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REVIEW ARTICLE

# New Technologies and Employment: The State of the Art

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## Abstract

The relationship between technology and employment has long been a subject 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 (AI). The primary objective of this paper is to provide insights into the relationship between innovation and employment by proposing a conceptual framework and reviewing the state of the art in the relevant debates and analyses.

**Keywords** Technology · Employment · Compensation theory · AI · Robot

**JEL Classification** O33

## 1 Introduction

The relationship between technology and employment has long been a topic of debate for both social scientists and policymakers, at least since the first industrial revolution. Indeed, claims of technology-induced unemployment tend to re-emerge at times of radical technological change, such as the one many countries are currently experiencing with the arrival of automation and artificial intelligence (AI) technologies.

Today, the debate focuses on three main questions: What are the roles of technology and innovation in explaining the long-term decline in manufacturing's 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?

To put these issues in context, McKinsey (2017) forecasts that nearly 50% of work activities could be automated by 2055. Specific sectors, such as "Accommodation and

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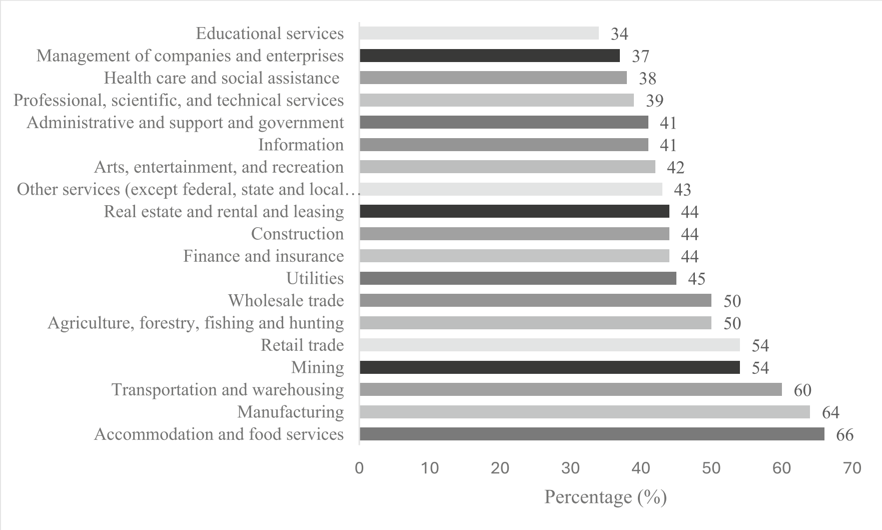


**Fig. 1** Potential automation by 2055 in different sectors. *Source* Oxford Economic Forecasting; U.S. Bureau of Labor Statistics; McKinsey analysis (2017)

Food Services" (66%), "Manufacturing" (64%), and "Transportation and Warehousing" (60%), are particularly susceptible to automation (Fig. 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 (Fig. 2).

This somewhat pessimistic outlook has attracted significant attention among scholars seeking to explore the potential impacts of new technologies on the labor market. New statistical tools and machine learning methods are enabling researchers to analyze with greater granularity how specific technologies affect particular jobs and tasks. For instance, Felten et al. (2018) and Felten et al. (2021) find 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. (2023a) find 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 logistics and healthcare workers, are increasingly exposed to robotic technologies.

However, the impact of innovation on employment is not trivial, and it requires understanding all the possible theoretical mechanisms involved in this relationship: labor-creating (mainly from product innovation), labor-saving (mainly from process

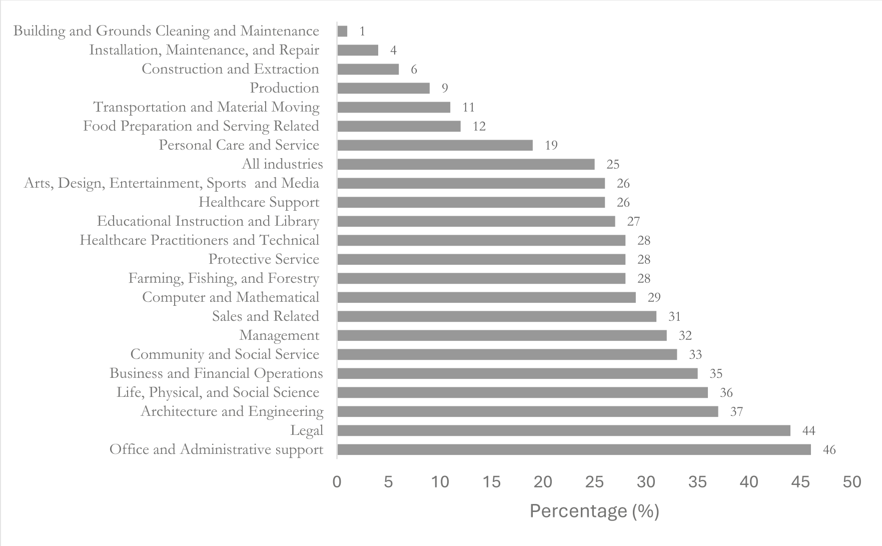


**Fig. 2** Share of the industry employment exposed to automation by AI: US. *Source* Adapted from Goldman Sachs Global Investment Research (2023)

innovation), and the so-called market compensation mechanisms, that may offset the initial labor-saving impact of innovation (see Sect. 2.2).

In more detail, while process innovation can be job-destroying, product innovation can entail the emergence of new firms, new sectors, and thus new jobs. However, 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 perspective is essential for better understanding the relationship between innovation and employment. Schumpeter (1939, 1947) argues that technological unemployment arises from mismatches 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 et al. 2024a, b).

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 introduce it, but also may 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 et al. 2024a, b; 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 and, on the other hand, the scope for job creation, and focusing in particular on the market and institutional mechanisms that can shape the final labor demand outcomes. To achieve this, we first propose an interpretative theoretical framework and then critically discuss the key empirical studies that have explored this relationship, including studies that focus on new technologies, such as robotics and artificial intelligence, in order to provide a comprehensive understanding of how these recent innovations affect employment.

While the issues discussed in this study have been investigated in previous articulated and comprehensive surveys (Calvino and Virgillito 2018; Díaz et al. 2024a, b; Filippi et al. 2023; Mondolo 2022; Montobbio et al. 2023b), these earlier works are not based on a detailed conceptualization of technological drivers (see in particular the next Sects. 2.1 and 2.3), are not characterized by a critical perspective of the current debate (see especially Sects. 2.2 and 2.4), and devote a limited attention to the systematic assessment of the empirical evidence on the topic (see Sect. 3). Building on these gaps, the novelty of the present contribution is multifaceted.[1]

Firstly, the theoretical framework put forward in Sect. 2 aims to delve into the complexity of the "economics of technology and employment", in response to a current debate which tends to oversimplify the analysis, reducing it to the balance between an initial "substitution effect" and a subsequent "productivity effect" (see Sect. 2.4). Secondly, the comparative discussion of the empirical literature (Sect. 3) is articulated at different levels (macro/industry/firm), since the level of analysis is crucial in interpreting the results obtained.[2] Moreover, intersectoral relationships, in terms of vertical linkages and global value chains, are also discussed. Thirdly, a specific focus is devoted to the impact of current technologies such as automation and AI (Sects. 3.4 and 3.5).

The remainder of the paper is structured as follows: Sect. 2 discusses the main theoretical mechanisms determining the relationship between innovation and employment. Section 3 reviews the empirical literature through a selection of previous studies. In Sect. 4 we summarize the main findings, and we put forward some key conclusions.

## 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

[1] The theoretical and empirical literature discussed in this study is vast (see the References), but not necessarily exhaustive; rather, the most relevant contributions have been selected with the aim to provide an articulated and updated investigation of the "economics of technology and employment," with particular reference to the theory of compensation (see Sect. 2).

