to operate as expected, and technological unemployment becomes structural. In fact, since process innovations are continuously introduced into the economy, a delay in expenditure decisions is sufficient to create a component of unemployment that persists over time (Vivarelli, 2014).

Finally, the effectiveness of the mechanism that plays out through lower prices depends on the assumption of perfect competition. In an oligopolistic market, this compensation mechanism is severely weakened since cost savings are not necessarily or entirely translated into lower prices (Vivarelli, 1995 and 2014).

2.2.3 The compensation mechanism via new investments

If the assumption of perfect competition is dropped, the decline in costs resulting from technological advances is not necessarily or immediately followed by falling prices. That means that the innovative firm can reap extra profits. If these extra profits are re-invested in the firm, this investment can create new jobs (Vivarelli, 2013 and 2014).

However, this compensation mechanism through new investments is based on another assumption: accumulated profits due to innovation are entirely and immediately translated into additional investments. In fact, because of cautious or even gloomy expectations, a firm may decide to postpone any new investment. In this case, again, a substantial delay in realization of this compensation mechanism may imply structural unemployment. Moreover, the nature of any new investment is important. If investments are capital- rather than labor-intensive, compensation for job losses through investment can only be partial (Vivarelli, 1995, 2013, 2014).

2.2.4 The compensation mechanism via declining wages

In a partial equilibrium framework that considers the equalizing of demand and supply only within the labor market (rather than dynamically, within the economy as a whole), the direct effect of labor-saving technologies may be compensated for within the labor market itself. Under the assumption again of perfect competition and full substitutability between labor and capital, technological unemployment leads to a decline in wages as a consequence of an excess supply of labor, and this impact in turn induces a shift back to more labor-intensive technologies.

However, countering this compensation mechanism of falling wages is the Keynesian theory of "effective demand." While falling wages might be expected to induce firms to hire additional workers, it may also be the case that the shrinking of aggregate demand as a result of falling wages could lower employers' business expectations and so their willingness to hire additional workers.

Moreover, this compensation mechanism assumes perfect substitutability between capital and labor, which is often not the case, especially under conditions of cumulative and irreversible technological progress (Freeman & Soete, 1987; Vivarelli, 1995).

2..2.5 On balance

The market compensation mechanisms discussed so far emerge as powerful forces counterbalancing the initial job destruction impact of process innovation. However, the functioning of these mechanisms is hindered by many institutional and market failures that can greatly weaken their efficacy. Eventually, determining how effective these mechanisms are is a matter for empirical analysis (see below). Interestingly enough, this "classical" theoretical framework is still a proper benchmark to assess the eventual employment impact of the new technologies brought about by the AI revolution.

2.3 Product innovation

The picture is far clearer in the case of product innovation than of process innovation. Obviously, the introduction of new products and the consequent emergence of new markets involve job-creation effects. Consider, for example, how many direct and indirect jobs were created as a result of the invention of the automobile at the beginning of the 20th century or of the personal computer later in that century. Nowadays, AI devices conceived as product innovations in the upstream industries may also entail job creation. Indeed, classical economists emphasized the labor-intensive impact of product innovation, and even the most severe critic of an optimistic vision of the employment consequences of technological change (such as Karl Marx) have admitted that product innovation leads to positive employment effects (Vivarelli, 1995, 2014).

However, from a theoretical point of view, the labor-friendly impact of product innovation may be stronger or weaker, depending on several circumstances (like, for instance, the occurrence of substantial organizational change as a necessary complement to product innovation, see Lee & Jung, 2024). Moreover, the "welfare effect" of product innovation (the creation of new goods, new industries and additional employment) needs to be balanced against the "substitution effect" (the displacement of mature products by new ones: think, for instance, of how smartphones have replaced cameras, music players, fax machines, and even computers (Katsoulacos, 1986). In other words, different technological advances result in different families of new products, which in turn may have different effects on employment. For example, while both the introduction of the automobile at the beginning of the 20th century and the diffusion of personal computers at the end of that century clearly had job creating effects, automobiles had a much greater labor-intensive impact than home computers in the past or AI nowadays (at least so far) (Acemoglu & Restrepo, 2020b; Freeman & Soete, 1987).

