Eurasian Business Review (2024) 14:35–68
https://doi.org/10.1007/s40821-024-00259-6

REGULAR ARTICLE

The effects of product and process innovation on employment: a meta-regression analysis

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Received: 10 July 2023 / Accepted: 2 January 2024 / Published online: 17 February 2024

Abstract

The fast emergence of intensive robotization in combination with artificial intelligence implies a reappearance of the debate about the effects of innovation on the labor market. Many empirical studies have explored this phenomenon at the micro level, especially since the surge of innovation surveys, which use worldwide standardized indicators at the firm level. Most empirical studies suggest a robust, positive labor effect generated by new products, while the impact of process innovations on employment seems to be ambiguous. This paper offers a meta-regression analysis to seek some logical explanations for the results reflected in studies that apply the model proposed by Harrison et al. Our meta-regression suggests that the effect of sales growth due to new products on employment seems to be homogeneous and positive by different types of sub-samples. However, the labor effect of process innovation on employment depends on different circumstances. Its magnitude seems to be more negative for developing countries, manufacturing sectors, and periods of crisis. On the other hand, the magnitude tends to be positive for samples with the methodological approach (using instrumental variables), control variables, and high-tech sectors. The exercise is repeated, splitting the sample between developing and developed countries.

Keywords Meta-analysis · Innovation · Employment · Technological change

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JEL Classification D2 · J23 · L1 · E31

1 Introduction

The theoretical framework of the economics of innovation has identified several arguments that explain the simultaneous positive and negative employment effects caused by the introduction of new technologies in terms of product and process innovation. The first empirical studies tried to estimate the global employment effects of innovation without disentangling the different mechanisms behind product and process innovation because of a lack of good innovative indicators. Most of the studies from the twentieth century used regional, national, or sector-level data to measure labor effects. These aggregate-level studies had problems isolating the impact of innovation on the labor market from other possible determinants such as economic growth cycles or international economic shocks.

The rise of innovation surveys in the 1990s (and other firm-level data sets) permitted more reliable firm-level analysis. Recently, some general agreement has been reached on measuring specific innovation concepts (including product and process innovation) based on standardized indicators defined in international manuals.[1] However, combining these practical aspects of measurement with more abstract theoretical concepts like "compensation mechanisms" to determine the final impact of innovation on employment is much more complicated. Moreover, once the innovation-related effect on employment is identified, the problem is to relate the practical aspects to each compensation mechanism. In fact, the empirical data available still impede decomposing the observed employment effects of innovation with all the mechanisms mentioned in the literature, although some models explain some of them.

In this sense, two main empirical approaches have tried to explain the relationship between innovation and employment at the firm level. The first one is basically an input-oriented model also known as the *"derived labor demand model"* based on the model proposed by Van Reenen (1997) and adapted by Bogliacino et al. (2014), and uses innovation inputs, such as research and development (R&D) expenditure as a proxy for innovation, although some studies apply this approach using patents (as a non-commercial output variable). The second one is an alternative approach that uses commercial results in terms of sales related to new products as an indicator of product innovation and a dummy for the introduction of process innovation. This output-oriented model was proposed by Harrison et al. (2014). Other branches of empirical approaches have also measured the effects of technological change on the labor market. On the one hand, some studies combine the labor effects of output innovation (product and process innovation, patents) and input innovation (R&D) (e.g., Lachenmaier & Rottmann, 2011; Goel et al., 2022). On the other hand, some studies explore the effect of specific technologies –for instance, robots– on

[1] Among others, the Frascati Manual (on R&D), The Oslo Manual (on innovation) or the Canberra Manual (on human resources).

employment (e.g., Acemoglu et al., 2020; Koch et al., 2021; Deng et al., 2021).[2] However, in this analysis, they are not considered because they do not adopt the most standard empirical firm-level approaches.

Most studies of the two main approaches agree on the positive labor effects generated by innovations that are captured by the introduction of new products or by R&D expenditures. However, in the case of process innovation, the studies observed contradictory effects (Calvino & Virgillito, 2018; Heijs et al., 2019; Hötte, 2023; Vivarelli, 2014). The meta-regression analysis of this paper, only for the Harrison et al. model, explains the contradictions and heterogeneity that appeared in the results of empirical studies that analyzed the relationship between innovation and employment (especially for process innovation).

We focus on the papers that used the approach proposed by Harrison et al. (2014) for four reasons. First, the Harrison et al. model detaches the direct effects of product and process innovation, which allows for verifying some of the theoretical mechanisms behind the relationship between innovation and employment. Second, it allows us to assess why contradictory results with no clear empirical pattern for the process innovation were observed. Third, we exclude or isolate the possible heterogeneity caused by the use of different empirical methodologies and can therefore focus on external determinants. Finally, a previous literature review of innovation and employment was elaborated by Ugur et al. (2018), who applied a meta-regression for the 35 articles that used the labor demand model. Their main results suggest that the effect of innovation (in terms of R&D expenditures) on employment is positive but small and highly heterogeneous. Only a small part of residual heterogeneity is explained by moderating factors (Ugur et al., 2018). The shortcoming of this first type of model is that it does not control for the kind of innovation (process or product innovation), while the Harrison et al. model does take that aspect into account.

Furthermore, several literature reviews analyze the numerous publications on the employment effects of innovation, synthesizing theoretical implications and empirical findings (e.g., Barbieri et al., 2020; Calvino & Virgillito, 2018; Heijs et al., 2019; Hötte et al., 2023; Mondolo, 2022; Vivarelli, 2014). They highlight the heterogeneity in the effects between the different types of countries. Moreover, they observe some contradictory effects found in studies of the same types of countries. One main contribution of this paper is to tackle the explanations for these countries' heterogeneity with the meta-regression analysis.

For the analysis, we detected and considered 27 articles with 313 estimations proposed in those papers. We consider two different meta-regression models that referee the two main parameters of the model of Harrison et al. (2014). One model analyzes the heterogeneity of the employment effects of sales growth due to new products as a proxy of product innovation, and another analyzes these effects in firms that introduced "only process innovations" (referring to firms that did not introduce any new product).

[2] Other studies focus on the effects of automation on employment at the sector level. (e.g., Acemoglu et al., 2018; Graetz & Michaels, 2018). For more details about the effects of robots on employment, see Montobbio et al. (2023).

We extend this analysis by splitting the sample into different types of countries (developing and developed) because several authors demonstrate that the employment effects of products and process innovations differ by the type of country (developed versus developing countries) (Vivarelli, 2014; Crespi & Tacsir, 2018; De Vries, 2020; Fu et al., 2021). Expenditures in R&D and innovation are highly concentrated in multinational companies, and firms from the most developed countries introduce an overwhelming number of innovations. By contrast, less developed countries import and adapt technologies as part of their catching-up strategy (lower-middle income countries) or their industrialization process (very low-income countries). This is because product and process innovations have different impacts, and the nature of such innovation (on the edge of the technological frontier versus imitation and adaptation of already-existing technologies) implies different labor effects (Crespi & Tacsir, 2018). Therefore, we included the type of country as an explanatory variable in our overall model of the meta-regression. However, we also estimated separate models for both kinds of countries.

In the case of firms that introduced product innovations, the empirical studies show a more homogeneous employment effect. However, the meta-regression suggests that two aspects positively impact the magnitude of the effect, "only process innovation" and instrumental variables as a methodology for correcting the endogeneity problem. Studies for periods of crisis have a negative effect on sales growth due to new products. Contrarily, the observed heterogeneity of the employment effect of "only process innovation" can be partially explained by the moderating role of the economic level of the country of the firms. Another interesting finding are the different effects-based on the historical moment of observation. The meta-regression suggests the following results. The effects of "only process innovation" on the labor market are negative when the period analyzed includes years of economic crisis and developing countries. Similar results are found for the case of manufacturing sectors. Other characteristics positively affect the sign of the impact of "only process innovation" on employment: the use of instrumental variables, high-tech sectors, and samples with large firms.

Furthermore, after splitting the samples, the results suggest more heterogeneity in developed than in developing countries in the case of sales growth due to new products, even though the real size effect estimation is almost the same in both types of countries. A contrary effect is found in the case of "only process innovation," where the heterogeneity is higher in developing countries than in developed countries. This heterogeneity is explained mainly by the use of Methodology (IV), high-tech sectors, large and small samples (positive effects), and the manufacturing sector (negative effects).