[2] Indeed, as discussed in the next section, the mechanisms operate differently across levels of analysis. Moreover, the employment effects observed in micro-level evidence may change (or even reverse) once aggregated at the industry or at the macro level (see Sect. 2.3).

industrial employees in total employment. However, more recently, automation and the diffusion of AI have made possible a similar labor-saving prospect in service industries ranging from the financial sector to trade and retail.

According to the innovation-economics literature, 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, statistically 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 and 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-sized 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 Fig. 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 it is adopted in the user sectors as a process innovation (e.g. a drop in the demand for bank clerks).

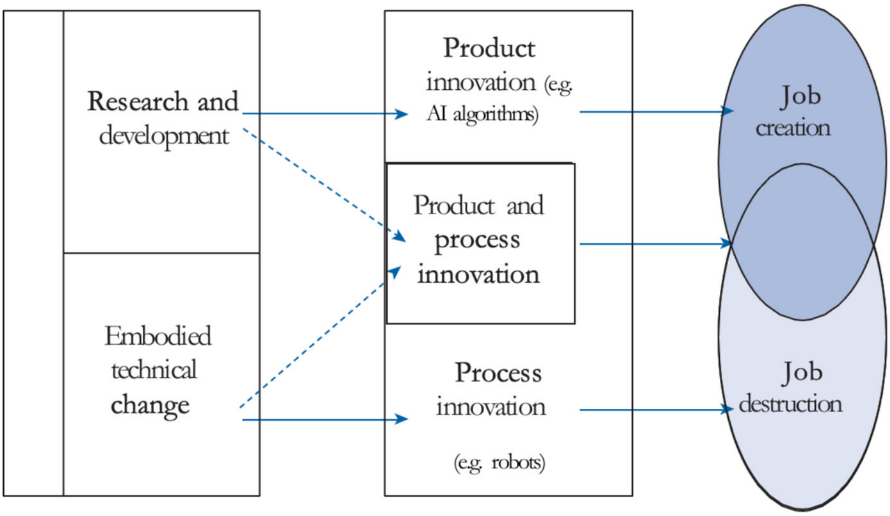


**Fig. 3** The two faces of innovation: how product and process innovation affect employment. *Source* Author's own illustration

### 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 fewer 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 adopt 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 must 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 production 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 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, 2013).

However, this line of reasoning does not take into account possible demand rigidities. For instance, pessimistic expectations among 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, 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 reinvested in the firm, this investment can create new jobs (Vivarelli 2013, 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 the 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 equalization 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 and Soete 1987; Vivarelli 1995).

### 2.2.5 On Balance

The market compensation mechanisms discussed so far can, in principle, act as powerful forces offsetting the initial job-destroying impact of process innovation. However, the functioning of these mechanisms is hindered by many institutional and market failures that can greatly weaken their efficacy. For instance, the compensation mechanism via new machinery operates when: (1) the labor cost embodied in new machines is lower than the labor cost associated with the displaced workforce (for producers and users); and (2) the mechanism only occurs through new investment, not through the replacement of obsolete machinery. The compensation mechanism via lower prices is effective when: (1) markets are competitive, so cost reductions translate into price reductions; and (2) demand is elastic, so lower prices generate sufficient additional demand to offset job losses. The compensation mechanism via new investment requires that: (1) markets allow innovative firms to generate extra profits; and (2) these profits are rapidly and fully translated into new investment. Finally, the compensation mechanism via declining wages is viable only when: (1) labor markets are perfectly competitive, and (2) labor and capital are fully substitutable.

Ultimately, determining how effective these mechanisms are is a matter for empirical analysis (see below). Notably, this "classical" theoretical framework remains a useful benchmark for assessing the overall employment impact of the new technologies brought about by the AI revolution. Moreover, employment compensation may be hindered by the intrinsic skill bias often associated with labor-saving innovation. Indeed, if the new technologies require skills and tasks that are different from those made obsolete by technological change, the entire compensation process may fail or, at least, be substantially slowed down.[3]

[3] The founding analysis explaining this phenomenon is the well-known Skill-Biased Technological Change (SBTC) hypothesis, proposed by Nelson and Phelps (1966), Griliches (1969), and Welch (1970). This hypothesis posits that new technologies are complementary to skilled workers, while they tend to be a substitute for unskilled labor. Indeed, the analysis of the qualitative impact of innovation on skills, tasks and occupations is out of the scope of the present study. While the reader is re-addressed to the extant vast literature on this subject (for a survey, see Barbieri et al. 2020a, b), it is important to remind that the original SBTC hypothesis has been developed first into the Routine-Biased Technological Change approach (implying polarization, where routinized middle skills are those more negatively affected by the new technologies) and then into the Task-Biased Technological Change framework, more focused on the single tasks potentially automatable [and dispersed across a wide range of occupations; see Autor et al. (2008), Goos et al. (2014) and Jaimovich and Siu (2018)].

### 2.3 Product Innovation

The picture is far clearer in the case of product innovation than in the case 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 twentieth 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) acknowledged 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 (for instance, the occurrence of substantial organizational change as a necessary complement to product innovation; see Lee and 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. For a theoretical model formalizing the interaction between the welfare effect and the substitution effect, see Katsoulacos (1986). Although developed earlier, this model can be usefully applied to current technologies).

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 twentieth century and the diffusion of personal computers at the end of that century clearly had job-creating effects (Freeman and Soete 1987), automobiles had a much greater labor-intensive impact than home computers in the past or AI nowadays (at least so far) (Acemoglu and Restrepo 2020b).

Finally, the employment impact of product innovations is multifaceted from a sectoral point of view. Indeed, it is important to identify three different types of firms: those companies that belong to the same industry (i.e., competitors), those companies that belong to the upstream sectors (i.e., providers), and those companies that belong to the downstream industries (which can be understood as customers).

In the first case, the impact of companies that introduce a product innovation in the same sector or related industries triggers two possible mechanisms. The first one is the well-known “business stealing effect,” which implies a positive impact on the employment of the innovative firm. The business stealing effect occurs when an innovating firm steals demand, through introducing new products, from obsolete products produced by non-innovating firms. Conversely, a positive effect can be found in the case in which competitors can imitate the innovative products of the innovating firms (Díaz et al. 2024a, b).

When a product innovation occurs in an upstream sector, the labor-friendly impact at that level should be compared with what is going to happen in the related downstream industries (as extensively discussed in the already mentioned Dosi et al. (2021)). If a product innovation in the upstream industry is a process innovation in a downstream sector (think, for instance, of a robot), the above-mentioned labor-friendly effect should be compared with the labor-saving effect of the same innovation within the adopting downstream industries. However, if the new products provided by the innovative upstream industry result in higher quality and/or cheaper inputs for the downstream industries, this can stimulate employment in the downstream sectors, as well (Hauknes and Knell 2009; Meyer-Krahmer 1992).

Turning our attention to a product innovation occurring in the downstream industries, indirect employment effects may affect the upstream sectors. On the one hand, the introduction of a product innovation in the downstream industries may stimulate the demand for inputs provided by the upstream sectors. Moreover, this input–output relationship may enhance beneficial mutual learning opportunities for both the upstream producers and the downstream adopters, fueling further innovation (von Hippel 1976; Lundvall 1992; Montresor and Marzetti 2008). On the other hand, it may well occur that the innovations generated in the downstream industries decrease the demand for inputs provided by the upstream sectors. This might happen when the innovation generated in downstream industries requires specific features that go beyond the competencies and capabilities of the current providers in the upstream sectors. For instance, companies in the downstream sectors may reduce their reliance on national suppliers in favor of foreign suppliers or develop the new inputs in-house (Boleros et al. 2001; Javorcik 2004).

