Structural Change and Economic Dynamics 69 (2024) 571–585

Contents lists available at ScienceDirect

Structural Change and Economic Dynamics

journal homepage: www.elsevier.com/locate/strueco

Does eco-innovation stimulate employment? The case of Spanish manufacturing firms

Sara Fernández [a,*], Celia Torrecillas [b], Guillermo Arenas Díaz [c]

[a] Department of Applied & Structural Economics & History, Faculty of Economics and Business, Complutense University of Madrid, Campus de Somosaguas, Pozuelo de Alarcón, Madrid 28223, Spain

[b] Department of Applied & Structural Economics & History, Faculty of Economics and Business and Instituto Complutense de Estudios Internacionales (ICEI), Universidad Complutense de Madrid, Finca Mas Ferre, Edificio A. Campus de Somosaguas, Pozuelo de Alarcón, Madrid 28223, Spain

[c] Department of Economic Policy, Università Cattolica del Sacro Cuore, Largo Gemelli 1, Milan 20123, Italy

A R T I C L E I N F O

Keywords:
Eco-innovations
Employment
Harrison model
High- and low-skilled
Dirty and clean industries

A B S T R A C T

The demand for eco-products due to the exigency of friendly and environmental production could affect the employment of the firms. This paper tests whether product and process eco-innovations boost employment in Spain differentiating by the environmental goals (material and energy efficiency and environment responsiveness), by the level of qualification of the workers, and by the dirtiness of the industries. We apply a Green Harrison model, using the Technological Innovation Panel (PITEC) for Spain from 2008 to 2016. Results show a positive relationship between all types of product eco-innovations and employment, while the influence of process eco-innovations on employment depends on the environmental goals, the level of skills, and the industry. Specifically, distinguishing by industry there is a labour-saving effect in clean industries and a labour-friendly effect for low-skilled employment in dirty industries.

1. Introduction

The growing concern about climate change has increased the analysis of economic growth considering green practices in the production processes. Climate change is demanding more eco-innovative practices of firms, being considered eco-innovations as the path-breaking of Porter's Hypothesis and the engine for satisfying a win-win situation between economic and green goals (Porter and Van der Linde, 1995; Colombelli et al., 2021; Stoever and Weche, 2018).

In this sense, the transition to the circular economy and the achievement of the sustainable development goals will require eco-innovations and a workforce with specific skills (Léger, 2016; Pérez Fernández de Retana and Buenetxea Aizpuru, 2020; Sachs et al., 2022; Wendler, 2019). Indeed, authors have pointed out that eco-innovations will have a positive effect on employment (Rennings et al., 2004; Coad and Hölzl, 2011; Colombelli et al., 2021).

Despite the importance of the link between eco-innovations and employment, the introduction of the green view of innovation and its connection with employment has been less studied by now, and the results are not still conclusive (Pfeiffer and Rennings, 2001; Rennings and Zwick, 2002; Colombelli et al., 2021; Gagliardi et al., 2016; Leoncini et al., 2019). In this sense, previous literature argues that the relationship between eco-innovation and employment could be affected by other factors such as the consideration of the environmental goals of eco-innovations, the profile of the workers and the industry, as has been noted by Rennings et al. (2004). In this sense, several papers have called for more research on this topic considering the effect of eco-innovation over employment by environmental goals (Colombelli et al., 2021), analysing the level of qualification of the workers (Aldieri et al., 2019b; Burger et al., 2019) and differentiating between the dirtiness of the industries (Kunapatarawong and Martínez-Ros, 2016).

Based on the above, this paper aims to fill the gaps detected in the literature by introducing in the analysis of eco-innovation and employment: the differentiation by type of innovation and environmental goal (Aldieri et al., 2019a; Caravella and Crespi, 2022; Costantini et al., 2018), by workers' skill level (Aldieri et al., 2019b; Burger et al., 2019) and by considering the industry's dirtiness (Kunapatarawong and Martínez-Ros, 2016). Therefore, considering these three aspects, we try to answer the general research question postulated in the title of this paper: does eco-innovation stimulate employment?

To achieve the purpose of this research, we apply a Green Harrison model -created from the well-known Harrison et al. (2014) model-

* Corresponding author.
E-mail address: sarafe21@ucm.es (S. Fernández).

https://doi.org/10.1016/j.strueco.2024.03.007
Received 20 September 2023; Received in revised form 14 February 2024; Accepted 26 March 2024
Available online 31 March 2024
0954-349X/

which considers the particularities of the eco-innovation variables. In addition, the data used to answer our research question comes from the Technological Innovation Panel (PITEC) elaborated in Spain for the period 2008–2016. This dataset collects the variables needed to answer our research questions.

Results show that there is a positive relationship between all types of product eco-innovation and employment, regardless of the skill level of the workers and the type of industry. However, the results of process eco-innovations are influenced by these factors. Specifically, while we find a positive effect of energy efficiency process eco-innovations on employment, distinguishing by industry there is a labour-saving effect in clean industries and a labour-friendly effect for low-skilled employment in dirty industries.

This paper contributes to the literature in the following ways. Firstly, this research proposes the green implementation of the Harrison et al. (2014) model, which is well-recognized in the innovation and employment literature. Secondly, we add evidence to the relationship between eco-innovations and employment by differentiating between types of innovation (product and process) and environmental goals (material and energy efficiency and environment responsiveness). Thirdly, we contribute to the literature by analysing the effects considering the level of qualification (high-skilled and low-skilled employees) and the level of pollution of the industry (clean and dirty). Finally, we develop some policy recommendations.

The paper is organized as follows. In the next section, we present the theoretical framework as well as the development of hypotheses. The third section describes the methodology and data and adds some descriptive statistics. In section number four, we show the main results. The final section draws the main conclusions and policy recommendations from the analysis.

2. Eco-innovation and employment. Hypothesis development

The achievement of sustainable development goals involves studying the relationship between eco-innovation and employment, given that eco-innovations could be the engine for the needed economic structural changes. In this sense, Crespi (2016, p.144), based on Porter and Van der Linde (1995), noted: "*Only if environmental policies are capable of generating innovation in products and processes that positively affect the dynamic efficiency of the economy, environmental goals may become compatibles with the promotion and competitiveness*".

Despite the popular belief that eco-innovations will affect positively employment, little research is studying this relationship empirically (Pfeiffer and Rennings 2001; Rennings and Zwick, 2002; Colombelli et al., 2021; Gagliardi et al., 2016; Leoncini et al., 2019). Thus, it still needed a more detailed analysis of the economic consequences, and particularly the effects on employment of the introduction of eco-innovations, as has been identified by Aldieri et al. (2019b).

Since pioneer contributions to the analysis of this relationship (Pfeiffer and Rennings, 2001; Rennings and Zwick, 2002; Rennings et al., 2004), empirical evidence has shown inconclusive results: positive influence of eco-innovations over employment (Aldieri et al., 2019b; Gagliardi et al., 2016; Horbach, 2010; Pfeiffer and Rennings, 2001; Kunapatarawong and Martínez-Ros, 2016; Triguero et al., 2017), negative relationship between both variables (Cainelli et al., 2011; Madaleno et al., 2020), and mixed effects (Aldieri et al., 2019a; Rennings and Zwick, 2002).