2.4 Current debate

Nowadays, a theoretical revival simplifies all the compensation mechanisms discussed above (Corrocher et al., 2024). This vision puts forward opposing forces affecting the relationship between innovation and employment (Acemoglu & Restrepo, 2018b, 2020a). The first force assumes that job tasks can be automated depending on factor prices and the elasticity of substitution between capital and labor (displacement effect). The other forces point to counterbalancing mechanisms that may offset the displacement effect. The first "self-correcting" force is the productivity effect involving the compensation mechanism via lower prices discussed above. The second "self-correcting" mechanism is called "capital accumulation," which is very similar to the compensation mechanism via new investments, also discussed above. Finally, the third "self-correcting" force is the reinstatement effect, which implicitly refers to the compensation mechanism operating through the emergence of new products and new industries. Similar to the compensation mechanism theory, the efficacy of these mechanisms depends on many institutional and market forces that can significantly weaken them (Acemoglu & Restrepo, 2018a).

The discussion above is put forward at the macro-level of analysis, but there are also some insights from the firm-level, where the displacement and compensation effects can work. For instance, companies that adopt labor-saving technologies (process innovation) to improve productivity can reduce prices (in non-monopolistic markets). This gives companies that adopt the new technologies a higher market share than the non-adopter firms ("business stealing effect"). Therefore, the net effect might well be an increase in the employment at the level of a single firm and a negative employment impact at the industry level. Also, companies can offset the displacement effects of labor-saving technologies by introducing new products or tasks. Finally, compensation via re-investment (due to the extra profits) might also mitigate the displacement effect at the firm level (Corrocher et al., 2024; Koch et al., 2021).

On the whole, the accomplishment of all mechanisms mentioned before is doubtful, especially because they depend on several factors, assumptions, and elasticities. This implies that economic theory is inconclusive about the relationship between employment and technological change. However, theoretical models can be complemented by empirical analyses to understand the phenomenon better.

3. Empirical evidence

As the discussion to this point has indicated, theoretical models do not provide clear-cut answers about the final employment impact of technological change. For that, empirical analyses are needed that can take into account the various forms of technological change, their direct effects on labor, the different compensation mechanisms at play in process innovation, and the likely impediments to these mechanisms.

3.1 Empirical evidence at the macro level

Very few macroeconometric studies have tried to test the validity of compensation mechanisms through aggregate empirical studies conducted within a general equilibrium framework.

Directly connected with the theoretical framework put forward in the previous section, one study estimated the direct labor-saving effect of process innovation, various compensation mechanisms (with their transmission channels and their possible drawbacks), and the job-creating impact of product innovation in two advanced Western economies, namely Italy and the US, over the period 1960–1988 (Vivarelli, 1995). This study found that the most effective compensation mechanism for limiting employment losses in both countries was falling prices; other mechanisms were less important. Moreover, the US economy was more product-oriented, as evident in an overall positive relationship between technological change and employment, than the Italian economy, where the various compensation mechanisms were unable to counterbalance the direct labor-saving effect of widespread process innovation(Vivarelli, 1995).

A more recent study uses the number of triadic patents (a set of linked patents at the European, Japanese, and US patent offices) in 21 industrial countries issued over the period 1985–2009 as an innovation indicator for assessing the impact of innovation on the aggregate unemployment rate (Feldmann, 2013). The results show that technological change tends to increase unemployment, although this effect does not persist in the long term.