## 2.4 Current Theoretical Debate

In recent years, a renewed theoretical debate has tended to simplify all the compensation mechanisms discussed above (Corrocher et al. 2024). This vision puts forward opposing forces affecting the relationship between innovation and employment (Acemoglu and Restrepo 2018a, 2019, 2020a, b). 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, which corresponds to the compensation mechanism via lower prices discussed above.[4] 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

[4] Acemoglu and Restrepo (2018a) state: "[…] capital performs certain tasks more cheaply than labor used to. This reduces the prices of the goods and services whose production processes are being automated, making households effectively richer, and increasing the demand for all goods and services." (*ibidem*, p. 203). It is striking how this reasoning resembles so closely the classical compensation mechanism discussed in Sect. 2.2.2.

reinstatement effect, which implicitly refers to the compensation mechanism operating through the emergence of new products and new industries.[5]

However, as with the compensation mechanism theory discussed above, the efficacy of these mechanisms obviously depends on many institutional conditions and market failures that can significantly weaken them. Thus, all the theoretical critiques and the market failures discussed above fully apply to the Acemoglu/Restrepo framework, although they are largely neglected in their analytical approach.

The first force, the displacement effect, is mediated by relative factor prices, as highlighted by Corrocher et al. (2024). This view has two important implications. First, innovation is not treated according to its intrinsic nature, as it would be in a Schumpeterian framework, but is instead seen as "induced" by market prices. Second, the compensation mechanism via decrease in wages is presented in a highly conventional manner (see above), because the relative price of labor drives the entire process of task substitution.

The second force, the productivity effect, is more or less powerful, depending on the specific technologies introduced. Yet, like the compensation mechanism via lower prices, it requires: (1) perfect competition and (2) elastic demand. Given these restrictive conditions, its effectiveness is particularly limited. The third force, capital accumulation, faces the same constraints as the compensation mechanism via new machinery: it depends on whether firms generate sufficient extra profits and whether these profits are rapidly and fully reinvested. As discussed previously, these conditions seldom hold in practice.

Moreover, in line with the standard economic approach, it is important to note that innovation is not explicitly treated in their model, but is assumed to be exogenous in nature (albeit characterized by a pace of implementation fully malleable by market forces; first of all, the relative price of labor *vs* capital).[6] In addition, it does not distinguish between product and process innovation, thereby overlooking the labor-creating effects of product innovation. Finally, the model abstracts from the existence of market failures inherent to innovation, and neglects the critical insights of Marx, Keynes (regarding animal spirits and effective demand), and more recent non-mainstream economists (Corrocher et al. 2024).

While the discussion above is put forward at the macro-level of analysis, there could also be some interesting theoretical insights from the industry and firm-level of analysis, where the displacement and compensation effects actually operate. 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 employment at

[5] Acemoglu and Restrepo (2018a) state: "We argue that there is a more powerful countervailing force that increases the demand for labor as well as the share of labor in national income: the creation of new tasks, functions and activities in which labor has a comparative advantage relative to machines" (*ibidem*, p. 198). Although introduced in terms of new tasks needed, the reinstatement effect requires that new technologies give raise to new functions and activities, that in turn require new products or even entire new industries.

[6] Indeed, tasks can be automated or not, depending on the relative factor prices and the elasticity of substitution between capital and labor: "When the wage rate is above the opportunity cost of labor (due to labor market frictions), firms will choose automation to save on labor costs" (Acemoglu and Restrepo 2018b, p. 1492).

the level of a single firm and a negative employment impact at the industry level. Moreover, companies can offset the displacement effects of labor-saving technologies by introducing new products or tasks. Finally, compensation via reinvestment (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 full realization of all mechanisms mentioned above 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. Indeed, the final employment outcome of a given innovation depends on a variety of factors including whether the innovation is a product or a process innovation (see Sect. 2.1), the actual effectiveness of the various compensation mechanisms (see Sect. 2.2), and the vertical relationships among industries (see Sect. 2.3). In such a complex context, economic theory can, at best, single out the different forces at play, but it is unable to provide a definitive answer to the question of whether innovation can be coupled with employment growth.

In this context, while empirical analyses are essential, they should take into account the dimensions underlined by the theories discussed above, namely the various forms of technological change, their direct effects on labor, the different compensation mechanisms at play, the likely impediments to these mechanisms, and the complex and articulated intersectoral effects of innovation.

In what follows, we survey the extant empirical literature starting from the macro-level and then shifting to the industry and firm-level studies. Obviously enough, the different levels of the empirical analysis have *pros* and *cons*. Macroeconomic and sectoral analyses have the advantage of fully taking into account the different inter-sectoral forces discussed in the previous theoretical section, such as the compensation mechanisms and the upstream/downstream relationships. On the other hand, they rely on aggregate data affected by compositional effects and on proxies of technology that are often imperfect (such as national R&D and/or national patenting activity). Firm level microeconometric studies have the advantage of relying on granular and precise data (such as corporate R&D expenditures) often organized in large panel datasets. However, micro studies cannot capture the entire theoretical picture discussed in detail above.

### 3.1 Empirical Evidence at the Macro Level

Most of the theoretical mechanisms discussed in the previous sections, namely, the direct labor-saving effect of process innovation, the labor-creating effect of product innovation, and the various compensation mechanisms (see Sects. 2.2–2.3), are conceptualized at the macroeconomic level. However, empirically testing these mechanisms is extremely challenging, given data limitations and the lack of suitable indicators. Very few macroeconometric studies have attempted to test the validity of compensation mechanisms through aggregate evidence within a general equilibrium framework. In this section we present the available studies that examine these relationships using macro-level data.[7]

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

Simonetti et al. (2000) apply the same simultaneous equations macroeconomic model, running three stages least squares regressions, using American, Italian, French, and Japanese data over the period 1965–1993. The authors show that the more effective compensation mechanisms are the ones "via decrease in prices" and "via increase in incomes" (especially in European countries until the mid-1980s, when increases in incomes were strictly correlated to productivity gains). The other mechanisms result less significant and conditional on the institutional structures of the respective countries. For instance, the "mechanism via decrease in wages" is relevant in the flexible American labor market. By the same token, product innovation significantly reveals its labor-intensive potentiality only in the technological leader country in that period, namely the USA.

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

In principle, as we mentioned, 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

[7] In this section, we focus exclusively on studies that conduct analysis at an aggregate level (e.g., the country level) and try to test the compensation mechanisms. Cross-country research relying on industry-level or firm-level data will be discussed in the following sections.

and price compensation mechanisms discussed above. In practice, however, such macroeconomic empirical exercises are difficult to implement and often controversial. First, measuring aggregate technological change is problematic. Second, the analytical complexity required to represent the various compensation mechanisms makes interpreting aggregate empirical results extremely complicated. Third, composition effects (in terms of sectoral input–output linkages) and the behavior of individual firms may render macroeconomic assessments unreliable or even uninformative. 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 rapidly expanding.

### 3.2 Empirical Evidence at the Industry Level[8]

The sectoral dimension is particularly important for 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 by market mechanisms. For instance, a study of Italian manufacturing finds 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 is that patents (innovation) and employment are positively and significantly correlated in two high-tech sectors (medical and optical equipment and electrical and electronics) and not correlated in the other two more traditional sectors (chemicals and transport equipment).

Furthermore, Bogliacino and Pianta (2010) examine the relationship between innovation and employment in eight European countries over the period 1994–2004 at the sectoral level (manufacturing and services). Their main findings suggest a positive association between technological competitiveness and employment, measured by the share of turnover from new products and R&D expenditure per employee, and, at the same time, a negative association between cost competitiveness and employment, captured by the share of firms innovating to reduce labor costs and expenditure on innovative machinery per employee. Moreover, the authors identify sectoral heterogeneities using an extended Pavitt taxonomy.

More recently, a study for eleven European countries (1998–2011) in manufacturing and service sectors find a job-destruction impact of capital formation (as a proxy for process innovation) due to the embodied technological change incorporated in gross

[8] In this section, we focus on studies that empirically analyse the impact of innovation in quantitative terms at the industry level. Studies that rely on qualitative analyses, such as the skilled-biased technological change (SBTC), routine-biased technological change (RBTC), and routine-replacing technological change (RRTC) frameworks, fall outside the scope of this article.

investment and a significant job-creation effect of R&D expenditure (especially in medium- and high-tech sectors) (Piva and Vivarelli 2018).