One possible explanation for these inconclusive results is that the effects of eco-innovations over employment could vary depending on a set of factors as has been recognized in Rennings et al. (2004). We will focus here on three of those factors: the first one is the type of innovation *-product and process-* together with the content of the environmental goals *-material and energy efficiency, and environment responsiveness-* (Horbach et al., 2012); the level of qualification of the workers *-skill--biased-* (Rennings et al., 2004; Cainelli et al., 2011) and the industries *-clean and dirty industries- (*García Marco et al., 2020; Costantini et al., 2018; Kunapatarawong and Martínez-Ros, 2016).

Regarding the type of innovation -product and process eco-innovations, the Economics of Innovation literature has already analysed the effect of general innovations over employment showing two opposing forces: labour-saving effects and labour-friendly effects (Vivarelli, 2014; Calvino and Virgillito, 2018; Pianta, 2005; Freeman and Soete, 1987; and Díaz et al., 2020), depending on product and process innovation.

On the one hand, product innovations may generate different effects on employment: a positive effect, due to the possible creation of new markets that require more jobs (*direct effect*), and whether product innovations complement the old product (*indirect effect*). On the contrary, a negative effect (*indirect effect*) is expected whether product innovation improves efficiency or substitutes old products (Vivarelli, 2014; Calvino and Virgillito, 2018; Díaz et al., 2020). However, the empirical literature has found that the positive effects –labour-friendly effect- of product innovations on employment outweigh the negative ones (Hall et al., 2008; Harrison et al., 2014; Leo and Steiner, 1994).

Following this line of reasoning, the expected results for *product eco-innovations* would be similar. In this sense, when the market has accepted a new or improved eco-product, the effect is the creation of employment. However, these positive effects also depend on whether the new goods replace older goods (substitution effects) or whether prices are higher due to the new products (income effects). If the substitution or income effects occur, the positive impact of product eco-innovation on employment could be mitigated (Pfeiffer and Rennings, 2001; Horbach and Rennings, 2013; Aldieri and Vinci, 2018). These ideas have been tested in the limited studies that analyse product eco-innovations showing a positive effect on job creation (Horbach, 2010; Licht and Peters, 2014), like what has been found for general innovations.

On the other hand, the introduction of process innovations increases the productivity of the firms, and it has a negative *direct impact* on employment since the increase in productivity leads to a reduction of labour and costs. Conversely, the compensation effect -*indirect effect*- is the increase in demand because of the reduction of costs and prices which stimulate the labour demand (Vivarelli, 2014; Calvino and Virgillito, 2018; Díaz et al., 2020). Therefore, a higher level of production would compensate for the labour losses and could generate new jobs. In this respect, the empirical literature has obtained results that are not entirely conclusive. The researchers find a positive relationship (Blanchflower and Burgess, 1999; Greenan and Guellec, 2000) or non-significant influence (Benavente and Lauterbach, 2008; Harrison et al., 2014; Hall et al., 2008; Hou et al., 2019).

The same dynamic has been noted for *process eco-innovations,* indicating that whether the *direct effects* are larger than the *indirect effect,* the net effect will be negative and vice versa (Rennings and Zwick, 2002; Horbach and Rammer, 2020). Empirical results in the field of process eco-innovations are also not entirely conclusive showing a negative effect on employment (Rennings et al., 2004), a positive one (Triguero et al., 2017), or a mixed one (Horbach and Rennings, 2013; Glagiardi et al., 2016).

Therefore, the authors agree that in *product eco-innovation,* the trend is *positive* for the increase in employment due to new products or services (Pfeiffer and Rennings, 2001; Rennings and Zwick 2002; Horbach, 2010; Licht and Peters, 2014). However, compensatory, and reinforcing effects could occur in the medium-long-term scenario (Cainelli et al., 2011). Furthermore, the authors also recognize that for *process eco-innovation* the trend seems to be *negative* due to the substitution effect of technical change and will only be positive when indirect effects are larger (Rennings and Zwick, 2002; Horbach and Rammer, 2020).

In addition, authors have pointed out that the ambiguity of the effects of eco-innovation over employment also depends on the *environmental goals* (Aldieri and Vinci, 2018; Aldieri et al., 2019a; Cainelli et al., 2011; Caravella and Crespi, 2022). In this sense, Rennings et al. (2004) recognized the importance of the differentiation between environmental goals in the analysis of eco-innovation and employment.

Distinguishing between environmental goals could sometimes be complex: ie, eco-innovations could reduce the use of materials -material efficiency-, energy resources -energy efficiency- or be environmentally friendly –environmental impact-.

In this sense, previous evidence has shown different effects on employment for material efficiency eco-innovations: positive (Horbach and Rennigns, 2013), negative (Aldieri et al., 2019a), or effects that depend on the characteristics of firms (Caravella and Crespi, 2022). Related to energy efficiency, authors have found a negative effect on employment growth (Costantini et al., 2018), while other authors have pointed out a positive or non-significant result (Horbach and Rennings, 2013; Demirel and Danisman, 2019). Finally, regarding the environmental impacts, literature has shown that the reduction of pollution affects positively employment growth (Aldieri et al., 2019a; Caravella and Crespi, 2022).

Therefore, based on the theoretical and empirical studies related to product eco-innovations, it seems that these could produce a labour-friendly effect regardless of the green goal considered. On the contrary, for the different process eco-innovations, theory indicated that the effects could be different, and the empirical results were not conclusive. In this case, we will consider that the labour-saving effect (*direct effect*) will predominate regardless of the green goal in process innovations, as has been found in studies carried out for the case of process innovations in Spain using the same database and model as in this study (Pizarro, 2013; Díaz et al., 2020).

Therefore, given the above, we propose the following set of hypotheses:

H1: There is a positive relationship between product eco-innovation -*material and energy efficiency and environment responsiveness*- and employment.

H2: There is a negative relationship between process eco-innovation -*material and energy efficiency and environment responsiveness*- and employment.

Regarding the level of qualification of employment, the economic literature on innovation has analysed the trade-off of the skill effect based on the Skill-Based Technological Change hypothesis (SBTC) and the Routine-Based Technological Change (RBTC) hypothesis.

On the one hand, the former focuses on the fact that the use of new technologies will require workers with higher qualifications and skills (Nelson and Phelps, 1966; Griliches, 1969). This complementarity between innovations and competencies will lead to an improvement in skilled employment by raising its productivity, while it will have a negative effect on the low-skilled (Violante, 2008). Applying these theories to the green part of innovation, eco-innovations require that employees not only have a good knowledge base but also that they can take advantage of and exploit the firm's internal and external resources appropriately. Consequently, to develop eco-innovations, employees will have to be highly qualified to know how to appropriately use the inputs provided by the company (Léger, 2016; Pérez Fernández de Retana and Buenetxea Aizpuru, 2020).

On the other hand, the routine-based technological change (RBTC) hypothesis states that new technologies tend to replace job functions that follow predictable and repetitive patterns (routine tasks), while more complex and non-routine tasks may require human intervention, which may lead to a displacement of unskilled workers (Goos et al., 2014; Jaimovich and Siu, 2020). This hypothesis could also be applied to eco-innovation by considering how technologies affect routine tasks in the context of sustainable practices. Furthermore, the skills of workers in this field will depend on their ability to adapt to emerging green technologies and adopt interdisciplinary approaches to address environmental challenges.