These results shed light on the limitations of the Harrison et al. model. First, capturing the real effect of process innovation in a dummy variable is difficult. Process innovation can be related to the introduction of new or substantially improved processes in a company or the use or adoption of new equipment and machinery (often on-the-shelf-technologies) produced in other companies and sectors (e.g., adopting robots in the automobile sector). The second main concern is that the Harrison et al. model uses a simplified dummy variable associated with "only process innovation" and does not include a variable of process innovation related to product innovation.

However, many new products require new processes. The results of the meta-regression analysis suggest that these limitations are more problematic in developing than in developed countries. Finally, the positive labor effect of product innovation might be mitigated because the Harrison et al. model does not consider the "business stealing effect." This effect arises when demand for old products produced by non-innovating firms decreases because their market share is "stolen" by innovating firms that introduce new products that meet the demand for the old ones (see Acemoglu et al., 2020).

In the following section, we offer some basic notions of the theoretical framework for the effect of innovation on employment in quantitative terms. Section 3 discusses the methodologies of input-oriented and output-oriented models (the studies on which our meta-regression is based) and the impact in developing and developed countries. The methodological design of such regression is explained in Sect. 4, and the information collected from the 27 studies used is described by the statistical data presented in Sect. 5. Finally, Sects. 6 and 7 present the results and the main conclusions of the meta-analysis.

2 Some basic notions of the effect of innovation on employment

2.1 Theoretical mechanism tested in the Harrison et al. model

One of the central theoretical debates on the impact of innovation on employment in quantitative terms are the direct and indirect effects on employment caused by product and process innovations. It is widely accepted by scholars (Pianta, 2005; Vivarelli, 1995) that product innovation has a *positive direct labor effect*, while process innovation is considered to affect employment negatively. However, indirect effects might mitigate the negative and positive labor effects in both cases.[3] Regarding product innovations, introducing new products might generate new demand, stimulating labor demand in the market (*direct demand effect of product innovation*). However, if new products are produced more efficiently than old products, they will require less labor input for a given output. Contrarily, extra employment will be generated if the production is less efficient for new products than old ones. This kind of revealed *indirect productivity effect of product innovations* would dampen (strengthen) the positive demand effect.

In addition, if new products are substitutive, the demand for new products may replace to a certain degree the demand for old products (product cannibalization[4]). However, if new products complement the old ones, new product demand stimulates old product demand and, therefore, the firm requires extra labor (*indirect demand effect of product innovation)* (Peters et al., 2017).

[3] In this section, we offer only a short discussion about these mechanisms, highlighting the most relevant aspects for this paper. For a detailed analysis, see Pianta (2005), Vivarelli (1995), Calvino & Virgillito (2018), Barbiery et al. (2020), Mondolo (2022), and Hötte et al. (2023).

[4] The reduction of the labor demand related to old products.

On the other hand, the negative direct labor effect of process innovations would be caused by the increase in innovators' production efficiency (*productivity effect of process innovation*) (Peters et al., 2017). This means that firms require less input to produce an item, hence reducing their labor demand. However, the increased efficiency of production reduces costs and, consequently, a *price effect* exists that could stimulate the overall demand for goods. The corresponding higher demand could compensate for the loss of employment because of new jobs (Say's law)(Vivarelli, 2014).

2.2 Other theoretical mechanisms

Four other compensation mechanisms might exist and are discussed in the literature associated with the negative effect of process innovation on employment. However, the success of these compensation mechanisms depends on different factors, for instance, the fulfilment of Say's law, the animal spirits and expectations of economic agents, the prices of the factors, and the principle of factor substitution.[5] Unfortunately, the discussion is only theoretical, and testing them empirically is difficult.

The first compensation mechanism is "via new investment," analyzed within the classical view (specifically, Ricardo). It assumes that cost reduction could be used, in the short term, to increase profits, which automatically leads to new investments and the creation of new jobs, thus partially compensating for the loss of employment. As Vivarelli (1995) states, "during the competitive gap between the decrease in costs and the consequent fall in prices, extra profits are accumulated; these profits are invested, and so new products and jobs are created."

A second compensation mechanism is "via the increase in incomes." It assumes that the direction of cost benefits, in terms of productivity gains, might increase workers' salaries. The effect would stimulate the aggregate demand, generating opportunities for firms to invest, and, as a consequence, this would imply the creation of new jobs (Vivarelli, 1995). The limitations of this indirect impact on employment are also discussed later within the theoretical approach of Keynes and Schumpeter.

A third compensation mechanism, introduced by the classical literature, is "via the new sector of machinery, equipment and tools," whose direct effect on employment is the extra labor required for the rise of the machine and tool sector (Say, 1803). In other words, the new industrial sector emerged to design and produce new machines, generate new employment to produce tools and provide technical service and training, and maintain the machinery. According to Say (1803), while process innovation expels employment in the sectors that use new machines and tools, there is a compensation mechanism that generates jobs in a new sector that produces the required machines and equipment goods.

A fourth compensation mechanism is "via the reduction of wages," caused by a decrease in labor demand as a consequence of a higher level of efficiency or

[5] For more detailed critiques, see Vivarelli (1995, 2014) and Calvino & Virgillito (2018).

productivity. This decrease generates more unemployment and, as a result, a downturn in the level of salaries. Such decreasing labor costs would, from the neoclassical perspective, induce businesspeople to orient their investments to more labor-intensive technologies and therefore hire more new workers (Hicks, 1932: pg. 56; Pigou, 1933: pg. 526; Wicksell, 1961: pg. 137).

All the schools of economic thought agree with the existence of the aforementioned compensation mechanisms. However, they differ on the functioning of the mechanisms, the recovery of the initial negative effect of process innovation on employment, and their ability to compensate for lost jobs. The classical and neoclassical analyses state that the compensation mechanisms are automatic processes that will always recover the initial loss of employment and assure full employment. Nevertheless, other schools like the Keynesian and Schumpeterian mention several of their shortcomings and deny the basic assumptions of the neoclassical school; this will be discussed in the following section (see Sect. 3.1).

2.3 The effects of product and process innovation by type of country

As mentioned, the labor effects of innovation differ between developing and developed countries. In fact, for several reasons, the net employment effects of innovations and the outcome of the compensation mechanisms discussed differ between less developed countries and more developed economies. Some of the compensation mechanisms mentioned cannot be applied in those countries. The first is related to the employment generated in the production of machinery or equipment because less developed countries rarely produce it. Also, compensation via a decrease in prices and salary reduction would be hindered because of a lack of competition in local markets. Moreover, the income compensation mechanism (based on more demand due to higher incomes and the benefits of investment) can be hindered by reorientating investments and purchasing luxury goods abroad.

Based on the difference between both types of countries, in terms of product and process innovation, it is taken for granted that the introduction of "new products" often generates new employment, as confirmed by most studies (Calvino & Virgillito, 2018; Heijs et al., 2019; Vivarelli, 2014). However, less developed countries (especially low-income countries) rarely introduce product innovation based on R&D (Vivarelli, 2014). In the case of process innovation, the labor effects are much more heterogeneous for developing countries. For many companies in these countries, the process of innovation is based on imports of machinery (frequently secondhand) and novel intermediate products (embodied technological change). Although they are probably labor-saving, the modernization of the production structure promotes their productivity. It might improve competition at the international level (facilitating exports) and the overall income level (creating a higher level of domestic demand). Consequently, process innovation might imply a positive labor effect in developing countries.[6]

The diverse effects of product and process innovation in the case of developing versus developed countries is especially relevant for the case studies that Harrison et al. used because there are many studies that apply this empirical approach to developing countries, especially Latin American countries. The meta-regression analysis can capture the differentiated impact of product and process innovations in different countries. Therefore, we included the type of country as an explanatory variable in the overall model and estimated splitting the sample for both types of countries.

3 The relationship between innovation and employment: a theoretical background

3.1 Macroeconomic theories

From a historical perspective, macroeconomic growth and development models have barely discussed technological change and its employment effects. As a first vision, the neoclassical discussion focuses on the relationship between technological change and economic growth, where technological change is assumed to be an exogenous variable.[7] The neoclassical theory assumes that full employment exists in the long term because a set of compensation mechanisms will neutralize the possible negative impact due to technological change (Petit, 1995). Thus, any non-frictional unemployment rate is caused by real wages that are too high. In this case, a reduction of salaries would compensate the labor market.

A second perspective is proposed by the post-Keynesian vision, which discusses structural short-term unemployment based on a lack of demand during declining business cycles. In this framework, supporting public investments to recover the loss of jobs is essential in avoiding the perpetuation of low levels of demand due to decreasing income caused by unemployment.[8] The post-Keynesian theory considers

[6] In other words, because of positive knowledge externalities or spillovers, a catching-up process could positively affect employment because of the intensification of exports to rich countries (Vivarrelli. 2014).