In principle, the ideal setting to fully investigate the link between technology and employment is a macroeconomic empirical model that jointly considers the direct effects of process and product innovation and all the indirect income and price compensation mechanisms discussed above. In practice, however, such empirical macroeconomic exercises are very difficult to arrange. They are also controversial, for several reasons. First, measuring aggregate technological change is problematic. Second, the analytical complexity required to represent the various compensation mechanisms makes interpreting the aggregate empirical results extremely complicated. And third, composition effects (in terms of sectoral input–output linkages) and the behavior of individual firms may render the macroeconomic assessment unreliable or meaningless. For these reasons, and because of the recent availability of reliable longitudinal data sets, the sectoral and microeconomic literature on the link between innovation and employment is larger and flourishing.

3.2 Empirical evidence at the sectoral level

The sectoral dimension is particularly important in investigating the overall employment impact of innovation. In particular, the compensation mechanism that works through new outputs—which today more often takes the form of compensation through new services rather than new products—may accelerate the secular shift from manufacturing to services (Vivarelli, 2014). On the other hand, in manufacturing, new technologies seem to be characterized mainly by labor-saving embodied technological changes that are only partially compensated for by market mechanisms. For instance, a study of Italian manufacturing found a negative relationship between productivity growth and employment, with product and process innovation having opposite effects on the demand for labor (Vivarelli et al., 1996).

In a similar line of analyses, a study used data on four manufacturing sectors across German regions for 1999–2005 to examine the co-evolution of R&D expenditures, patents, and employment (Buerger et al., 2012). The main finding was that patents (innovation) and employment are positively and significantly correlated in two high-tech sectors (medical and optical equipment and electrics and electronics) and not correlated in the other two more traditional sectors (chemicals and transport equipment).

More recently, a study for eleven European countries (1998-2011) found a job-destruction impact of capital formation (as a proxy of process innovation) due to the embodied technological change incorporated in gross investment and a significant job-creation effect of R&D expenditure (especially in medium- and high-tech sectors) (Piva & Vivarelli, 2018).

Other studies analyze the effects of the innovativeness of upstream and downstream sectors on employment. Using sectoral data from 19 European countries over the time span 1998-2016, Dosi et al. (2021) assume that upstream sectors pursue R&D activities while downstream sectors invest to replace or expand fixed capital. Their main findings are a negative effect of capital replacement and a weaker positive effect of expansionary capital investment. Also, the job-creation labor effect of R&D is found, but it is weakly significant (Dosi et al., 2021). Although this study does not explicitly refer to AI technologies, its theoretical framework can be used as a benchmark for assessing the controversial employment impact of robots and AI. According to this model and its econometric test, new technologies should imply significant job losses in the downstream sectors (adoption of AI and robots) and a (weaker) job creation in the supply upstream industries.

Along the same line, Díaz et al. (2024) use input-output linkages to analyze the employment effect of product innovation in the upstream, downstream, and within the same sector of the focal firm for the Spanish manufacturing sector from 2005 to 2015. Partially in contrast with the previous study, the results show a labor-saving impact in upstream and same sectors (mainly for low-skilled workers) while non-significant labor effects in downstream sectors (Díaz et al., 2024).

3.3 Empirical evidence at the firm level

Several recent microeconometric studies have fully taken advantage of the newly available longitudinal data sets to apply panel data econometric methods that jointly take into account both the time dimension and the cross-section firm-level variability.

There are two main empirical frameworks at the micro-level of analysis. The first one is the input-oriented model, where the proxy of innovation, most of the times, is R&D expenditure as proxy for product innovation and gross capital investment (embodied technological change) as proxy for process innovation. The second one is the output-oriented model, where the proxies of innovations are sales growth due to new products (product innovation) and sole process innovation (the process innovation not associated with product innovation) (Díaz, Guerrero, et al., 2024).

The first study to use the input-oriented model matched the London Stock Exchange database of manufacturing firms with the innovation database of the Science Policy Research Unit at the University of Sussex (SPRU) to create a panel of 598 British firms over 1976–1982 (Van Reenen, 1997). The study found a positive employment impact of innovation, a finding that remained even in several variations of the model specification.