Based on both perspectives, it is expected that the contributions related to eco-innovations also point out a skill-biased hypothesis associated with eco-technological change (Pfeiffer and Rennings, 2001; Rennings and Zwick, 2002; Rennings et al., 2004; Cainelli et al., 2011).

In this regard, studies related to eco-innovation note that eco-innovations require high skills (Rennings et al., 2004; Aldieri et al., 2019b). Specifically, Burger et al. (2019) argue that the introduction of green activities demands more manual and technological skills and more complex cognitive skills. Therefore, it is possible to state that eco-innovations imply an increase in the demand for high-skilled labour and a reduction in low-skilled employment (Rennings et al., 2004; Aldieri et al., 2019b; Cainelli et al., 2011). In this sense, Cainelli et al. (2011) find a negative link between environmental innovations and employment. However, the authors note that this may be due to job destruction for the less skilled and job creation for the more skilled. Thus, they consider that there can be a net effect between the destruction of low-skilled employment and the creation of high-skilled jobs. This argument has been also defended by Gagliardi et al. (2016) who point out the skill bias nature of the eco-technological change, mentioning a positive impact on the employment of high-skilled individuals and a negative-labour effect for low-skilled workers.

On the contrary, the question still to be resolved is whether each type of eco-innovation will affect the growth of high- and low-skilled employment in the same way. To develop product eco-innovations, high-skilled employees will be needed, and the increasing demand for such eco-innovative products will lead to an even higher number of such employees, allowing the less skilled labour force to be replaced. In the same line, the implementation of process eco-innovations will also require high-skilled employees. In contrast, the increase in efficiency that these changes will generate will lead to the dismissal of employees, particularly affected by low-skilled workers.

Therefore, evidence considering the type of eco-innovations and type of employment is still scarce even when there are some calls for papers about the differentiation by the level of qualification of the workers (Cainelli et al., 2011; Costantini et al., 2018). Thus, considering the above, we propose the following set of hypotheses:

H3. There is a positive relationship between the introduction of all types of eco-innovations and high-skilled employment.

H4. There is a negative relationship between the introduction of all types of eco-innovations and low-skilled employment.

Finally, the dirtiness of the industries requires a special mention for the analysis of the effect of eco-innovation on employment (Rennings and Zwick, 2002; Rennings et al., 2004 Kunapatarawong and Martínez-Ros, 2016; Shan and Wang, 2019; Horbach and Janser, 2016). In fact, Costantini et al. (2018, 251) argue that *"there are differentiated patterns among countries and sectors in the relationship between eco-innovation and employment"*.

In this regard, industries can be classified according to the levels of pollution and toxins supplied into the environment. On the one hand, dirty industries include pollution-intensive sectors such as, among others: chemicals, rubber and plastics, vehicles, pharmaceuticals, non-metallic mineral products, and electrical products. On the other hand, clothing, machinery, and equipment or transport equipment are examples of clean industries (Al-Ayouty et al., 2017). A similar classification of dirty and clean industries has been considered for a Chinese sample to test the relationship between eco-innovation and employment (Shan and Wang, 2019; Pawlowski and Yu, 2017) and for a Spanish sample (Kunapatarawong and Martínez-Ros, 2016).

According to García-Marco et al. (2020) and Janahi et al. (2021), firms belonging to each industry are subjected to different environmental regulatory pressures, and therefore regulation is one of the factors that would affect this relationship (Rennings et al., 2004). In this regard, while companies in sectors that are considered dirty are scrutinized by the public and can be subject to very strict environmental regulations, clean sectors do not face the same pressure, being this environmental pressure lighter. Dirty sectors must make more efforts to ensure that their image is not overly damaged by their activities. Therefore, these types of companies will undertake eco-innovation activities not only to capture business opportunities but also to demonstrate that they are carrying out efforts to improve their environmental

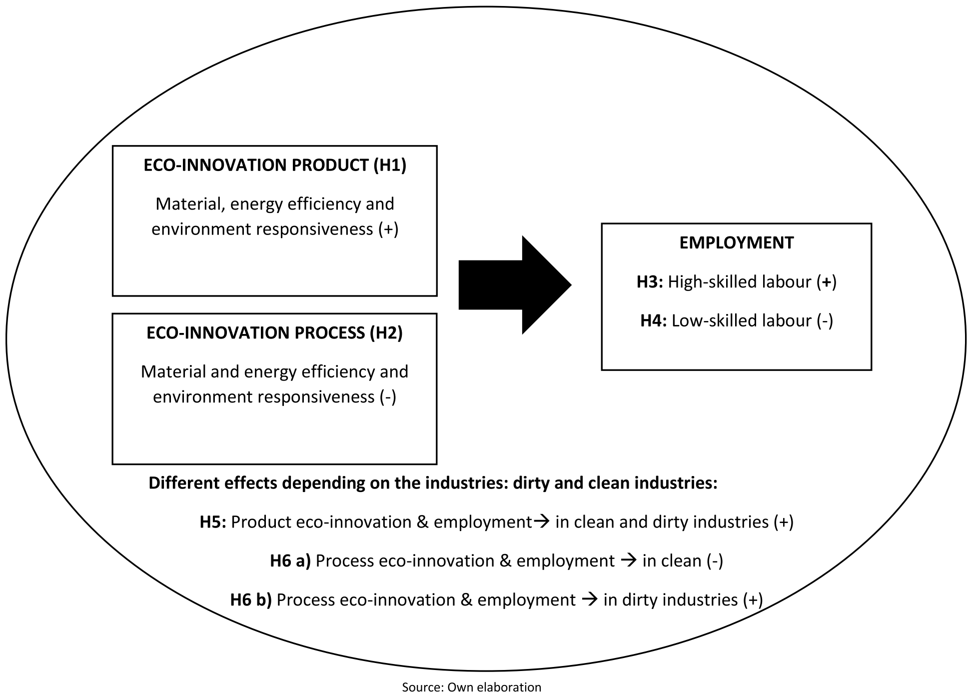

Fig. 1. Theoretical framework.
Source: Own elaboration.

impact and thus be less punished by public opinion (García-Marco et al., 2020; Kunapatarawong and Martínez-Ros, 2016).

In the same vein, the increased demand for green products and processes could be a determining factor in the final effect on employment. This demand depends on environmental awareness, corporate social responsibility (CSR) of firms, and the final quality of products (Sun and Yoon, 2022). In dirty industries, there is more pressure from consumers (who will follow firms closely), forcing them to do more in terms of CSR and compensate for their negative environmental impacts (Ghisetti, 2018; Horbach and Rammer, 2018). This consumer monitoring will ensure that any changes made by the firm in terms of greener products or processes will be quickly detected. Since these industries start from lower levels of environmental sustainability, any effects will have more significant impacts (Horbach and Rammer, 2018). In contrast, the expected effects on clean industries that are considered more sustainable from the outset will be lower.

In addition, we have not found evidence regarding the type of innovation (product and process) and their green goals (material and energy efficiency and environment responsiveness) by clean and dirty industries. As mentioned in the previous hypotheses (H1 and H2), the impact of eco-innovations on employment is likely to be different depending on the process or product innovation.