[7] Moreover, the economic growth models (based on the neoclassical framework) treat technological change as an exogenous aspect and imply the absence of unemployment (Petit, 1995). The effect of technological change on economic growth in the Solow models is exogenous, assigned as the "Solow Residual," which is a part of the growth not explained by capital or employment. Petit (1995) considers the New Growth Theory (Lucas, 1988; Romer, 1986) to be the main adjustment of the Solow model based on growth models. Their models point to a holistic approach that stresses Marshallian externalities because of Arrow's concept of "Learning by Doing" (Arrow, 1962) and the corresponding improvement of human and physical capital.

[8] The post-Keynesian paradigm considers the supply side more or less constant, and the cause of the unemployment would be a lack of demand. This might be perpetual if the growing unemployment implies a decrease in demand. Keynes himself was not upset by the problem of long-term unemployment, suggesting in 1930 that productivity growth would permit a work week of around 15 h in 2030, resulting in an increase in leisure time, considered a positive tendency (Keynes, 1930).

that public intervention should focus on increasing effective demand because the impact of supply-based policies, a reactive measure, will usually take time. Moreover, cutting wages would decrease demand again and aggravate rather than alleviate unemployment.

In fact, technological change is handled by the post-Keynesian strand as a rather abstract concept, while the Schumpeterian (third vision) tradition defines different forms of innovation or technological change, each with specific employment effects (Petit, 1995). This third vision analyzes the nature and dynamics of innovations within the change of the technological paradigm. Instead of focusing on the overall labor supply and demand, Schumpeter (1939, 1947) considers (based on his concept of creative destruction) that technical unemployment is the effects of the differences in the skills and abilities of workers expelled from old sectors and workers required for emerging ones. Their adaptation and reinsertion into the labor market would be a slow, time-consuming macroeconomic process (Freeman & Soete 1987; Petit, 1995). Several authors have developed theoretical studies (for an overview, see Feldmann, 2013) to understand and reflect the severe and prolonged impact caused by creative destruction, the skilled bias, and other employment effects of innovation, showing ambiguous results (Feldmann, 2013).

There is no clear-cut division line between the Keynesian and Schumpeterian approaches (Petit, 1995). For example, Solow stated that Schumpeter's analyses of the dynamics of a profit-driven oriented innovation in firms and innovation-driven economic growth complement the ideas of the post-Keynesian approach. He explains that "Keynes is about short-run economic fluctuations brought about by erratic variations in the willingness of investors and governments to spend; Schumpeter is about the long-run trajectory driven by the erratic march of technological progress (Solow, 2007)."[9]

3.2 Microeconomics theories: the output-oriented approach and the input-oriented labor demand model

The empirical test of the existence of the effects at a macroeconomic level is difficult, and most studies try to shed some light on their existence using data at the firm level. In particular, the worldwide appearance of innovation surveys with detailed firm-level data on innovation activities and employment has made it possible to carry out specific studies on the relationship between both aspects. We detected two main empirical approaches that analyze the labor effects of innovation at the firm level: the "input-oriented labor demand model" and the "output-oriented Harrison et al. model."

[9] Robert M. Solow. "Heavy Thinker," published in the magazine *The New Republic* on May 21st, 2007. https://newrepublic.com/article/61183/heavy-thinker

3.2.1 Input-oriented labor demand model

A first main strand of studies is based on the model proposed by Van Reenen (1997) and adapted by Vivarelli (2014) and Bogliacino et al., (2012, 2014). This empirical approach has been used to analyze the innovation effect on employment (e.g., Pellegrino et al., 2019; Bogliacino et al., 2012, 2014; Dosi et al., 2021) and on types of skills (e.g., Piva et al., 2004; Araújo et al., 2011). According to Bogliacino et al. (2012), the adopted methodology takes into account the sticky and path-dependent nature of a firm's labor demand because of institutional factors such as labor protection and high adjustment costs in hiring and firing. The empirical specification uses a CES function (see Eq. 1), considering a competitive firm. It is supposed that the firm maximizes its profits.

$$Y = A\left[(\alpha L)^{\rho} + (\beta K)^{\rho}\right]^{\frac{1}{\rho}} \tag{1}$$

where Y is the output, L is the labor input, and K is the capital input. A is a measure of the potential Hicks-neutral technological change. α and β capture the reaction of labor and capital to a technological shock. Finally, ρ has values between 0 and 1 ($0 < \rho < 1$). Taking into account that P is the price of output and W is the cost of labor, it is possible to find Eq. 2, which is the equation of profits (Π).

$$\Pi = \left(A\left[(\alpha L)^{\rho} + (\beta K)^{\rho}\right]^{\frac{1}{\rho}}\right)P - (WL) \tag{2}$$

Maximizing Eq. 2 leads to the following demand (in logarithm form).

$$\ln(L) = \ln(Y) - \sigma \ln\left(\frac{W}{P}\right) + (\sigma - 1)\ln(\alpha) \tag{3}$$

where the elasticity of substitution between capital and labor is $\sigma = 1/(1-\rho)$. According to Bogliacino et al. (2012), the stochastic version of (3), augmented by including innovation for a panel of firms (i) over time (t), is[10]

$$l_{i,t} = \beta_1 y_{i,t} + \beta_2 w_{i,t} + \beta_3 r\&d_{i,t} + \beta_4 g_{i,t} + (\varepsilon_i + v_{i,t}) \tag{4}$$

All the variables of the model are in logarithms, which makes it possible to interpret their coefficients as elasticities. $l_{i,t}$ is employment, $y_{i,t}$ is output (sales as a proxy variable), $w_{i,t}$ is the wage, $r\&d_{i,t}$ is research and development (R&D) expenditure, $g_{i,t}$ is gross investment, ε_i is the idiosyncratic individual and time-invariant firm fixed effect, and $v_{i,t}$ is the usual error term (Bogliacino et al., 2014).[11]

[10] See Van Reenen (1997)for a similar approach.

[11] It is important to mention that the last equation is used in the Bogliacino et al. work (2012, 2014) since Van Reenen's work (1997) did not utilize an input of innovation as an exogenous variable (research and development expenditure), but instead a measure of innovative output (patents, new products and/or new processes).

3.2.2 The output-oriented Harrison et al. model

Section 3.2.2 shows the second methodology of one of the most used empirical models that analyze the relationship between innovation and employment. This model was initially proposed by Rupert Harrison, Jordi Jaumandreu, Jacques Mairesse, and Bettina Peters (2014).[12] According to Dachs and Peters (2014), this model has several advantages. First, the model permits disentangling some of the specific direct and indirect mechanisms mentioned in the previous section. The intuitive interpretation of the components of the models is the main advantage of this methodology. From a conceptual point of view, the parameters of the model can be interpreted in terms of specific efficiency gains according to two forms of innovation (product and process). Second, the data from innovation surveys make it suitable to apply and reply to the model in a comparable way in many different environments and countries (Dachs & Peters, 2014; Peters et al., 2017), especially those that applied the standard innovation survey used by the OCDE and the European Union. In fact, we found 27 studies covering developed and developing countries based on this model.

The Harrison et al. model assumes that a company can produce old (i = 1) and new (i = 2) products in two periods of time (a firm can introduce new products between t = 1 and t = 2). In the first period, all the products are old Y_{11}. However, in the second period, firms can produce a combination of new (Y_{22}) and old (Y_{12}) products in the case that a firm has not introduced any new product between the two moments of observation (Harrison et al., 2014).

The production function is composed of capital (K), labor (L), and intermediate inputs (M) which present constant returns to scale in the production of technology. Also, the production function can be divided into two separable equations with different technological productivity (Hicks-neutral parameter θ).

$$Y_{it} = \theta_{it} F\left(K_{it}, L_{it}, M_{it}\right) e^{\eta + \omega_{it}} \tag{5}$$

Furthermore, η is a fixed effect that captures the idiosyncrasy of the firm. The last parameter represents all the factors –non-observables– that make a firm more productive than the average firm using the same technology (in this case θ). ω represents unanticipated productivity shocks (E(ω_{it}) = 0). Minimizing the cost and applying Shephard's lemma, it is possible to derive the labor demand for old and new products.

$$L_{1t} = c_{wL}\left(w_{1t}\right) \frac{Y_{1t}}{\theta_{1t} e^{\eta + \omega_{1t}}} \tag{6}$$

$$L_{22} = c_{wL}\left(w_{22}\right) \frac{Y_{22}}{\theta_{22} e^{\eta + \omega_{22}}} \tag{7}$$

[12] The structural model of Harrison et al. (2014) is based on previous works by Harrison et al. (2008), Jaumandreu (2003), and Peters (2005).