Other studies analyze how innovation in upstream and downstream sectors affects employment. Using sectoral data from 19 European countries over 1998–2016, Dosi et al. (2021) assume that upstream sectors undertake R&D activities, while downstream sectors invest to replace or expand fixed capital. Their main findings include a negative effect of capital replacement and a weaker positive effect of expansionary capital investment. They also detect a job-creating effect of R&D, although it is only weakly significant (Dosi et al. 2021). Although this study does not explicitly refer to AI, its framework can serve as a benchmark for assessing the contested employment impact of robots and AI. According to this model and its econometric test, new technologies should imply significant job losses in downstream sectors (adoption of AI and robots) and a weaker job-creation effect in upstream supply industries.

Autor and Salomons (2018) also assess the relationship between innovation and employment, using input–output tables and EU KLEMS data for nineteen OECD countries over the period 1970–2007. One of their main findings is that Total Factor Productivity (TFP), used as a proxy for technological change, has a negative direct effect on employment, as rising productivity reduces labor input in the sectors where it originates (upstream sectors). However, these negative effects are offset by two indirect mechanisms: employment gains in downstream customer sectors, and increased demand stimulated by price declines triggered by productivity growth (see Sect. 2.2.2).

Along the same line, Díaz et al. (2024a, b) use input–output linkages to analyze the employment effect of product innovation in upstream sectors, downstream sectors, and within the focal firm's own sector for Spanish manufacturing over 2005–2015. The results show a negative effect on employment for the introduction of new products in upstream sectors, which results in the reduction of labour demand in the focal firm (mainly for low-skilled workers); (Díaz et al. 2024a, b). The authors argue that new products developed in upstream industries may improve production processes in downstream firms, thereby exerting a detrimental impact on labor demand. This interpretation is consistent with Dosi et al. (2021), who document a negative effect of fixed-capital investment aimed at replacing vintage capital.

Indeed, most studies at the sectoral level focus on the manufacturing sector. However, a smaller number have also examined the impact of innovation on employment in the service sector. Evangelista and Savona (2002) analyze this relationship for Italy using data from the Community Innovation Survey (CIS) covering the period 1993–1995. The authors classify service industries into three categories: technology users, science- and technology-based, and ICT users, and construct *weighted normalized indexes* to capture the employment impact of innovation. Their results indicate that innovation has a positive effect on employment, particularly among small firms and those operating in industries with a strong scientific and technological base. By contrast, large firms in capital-intensive and financial-related sectors (banking, insurance, and other financial services) experience a negative employment impact of innovation. A key characteristic of these sectors is their intensive use of information and communication technologies (ICTs). In a subsequent study, Evangelista and Savona (2003) report similar findings.

More recently, Cirillo et al. (2018) examine how technology, education, and wages have shaped the evolution of four occupational groups: managers, clerks, craft workers, and manual workers (based on ISCO 1-digit classifications) across manufacturing and service sectors in five European countries (Germany, France, Spain, Italy, and the United Kingdom). The analysis covers two periods, 2002–2007 and 2007–2011, to capture both the upswing and downswing phases of the business cycle. Their results indicate that product innovation positively affects employment among managers, particularly during upswings, while clerical workers experience negative effects from product innovation during downswings. In contrast, process innovation has a negative impact on managers and clerks in the upswing phase and reduces employment across all occupational categories during downswings.

### 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 is the input-oriented model, where innovation is proxied, most of the time, by R&D (product innovation) and gross capital investment (embodied technological change) (process innovation). The second is the output-oriented model, where innovation is proxied by sales growth due to new products (product innovation) and by the dummy for "sole process innovation" (process innovation not associated with product innovation) (Díaz et al. 2024a, b).

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 finds a positive employment impact of innovation, a finding that remained even in several variations of the model specification.

Using the same approach, Piva and Vivarelli (2005) find 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 shows 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 and Vivarelli (2005)).

Another study using 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. In summary, the impact of R&D on employment is bigger for the service sector than for the manufacturing sector.

More recent studies for European countries, using longitudinal data and a better measure of embodied technological change, find the labor-friendly nature of R&D

expenditures but a possible overall labor-saving impact of embodied technological change, albeit of limited magnitude (Barbieri et al. 2020a, b; Pellegrino et al. 2019).

A meta-regression analysis by Ugur et al. (2018), which examines 35 studies employing the input-oriented models, 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 theoretical predictions (particularly those concerning the expected effects of process and product innovation). According to the authors, this mismatch may stem from limitations in the underlying empirical evidence, including issues of data quality and model specification (Ugur et al. 2018). In theory, as discussed in Sects. 2.2–2.4, product innovation is expected to exert a positive impact on employment, whereas process innovation is expected to have a negative effect on labor demand.

Turning to the output-oriented approach, the first study applying this framework used firm-level data from the third wave of the Community Innovation Survey for France, Germany, Spain, and the UK (Harrison et al. 2014). The study concludes that process innovation tends to displace employment, whereas product innovation is broadly labor-friendly (see also Vivarelli 2014). The study find that product innovation has a positive and statistically significant impact on employment across all the countries considered (the United Kingdom, France, Germany, and Spain) in both the manufacturing and service sectors. These findings provide clear empirical support for the labor-creating nature of product innovation, consistent with the discussion in Sect. 2.3, where product innovation is expected to generate new markets and thereby stimulate employment.[9] Conversely, process innovation has a negative effect on employment in the manufacturing sector in Germany and the United Kingdom, while no significant evidence is found for process innovation in the service sector. To be precise, the impact of product innovation is greater in the manufacturing sector than in the services sector for both Germany and Spain. Contrarily, the effect of product innovation is greater in service than in manufacturing for France and the UK. For process innovation, the labor-saving impact is only significant for the manufacturing sector in the case of Germany and the UK. 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, Díaz et al. (2024a, b), 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. 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 find a labor-saving impact of process innovation (Díaz et al. 2020; Lim and Lee 2019). One major critique of this body of work is that the "sole process innovation" dummy fails to capture a firm's process-innovation strategy in terms of intensity and dynamics (Díaz et al. 2024a, b).

[9] The output-oriented model also captures the indirect effect of product innovation on efficiency by comparing the efficiency of new versus old products. When the estimated coefficient is lower than one, this indicates that new products are produced more efficiently. However, the approach does not account for the business-stealing effect.

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 and Rottmann 2011). According to this work, innovation is uniformly 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 find a positive impact of innovation on employment, but only for firms in high-tech manufacturing sectors (Van Roy et al. 2018). Furthermore, the authors find that the positive impact of patents is primarily found in the manufacturing sector, rather than in the services sector. Another study from Spain from 1991 to 2012 find 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 and Pellegrino 2019). A most recent study used the Enterprise surveys dataset from the World Bank and find that R&D expenditure and process innovation foster firms' employment growth (Goel and Nelson 2022).

At the firm level, few studies have examined the impact of innovation on employment specifically focusing on the service sector. For instance, Evangelista and Savona (2003) analyze Italian service firms using Community Innovation Survey (CIS) data for the period 1990–1995. Their results indicate a positive association between innovation and employment, although the magnitude and direction of the effect vary according to firm size. In particular, small firms and around half of the service industries included in the sample experience a net positive employment effect from innovation, whereas the negative impacts are mainly concentrated among large firms.

Subsequent studies adopting the output-oriented approach have also examined the effect of innovation on employment in the service sector using firm-level data. For instance, Dachs and Peters (2014) examine the impact of innovation on employment by ownership type: foreign owned versus domestically owned firms, across sixteen European countries between 2002 and 2004, covering both manufacturing and service sectors. Their results indicate that product innovation has a positive and statistically significant effect on employment for all ownership types, with a stronger impact in manufacturing than in services. By contrast, process innovation has a negative and significant effect only in the manufacturing sector, while showing no significant relationship with employment in services.