Focusing on *product eco-innovations* and assuming that the effect on employment is expected to be positive (according to our previous H1), the point is whether belonging to one industry or another will change this outcome. In this sense, in the case of clean industries, consumers will demand the new eco-innovative products despite the higher price, assuming that a large group of consumers would be willing to pay a higher price because it is an environmentally friendly product (McDonagh and Prothero, 2014; Sun and Yoon, 2022). Furthermore, in a dirty industry that is under high pressure to reduce its negative impact on the environment, firms would make a greater effort to improve their CSR and consumers will reward this type of company for such behaviour by demanding more of their new products (Ghisetti, 2018; Horbach and Rammer, 2018) and thus generating an increase in employment.

In the case of *process eco-innovations,* firms in both types of industries will improve their efficiency causing a direct negative effect on employment (according to our previous H2). In this sense, the indirect effect of increased demand might be different depending on the type of industry. As noted above, there is more regulatory and consumer pressure in dirty industries (Ghisetti, 2018; Horbach and Rammer, 2018; Kunapatarawong and Martínez-Ros, 2016), making the positive impact on employment stronger than in clean industries.[1] Thus, the introduction of eco-innovation in process and the consequent increase in consumer demand to reward their efforts could offset the negative effect of labour and cost savings by generating a generally positive impact. In contrast, in clean sectors that are based on inherently greener production processes, the impacts are expected to be lower and therefore, the negative impact of process eco-innovations could prevail.

Despite the importance of this industrial distinction, few studies have considered it when analysing the effects of eco-innovation on employment. Kunapatarawong and Martínez-Ros (2016), in a study of Spanish companies, find a positive influence of eco-innovation on employment, which is more intense in dirty industries. In addition, García-Marco et al. (2020) argue that dirty industries will demand more skilled labour due to the stronger environmental regulation, and therefore, dirty industries require greater employee knowledge, expertise, and training.

Considering the results obtained by Kunapatarawong and Martínez-Ros (2016) mentioned above, and the evidence shown in the development of our hypotheses 1 and 2 (Pfeiffer and Rennings, 2001; Rennings and Zwick, 2002; Cainelli et al., 2011), we hypothesize that:

H5: There is a positive relationship between product eco-innovation *-material and energy efficiency and environment responsiveness-* and employment in clean and dirty industries.

H6a: There is a negative relationship between process eco-innovation *-material and energy efficiency and environment*

[1] We could argue here, that the indirect effect in process eco-innovation and in dirty industries overcome the direct effects. In addition, the literature also recognizes five more compensation mechanics that mitigate the labour-saving effect of process innovation. However, their discussion is at macro level analysis and testing them empirically is difficult (Vivarelli, 1995; Pianta, 2005; Freeman and Soete, 1987).

responsiveness- and employment in clean industries.

H6b: There is a positive relationship between process eco-innovation -*material and energy efficiency and environment responsiveness*- and employment in dirty industries.

In addition, we propose two robustness check. The first one refers to the analysis of the effects of eco-innovation on different types of employment by industries (clean and dirty) following García-Marco et al. (2020). In the second one, we control for the effects of non-eco-innovation variables in the baseline model (Table A4 in Appendix A). Fig. 1 describes the theoretical framework.

3. Methodology and data

This research applies a green implementation of the Harrison et al. (2014) model. The main reason to use this empirical approach is that the model establishes a theoretical link between firm-level employment growth and different types of innovations -new products and processes- (Dachs et al., 2016; Dachs and Peters, 2014), and it can be easily adapted to the eco-innovation goals. Based on Crespi et al. (2019), De Elejalde et al. (2015), Díaz et al. (2020), and Harrison et al. (2014), the main equation of the Harrison et al. model is written as follows[2]:

$$l - g_1 - \pi = \alpha_0 + \alpha_1 d + \beta g_2 + \varepsilon_i \tag{1}$$

We transform the Harrison et al. (2014) model introducing the eco variables respecting the original equation. Therefore, the Green Model[3] applied in this paper would be expressed in the following equation:

$$l - g_{1eco} - \pi = \alpha_0 + \alpha_1 d_{eco} + \beta g_{2eco} + \varepsilon_{ieco} \tag{2}$$

Where, the dependent variable is a compound variable of the growth rate in the number of employees between two periods (l), the eco sales growth due to old products (g_{1eco})and the growth rate of the prices (π)while the *independent variables* capture the eco-innovative strategy of the companies, the only process eco-innovation variable, $d_{(eco)}$, and the sales growth due to new products eco-innovation variable, g_{2eco}.

The interpretation of the Green Harrison et al. model is the same as the original Harrison et al. model. α_0 is the average efficiency in the production of old eco-products. This parameter shows the increase in the efficiency of the production process which is not associated with any kind of eco-innovation. α_1 is the parameter associated with the eco "only process innovation" (d_{eco}). The expected sign of this variable on the employment growth is negative because firms that only introduce eco-process innovation probably focus their technological progress in terms of cost reduction. However, it might change if the indirect effects offset the labour-saving impact of process innovation (See Fig. 1). β is the parameter related to the eco growth sales due to new products (d_{eco}). It captures the relative efficiency of the production of old and new eco-products. If the $\beta < 1$ means that the new eco products are produced more efficiently than the old ones.

To transform the Harrison et al. model to the green Harrison model, we depart from Eq. (2) and compute the new variables for g_1, g_2, and d. First, "s" is the percentage of the sales due to new production in the last two periods.[4] It must be multiplied by the eco-variables (material, energy, and environment responsiveness), labelled as "*ecodummy*" (Eq. (3)).

[2] The main aspects of the original Harrison et al. model can be found in Appendix B.

[3] There are some transformations of the structural model proposed by Harrison et al. For instance, Mairesse and Wu (2019) changed the final specification to analyze the impact of domestic and export output on the labour market in China.

[4] New to the market and new to the firm.

Table 1
Classification of sectors. Dirty and clean industries.

Dirty Industries	Clean industries
Food, beverages, and tobacco	Clothing
Textile	Machinery and equipment
Leather and footwear	Transport equipment
Wood and cork	Other manufacturing activities
Pulp and paper	Machinery repair
Graphic arts and reproduction	
Chemicals	
Rubber and Plastics	
Pharmaceutical	
Non-Metallic mineral products	
Metallurgy	
Metal	
Computers and electronics	
Electrical products	
Vehicles	
Shipbuilding	
Spaceship and airplanes	
Furniture	

Source: own elaboration based on Kunapatarawong and Martínez-Ros (2016).

$$s * ecodummy \equiv \left(\frac{current\ sales\ new}{current\ sales\ old + current\ sales\ new}\right) * ecodummy = s\_eco \tag{3}$$

s_*eco* represents the percentage of green sales due to new products. Then, we computed the green sales due to new products $g_{2eco} \equiv s\_eco(1+\widehat{g})$ and nominal green sales growth due to old products $\widehat{g_{1eco}} \equiv \widehat{g} - g_{2eco}$, where $\widehat{g}$ is the total growth sales. To compute the real sales growth due to old eco-products, we use the inflation at the sectorial level to deflate it ($g_{1eco} \equiv \widehat{g_{1eco}} - \pi$). Finally, to get eco-process innovation, we multiply eco-variables (material, energy, and environment responsiveness) by "only process innovation."

$$d_{eco} = d * ecodummy \tag{4}$$

Moreover, to obtain the eco-innovation variables (d_{eco}, g_{1eco} *and* g_{2eco}), we follow a similar methodology to Fernández et al. (2021), Torrecillas and Fernández (2022), Triguero et al. (2018) and Torrecillas et al. (2023). Specifically, three variables have been created which indicate whether the innovation carried out by the firm has had the objective of reducing the use of materials and energy per unit produced (MATER and ENERG) or reducing the environmental impact (ENVIR). These variables are dummies with a value of 1 if the importance of these objectives for the firm is high or medium, and 0 otherwise. Subsequently, we interact the innovation variables of the Harrison et al. model (d and g_2) with the three eco-variables (MATER, ENERG, ENVIR), generating a total of 6 independent variables: product and process –*material efficiency, energy efficiency, and environment responsiveness*- (Prod-Mater, Prod-Energy, Prod-Envir, Proc-Mater, Proc-Energy, Proc-Envir). Tables A1–A3 in Appendix A show the description of variables, descriptive statistics, and correlation matrix respectively. In addition, a detailed development of Eq. (2) is found in Appendix C -The green Harrison model equations-.