The expression $c_{wL}(\cdot)$ represents the derivative of $c(\cdot)$ with respect to the wage (w_{it}). Decomposing employment growth into 2 years (t = 1 and t = 2) and assuming that the price of inputs is constant in all the years,[13]

$$\frac{\Delta L}{L} = \frac{L_{12} + L_{22} - L_{11}}{L_{11}} = \frac{L_{12} - L_{11}}{L_{11}} + \frac{L_{22}}{L_{11}} \simeq ln\frac{L_{12}}{L_{11}} + \frac{L_{22}}{L_{11}} \tag{8}$$

In theory, the growth rate of new products is defined as L_{22}/L_{11}. Replacing Eqs. 6 and 7 in Eq. 8 and applying logarithms gives us the equation:

$$\frac{\Delta L}{L} \cong -(\ln\theta_{12} - \ln\theta_{11}) + (lnY_{12} - \ln Y_{11}) + \frac{\theta_{11}}{\theta_{22}}\frac{Y_{22}}{Y_{11}} - (\omega_{12} - \omega_{11}) \tag{9}$$

Equation 9 describes the growth of employment in four terms: (1) $-(\ln\theta_{12} - \ln\theta_{11})$ captures the change in the efficiency of old products in the production process. (2) $(\ln Y_{12} - \ln Y_{11})$ is the rate of change of the demand of old products. (3) $\frac{\theta_{11}}{\theta_{22}}\frac{Y_{22}}{Y_{11}}$ expresses the increase of production related to new products. (4) $-(\omega_{12} - \omega_{11})$ is the impacts of non-technological perturbation of productivity. Harrison et al. (2014) propose the following structural equation in its reduced form based on Eq. 9.

$$l - y_1 = \alpha_0 + \alpha_1 d + \beta y_2 + u \tag{10}$$

where the constant term (parameter α_0) reflects the increase in the efficiency of the existing production process. In theory, the efficiency is always expected to improve over time for a particular good as part of the overall learning effect. Therefore, the constant term is expected to be negative, representing the average efficiency growth in the production of the old products.

The binary variable d picks up the additional effect of process innovations on employment related to old products of the efficiency parameter α_1. The variable d is equal to 1 if the firm has implemented a process innovation not associated with product innovation (the firm introduced "only process innovations" and did not commercialize new products). The expected sign of employment growth due to "only process innovation" is negative according to the theory explained in Sect. 2 (labeled as the *productivity effect of process innovation).*

Finally, the parameter β captures the relative efficiency of the production of old and new products (*productivity effect of product innovation*). According to Harrison et al. (2014), parameter β determines the impact of product innovation on employment growth and relative efficiency in producing old and new products. If the value of the parameter is less than 1, it means that the new products are produced more efficiently than the old products.

Harrison et al. mentioned that they do not directly have either y_1 or y_2. They only observe the increase in sales that include the effect of prices (for new and old products). The problem is related to the unavailability of firm prices. To solve this issue, Harrison et al. (2014) suggested using the prices at the industrial level (π) to deflate

[13] $C_{WL}(W_{11}) = C_{WL}(W_{12}) = C_{WL}(W_{22})$.

the growth of sales due to old products (substitute g_1 for y_1). Also, y_2 will be replaced by g_2 because it is only observed sales growth due to new products (see Eq. 11).

$$l - g_1 - \pi = \alpha_0 + \alpha_1 d + \beta g_2 + \varepsilon_i \tag{11}$$

In the case of Harrison's model, the endogeneity problem appears because of the structural specification. According to Harrison et al. (2014), the parameter β associated with the variable sales growth due to new products (g_2) is biased for two reasons. First, there is a problem of measurement error in variables in g_2. Second, there is a lack of firm-level price information, a problem related to g_1. If there is a divergence between the prices of the firm and the industry, it will cause an identification problem. In other words, we would underestimate the displacement effect of process innovation. Harrison et al. (2014) assume that in the absence of firm-level price information, we can only identify an impact of process innovation on the employment net of (direct) compensating firm-level price variation.[14] Therefore, they use the instrumental variable methods in the regression model as a solution to solve the endogeneity problem. More precisely, it is necessary to seek instruments for g_2.

It is not easy to identify instrumental variables that satisfy the inclusion and exclusion requirement. Harrison et al. (2014) recommend some variables to be used as instruments. Their preferred instrument is "increased range of products," although they check robustness by trying other instruments, such as an increased market share, improved quality of products, or the importance of clients as a source of information, and others.

4 Meta-regression analysis

In order to explain the heterogeneity observed in the studies that apply the Harrison et al. model, we use a meta-regression analysis (MRA), estimating two models and including the principal regression coefficients of the Harrison et al. model as the dependent variables: (g2) sales growth due to new products and (d) "only process innovation."

To achieve the goal of this section, we adapted the methodology initially proposed by Stanley and Doucouliagos (2012) called "meta-regression analysis." This method involves the analysis of the distribution of estimated coefficients and identifying elements that drive heterogeneity, including the so-called publication bias. Such bias in the results exists because papers with statistically significant results have a higher chance of being published, not only in journals but also in working papers, PhD theses, etcetera (Stanley, 2005; Stanley & Doucouliagos, 2012). Following the authors mentioned, the MRA models the relationship between the analyzed effect and its standard error to quantify the publication bias using Eq. 12:

$$effect_i = \beta_0 + \beta_1 \sigma_i + \epsilon_i \tag{12}$$

[14] For more information about these problems, see Harrison et al. (2014).

where $effect_i$ captures the estimated coefficients of each study i. The coefficient β_0 reflects the real employment effect (the average effect without the bias) of either sales growth due to new products (g2) or "only process innovation" (d) adjusted for the standard errors of the estimated $effect_i$ reflected in the papers, while coefficient β_1 captures the presence of publication bias. The null hypothesis is the absence of publication bias ($H_0 : \beta_1 = 0$). When the null hypothesis is rejected, it implies evidence of bias.

Because the estimated coefficients ($effect_i$) come from different studies based on different datasets, sample sizes, and different controls or methods, they normally generate both heterogeneity and heteroskedastic error terms. Therefore, it is prudent to use a weighted least squares (WLS) regression (Costa-Font et al., 2011). Equation 12 can be transformed into Eq. 13, dividing by the standard error σ_i, which is equivalent to using WLS precision-square ($\frac{1}{\sigma^2}$) as the analytical weight.

$$t_i = \frac{effect_i}{\sigma_i} = \beta_0\left(\frac{1}{\sigma_i}\right) + \beta_1 + v_1 \tag{13}$$

In Eq. 13, the dependent variable becomes the t-value associated with the i*th* reported estimate in the MRA dataset. However, the interpretation is the same as Eq. 12. Equation 13 represents what it is known as a precision effect test (PET) and allows us to test for the presence of publication bias ($\mathrm{H}_0{:}\beta_0 = 0$). When H_0 is rejected, we have evidence of the presence of publication selection, while testing $\beta_1 = 0$ is the funnel asymmetry test (FAT). An asymmetric funnel indicates whether there is a systematic difference in the size or sign of a regression coefficient related to each study's size or precision.

However, the specification on Eq. 13 still has some problems. According to Andrews and Kasy (2019), the conditional expectation of the effect size across studies is not lineal in the standard errors; it might cause a β_0 to be misguided in the interpretation as selection-corrected. To address this issue, some studies suggest introducing a quadratic specification (see Eqs. 14 and 15).

$$effect_i = \beta_0 + \gamma_1\sigma_i^2 + \delta_i \tag{14}$$

Equation 14 is known as the "precision-effect test corrected for standard errors" (PEESE). This specification is also used to test heterogeneity, transforming Eq. 14 into Eq. 15 by including additional regressors.

$$effect_i = \beta_0 + \gamma_1\sigma_i^2 + \sum_m \gamma_m Z_m + \delta_i \tag{15}$$

The observed heterogeneity is modeled through a set of binary (Z) variables that moderate the magnitude of the effect size estimates (Ugur et al., 2020). Equation 15 is also estimated by WLS, using the inverse of the variance of the estimated coefficients as weights $\left(\frac{1}{\sigma^2}\right)$.