Using the same approach, Piva & Vivarelli (2005) found evidence of a positive effect of innovation on employment at the firm level. In particular, after applying panel methodologies to a longitudinal data set of 575 Italian manufacturing firms over 1992–1997, the study found evidence of a small but significant positive link between a firm's gross investment in innovation and its employment (for an in-depth discussion, see Piva & Vivarelli (2005)).

Another study that used a panel database covering 677 European manufacturing and service firms over 19 years (1990–2008) detected a positive and significant employment impact of R&D expenditures only in services and high-tech manufacturing but not in the more traditional manufacturing sectors (Bogliacino et al., 2012). In the more traditional manufacturing sectors, the employment effect of technological change is not significant.

More recent studies for European countries, using longitudinal data and a better measure of embodied technological change, found the labor-friendly nature of R&D expenditures but a possible overall labor-saving impact of embodied technological change (a limited effect) (Barbieri et al., 2020; Pellegrino et al., 2019).

A meta-regression analysis that investigated the input- oriented model used in 35 studies shows that the net impact of innovation on employment is generally positive but small in magnitude and highly heterogeneous. The study also highlights the lack of consistency between meta-analysis findings and some general predictions that might be generated by a limited informational content in terms of the evidence taken into account (Ugur et al., 2018).

Shifting to the second empirical methodology, the first study that applied the output-oriented model used firm-level data obtained from the third wave of the Community Innovation Survey for France, Germany, Spain, and the UK (Harrison et al., 2014). This study came to the conclusion that process innovation tends to displace employment, while product innovation is basically labor-friendly (see also Vivarelli (2014)). This approach has been widely applied in developing and developed countries and different sectors (manufacturing and services, high-tech and low-tech). Another meta-regression analysis of 27 studies that applied this output-oriented approach suggests that the employment impact of sales growth due to new products is positive and homogeneous, being a good proxy for product innovation. In contrast, the negative labor effect of the dummy "sole process innovation" is very heterogeneous, and its magnitude and statistical significance depend on various circumstances (for instance, developing vs. developed countries, sectors, period of crisis, different methodologies). Indeed, only few studies found out a labor-saving impact of process innovation (Díaz et al., 2020; Lim & Lee, 2019). One of the main critique addressable to this bunch of studies is that the dummy variable "sole process innovation" fails to fully capture firm's process innovation strategy, its actual size and its variability (Díaz, Guerrero, et al., 2024).

Other studies have not adopted the two main approaches mentioned above. For instance, a study - using a dynamic employment model and a longitudinal data set on German manufacturing firms over the period 1982–2002 - has found a significantly positive impact of various current and past product and process innovation variables on labor demand (Lachenmaier & Rottmann, 2011). According to this work, innovation is homogeneously employment friendly.

More recent studies have used different types of measures of innovation. A study that used patents as a proxy of innovation for 20,000 European companies from 2003 to 2012 found a positive impact of innovation on employment, but only for firms in high-tech manufacturing sectors (Van Roy et al., 2018). Another study from Spain from 1991 to 2012 found a positive effect of product innovation on employment growth and no significant impact of process innovation (both using dummy variables as proxies of innovation) (Bianchini & Pellegrino, 2019). A most recent study used the Enterprise surveys dataset from the World Bank and found that R&D expenditure and process innovation foster firm's employment growth (Goel & Nelson, 2022).

3.4 Empirical evidence for specific technologies: robots and artificial intelligence

The emergence of the current new technological paradigm has generated a desire to explore the empirical effect of specific technologies (namely robots and artificial intelligence) on the labor market.

In the case of robots, studies at the industrial level that used data from the International Federation of Robotics and EUKLEMS for developed countries have found a negative effect on employment (specifically for low-skilled workers and in services sectors) (Acemoglu & Restrepo, 2020a; Chiacchio et al., 2018; Graetz & Michaels, 2018).

In contrast, most studies at the firm level found positive impacts of robots on employment (mainly in countries such as France, Spain, Canada, and Germany) (Dauth et al., 2021; Dixon et al., 2021; Domini et al., 2021; Koch et al., 2021). However, optimistic employment results obtained at the firm level of analysis can be entirely due to the "business stealing effect" (see above) and job creation at the firm level can well coexist with job destruction at the industry level (Acemoglu et al., 2020).