We are also interested on the effects of eco-innovation variables on different types of workers. Following previous authors (Crespi et al., 2019; Díaz et al., 2020), we have incorporated two equations to be estimated for high and low skilled workers in the green model.

$$l^{hs} - g_{1eco} - \pi = \alpha_0 + \alpha_1 d_{eco} + \beta g_{2eco} + \varepsilon_{ieco}{}^{hs} \tag{5}$$

$$l^{ls} - g_{1eco} - \pi = \alpha_0 + \alpha_1 d_{eco} + \beta g_{2eco} + \varepsilon_{ieco}{}^{ls} \tag{6}$$

Where l^{hs} refers to high-skilled workers and l^{ls} refers to low-skilled employment (both in growth rates). These two variables are built using the percentage of personnel with a university degree. More precisely, high-skilled (low-skilled) workers are those with (without) university degrees. Finally, we also estimate eco-innovation effects on the labour market (total, high- and low-skilled employment) by dirty and clean industries. For this, we follow the classification of Kunapatarawong and Martínez-Ros (2016), which is conducted by considering the level of pollution and toxins that each industry is discharging to the environment, according to the Toxic Release Invent (TRI)'s annual reports and the US Environmental Protection Agency (EPA) reports (see Table 1).

Furthermore, the original model of Harrison et al. (2014), faces an endogeneity problem because of errors in the variables, generated basically due to a lack of prices at the firm level and some anticipated shocks might be correlated. These issues might cause bias in the estimation of β. To deal with these problems, the Harrison et al. (2014) model suggests the use of instrumental variables (IV) instead of ordinary least squares (OLS) .[5]

In this sense, two variables will be included as instrumental variables. The first one refers to the importance given to increasing the range of goods and services (*Rangegs*). This variable takes a value of 0 if the objective of increasing the range of products and services is not relevant, 1 if low importance is assigned to this objective, 2 if it is of medium importance, and 3 if it is of high importance. According to Harrison et al. (2014), "*the degree by which product innovation is aimed to increase the range of products is likely to be correlated with planning and the expectations of sales. On the other hand, expanding the range of products does not imply any particular direction for price changes. It also seems unlikely that the range of products is correlated with unanticipated productivity shocks* (Harrison et al., 2014, p. 36)."[6]

The second instrumental variable refers to market share (*Marketshare*). Specifically, it represents how important it is for the company that innovations generate a higher market share, where 0 is not relevant, 1 is of low importance, 2 is of medium importance and 3 is of high importance. To introduce them as instrumental variables, we have transformed them by considering only high relevance (3) and no relevance (0). Focusing on the model of Harrison et al., the same theoretical argument for the increasing range of goods and services as an instrumental variable applies to market share. The choice of these instruments is supported by numerous empirical studies such as Harrison et al. (2014), Díaz et al. (2020), Crespi et al. (2019). Based on the above, the model has been estimated by ordinary least squares, instrumental variables, and random effects. In addition, all the estimations include dummy variables for sector and year and the inclusion and exclusion test to verify the use of the methodology.

Finally, to implement this model, we use the Technological Innovation Panel (PITEC) which is the Spanish Community Innovation Survey (CIS). This database offers a large amount of information at the company level from 2003 to 2016, providing data not only related to innovation but also on the basic characteristics of the companies and their environmental objectives. Therefore, this database allows us to analyse the effect of different types of eco-innovation on employment growth in Spanish manufacturing industries in the period 2008–2016.[7]

A descriptive analysis of the average number of employees per year and type of eco-innovation (*material-efficiency, energy-efficiency, and environment-responsiveness)* is presented in Fig. 2. This figure shows a similar tendency for the three variables mentioned, with lower values in 2010 and higher values at the end of the period, after the 2008 economic crisis recovery. On the one hand, the average number of employees is higher in eco-innovations related to material efficiency in all years of the period studied, reaching its maximum in 2015 with 154.92 employees on average. On the other hand, eco-innovations related to the environment have the lowest results in terms of the average number of employees, reaching their minimum in 2010 with 105.01 workers.

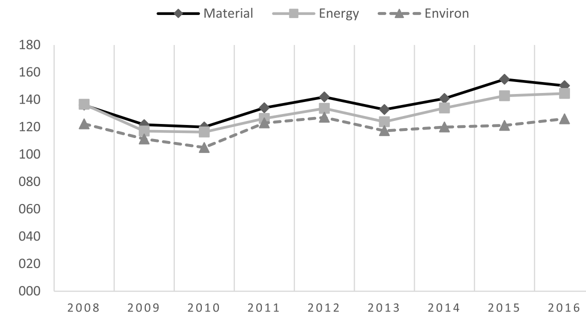

Fig. 2. Average number of employees by type of eco-innovation: Material efficiency, Energy efficiency and Environmental Responsiveness.
Source: Own elaboration based on PITEC.

Regarding the distribution of the firms, Table 2 shows the percentage of companies in the total sample and by type of eco-innovation according to different characteristics. On the one hand, we distinguish by skill level, considering high-skilled workers as those with tertiary education and low-skilled workers as those without it. As can be seen in the table, practically all firms have both types of workers, with a slightly higher presence of low-skilled employees. Similar results are shown when we focus on eco-innovative firms. On the other hand, analysing the types of eco-innovation, firms that carry out any type of product eco-innovation tend to have more highly qualified employees than firms that carry out process eco-innovations. Finally, concerning the industry type, we have divided the sample between clean and dirty sectors following the classification used by Kunapatarawong and Martínez-Ros (2016).[8] In line with this research, there are more companies belonging to dirty than clean sectors. In this case, it is in process eco-innovations where there is a greater presence of firms from the dirty sectors, with the highest percentage (84.39 %) in process eco-innovations related to efficiency in the use of materials.

In addition, Table 3 shows the growth[9] of employment and sales for non-innovative, innovative, and eco-innovative firms. First, a diminution in the employment of 16.63 % is observed for non-innovative firms, while the growth for the rest is positive. In this case, innovative companies are those with the highest employment growth, followed by green innovators. Concerning sales growth, it is again the non-innovative companies that reach a negative value, although in this case, it is close to 0 %. Moreover, the green innovators are those who experimented the greatest growth in sales over the period.