5 Descriptive statistics

The first steps in meta-analysis are the search for or identification and selection of the studies included. Since this study aims to verify the effect of innovation on employment in developed and developing countries, international databases were reviewed. In particular, major academic websites on which the original texts were searched, like Google Scholar, Proquest, and Web of Science, were consulted. The search on these sites was based on combinations of the following keywords: "innovation," "employment," "product innovation," and "process innovation." The search was limited to scholarly journals and studies, and only studies that were written in Spanish or English were extracted. We included literature in Spanish because we found several studies for Spain and Latin America in both languages.

A total of 52 studies on the employment effects of innovation were identified, but we excluded studies that used other empirical methodologies unrelated to Harrison et al. (2014). In other words, we eliminated overlapping studies and checked the practical approach manually. We selected a total of 27 studies suitable for the purpose and scope of this study.[15] In the following pages, we offer the descriptive statistics for the key variables used for the meta-regression analysis (Table 1) and additional statistics for our dependent variables (coefficients of product and process innovation) according to the subsamples analyzed (Table 2).

Table 1 reflects that the average results among the studies that estimate employment effects derived from sales growth due to new products (g_2) is 0.95, and the minimum and maximum values of this variable are (−0.25) and 4.77, respectively. These results suggest that most of the studies that have applied the Harrison et al. model obtained a positive and significant effect of this variable on employment, which is in line with what is expected by the theory mentioned above. Moreover, the standard deviation associated with the estimated coefficients is low, with a mean of 0.11.

In the case of "only process innovation," the average employment effect is negative (− 0.86). However, there is a big dispersion in the values of this regression coefficient (with a minimum value of − 12.50 and a maximum of + 26.26) reflected by a standard deviation of 4.15. These results suggest that the relationship between only process innovation and employment is very heterogeneous and includes contradictory effects. Moreover, the standard deviation associated with the regression coefficient of only process innovation suggests that many of these coefficients are not significant. The average of this variable is 2.20, with a maximum value of 12.66 and a minimum value of (− 1.30). Such results justify the meta-regression analysis to explain the underlying causes.

Table 1 also shows some other methodological specifications and the sample characteristics. For instance, around half of the studies estimate by using control variables, crisis years, and developing country samples. On the other hand, some studies (approximately 10%) estimate the differentiated effects by sector

[15] See Appendix A for details of the setting of the studies included in the MRA.

Table 1 Descriptive statistics of the variables and other aspects of models included in the meta-regression analysis

Variable	Obs	Mean	Std. dev	Min	Max	Description
Dependent and independent variables used						
Value of g2: Sales growth due to new products	313	0.95	0.36	− 0.25	4.77	The coefficients that capture the effect of sales growth due to new products on employment growth
Standard error of sales growth due to new products	313	0.11	0.22	0.01	2.75	The standard errors associated with the coefficients of g2
Value of d: Only process innovation	313	− 0.86	4.15	− 12.50	26.26	The coefficients that capture the effect of only process innovation on employment growth
Standard error of only process innovation	313	2.20	1.98	− 1.30	12.66	The standard errors associated with the coefficients of d
Methodology used and setting by time frame and type of country						
Methodology (IV)	313	0.64	0.48	0	1	The variable takes value 1 if the study estimates with an instrumental variables methodology, 0 otherwise
Control variables	313	0.56	0.50	0	1	The variable takes value 1 if the study estimates with control variables, 0 otherwise
Period of crisis	313	0.58	0.49	0	1	The variable takes value 1 if the study period is between 2008 and 2014, 0 otherwise
Developing countries	313	0.54	0.50	0	1	The variable takes value 1 if the study is for developing countries, 0 otherwise
Specification of the samples by type of firm						
Only manufacturing firms	313	0.81	0.39	0	1	The variable takes value 1 if the study sample is for the manufacturing sector, 0 otherwise
Only high-tech firms	313	0.10	0.30	0	1	The variable takes value 1 if the study sample is for the high-tech sector, 0 otherwise
Only low-tech firms	313	0.10	0.30	0	1	The variable takes value 1 if the study sample is for the low-tech sector, 0 otherwise
Only large firms	313	0.07	0.25	0	1	The variable takes value 1 if the study sample is for large firms, 0 otherwise
Only small firms	313	0.16	0.36	0	1	The variable takes value 1 if the study sample is for small firms, 0 otherwise

Table 2 Descriptive statistics by type of sample, country and methodology

Variable	Sales growth due to new products (g2)					Only process Innovation (d)			
	Obs	Mean	Std. dev	Min	Max	Mean	Std. dev	Min	Max
Total sample	313	0.95	0.36	– 0.25	4.77	– 0.86	4.15	– 12.51	26.26
Time frame of the sample (whether it includes years of economic crisis or not)									
Observations financial and economic crisis 2008–2014	166	0.94	0.43	– 0.25	4.77	– 1.14	4.67	– 12.51	26.26
Observations before the crisis	130	0.96	0.26	0.36	2.14	– 0.61	3.67	– 10.13	15.42
Observations after the crisis	17	0.83	0.28	0.33	1.39	– 0.08	0.37	– 0.49	0.96
Methodology									
Regressions based on instrumental variables	112	0.83	0.25	– 0.25	2.65	– 1.87	4.20	– 12.51	17.81
Regressions based on OLS	201	1.01	0.40	0.26	4.77	– 0.29	4.01	– 7.32	26.26
Level of development of the country analyzed									
Samples of developed countries	145	0.92	0.12	0.42	1.18	– 1.94	3.41	– 12.51	7.96
Samples of developing countries	168	0.97	0.48	– 0.25	4.77	0.06	4.50	– 5.84	26.26
Specification of the samples by type of sector									
Only manufacturing firms	254	0.96	0.38	0.22	4.77	– 1.09	4.43	– 12.51	26.26
Only service sector firms	46	0.89	0.18	0.30	1.16	– 0.03	2.69	– 4.99	7.96
Only low-tech firms	30	0.91	0.26	0.22	1.54	– 1.06	1.73	– 5.30	1.56
Only high-tech firms	30	1.11	0.73	0.66	4.77	– 0.45	3.41	– 5.78	8.17
Specification of the samples by size									
Only large firms	21	0.97	0.14	0.73	1.24	– 2.70	4.61	– 12.51	3.71
Only small and medium-sized firms	49	0.98	0.31	0.69	2.14	– 1.87	4.88	– 11.23	15.42
Time frame of the sample (whether it includes years of economic crisis 2008–2014)									
Observations before the crisis	130	0.96	0.26	0.36	2.14	– 0.61	3.67	– 10.13	15.41
Observations during and after the crisis	183	0.93	0.42	– 0.25	4.77	– 1.03	4.46	– 12.51	26.26

(high- or low-tech sectors). Finally, many studies (81%) carry out the analysis only for manufacturing companies.

Furthermore, Table 2 displays the mean values for sales growth due to new products and “only process innovation” estimated coefficients for all the envisaged cases of the analysis. As can be seen in the table, sales growth due to new products shows a homogeneous pattern, possessing positive coefficients. Even in the case of using subsamples, the average of the coefficients is very similar between firms of different types of sectors or sizes.

However, in the case of “only process innovations,” the coefficients differ significantly among each other. In particular, there is a change of sign in the case of developing and developed countries (0.06 and − 1.94, respectively). The second most notable difference for “only process innovation” is found for means by type of methodology followed since the average value for the estimations based on instrumental variables of is (− 1.87), while for the estimations using OLS, the value is only (− 0.29). These differences are also present when we compare by types of sectors, where the value found for the services sector is (− 0.03) and for high-tech firms (− 0.45). The negative effect is much more noticeable for manufacturing and low-tech firms (− 1.09 and − 1.06, respectively). Although the means for the majority types of (sub)samples present negative values, looking at the maximum value, it can be stated that for all the (sub)samples, at least one study reflects a positive impact. For instance, for all subgroups of Table 2, the maximum value for the coefficient of “only process innovation” is positive.

Finally, the descriptive data of the studies included reflect that the labor-creating effect of sales growth due to new products apparently seems to be slightly lower in the period during and after the crisis. The negative employment effect of “only process innovation” is clearly more intense since the beginning of the crisis. In any case, the meta-regression analysis should reveal whether the differences (in terms of descriptive statistics) explain the heterogeneity of the results obtained in a causal way.

6 Results

6.1 Detection of publication bias

In this section, we deal with the well-known “publication bias.” One of the main tools for assessing the existence of this phenomenon is the Funnel Plot, which is a descriptive presentation of the relationship between the regression coefficients and standard deviation. The vertical line in Fig. 1 shows the fixed-effect weighted mean (FEWM). An indicator of publication bias is the asymmetric distribution around the FEWM. Furthermore, we can also explore a degree of residual heterogeneity if the effect size estimate is outside of the boundaries at 95% of pseudo confidence interval limits (dashed lines) (Ugur et al., 2020).