New empirical methodologies (such as natural language processes and text analyses) allow to explore other sources of information (e.g., job posts and patents). These types of studies analyze the exposure and the impact of artificial intelligence (robots) on the labor market. Also, these types of studies can assess the proximity between specific innovations, occupations, and tasks. For instance, one study tries to look at AI-exposed establishments by combining job posts using Burning Glass Technology data and SOC occupational codes. The study found no apparent effect at the industry and occupational levels, but it did find a re-composition toward AI-intensive jobs (Acemoglu et al., 2022). Other studies using patents (AI-related inventions) show a moderative positive employment impact of AI patenting within the industries which patent in AI, that is the upstream sectors which provide the new technologies (see above) (Damioli et al., 2024).

Other approaches distinguish between labor-saving innovations and labor-complementary technologies. For instance, one study that uses the textual description of tasks in the fourth edition of the Dictionary of Occupation Titles (DOT) and the breakthrough innovations (through patents) found that the most exposed occupations experienced a decrease in wage and employment level (mainly white-collar workers relative to blue-collar workers) (Kogan et al., 2021). More recently, another study identified labor-saving innovations using textual analysis of USPTO patent applications in robotics. The main results show that some activities are more exposed to labor-saving innovation, such as those related to transport, storage, packaging, and moving objects. Along the same line, an update of the previous study shows that occupations most exposed to robotic labor-saving technologies are associated with lower employment and wage rates (Montobbio et al., 2022, 2023).

4. Main findings

Theoretical models cannot claim to have a clear answer on the final employment impact of process and product innovation.

While the price and income mechanisms described here have the potential to compensate, fully or in part, the direct labor-saving impact of process innovation, the precise outcome is uncertain. Determining factors include such variables as the degree of competition, demand elasticity, elasticity of substitution between capital and labor, and expectations of consumers and employers. Overall, depending on market structure and institutional contexts, compensation mechanisms can be more or less effective, and the unemployment impact of process innovation can be totally, partially, or not at all neutralized.

Similarly, the findings of empirical studies are not fully conclusive about the possible employment impact of innovation and technological change. However, most recent panel investigations support a positive link. This positive link is especially evident when R&D or product innovation are adopted as proxies for technological change and when the focus is on high-tech sectors and high-growth firms (Vivarelli, 2013, 2014). In many sectors, however, especially in services, product and process innovation are intermingled and difficult to disentangle. Moreover, while process innovations display clear direct labor-saving effects, some product innovations may also involve job displacement. Therefore, it is not always easy and straightforward to design industrial and innovation policies that can effectively maximize the positive employment impact of innovation. Additional microeconometric studies of the type addressed by the current research literature are needed to further disentangle the labor impact of innovation across different sectors and different types of firms. Indeed, new statistical techniques and sources of information are being used nowadays to construct different measures of labor market exposure to technological change.

With specific regard to the AI technologies, the scarce available evidence (see above) suggests that technological leaders within the emergence of the AI paradigm can realize (moderate) labor-friendly outcomes. However, other companies (particularly in manufacturing) may reveal to be unable to couple product innovation with job creation.

Moreover, compared with the labor-saving impact implied by the adoption of AI and automation technologies (massive according to some studies, see above), the labor-friendly extent in the supply industries appears limited in magnitude and scope (just as a narrative example: the hiring of data scientists in upstream services and AI big-tech would hardly compensate job losses due to robots in downstream manufacturing).

As a gap in the current literature, much is needed in terms of additional empirical evidence able to compare the actual magnitude of possible employment complementary effects within the providers of new AI technologies with the possible job-losses due to the substitution effects within the users of new AI and automation technologies.