### 3.4 Empirical Evidence for Specific Technologies: Robots and Automation Technologies

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, industrial-level studies that use data from the International Federation of Robotics (IFR) and EU KLEMS for developed countries have found a negative effect on employment (especially for low-skilled workers and in service sectors). For instance, Acemoglu and Restrepo (2020a) analyze the effects of industrial robots on U.S. labor markets over the period 1993–2014. Their results reveal displacement effects among low-wage workers. In the same vein, Chiacchio et al. (2018) examine the impact of industrial robots on employment and wages in six European countries: Finland, France, Germany, Italy, Spain, and Sweden, by combining data from IFR, the European Community Household Panel (ECHP), and the European Union Statistics on Income and Living Conditions (EU-SILC). Their sample includes 16 NUTS-2 regions observed between 1995 and 2007, and the results indicate that robot adoption is negatively associated with employment rates. Similarly, Graetz and Michaels (2018) merge IFR data with EU KLEMS to analyze the impact of robots on employment across 17 countries from 1993 to 2007. They find that robots do not significantly reduce total employment, although they decrease the employment share of low-skilled workers.

Finally, Dauth et al. (2021), using IFR data for the period 1994–2014, construct a regional measure of local robot exposure in Germany. Their findings show that robot adoption leads to displacement in manufacturing, but these effects are fully offset by job creation in the service sector. Building on the U.S. (Acemoglu and Restrepo 2020a) and German (Dauth et al. 2021) evidence, Dottori (2021) investigates the impact of robots on employment outcomes in Italy from 1990 to 2016 at the local labor market (LLM) level and at the worker level using an instrumental variables approach. The results show no harmful effect on total employment at the LLM level, and, while the estimated effect on manufacturing employment is negative, its statistical significance becomes weak or disappears altogether once concurrent trends in trade and ICT adoption are accounted for. At the worker level, the author finds a positive, albeit modest, employment effect, particularly within the manufacturing sector.

In contrast, most studies at the firm level find positive impacts of robots on employment. For instance, Domini et al. (2021) investigate changes in worker flows (namely net employment growth, hiring, and separation rates) around investments in automation-intensive goods and, within firms, across occupational categories, using data for French manufacturing employers from 2002 to 2015. Their results indicate that automation spikes are associated with increases in firms' contemporaneous net employment growth, driven by higher hiring rates and lower separation rates. Moreover, the authors find that robot adoption or the import of capital equipment does not lead to labor displacement, but rather to employment expansion. Similarly, Bisio et al. (2025), analyzing Italian firms over the period 2011–2019, find a positive average adoption effect on employment among adopters, particularly for small firms. By contrast, medium and large firms experience a predominant negative displacement effect. At the sectoral level, the authors also identify that the adoption of automation technologies has a weakly negative effect on aggregate employment, as non-adopters suffer losses in sales and employment, consistent with a business-stealing effect (discussed in Sect. 2.3).

Similarly, Dixon et al. (2021) analyze how employment and organizational structures evolve in response to robot adoption, drawing on comprehensive firm-level data for the Canadian economy from 2000 to 2015. They find that robot adoption is associated with increases in total employment among robot-adopting firms.

In contrast, Bonfiglioli et al. (2024), using firm-level data for French manufacturing firms over the period 1994–2013, show that while demand shocks generate a positive correlation between robot imports and employment at the firm level, exogenous exposure to automation results in job losses. By contrast, Humlum (2021), using rich administrative data linking workers, firms, and robots in Denmark, examines the distributional impact of industrial robot adoption across manufacturing and service sectors over the period 1995–2015. Employing an event-study approach, the author finds that robot adoption has adverse effects on employment, particularly among production workers.

As can be seen, results from the extant literature are controversial with regard to the employment impact of robotization at the company level. 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 company level can coexist with job destruction at the industry level (Acemoglu et al. 2020). In fact, in their study for French manufacturing firms from 2010 to 2015, Acemoglu et al. (2020) find that, at the firm level, robot adopters expand their employment. However, this expansion comes at the expense of their competitors, generating an overall negative impact of robot adoption at the industry level.[10]

In the same vein, Koch et al. (2021) examine the microeconomic implications of robot adoption, specifically its effects on output and employment, using a rich panel dataset of Spanish manufacturing firms covering the period 1990–2016. Their findings indicate that robot adoption leads to net job creation at an annual rate of around 10%. However, when the authors aggregate the data at industry level, they show that an increase in robot density has a significantly negative impact on employment in firms that do not adopt robot technology, supporting the idea that robot adopters expand their market share and create jobs, whereas non-adopters experience declines in output and employment as they face intensified competition from high-technology firms. The authors interpret these results through the theoretical framework proposed by Acemoglu and Restrepo (2018b), arguing that compensation effects offset the replacement effect, resulting in a net positive impact of robots on employment at the firm level. At the sectoral level, their findings implicitly assume the presence of a business-stealing effect, whereby robot adopters expand their scale of operations and employment, while non-adopters suffer losses in both output and jobs as competitive pressure from technologically advanced firms increases.

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

[10] Aghion et al. (2020) investigate the effects of automation technologies on employment, wages, prices, and profits using micro-level data for French manufacturing firms between 1994 and 2015. Their results show that automation has a positive impact on employment (at the plant, firm, and industry levels) even for unskilled industrial workers, suggesting that productivity gains from automation outweigh its potential displacement effects (but only in industries open to international competition, again pointing to the possibility of exporting the business-stealing effect).

previous study shows that occupations most exposed to robotic labor-saving technologies are associated with lower employment and wage rates (Montobbio et al. 2022, 2023a).

On the whole, robot adoption per se may imply competitive gains and employment growth at the company level, but robot adoption in general (at the industry and macro levels) has been empirically confirmed in its labor-saving nature.

### 3.5 Empirical Evidence for Specific Technologies: Artificial Intelligence

New empirical methodologies (such as natural language processing and text analysis) allow researchers to explore other sources of information (e.g., job posts and patents). These types of studies are particularly popular for analyzing exposure to and the impact of artificial intelligence on the labor market. In addition, these approaches can assess the proximity between specific innovations, occupations, and tasks.[11]

For instance, in their very influential study, Felten et al. (2021) create a new index of occupations' exposure to AI in the US. The authors merge two datasets: the Electronic Frontier Foundation (EFF) dataset within the AI Progress Measurement initiative with O*NET abilities. One of the main results of their study is that middle-skilled workers are more exposed to AI.[12]

In the same vein, Webb (2020) employs patent data to measure the exposure of the labor market to artificial intelligence (AI). The author constructs an index of task exposure to automation by analyzing the textual overlap between job task descriptions and patent documents. His results indicate that high-skill occupations are the most exposed to AI, particularly those requiring a college or postgraduate degree.[13]

Acemoglu et al. (2022) investigate AI-exposed establishments by combining job posts using Burning Glass Technology[14] data and SOC occupational codes. Their study find no apparent effect at the industry and occupational levels, but it does find a recomposition toward AI-intensive jobs (Acemoglu et al. 2022).

Using a similar approach, Albanesi et al. (2023) examine the relationship between labor market dynamics and the diffusion of artificial intelligence (and related software) across European countries during the period 2011–2019. The authors merge an O*NET-based Artificial Intelligence Occupational Exposure (AIOE) index with European 3-digit occupational classifications. Their results show that, on average, employment shares have increased in occupations more exposed to AI, particularly among younger and more highly skilled workers.

[11] While in this subsection we focus on the employment and occupational exposure to AI, other studies have investigated the impact of AI on other dimensions of the labor market, such as wages, organization, inequality, etc. (see for instance: Bircan and Özbilgin 2025; Engberg et al. 2025; Jaccoud 2025; Lábaj et al. 2025; Staccioli and Virgillito 2025).

[12] A serious problem of the Felten et al. (2021)'s approach is that their exposure measure is irrespective of the fact that AI is a complement or a substitute for human labor, resulting in outcomes that are very difficult to interpret in terms of their final impact on aggregate employment.