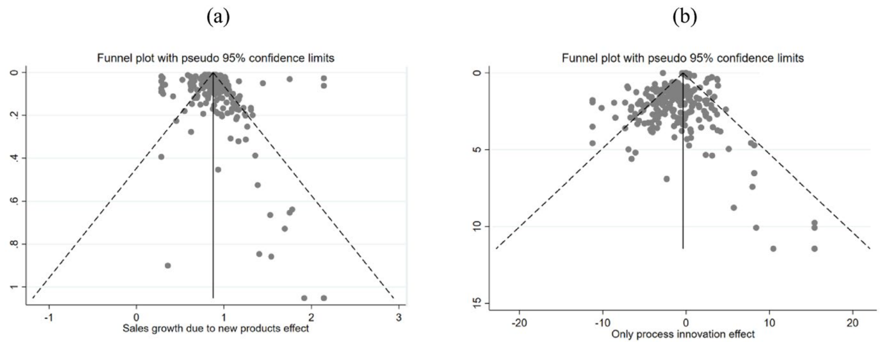

Fig. 1 Funnel graphs for sales growth due to new products and only process innovation. To deal with the outliers, we apply the winsor at 1%

Figure 1 shows the funnel plots for sales growth due to new products (Panel a) and for "only process innovation" (Panel b).[16] The funnel plot for sales growth due to new products does not offer a clear result; it might be positively biased, with a value close to 1. Furthermore, its sampling variation is not very high and can explain the extent of residual heterogeneity. The result is in line with the theoretical model proposed by Harrison et al. (2014).

In the case of "only process innovation," the funnel plot shows that the distribution of the effect sizes seems to be biased to be negative. The plot suggests that the distribution of the effect sizes around FEWM may be asymmetric, more concentration on the left, but there are more effects on the right than on the left. Furthermore, the plot displays that sampling variation cannot explain the extent of residual heterogeneity. In other words, the funnel plot suggests the existence of heterogeneity for this variable.

To better comprehend the existence of publication bias and size effect estimation, we estimate Eqs. 12 (PET and FAT, columns 1 and 3 of Table 3) and 14 (PEESE, columns 2 and 4 of Table 3). In the case of sales growth due to new products, the results suggest the presence of publication bias because the associated coefficient (PET/FAT) is significant.

However, the real effect size estimation for sales growth due to new products on employment is 0.86 for PET/FAT and 0.88 for PEESE. It is worth noting that the average effect calculated without controlling for standard errors is statistically equal to 1 (see Table 1). It suggests that new and old products are fabricated at the same level of efficiency. Nevertheless, the real size effect estimation using Eq. 14 indicates that new items are produced more efficiently than old ones.

In the case of "only process innovation," the results suggest the existence of a publication bias because the PET/FAT is negative and significant, which means that its effect size is asymmetric (on the left), but the mean value is not representative.

[16] We exclude the outliers, applying the Winsor command at 1%, included in Stata.

Table 3 Labor effect estimates by product and process innovation

Variables	Sales growth due to new products (g2)		Only process Innovation (d)	
	(1)	(2)	(3)	(4)
	PET/FAT	PEESE	PET/FAT	PEESE
Effect (β_o in PET and PEESE)	0.8551***	0.8780***	– 0.0535	– 0.0655
	[0.036]	[0.026]	[0.041]	[0.044]
Selection bias	0.9673*		– 0.6381*	
	[0.564]		[0.353]	
Standard error		1.1283**		– 0.0964
		[0.515]		[0.082]
Observations	313	313	313	313
R-squared	0.010	0.002	0.045	0.010

*** $p<0.01$, ** $p<0.05$, * $p<0.1$. Standard errors clustered at the study level in brackets. The estimation method is weighted least squares (WLS), considering weights based on the inverse of the variance of the estimated coefficient with an alternative standard error

Besides, the accurate size effect estimation for "only process innovation" on employment is (– 0.05) for PET/FAT and (– 0.07) for PEESE, but they are not significant.

To sum up, the results suggest that the size effect estimation of sales growth due to new products on employment is very homogeneous because there is a significant mean value, but it is conditioned by the presence of a publication bias. On the contrary, the results for "only process innovation" suggest a problem of publication bias, while real size effect estimation is negative but not significant. It suggests that the proxy variable used for process innovation (a dichotomous variable) fails to capture firms' process innovation strategies. Besides, we found evidence of heterogeneity that other variables might explain outside their sampling variation. To tackle this last issue, we try to capture the determinants of this heterogeneity in the following section.

6.2 Heterogeneity

Once the publication bias is analyzed, we present the results of the meta regression analysis in Table 4, which has the following structure. The results of sales growth due to new products are in columns 1–3, while the results of "only process innovation" are in columns 4 to 6. The independent variables for Columns 1 and 4 are the estimated coefficients of innovation variables (sales growth due to new products and "only process innovation") and the standard deviation associated with the coefficients. Columns 2 and 5 add variables that capture the characteristics of the studies: level of economic development of the country (developing), the time frame (years of the crisis), the use of the instrumental variables approach (IV), and whether the studies introduce control variables (wage, location and so on). Finally, the characteristics of the samples are included in Columns 3 and 6.

Regarding product innovation, the results suggest that the simultaneous effects of "only process innovation" (d), periods of crisis, and methodology (IV) affect the size of g2, with the employment effect of product innovation measured by sales growth due to new products. A one-point increase in the coefficient of only process innovation is associated with an increase of 0.013 in the value of the coefficient of sales growth due to new products. In other words, in settings where process innovation shows a larger (positive) effect on employment, the impact of product innovation on employment is also larger. On the other hand, the results also suggest that the positive effect of product innovation on employment is mitigated by the economic cycle since the periods of crisis variable shows a negative effect. Finally, the use of the method of IV has a positive and significant impact on sales growth due to new products, justifying the use of instrumental variables to correct the endogeneity problem that appears when an ordinary least square is used.

For "only process innovation," the results suggest that the heterogeneity of estimated coefficients is related to sample characteristics. First, when the country's economic level is considered, we find that the effect of process innovation is smaller for developing countries. A possible explanation for these results is that the labor market in developing countries is more labor intensive because of low wage costs, which implies that the introduction of new production processes will destroy more jobs.

On the other hand, in a period of crisis, the effect of process innovation on employment tends to be smaller. The cause might be that, in periods of declining demand, firms use the process innovation strategy to reduce labor costs and be competitive rather than gain market shares in such periods. In addition, the use of instrumental variables and control variables make the effect of process innovation on employment greater.

Then, the labor effect of "only process innovation" is negative in manufacturing sectors. Interestingly, the introduction of new processes tends to eliminate more employment in manufacturing firms which is consistent with the idea of automation. In these types of firms, it is easier to use process innovation oriented to the reduction of labor costs by replacing labor. On the other hand, the results suggest a positive labor effect of "only process innovation" in the case of high-tech sectors. However, employment loss is lower for large firms, perhaps because their competitive strategy is different and does not seek to reduce costs but might be oriented towards gaining market share or increasing their exports. The rest of the variables included in the model are not significant.

To sum up, the meta-regression analysis results suggest that the use of "only process innovation," instrumental variables, and period of crisis affects the estimated parameter of product innovation. On the other hand, in the case of "only process innovation," the heterogeneity behind the results of the studies is explained by the type of country, period of crisis, method (IV), control variables, the kind of sector, and the sample.