Given the importance of employment growth in this study, it is interesting to analyse employment growth by type of eco-innovation (Fig. 3). Notably, employment growth has been higher for companies carrying out product eco-innovations, with a difference of almost 6 percentage points for the process. The highest growth is obtained for those implementing energy efficiency eco-innovations (11.24 %), closely followed by material efficiency eco-innovations (10.41 %). Employment growth for firms that only carry out process eco-innovations is much lower, between 4.5 % and 5 %. In this case, the highest growth is obtained for environment responsiveness process eco-innovations, although the differences are very small.

4. Results

Tables 4–8 show the empirical results of the Green Harrison model, differentiating by the environmental goals, the qualification of

[5] The instrumental variables must be correlated with g_{2eco}, and not with the endogenous variable to satisfy the exclusion restriction.

[6] We examined the weak exogeneity, showing the first-stage tests.

[7] The variables related to eco-innovation were not introduced until 2008, so the analysis can only be carried out from that year onwards.

[8] The classification is shown in Table 1.

[9] The growth rate has been calculated using 2008 as the starting year and 2016 as the ending year.

Table 2
Sample characteristics by type of eco-innovation (percentages of the companies).

Characteristics	Total no. of firms (%)	% of Eco-innovators	% of Prod-Mater	% of Prod-Energy	% of Prod-Envir	% of Proc-Mater	% of Proc-Energy	% of Proc-Envir
Skill level								
High-skilled	82.43 %	86.18 %	87.78 %	88.03 %	87.94 %	82.66 %	82.81 %	82.07 %
Low-skilled	98.79 %	99.26 %	99.04 %	98.95 %	98.95 %	99.23 %	99.16 %	99.13 %
Industry								
Clean	19.17 %	20.37 %	22.05 %	22.61 %	23.38 %	15.61 %	16.60 %	16.29 %
Dirty	80.83 %	79.63 %	77.95 %	77.39 %	76.62 %	84.39 %	83.40 %	83.71 %

Source: Own elaboration based on PITEC.

Table 3
Employment and sales growth.

	Employment growth	Sales growth
Non-innovators	-16.63 %	-0.96 %
Innovators	10.80 %	30.74 %
Green innovators	9.79 %	31.99 %

Source: Own elaboration based on PITEC.

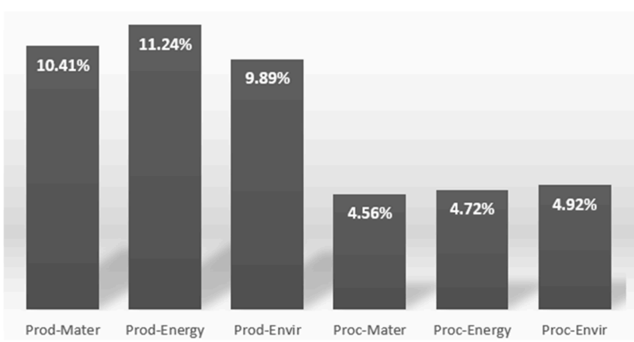

Fig. 3. Employment growth by type of eco-innovation.
Source: Own elaboration based on PITEC.

Table 4
Effects of eco-innovations on employment growth.

VARIABLES	1	2	3
Proc-Mater	0.018		
	[0.015]		
Prod-Mater	1.129***		
	[0.088]		
Proc-Energy		0.028*	
		[0.017]	
Prod-Energy		1.140***	
		[0.098]	
Proc-Envir			0.014
			[0.013]
Prod-Envir			1.136***
			[0.080]
Constant	-0.047***	-0.050***	-0.044***
	[0.013]	[0.015]	[0.010]
Observations	22,259	22,259	22,259
Industrial Dummies	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes
F (Ho: β=1)	2.157	2.05	2.876
P-value	0.142	0.152	0.09
Sargan-Hansen Test	0.836	0.543	0.191
P-value	0.841	0.909	0.979
First-stage	95.12	81.59	114.8
P-value	0.000	0.000	0.000

Note: Robust standard errors in brackets. The instrumental variables are increased range of goods and services and market share.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

employment, and the type of industry. Specifically, Table 4 shows the results of the green Harrison model adaptation considering different types of eco-innovations (material efficiency, energy efficiency, and environment responsiveness) and applying random effects with instrumental variables (REIV).[10,11]

Regarding product eco-innovations, a positive influence of all types of product eco-innovations on employment is found, showing an increase in employment due to new eco-products (labour-friendly effect). These results are consistent with what has been previously found in the literature (Pfeiffer and Rennings, 2001; Rennings and Zwick, 2002; Horbach and Rennings, 2013), showing that the introduction of eco-innovations in the form of material efficiency, energy efficiency or environment responsiveness produce a positive labour-effect. In addition, it should be noted that the coefficient associated with the product eco-innovation variables indicates the efficiency in the production of new eco-products for the old ones. In our case, these coefficients are close to one, showing no difference in the production efficiency between old and new eco-products.[12]

However, this positive relationship is not confirmed for process eco-innovation, where we have not found significance, except for process eco-innovations related to energy efficiency which is positive and significant. Although the introduction of process eco-innovations could produce a labour-saving effect, reducing costs and labour and increasing productivity, there are also compensatory effects such as the increase of demand due to the reduction of costs that could, at the same time, lead to increased demand of employees (Rennings and Zwick, 2002). The results reveal that the latter effect has more weight for a particular type of process eco-innovation -energy efficiency-. This result has been argued also by Horbach and Rennings (2013).

Following the theoretical framework of the model, the analysis of constant term is also important. In the three models, the constant term (α_0) is negative and significant, which highlights that there are productivity gains that are not associated with innovation effects.[13] In fact, most studies applying the Harrison et al. (2014) model obtain a similar result (Dachs and Peters, 2014; Harrison et al., 2014; De Elejalde et al., 2015). These results confirm our hypothesis H1 and do not support our hypothesis H2.

Previous empirical literature showed mixed results, indicating that the effects of eco-innovations on employment vary depending on the level of qualification of the worker. This is shown in Table 5.

The findings obtained differentiating by the skill level of the workers

[10] We have also estimated POOL IV and Fixed Effects IV. However, the value of standard errors for Fixed Effects IV is more than double that of POOL IV and Random Effects IV. It affects our results, especially for "only process innovation." For this reason, we decided only to present the results of Random Effects IV.

[11] We estimate a model that includes the non-eco innovation variables as a robustness check (see Table A4 in the Appendix A). The results are similar for the baseline model. However, we transformed the model proposed in Section 3 to create this robustness check.

[12] To verify, we apply an F test, whose Null Hypothesis is β=1.

[13] We de-meaned the time and industry dummies to hold the interpretation of the constant term in all the models.

Table 5
Effects of eco-innovations on employment growth by skill level.