[13] Here again, the same limitation discussed in the previous footnote also applies.

[14] Burning Glass Technology provide wide coverage of firm-level online job postings, linked to SOC occupational codes.

Guarascio and Reljic (2025) use the Felten et al. (2021) AI exposure indicator and find that occupations more exposed to AI technologies experience stronger employment growth, ceteris paribus. However, these effects are not uniform across the EU, with positive employment outcomes concentrated in the European leading innovative countries.

By the same token, Guarascio et al. (2025) examine the relationship between exposure to artificial intelligence (AI) technologies and employment patterns in European regions. Building again on the methodology proposed by Felten et al. (2021), the authors construct an AI exposure indicator that links various AI applications to 52 workplace abilities, based on data collected through the mTurk web survey.[15] Overall, at the regional level, the labor market impact of AI remains uncertain, although the authors find a positive correlation between AI exposure and employment growth in advanced manufacturing European core regions, characterized by strong industrial bases, able to readily assimilate AI technologies.

Some studies, however, find a negative impact of AI on employment. For instance, Bonfiglioli et al. (2025) examine the effects of AI adoption on employment across U.S. commuting zones (CZs) over the period 2000–2020. The authors employ a shift–share instrumental variable that combines industry-level AI adoption with local industry employment. Their results show robust negative effects of AI exposure on employment across CZs and over time, particularly among low-skilled and production workers.

Hui et al. (2023) measure the impact of Generative AI (for instance ChatGPT) on the labor market (specifically on the employment outcomes of freelancers on a large online platform), based on the Global digital platform for freelancers Upwork. Their results show that freelancers in highly affected occupations suffer from the introduction of generative AI, experiencing reductions in employment.

More recently, some studies attempt to measure the impact of AI on employment at the supply level (that is the upstream sectors where AI devices are discovered and patented). For instance, Damioli et al. (2024) study the possible job creation effect of AI innovation activity from 2000 to 2016. The authors use patents (AI-related inventions) and show a moderately 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). These results support the idea that product innovation in AI-supplying industries is labor-friendly, as it represents the introduction of new products in upstream sectors (Dosi et al. 2021).

On the whole, the empirical studies devoted to assessing the employment impact of innovation in AI supports the important theoretical distinctions put forward in Sect. 2; while the supply of AI innovation at the upstream level may well imply job-creation, the widespread adoption of AI in the user industries may involve controversial labor market impacts, including substantial employment losses in those tasks/occupations/industries/regions most negatively exposed to AI diffusion.

[15] Using a cluster analysis, they classify EU regions into four groups: high-tech service and capital centers, advanced manufacturing cores, southern peripheries, and eastern peripheries. The results suggest that high-tech service and capital centers benefit the most from AI exposure, owing to preexisting local capabilities that complement AI technologies. By contrast, southern European regions exhibit limited capacity to capitalize on AI-related benefits.

### 3.6 The Role of the Global Value Chains

A further step in analyzing the impact of new technologies on the labor market is to take into account the various linkages involved in producing a final product at the international level. In this respect, the global value chain (GVC) framework provides a useful lens for this analysis (Brancati et al. 2024).[16]

According to Timmer et al. (2014), the production process has become increasingly fragmented across national borders, particularly in the manufacturing sector. Moreover, the factor content of these production processes tends to be biased toward skilled labor and capital, both in high-income countries and in emerging economies. Therefore, the final outcome in terms of the employment impact of innovation depends on the particular location of technological change within the GVC, its nature (either product or process innovation), the specific input–output linkages (see the previous section) within the GVC, and the institutional characteristics of the different national labor markets involved in the GVC (primarily the wage differentials). For instance, it may be well the case that labor-friendly product innovation only occurs in the core of the GVC (for instance in the multinational headquarters), while labor-saving process innovations are mainly introduced in the periphery of the GVC where labor-intensive productions are localized.

Moreover, a higher rank in the hierarchical position of a given GVC implies a higher propensity to adopt technologies that are more intensive in capital and skilled labor. For instance, in a recent study, Reljic et al. (2023), examine the impact of robots on employment by testing for the existence of two distinct robotization regimes: a labor-friendly regime and one characterizing weaker countries and regions. The former is defined by a technologically advanced manufacturing base, a central position within the GVCs, a preference for competitiveness strategies centered on innovation, and an intensive use of high-skilled labor. The peripheral regime, by contrast, relies on cost-competitive strategies and tends to adopt technologies such as robots and automation. Their results show that possible labor-friendly effects are concentrated in the core, while the labor-saving impact is shifted to the periphery.

A synoptic summary of the empirical studies discussed in Sect. 3 is reported in Table 1.

## 4 Main Findings and Conclusions

Given the complexity of the relationship between technology and employment (see Sect. 2), one main conclusion of this study is that theoretical models cannot claim to have a clear answer regarding the final employment impact of process and product innovation. As discussed in Sect. 2.4, the current debate tries to simplify the issue, by neglecting all the frictions and market failures that can actually hinder (or even annihilate) the efficacy of the different compensation mechanisms discussed in Sects. 2.2–2.4. Indeed, if all the critiques of the different compensation mechanisms are

[16] While GVCs as such are not within the scope of this study, in this subsection we offer a brief discussion and report some empirical results that we think are relevant to the investigated topic and possibly deserving further research.

**Table 1** Summary of the studies

| Authors | Period | Country or region | Sector | Main results | Difference between manufacturing and services sector |
|---|---|---|---|---|---|
| *Macro level* | | | | | |
| Vivarelli (1995) | 1960–1988 | Italy and the US | – | Labor-saving effect of process innovation. Positive relationship between product innovation and employment. The most important compensation mechanism operates through prices | |
| Simonetti et al. (2000) | 1965–1993 | US, Italy, France, and Japan | – | The more effective compensation mechanisms are the ones “via decrease in prices” and “via increase in incomes” (especially in European countries until the mid-1980s). The other mechanisms are less significant and conditional on the institutional structures of the respective countries | |
| Feldmann (2013) | 1985–2009 | Europe, Japan, and the US | – | Technological change tends to increase unemployment | |

**Table 1** (continued)

| Authors | Period | Country or region | Sector | Main results | Difference between manufacturing and services sector |
|---|---|---|---|---|---|
| *Sectoral level* | | | | | |
| Vivarelli (1996) | 1981–1985 | Italy | Manufacturing | Negative relationship between productivity growth and employment. Product and process innovations have opposite effects on labor demand | |
| Buerger et al. (2012) | 1999–2005 | Germany | Manufacturing | Patents (as a proxy for innovation) and employment are positively and significantly correlated in two high-tech sectors (medical and optical equipment, and electronics and electrical equipment) | |

**Table 1** (continued)

| Authors | Period | Country or region | Sector | Main results | Difference between manufacturing and services sector |
|---|---|---|---|---|---|
| Bogliacino and Pianta (2010) | 1994–2004 | Europe | Manufacturing and services | A positive association between technological competitiveness and employment. Alongside a negative association between cost competitiveness and employment. Moreover, the authors identify sectoral heterogeneities using the Pavitt taxonomy | |
| Piva and Vivarelli (2018) | 1998–2011 | Europe | Manufacturing and services | Job-destruction impact of capital formation (proxy for process innovation). Significant job-creation effect of R&D expenditure, especially in medium- and high-tech sectors | Although the sample contains information on the manufacturing and services sectors, the authors do not estimate for each sector |
| Dosi et al. (2021) | 1998–2016 | Europe | Manufacturing and services | Negative effect of capital replacement in downstream sectors. Weaker positive effect of expansionary capital investment in downstream sectors. Job-creation effect of R&D is found but weakly significant in upstream sectors | Although the sample contains information on the manufacturing and services sectors, the authors do not estimate for each sector |