Table 4 Meta-regression for sales growth due to new products and only process innovation

Dependent variables	Sales growth due to new products (g2)			Only process Innovation (d)		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Standard error of sales growth due to new products	0.9219**	0.5315	0.9034	–	–	–
	[0.444]	[0.374]	[0.545]	–	–	–
Standard error of only process innovation	–	–	–	− 0.0929	− 0.0987	− 0.1028
	–	–	–	[0.086]	[0.088]	[0.094]
Only process innovation	0.0108***	0.0103***	0.0139***	–	–	–
	[0.003]	[0.002]	[0.005]	–	–	–
Sales growth due to new products	–	–	–	0.1317	0.1086	− 0.3054**
	–	–	–	[0.153]	[0.179]	[0.114]
Developing countries	–	− 0.0538	− 0.0699		− 0.0805	− 0.3422**
	–	[0.052]	[0.057]		[0.091]	[0.131]
Periods of crisis	–	− 0.0859*	− 0.0901**		− 0.1258	− 0.4044***
	–	[0.047]	[0.043]		[0.090]	[0.129]
Methodology (IV)	–	0.0415*	0.0489*		− 0.0684	0.0940**
	–	[0.024]	[0.027]		[0.067]	[0.041]
Control variables	–	0.0100	0.0206		0.0219*	0.0463***
	–	[0.030]	[0.029]		[0.011]	[0.012]

Table 4 (continued)

Dependent variables	Sales growth due to new products (g2)			Only process Innovation (d)		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Manufacturing sector only	–	–	0.2217			− 0.3603**
	–	–	[0.167]			[0.130]
High-tech sector only	–	–	− 0.0005			0.2489***
	–	–	[0.047]			[0.076]
Low-tech sector only	–	–	− 0.0179			0.0176
	–	–	[0.034]			[0.030]
Large firm sample only	–	–	0.0290			0.4724**
	–	–	[0.034]			[0.170]
Small firm sample only	–	–	− 0.0029			0.0610
	–	–	[0.031]			[0.153]
Constant	0.8997***	0.9227***	0.9034***	− 0.1730	− 0.1009	0.3268**
	[0.026]	[0.023]	[0.026]	[0.158]	[0.150]	[0.142]
Observations	313	313	313	313	313	313
R-squared	0.036	0.079	0.149	0.031	0.063	0.284

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors clustered at the study level in brackets. The estimation method is weighted least square (WLS), considering weights based on the inverse of the variance of the estimated coefficient with an alternative standard error

6.3 Heterogeneity by type of country: developing and developed

Based on the previous results presented in Sects. 6.1 and 6.2, we repeat the same analysis between developing and developed countries. The main reason is that we found a high degree of heterogeneity of the employment effects in both types of countries. Table 5 shows the results for the detected publication bias and size effect estimation. Columns 1 and 3 present the PET and FAT for developing and developed countries for sales growth due to new products. Columns 5 and 7 present the PET and FAT for both types of countries for “only process innovation.” The PEESE are shown in Columns 2 and 4 for sales growth due to new products and in Columns 6 and 8 for both models of “only process innovation.”

In the case of sales growth due to new products, the results for developing countries suggest no publication bias (the associated coefficient, FAT, is non-significant). Contrarily, the results for developed countries suggest a publication bias. The real size effect estimation for sales growth due to new products on employment is similar in both countries (0.875 for developing and 0.876 for developed countries), suggesting that new items are produced more efficiently than old ones in both types of countries.

In the case of “only process innovation,” the results for developing countries suggest no publication bias. On the other hand, for developed countries, the results suggest the existence of a publication bias with an FAT that is negative and statistically significant. They also show that its size effect is asymmetric (on

Table 5 Labor effect estimates by product and process innovation by type of countries: developing and developed

Variables	Sales growth due to new products (g2)				Only process innovation (d)			
	Developing countries		Developed countries		Developing countries		Developed countries	
	1	2	3	4	5	6	7	8
	PET/FAT	PEESE	PET/FAT	PEESE	PET/FAT	PEESE	PET/FAT	PEESE
Effect (β_0 in PET and PEESE)	0.8616***	0.8748***	0.8453***	0.8756***	− 0.0923	− 0.0959	− 0.0153*	− 0.0304***
	[0.063]	[0.045]	[0.040]	[0.036]	[0.079]	[0.080]	[0.008]	[0.008]
Selection bias	0.5436	–	1.5528**	–	− 0.1543	–	− 1.0973**	–
	[0.840]		[0.665]		[0.491]		[0.445]	
Standard error	–	0.9139**	–	70.141	–	0.0055		− 0.3449**
		[0.411]		[6.475]		[0.051]		[0.124]
Observations	168	168	145	145	168	168	145	145
R-squared	0.002	0.001	0.125	0.031	0.002	0.000	0.260	0.150

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors clustered at the study level in brackets. The estimation method is weighted least squares (WLS), considering weights based on the inverse of the variance of the estimated coefficient with an alternative standard error the left). Besides, the accurate size effect estimation for "only process innovation" on employment in developing countries, although negative, is not significant. By contrast, in developed countries, it is negative and significant (− 0.030) for PEESE.

The results suggest that the size effect estimation of sales growth due to new products on employment is very homogeneous. However, the results detect a publication bias in the case of developed countries. By contrast, the results for "only process innovation" are not homogeneous among developing and developed countries, and there is evidence of a publication bias problem in developed countries. These results confirm that the proxy variable used for process innovation (a dichotomous variable) seems to fail to capture firms' process innovation strategies, especially in developing countries.

Publication bias is based not only on the idea that models with significant effects are easier to publish, but once the "correct" orientation of the expected effects is established, it is difficult to publish a paper with opposite conclusions. Taking into account that, for developing countries, the expected effects are not clear**,** there are fewer constraints to publish papers in which one type of innovation has no significant employment effects. Therefore**,** the absence of publication bias for studies of these types of countries is not surprising.

Once the publication bias is analyzed, we present the results of the meta-regression analysis in Table 6 by types of countries to explain the causes of the heterogeneity, which has the following structure. The results for sales growth due to new products are in Columns 1 and 2 (developing and developed countries), while the results of "only process innovation" for both types of countries are in Columns 3 and 4.

Regarding product innovation, the results suggest that samples with only firms of the manufacturing sector affect the size of sales growth due to new products for developing countries. In the case of developed countries, the size of sales growth due to new products is affected by "only process innovation," methodology (IV), control variables, the low-tech sector and small firms. Despite these results, the effect of product innovation on employment is almost the same for developing and developed countries (see the PEESE in Table 5), with more heterogeneous results in the case of developed countries.

For "only process innovation," the results of the estimations suggest different effects by type of country, revealing more heterogeneity in developing than in developed countries. In the case of developing countries, the size effect is affected by sales growth due to new products, methodology (IV), the manufacturing sector, the high-tech sector, and large firms. In the case of developed countries, the size effect of "only process innovation" is explained by methodology (IV) and small firms. Nevertheless, as stated in the previous paragraph, the results show that the variable "only process innovation" varies greatly (with a more heterogeneous effect in developing countries than in developed countries), and it is difficult to identify its specific effect on employment.

In summary, splitting the sample sheds light on the fact that the employment effects of innovation are not equal for developing and developed countries. On the one hand, the real size effect of "sales growth due to new products" is almost the

Table 6 Meta-regression for sales growth due to new products and only process innovation by type of countries: developing and developed

PEESE	1	2	3	4
	Sales growth due to new products (g2)		Only process Innovation (d)	
Variables	Developing	Developed	Developing	Developed
Standard error of sales growth due to new products	1.1701*	– 26.99	–	–
	[0.543]	[3.953]	–	–
Standard error of only process innovation	–	–	0.0205	– 0.2596***
	–	–	[0.054]	[0.071]
Only process innovation	0.0157	0.0069***	–	–
	[0.014]	[0.001]	–	–
Sales growth due to new products	–	–	– 0.3268**	– 0.5982
	–	–	[0.126]	[0.857]
Periods of crisis	– 0.0769	– 0.0001	– 0.2576	– 0.7329
	[0.065]	[0.016]	[0.336]	[0.680]
Methodology (IV)	– 0.0452	0.1040***	0.0924*	3.2421***
	[0.053]	[0.009]	[0.046]	[0.844]
Control variables	– 0.0073	0.0443***	– 0.13	0.0482
	[0.089]	[0.011]	[0.330]	[0.034]
Manufacturing sector only	0.4872*	0.0176	– 0.3796**	– 0.8461
	[0.264]	[0.014]	[0.125]	[0.558]
High-tech sector only	– 0.0298	0.0089	0.2984***	0.0381
	[0.050]	[0.011]	[0.066]	[0.033]
Low-tech sector only	– 0.0525	– 0.0182*	0.0354	– 0.0031
	[0.044]	[0.009]	[0.060]	[0.005]
Large firm sample only	– 0.0077	0.0188	0.5172***	– 0.6253
	[0.034]	[0.016]	[0.154]	[0.409]
Small firm sample only	0.0417	– 0.0157*	0.098	– 1.5990***
	[0.092]	[0.008]	[0.136]	[0.501]
Constant	0.8004***	0.9384***	0.2010*	– 0.4704
	[0.043]	[0.009]	[0.094]	[0.900]
Observations	168	145	168	145
R-squared	0.21	0.795	0.515	0.515

*** $p < 0.01$, ** $p < 005$, * $p < 0.1$. Standard errors clustered at the study level in brackets. The estimation method is weighted least square (WLS), considering weights based on the inverse of the variance of the estimated coefficient with an alternative standard error

same for both types of countries, even though we found heterogeneity in the case of developed countries. On the other hand, more heterogeneous effects were found in developing countries than in developed countries for the case of "only process innovation."