	High-skilled			Low-skilled		
Variables	(1)	(2)	(3)	(1)	(2)	(3)
Proc-Mater	0.012			0.015		
	[0.034]			[0.017]		
Prod-Mater	1.036***			1.117***		
	[0.193]			[0.101]		
Proc-Energy		0.030			0.027	
		[0.037]			[0.019]	
Prod-Energy		1.065***			1.136***	
		[0.209]			[0.111]	
Proc-Envir			0.004			0.016
			[0.028]			[0.015]
Prod-Envir			1.027***			1.176***
			[0.170]			[0.093]
Constant	0.057*	0.051	0.058***	-0.052***	-0.056***	-0.056***
	[0.029]	[0.032]	[0.022]	[0.015]	[0.017]	[0.012]
Observations	19,184	19,184	19,184	22,095	22,095	22,095
Industrial Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
F (Ho: β=1)	0.034	0.095	0.025	1.334	1.480	3.551
P-value	0.85	0.76	0.88	0.25	0.22	0.06
Sargan-Hansen Test	5.619	6.423	5.498	5.211	4.047	3.065
P-value	0.132	0.093	0.139	0.157	0.256	0.382
First-stage	95.12	81.59	114.8	95.12	81.59	114.8
P-value	0.000	0.000	0.000	0.000	0.000	0.000

Note: Robust standard errors in brackets. The instrumental variables are increased range of goods and services and market share.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6
Clean vs. Dirty industries.

	CLEAN INDUSTRIES			DIRTY INDUSTRIES		
VARIABLES	(1)	(2)	(3)	(1)	(2)	(3)
Proc-Mater	-0.062*			0.043**		
	[0.037]			[0.017]		
Prod-Mater	0.755***			1.282***		
	[0.149]			[0.110]		
Proc-Energy		-0.070*			0.054***	
		[0.042]			[0.018]	
Prod-Energy		0.701***			1.303***	
		[0.170]			[0.117]	
Proc-Envir			-0.080**			0.038***
			[0.038]			[0.014]
Prod-Envir			0.706***			1.277***
			[0.170]			[0.094]
Constant	0.039	0.051	0.054	-0.063***	-0.067***	-0.056***
	[0.034]	[0.039]	[0.040]	[0.016]	[0.017]	[0.011]
Observations	4062	4062	4062	18,197	18,197	18,197
Industrial Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
F (Ho: β=1)	2.687	3.110	2.988	6.617	6.751	8.599
P-value	0.101	0.078	0.084	0.010	0.009	0.003
Sargan-Hansen Test	1.660	1.561	1.216	3.355	1.971	0.844
P-value	0.646	0.668	0.749	0.340	0.579	0.839
First-stage	28.39	23.18	24.65	70.21	63.77	91.53
P-value	0.000	0.000	0.000	0.000	0.000	0.000

Note: Robust standard errors in brackets. The instrumental variables are increased range of goods and services and market share.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

are not showing many differences. On the one hand, in relation to the product eco-innovation variables, there is a positive and significant relationship regardless of the qualifications of the employees. In this regard, other studies had pointed out that eco-innovations require higher qualifications, showing a positive link with high-skilled employment. However, they pointed out a negative relationship with low-skilled employment due to the skill-biased nature of the technological change (Aldieri et al., 2019b; Cainelli et al., 2011; Gagliardi et al., 2016). Our results show a positive relationship for both types of workers similar to the one obtained by Díaz et al. (2020) for innovations. On the other hand, we have not obtained evidence for process eco-innovations in any of our models. Therefore, the displacement effect of process eco-innovation is not found when we consider the skill level of the workers.

The main differences in this analysis are found in the constant term. In the model for low-skilled employees, it is negative and significant, indicating efficiency gains in the production of old eco-products. However, for high-skilled employees, the constant term (α_0) is positive and significant in the models that include eco-innovations related to material efficiency and environmental responsiveness. This result is similar to that found by Díaz et al. (2020), showing a drop in productivity not associated with eco-innovation. This could be explained by the fact that

Table 7
Robustness test by skill level: clean industries.

	High-skilled			Low-skilled		
Variables	(1)	(2)	(3)	(1)	(2)	(3)
Proc-Mater	-0.071			-0.073*		
	[0.076]			[0.042]		
Prod-Mater	0.775**			0.712***		
	[0.327]			[0.171]		
Proc-Energy		-0.042			-0.068	
		[0.091]			[0.047]	
Prod-Energy		0.786**			0.674***	
		[0.387]			[0.195]	
Proc-Envir			-0.085			-0.075*
			[0.079]			[0.043]
Prod-Envir			0.743**			0.735***
			[0.371]			[0.194]
Constant	0.150*	0.144	0.161*	0.050	0.058	0.050
	[0.079]	[0.095]	[0.093]	[0.040]	[0.046]	[0.046]
Observations	3512	3512	3512	4021	4021	4021
Industrial Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
F (Ho: β=1)	0.476	0.305	0.478	2.825	2.798	1.861
P-value	0.49	0.58	0.49	0.09	0.09	0.17
Sargan-Hansen Test	4.800	5.417	4.601	2.018	2.131	2.286
P-value	0.187	0.144	0.203	0.569	0.546	0.515
First-stage	28.39	23.18	24.65	28.39	23.18	24.65
P-value	0.000	0.000	0.000	0.000	0.000	0.000

Note: Robust standard errors in brackets. The instrumental variables are increased range of goods and services and market share.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

in recessionary periods, firms do not fire as many employees as would be expected as they prefer to keep them for the next expansionary period due to the knowledge they have already acquired (Díaz et al., 2020; Dachs et al., 2016). These results support partially our hypothesis H3 and no evidence is found to confirm hypothesis 4.

The analysis distinguishing between clean and dirty industries is shown in Table 6. In this case, the results reveal several differences. Firstly, product eco-innovations (material efficiency, energy efficiency, and environment responsiveness) boost employment in firms belonging to both types of industries (Kunapatarawong and Martínez-Ros, 2016). This result is in favour of our hypothesis H5. However, the magnitude of the coefficient differs. On the one hand, in clean industries, all three types of product eco-innovations show a coefficient close to the unity, showing that the production efficiency is the same for old and new eco-products. On the other hand, in the case of dirty industries, the efficiency of the production of old eco-products is greater than the new ones.

Secondly, the effect of process eco-innovations differs when comparing by sector, as we expected. In clean industries, process eco-innovations negatively affect employment, showing the labour-saving effect recognized in the literature (Rennings and Zwick, 2002; Audretsch et al., 2014; Díaz et al., 2020). This result confirms the

Table 8
Robustness test by skill level: dirty industries.

	HIGH-SKILLED			LOW-SKILLED		
VARIABLES	(1)	(2)	(3)	(1)	(2)	(3)
Proc-Mater	0.024			0.044**		
	[0.038]			[0.020]		
Prod-Mater	1.072***			1.294***		
	[0.231]			[0.128]		
Proc-Energy		0.036			0.056***	
		[0.039]			[0.021]	
Prod-Energy		1.083***			1.323***	
		[0.239]			[0.134]	
Proc-Envir			0.021			0.040**
			[0.029]			[0.016]
Prod-Envir			1.100***			1.326***
			[0.187]			[0.110]
Constant	0.048	0.046	0.047**	-0.072***	-0.076***	-0.067***
	[0.034]	[0.035]	[0.023]	[0.019]	[0.020]	[0.013]
Observations	15,672	15,672	15,672	18,074	18,074	18,074
Industrial Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes	Yes	Yes	Yes
F (Ho: β=1)	0.097	0.121	0.286	5.319	5.782	8.724
P-value	0.76	0.73	0.59	0.02	0.02	0.00
Sargan-Hansen Test	4.592	5.002	4.424	7.242	5.379	3.425
P-value	0.204	0.172	0.219	0.065	0.146	0.331
First-stage	70.21	63.77	91.53	70.21	63.77	91.53
P-value	0.000	0.000	0.000	0.000	0.000	0.000

Note: Robust standard errors in brackets. The instrumental variables are increased range of goods and services and market share.
***$p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9
Hypothesis.