**Table 1** (continued)

| Authors | Period | Country or region | Sector | Main results | Difference between manufacturing and services sector |
|---|---|---|---|---|---|
| Díaz et al. (2024a, b) | 2005–2015 | Spain | Manufacturing | Labor-saving impact in upstream and same sectors (mainly for low-skilled workers). Non-significant labor effects in downstream sectors | |
| Autor and Salomons (2018) | 1970–207 | OCDE countries | Manufacturing and seriveces | Total Factor Productivity (TFP) has a negative direct effect on employment, as rising productivity reduces labor input in the sectors where it originates (upstream sectors). However, these negative effects are offset by two indirect mechanisms: employment gains in downstream customer sectors, and increased demand stimulated by price declines triggered by productivity growth | |

**Table 1** (continued)

| Authors | Period | Country or region | Sector | Main results | Difference between manufacturing and services sector |
|---|---|---|---|---|---|
| Evangelista and Savona (2002, 2003) | 1993–1995 | Italy | Services | Positive employment effect, particularly among small firms and those operating in industries with a strong scientific and technological base. Large firms in capital-intensive and financial sectors (banking, insurance, and other financial services) experience a negative employment impact of innovation | |
| Cirillo et al. (2018) | 2007–2011 | Germany | Manufacturing and services | Product innovation positively affects employment among managers, particularly during upswings, while clerical workers experience negative effects from product innovation during downswings. Process innovation has a negative impact on managers and clerks in the upswing phase and reduces employment across all occupational categories during downswings | |

**Table 1** (continued)

| Authors | Period | Country or region | Sector | Main results | Difference between manufacturing and services sector |
|---|---|---|---|---|---|
| | | France, Spain, Italy and United Kingdom | | | |
| *Firm level* | | | | | |
| Van Reenen (1997) | 1976–1982 | United Kingdom | Manufacturing | Positive employment impact of innovation | |
| Piva and Vivarelli (2005) | 1992–1997 | Italy | Manufacturing | Small but significant positive link between a firm's investment in innovation and its employment | |
| Bogliacino et al. (2012) | 1990–2008 | Europe | Manufacturing and services | Positive and significant employment impact of R&D expenditure in services and high-tech manufacturing, but not in traditional manufacturing sectors | The effect on services is bigger than in manufacturing |
| Barbieri et al. (2020a, b) | 1998–2010 | Italy | Manufacturing | Innovation expenditure shows a labor-friendly nature. Positive employment effects of innovation and R&D are driven by firms operating in high-tech industries and large companies | |

**Table 1** (continued)

| Authors | Period | Country or region | Sector | Main results | Difference between manufacturing and services sector |
|---|---|---|---|---|---|
| Pellegrino et al. (2019) | 2002–2013 | Spain | Manufacturing | Job-creation impact of R&D expenditure becomes highly significant when focusing on high-tech firms. Employment tends to be labor-saving when SMEs are analyzed separately | |
| Harrison et al. (2014) | 1998–2000 | France, Germany, Spain, and the UK | Manufacturing and services | Process innovation tends to displace employment, whereas product innovation is generally labor-friendly in manufacturing sector. In service sector, the results show that product innovation has a positive and statistically significant impact on employment in all the countries considered (the United Kingdom, France, Germany, and Spain). However, no significant evidence is found for process innovation | The impact of product innovation is greater in the manufacturing sector than in the services sector for both Germany and Spain. Contrarily, the effect of product innovation is greater in service than in manufacturing for France and the UK. For process innovation, the labor-saving impact is only significant for the manufacturing sector in the case of Germany and the UK |

**Table 1** (continued)

| Authors | Period | Country or region | Sector | Main results | Difference between manufacturing and services sector |
|---|---|---|---|---|---|
| Díaz et al. (2020) | 2006–2014 | Spain | Manufacturing | Product innovation has a positive effect on employment, especially for high-skilled workers. Process innovation exhibits a labor-saving effect | |
| Lachenmaier and Rottmann (2011) | 1982–2002 | Germany | Manufacturing | Significantly positive impact of current and past product and process innovations on labor demand | |
| Van Roy et al. (2018) | 2003–2012 | Europe | Manufacturing and services | Positive employment impact of innovation is statistically significant only for firms in high-tech manufacturing sectors, and not significant in low-tech manufacturing or services | The positive impact of patents is primarily found in the manufacturing sector, rather than in the services sector. Especially in the high-tech manufacturing sector |
| Bianchini and Pellegrino (2019) | 1991–2012 | Spain | Manufacturing | Positive effect of product innovation on employment growth; no significant impact of process innovation | |

**Table 1** (continued)

| Authors | Period | Country or region | Sector | Main results | Difference between manufacturing and services sector |
|---|---|---|---|---|---|
| Goel and Nelson (2022) | 2006–2018 | 69 countries | Manufacturing and services | R&D expenditure and process innovation foster firms' employment growth | Although the sample contains information on the manufacturing and services sectors, the authors do not estimate for each sector |
| Evangelista and Savona (2003) | 1990–1995 | Italy | Services | A positive association between innovation and employment, although the magnitude and direction of the effect vary according to firm size and industry | |
| Dachs and Peters (2014) | 2002–2004 | Europe | Manufacturing and services | Product innovation has a positive and significant effect on employment for all ownership types, whereas process innovation has no significant effect in either foreign- or domestically owned firms within the service sector | The impact of product innovation is higher in manufacturing sectors than in services sectors. Process innovation is negative and significant only in the manufacturing sectors |

**Table 1** (continued)

| Authors | Period | Country or region | Sector | Main results | Difference between manufacturing and services sector |
|---|---|---|---|---|---|
| *Empirical evidence for specific technologies: robots* | | | | | |
| Acemoglu and Restrepo (2020a) | 1993–2014 | US | Manufacturing, services, and others | Displacement effects on low-wage workers | |
| Chiacchio et al. (2018) | – | European Union: Finland, France, Germany, Italy, Spain, and Sweden | Manufacturing and others | Robot introduction is negatively associated with the employment rate | |
| Graetz and Michaels (2018) | 1993–2007 | 17 countries | Manufacturing | Robots did not significantly reduce total employment, although they reduced the employment share of low-skilled workers | |
| Dauth et al. (2021) | 1994–2014 | Germany | Manufacturing and services | Robot exposure is associated with displacement effects in manufacturing, but these are fully offset by new job creation in services | Robot exposure is associated with displacement effects in manufacturing, but these are fully offset by new job creation in services |

**Table 1** (continued)

| Authors | Period | Country or region | Sector | Main results | Difference between manufacturing and services sector |
|---|---|---|---|---|---|
| Dottori (2021) | 1990–2016 | Italy | Manufacturing and Non-manufacturing | No harmful effect on total employment at the LLM level, and while the estimated effect on manufacturing employment is negative, its statistical significance becomes weak or disappears altogether once concurrent trends in trade and ICT adoption are accounted for. At the worker level, a positive, albeit modest, employment effect, particularly within the manufacturing sector | |
| Domini et al. (2021) | 2002–2015 | France | Manufacturing | Robot adoption or the import of capital equipment does not lead to labor displacement, but rather to employment expansion | |

**Table 1** (continued)

| Authors | Period | Country or region | Sector | Main results | Difference between manufacturing and services sector |
|---|---|---|---|---|---|
| Bisio et al. (2025) | 2011–2019 | Italy | Manufacturing and Non-manufacturing | A positive average adoption effect on employment among adopters, particularly for small firms. By contrast, medium and large firms experience a predominant negative displacement effect | At the sectoral level, the authors also identify that the adoption of automation technologies has a weakly negative effect on aggregate employment, as non-adopters suffer losses in sales and employment, consistent with a business-stealing effect |
| Bonfiglioli et al. (2024) | 1994–2013 | France | Manufacturing | While demand shocks generate a positive correlation between robot imports and employment at the firm level, exogenous exposure to automation results in job losses | |
| Humlum (2021) | 1995–2015 | Denmark | Manufacturing and services | Robot adoption is harmful for employment (specially for production workers) | Although the sample contains information on the manufacturing and services sectors, the authors do not estimate for each sector |