7 Conclusions

This paper attempts to explain the apparent heterogeneous results observed in the empirical studies that measure labor effects of product and process innovations. The main conclusion is that Harrison's model correctly estimates the effect of product innovation, but it has limitations when the effect of process innovation is considered.

In the case of product innovation, the few small differences observed between the 313 models analyzed are not related to the type of country, the sector or the size of the firms in the sample. The heterogeneity in the results can be explained basically by the methodological approach (using instrumental variables), control variables, and by "only process innovation." On the other hand, the results suggest many possible causes of the observed heterogeneity for "only process innovation." The negative labor effect of "only process innovation" is more notable for firms in developing countries and manufacturing sectors. Similar results are found in studies that analyze the sample during a period of crisis. However, some other factors impact positively in the real size of "only process innovation," such as the methodological approach (using instrumental variables), control variables, and high-tech sectors.

The theoretical background, the descriptive statistics, and the results of the meta-analysis also suggest an intermediating role of the type of country on the employment effects of "only process innovation." For this reason, we decided to extend the analysis, splitting the sample between developing and developed countries and estimating the meta-regression analysis for each type of country. The results suggest that the size effect of sales growth due to new products on employment is almost the same for both types of countries, even though we found more heterogeneity for the case of developed countries. On the other hand, heterogeneous effects were found for the case of "only process innovation," which is more persistent in developing than in developed countries.

Specifically, for "only process innovation," the different results found in developing countries might be explained by sales growth due to new products, methodology (IV), manufacturing sectors, high-tech sectors, and large firms. On the other hand, in the case of developed countries, the size effect of "only process innovation" is explained by methodology (IV) and small firms. It suggests that the proxy variable used for process innovation (a dichotomous variable for "only process innovation") fails to capture firms' specific process innovation strategies, especially in developing countries. The results show that the employment effects of the variable "only process innovation" vary greatly, and it is difficult to identify their specific size. In any case, more heterogeneity exists from its effect in developing than in developed countries.

The paper reveals several possible explanations for the heterogeneous results of studies on the labor effects of innovation. However, a lot of work must be done for "only process innovation" because the way to measure such innovations is very limited. The innovation surveys define this kind of innovation simply with a binary variable (yes or no), which is insufficient. This variable captures very different firm strategies which take the value 1 regardless of the importance of the innovation for the companies or the number of process innovations carried out. Moreover, the effects of both product and process innovations are only measured with regard to labor effects within the firms. However, they do not include the indirect impact on employment in the other firms in the sector, especially those which are direct competitors (e.g., the Harrison et al. model does not consider the "business stealing effect" that might mitigate the positive effect of product innovation on employment). Therefore, there are still many lines of research that could broaden the knowledge on this topic.

Our meta-analysis has some limitations, the most outstanding ones are the following. First, most papers focus on Europe and Latin America. Having more articles from other parts of the world (for instance, the emerging countries in Southeast Asia) would provide more information about the differentiated effects of product and process innovation on the labor market by type of country. Second, it would be interesting to have information that could account for the "business stealing effect" to capture the possible overestimation of positive employment growth related to sales growth due to new products. Finally, it would be helpful to have other ways to measure process innovation and introduce the Harrison et al. model, for instance, embodied technological change, proposed by Pellegrino et al. (2019). However, this variable is not part of the surveys based on Community Innovation Surveys (CIS), and most of the time it is not allowed or it is impossible to merge its data with other sources of microdata, limiting the analysis. In any case, these last two aspects are more a problem of the model than of the meta-regression.

Appendix A. Studies on MRA database

Study	Period Analyzed	Methodology	Type of datum	Overall sample characteristics All types, or firms from certain sector or size	Include model subsamples Type of sector or by size	Types of countries analyzed
Dachs and Peters (2014)	1998–2010	OLS/2sls	Cross Section	Manufacturing, Services	Total workers	EU
Harrison et al. (2014)	1998–2000	OLS/2sls	Cross Section	Manufacturing, Services	Total workers	EU
Rojas (2013)	2004–2010	OLS/2sls	Panel	Manufacturing	Total workers	Spain
Crespi &Tacsir (2012)	1998–2009	OLS/2sls	Cross Section	Manufacturing	Total workers, high-skilled, low-skilled	LA

Study	Period Analyzed	Methodology	Type of datum	Overall sample characteristics All types, or firms from certain sector or size	Include model sub-samples Type of sector or by size	Types of countries analyzed
Elejalde et al. (2015)	1998–2001	OLS/2sls	Cross Section	Manufacturing, High-tech, Low-tech	Total workers, high-skilled, low-skilled	Argentina
Aboal et al. (2015)	1998–2009	OLS/2sls	Panel	Manufacturing, High-tech, Low-tech	Total workers, high-skilled, low-skilled	Uruguay
Alvarez et al. (2011)	1995–2007	OLS/2sls	Panel	Manufacturing, High-tech, Low-tech	Total workers, high-skilled, low-skilled	Chile
Fioravante and Maldonado (2008)	2001–2003	OLS/2sls	Cross Section	Manufacturing	Total workers	Brazil
Harrison et al. (2008)	1998–2000	OLS/2sls	Cross Section	Manufacturing, Services	Total workers	EU
Peters et al. (2017)	1998–2010	OLS/2sls	Panel	Manufacturing	Total workers	EU
Dachs et al. (2016)	1998–2010	OLS/2sls	Panel	Manufacturing, Services, High-tech, Low-tech	Total workers	EU
Leitner et al. (2011)	2002–2004	OLS/2sls	Cross Section	Manufacturing, Services	Total workers	EU
Hall et al. (2008)	1995–2003	OLS/2sls	Cross Section	Manufacturing	Total workers	Italy
Benavente and Lauterbach (2008)	1998–2001	OLS/2sls	Cross Section	Manufacturing	Total workers	Chile
Peters (2005)	1998–2000	OLS/2sls	Cross Section	Manufacturing, Services	Total workers	Germany
Jaumandreu (2003)	1998–2000	OLS/2sls	Cross Section	Manufacturing, Services	Total workers	Spain
Crespi et al. (2019)	2010–2012	OLS/2sls	Cross Section	Manufacturing, High-tech	Total workers, high-skilled, low-skilled	LA

Study	Period Analyzed	Methodology	Type of datum	Overall sample characteristics All types, or firms from certain sector or size	Include model subsamples Type of sector or by size	Types of countries analyzed
Nolazco et al. (2020)	2012–2014	OLS/2sls	Cross Section	Manufacturing, High-tech, Low-tech	Total workers, high-skilled, low-skilled	Peru
Hou et al. (2019)	2002–2004	OLS/2sls	Cross Section	Manufacturing, Services	Total workers	EU
Foronda et al. (2021)	2013–2015	OLS/2sls	Cross Section	Total sample	Total workers	Bolivia
Granada and Mejia (2020)	2007–2010	OLS/2sls	Cross Section	Manufacturing, Services, High-tech, Low-tech	Total workers	Colombia
Naidoo et al. (2023)	2002–2016	OLS/2sls	Cross Section	Total sample	Total workers	South Africa
Peters et al., (2022)	1998–2014	OLS/2sls	Cross Section	Manufacturing	Total workers	EU
Cirera and Sabetti (2019)	2013–2015	OLS/2sls	Cross Section	Total sample	Total workers	Africa and Asia
Rochina et al. (2023)	2009–2011	OLS/2sls	Cross Section	Total sample	Total workers	Ecuador
Arenas Díaz et al., (2020)	2006–2014	OLS/2sls	Panel	Manufacturing	Total workers	Spain
Arenas Díaz et al., (2024)	2006–2014	OLS/2sls	Panel	Manufacturing	Total workers	Spain

EU European countries, *LA* Latin American countries

Author contributions GAD: conceptualization, data curation, methodology, writing-original draft, writing-review and editing, supervision. AJG: data curation, methodology, writing-original draft, writing-review and editing, supervision. JH: Writing-original draft, writing-review and editing, supervision. All authors read and approved the final manuscript.

Funding Open access funding provided by Università Cattolica del Sacro Cuore within the CRUI-CARE Agreement. This research has been partially financed by DGAPA-UNAM (project UNAM-PAPIIT IN302223), by the Spanish Ministry of Economy and Competitiveness under Grant (project PID2020-112984GB-C21), and by FUNCAS (project UCM-271–2022).

Data availability The data that support the findings of this study are available from the corresponding author, Guillermo Arenas Díaz, upon reasonable request.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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