Finally, one crucial aspect is that most studies that analyze the relationship between employment and innovation focus on developed countries. However, the larger effects of automation and innovation might be in developing countries where many activities and job tasks can be easily substituted by robots and AI algorithms (think about manufacturing jobs displaced by robots or call-center jobs displaced by chatbots). With few exceptions (see above (Goel & Nelson, 2022)), there is a lack of empirical studies for developing countries that can provide more evidence of these phenomena.

5. Conclusion and policy implications

The literature, both theoretical and empirical, has examined the main technological drivers that can play a role in the loss of jobs and the creation of technological unemployment. Indeed, innovation affects the economy through both process and product innovation, both of which can have employment impacts. For the most part, R&D expenditures that result in product innovation are generally labor-friendly, creating new jobs, while embodied technological change that results in process innovation is generally job-destroying. A clear policy implication would seem to be that economic policy should try to foster job creation by supporting R&D investments and product innovation. In the AI era this means to foster emerging industries and innovative startups, active in AI design, engineering and patenting.

However, the picture is more complicated than that. Product and process innovation are often interrelated, and process innovation does not always lead to job destruction. Indeed, much of the theoretical literature on the employment impact of technology has focused on various market compensation mechanisms that can counteract most if not all of the technological unemployment impacts of process innovation (see the classical compensation theory discussed above, and its recent revival put forward by Acemogulglu and Restrepo).

Thus, a general theoretical and empirical conclusion is that compensation mechanisms are always at work but that the full reabsorption of workers dismissed as a result of technological change cannot be assumed ex ante. In particular, to work properly, compensation mechanisms require competition (to facilitate the compensation mechanism that works through lower prices), optimistic expectations (to facilitate the compensation mechanisms that work through lower prices and new investments), and a high elasticity of substitution between capital and labor. In this framework, competition policies that lower entry barriers and reduce monopolistic rents, along with expansionary policies targeting intermediate and final demand for new products, can be important drivers of job creation. In this respect, the concentration of AI research and patenting in the hands of the "big tech" is extremely worrying and should be contrasted by a fierce antitrust policy.

Since economic theory offers no clear-cut answer on the employment effect of innovation, answers need to come from empirical analyses. Empirical studies can consider different forms of technological change, their direct effects on employment, various compensation mechanisms at work, and any possible impediments to these mechanisms.

In particular, microeconometric studies have the great advantage of enabling direct and precise firm-level mapping of input and output innovation variables (Vivarelli, 2013, 2014) . Overall, the empirical literature, particularly the most recent microeconometric panel data analyses, tends to support a positive link between technological advances and employment, especially when the focus is on R&D, product innovation and upstream high-tech firms. These positive employment outcomes of evidence-based studies are consistent with a lifecycle view of different industries, with emerging sectors characterized by product innovation (mostly labor-friendly) and more traditional, mature industries more likely to experience process innovation (mostly labor-saving). As a policy implication, policy makers should foster the emergence and the strengthening of upstream AI-intensive industries, where the job creation impact is concentrated (see above).

However, while supporting R&D investments and promoting knowledge and AI-intensive industries (Antonelli et al., 2023), can be a mean of fostering competitiveness, economic growth and job creation, both industrial policies and innovation policies need carefully to take into account a series of complex interactions between process innovation and product innovation, between mature sectors and new sectors, and between job-creation effects in the upstream industries and job-destruction effects in the downstream industries (see above). These complex interrelationships, difficult to predict in advance, highlight the need for a continuous monitoring of policy implementation. For instance, safety nets and active labor market policies are necessary to deal with the employment displacement due to the widespread diffusion of AI and automation technologies in the user industries.

Finally, as discussed above, it is urgent to generate more empirical analysis to know the actual effects of new technologies on the labor markets outside Europe and the United States. Indeed, the most vulnerable countries to new technological changes are those that execute routine tasks (for instance, assembly plants or traditional services), and those are usually developing countries. Policymakers' vision should consider this global effect of technological change on the labor markets, particularly within international organizations such as the UN, World Bank, IMF, etc.

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