**Table 1** (continued)

| Authors | Period | Country or region | Sector | Main results | Difference between manufacturing and services sector |
|---|---|---|---|---|---|
| Acemoglu et al. (2020) | 2010–2015 | France | Manufacturing | At firm-level analysis the adopters expand their overall employment as well. However, this expansion comes at the expense of their competitors. However, the authors also show that the overall impact of robot adoption on industry employment is negative | |
| Koch et al. (2021) | 1990–2016 | Spain | Manufacturing | Robot adoption leads to net job creation at an annual rate of around 10% | |
| Dixon et al. (2021) | 1996–2017 | Canada | Manufacturing | Robots are associated with an increase in the span of control for supervisors remaining within organizations | |

**Table 1** (continued)

| Authors | Period | Country or region | Sector | Main results | Difference between manufacturing and services sector |
|---|---|---|---|---|---|
| Aghion et al. (2020) | 1994–2015 | France | Manufacturing | Automation has a positive impact on employment (at the plant, firm, and industry levels) even for unskilled industrial workers, suggesting that productivity gains from automation outweigh its potential displacement effects (but only in industries open to international competition, again pointing to the possibility of exporting the business-stealing effect) | |

**Table 1** (continued)

| Authors | Period | Country or region | Sector | Main results | Difference between manufacturing and services sector |
|---|---|---|---|---|---|
| *Empirical evidence for specific technologies: artificial intelligence* | | | | | |
| Felten et al. (2021) | | US | – | Middle-skilled workers are more exposed to AI | |
| Webb (2020) | 1980–2010 | US | – | High-skill occupations are the most exposed to AI, particularly those requiring a college or postgraduate degree | |
| Acemoglu et al. (2022) | 2010–2018 | US | Manufacturing and others | No significant effect at the industry and occupational levels, but a re-composition toward AI-intensive jobs is observed | Although the sample contains information on the manufacturing and services sectors, the authors do not estimate for each sector |
| Albanesi et al. (2023) | 2011–2019 | Europe | – | On average, employment shares have increased in occupations more exposed to AI (particularly younger and skilled workers) | |

**Table 1** (continued)

| Authors | Period | Country or region | Sector | Main results | Difference between manufacturing and services sector |
|---|---|---|---|---|---|
| Guarascio et al. (2025) | 2011–2018 | Europe | – | A positive correlation between AI exposure and employment growth in advanced manufacturing core regions. Eastern European peripheral regions recorded the highest employment growth during the period studied, mainly in low-skill and labor-intensive activities, sectors that are particularly vulnerable to automation | |
| Bonfiglioli et al. (2025) | 2000–2020 | US | Manufacturing and services | Negative effects of AI exposure on employment across CZs and over time, particularly among low-skilled and production workers | Although the sample contains information on the manufacturing and services sectors, the authors do not estimate for each sector |
| Hui et al. (2023) | 2022–2023 | Worldwide | – | Freelancers in highly affected occupations suffer from the introduction of generative AI, experiencing reductions in employment | |

**Table 1** (continued)

| Authors | Period | Country or region | Sector | Main results | Difference between manufacturing and services sector |
|---|---|---|---|---|---|
| Damioli et al. (2024) | 2000–2016 | Worldwide | Manufacturing and services | Moderate positive employment impact of AI patenting in industries that develop AI technologies, mainly in upstream sectors | Although the sample contains information on the manufacturing and services sectors, the authors do not estimate for each sector |
| Guarascio et al. (2025) | 2012–2022 | Europe | | A labor-creating effect of AI, although this positive impact is asymmetrically distributed, being concentrated in countries with stronger innovation systems | |
| Montobbio et al. (2022, 2023a, b) | 2008–2018 | US | – | Occupations most exposed to labor-saving technologies (including robotics) are associated with lower employment and wage rates | |

properly taken into account, the theoretical setting appears open to very different possible outcomes.

In more detail, while price and income mechanisms have the potential to compensate, fully or in part, the direct labor-saving impact of process innovation, the final outcome in terms of employment is uncertain. As extensively discussed in Sect. 2, driving factors and mitigators include such variables as the degree of competition, the demand elasticity, the elasticity of substitution between capital and labor, and the expectations of consumers and employers. Overall, depending on market structure and institutional contexts, compensation mechanisms can be more or less effective, and the negative employment impact of process innovation can be totally, partially, or not at all neutralized.

Moreover, inter-industry linkages also play an important role in increasing the theoretical uncertainty about the final employment impact of innovation and technological change. As fully developed in the agent-based model put forward in Dosi et al. (2021), the distinct dynamics of upstream and downstream industries should always be taken into account. Indeed, different sectors are characterized by different dynamics of technological change, which is disembodied (R&D) in the upstream industries and embodied in the downstream ones. In such a framework, the same innovation is a product innovation in the upstream aggregate, while being a process innovation in the downstream aggregate (think, for instance, of a robot or an AI algorithm), implying opposite impacts in terms of employment. Which one prevails is a matter of empirical testing.

In this context, for instance, as shown by the empirical studies discussed in Sects. 3.4, and 3.5, the employment impacts of current technologies in the automation and in the AI domains seem to confirm the crucial role of the relative position of the investigated focal firm. Indeed, while robot constructors and robot first-adopters may enjoy employment gains, robot users and lagging adopters may encounter significant job losses. By the same token, companies patenting AI devices and algorithms may experience job creation, while AI users are characterized by complementary and substitution effects, the total balance of which is difficult to predict. On the whole, the outcomes of the extant empirical evidence on the employment impact of automation and AI are consistent with the upstream/downstream theoretical framework recalled in this section (see above).

However, the findings of the extant empirical studies are also not fully conclusive about the possible employment impact of innovation and technological change. On average, 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; Montobbio et al. 2023a, b). However, in many industries, 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 straightforward to design industrial and innovation policies that can effectively maximize the positive employment impact of innovation. Additional microeconometric studies of the type adopted in the current literature are needed to further disentangle the labor impact of innovation across different sectors and different types of firms. However, compared with the labor-saving impact implied by the adoption of AI and automation technologies (massive according to some studies), the labor-friendly extent in the supply industries might be limited in magnitude and scope (just as a narrative example: the hiring of data scientists in upstream services and AI big-tech companies would hardly compensate job losses due to the massive introduction of robots, AI algorithms and other automation devices in the manufacturing industries and in platform-based services). As a gap in the current literature, more work is needed in terms of additional empirical evidence able to compare the actual magnitude of possible employment complementary effects within the providers of new technologies with the possible job-losses due to the substitution effects within the users of AI and automation technologies.

In terms of policy implications, industrial and innovation policies should try to foster job creation by supporting R&D investments and product innovation on the supply side (the companies providing the new technologies). In the AI era, this means supporting innovative companies active in AI design, engineering and patenting; to foster emerging industries and to promote innovative startups active in AI.

Moreover, since AI and automation are also embodied as process innovation in the user industries and firms, the compensation of the direct labor-saving effects should also be facilitated by economic policy. For instance, competition policies that lower entry barriers and reduce monopolistic rents, along with expansionary policies targeting intermediate and final demand, can be important drivers of job creation, making the compensation mechanisms "via lower prices" more effective.

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 and innovation policies need to carefully take into account the complex interactions between process innovation and product innovation, between mature and new industries along a given value chain, between job-creation effects in the upstream industries and job-destruction effects in the downstream industries (see above). These complex interrelationships, difficult to precisely assess in advance, highlight the need for continuous monitoring of policy implementation. For instance, safety nets and active labor market policies might be necessary to deal with the employment displacement due to the widespread diffusion of AI and automation technologies in the user industries. However, current European policy initiatives dealing with the diffusion of new technologies (such as the European Data Act and the Cybersecurity Act) seem to prioritize competitiveness and strategic autonomy, rather than dealing with the possible adverse labor-market impacts of technological change.

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