Hypothesis	Results	Observations
H1: There is a positive relationship between product eco-innovation -material and energy efficiency and environment responsiveness- and employment.	Supported	
H2: There is a negative relationship between process eco-innovation -material and energy efficiency and environment responsiveness- and employment.	Partially supported	Only in clean industries.
H3. There is a positive relationship between the introduction of all types of eco-innovations and high-skilled employment.	Partially supported	Only for product eco-innovations.
H4. There is a negative relationship between the introduction of all types of eco-innovations and low-skilled employment.	Partially supported	Only in clean industries (material efficiency & environment responsiveness process eco-innovations).
H5: There is a positive relationship between product eco-innovation -material and energy efficiency and environment responsiveness- and employment in clean and dirty industries.	Supported	
H6 a): There is a negative relationship between process eco-innovation -material and energy efficiency and environment responsiveness- and employment in clean industries. b): There is a positive relationship between process eco-innovation -material and energy efficiency and environment responsiveness- and employment in dirty industries.	Supported	

Source: own elaboration.

hypothesis 6a showing that in clean industries the increase in demand due to the use of eco-processes is not intense enough to compensate for the negative impact on employment due to improved efficiency. In addition, this result also helps to partially explain H2 about the negative effect of process eco-innovation. However, in dirty industries the relationship between the three types of eco-innovations and employment is positive, supporting the H6b. This finding indicates that the increase in demand due to cost reduction that is associated with an increase in employment has a greater weight in these industries (Rennings and Zwick, 2002). Finally, the dirty industries model also indicates an increase in productivity not associated with eco-innovations in line with the results of innovation models of Harrison et al. (2014) or Dachs and Peters (2014).

Given that the results by type of industry show important differences, as a robustness check, the study has been replicated for clean and dirty industries and distinguished by the level of qualification of the workers (Tables 7 and 8). Table 7 shows the results by skill level in clean industries. Again, all product eco-innovations show a labour-friendly effect regardless of whether we are considering high- or low-skilled workers. On the other hand, process eco-innovations related to energy efficiency and environmental responsiveness reduce low-skilled employment in these industries, providing partial evidence of our H4. This result is in line with previous evidence shown by Costantini et al. (2018), which pointed out that energy efficiency gains could have a negative effect on employment. On the other hand, Table 8 provides the same analysis in dirty industries. The eco-product variables behave similarly to the previous models, while process eco-innovations in dirty industries seem to favour the hiring of low-skilled employees. Finally, Table 9 summarizes our set of hypotheses with the obtained results.

5. Conclusions and policy implications

This paper analyses the detailed effects of eco-innovations over employment. Considering product and process eco-innovation, different environmental goals -material and energy efficiency and environment responsiveness-, the level of qualification of the employees -high- and low-skilled-, and the industry -clean and dirty-, we tried to add some evidence to the previous mixed results found in the relationship eco-innovation and employment. For this purpose, we have performed a green application of the Harrison et al. (2014) model, which has been applied to Spanish manufacturing companies in the period 2008–2016.

Results show different effects of eco-innovations on employment. While all types of product eco-innovations increase employment, the relationship between process eco-innovations and employment depends on the type of eco-innovation, the skill level, and the type of industries. Specifically, our findings show a positive effect of product eco-innovations in material and energy efficiency and environment responsiveness in all our estimations –also differentiating by the level of qualification of the employees and by the level of dirtiness of the industry-. However, different results for process eco-innovations are found. On the one hand, results only confirm a labour-friendly effect in energy efficiency process eco-innovations. On the other hand, the evidence points out a labour-saving effect in clean industries for all types of process eco-innovations, while in dirty industries we have found a labour-friendly effect. In addition, our robustness test allows us to distinguish by industry and type of employment at the same time while clarifying the effect of process eco-innovations. In this regard, while in dirty industries all types of process eco-innovations produce a labour-friendly effect for low-skilled workers, a reduction of this type of employment is observed in clean industries for material efficiency and environment responsiveness eco-innovations.

The above findings show that the effects of eco-innovations over employment should consider the peculiarities analysed in this paper. Otherwise, the analyses, specifically for process innovation, do not capture the specific effects of this relationship.

Our main contribution to the literature is the implementation of the Green Harrison model for testing the relationship between eco-innovation and employment. This model has been widely used in the literature relating to innovation and employment (Dachs and Peters, 2014; Díaz et al., 2020; Harrison et al., 2014), but as far as we know, it has not been applied to green innovations. In addition, we contribute to the existing debate of whether technological change related to sustainability and environmental aspects boost positive changes in employment outcomes at the firm level (Gagliardi et al., 2016), considering the type of eco-innovation (Aldieri et al., 2019a; Costantini et al., 2018), the qualification of the employment (Aldieri et al., 2019b; Burger et al., 2019) and the level of dirtiness of the industries (Kunapatarawong and Martínez-Ros, 2016).

These results have several political and managerial implications. On the one hand, governments should design and coordinate different policies -Innovation, Environmental, and Labour policies- to strengthen the positive effect of eco-innovation over employment (Crespi, 2016). In this sense, only policies designed to promote environmental sustainability should be able to support economic recovery and employment growth (Crespi, 2016). Governments and managers should propose several actions to develop high skills in the labour force and should differentiate these actions according to the level of dirtiness of the industry.

These findings are subject to several limitations. Firstly, the effects of eco-innovation over employment take time (Gagliardi et al., 2016).

Although the Harrison Green model is a short-run model since it introduces employment growth between t and t-2, we are not able to capture the dynamic effects that the introduction of several lags would provide. Secondly, the variables used to measure process eco-innovations are not continuous variables, as are the eco-product ones. This is a common limitation of the Harrison model pointed out in the specialized literature (Vivarelli, 2014; Calvino and Virgillito, 2018). Thirdly, the indicator used for high- and low-skilled workers in the database only distinguishes between two groups of employees based on their educational level and does not differentiate between the type of work they carry out (Díaz et al., 2020). In addition, our empirical approach does not consider non-eco innovation. However, this future line of research might require another empirical approach and possibly other theoretical mechanisms. Finally, we propose as future research to go further in this analysis by considering different countries' samples, testing other specific eco-innovations variables, and considering green employment.

CRediT authorship contribution statement

Sara Fernández: Writing – review & editing, Writing – original draft, Supervision, Data curation, Conceptualization. **Celia Torrecillas:** Writing – review & editing, Writing – original draft, Supervision, Data curation, Conceptualization. **Guillermo Arenas Díaz:** Writing – review & editing, Writing – original draft, Methodology, Data curation.

Data availability

The authors do not have permission to share data.

Acknowledgments

Authors appreciate the comments provided by Jacques Mairesse in the 8th conference SEM "Society for Economic Measurement" developed in Milan in 2023. We also acknowledge funding from INFESE Project PID2020112984GB-C21 funded by the Ministry of Science and Innovation of Spain and GRIPICO Group funded by the University Complutense of Madrid.

Appendix A. Tables

Table A1
Variables description.

	Meaning
Eco-variables	
Product innovation	% of sales due to products new to the market and to the firm. This is a continuous variable
Process innovation	=1 if firm has introduced in the market a new or significantly improved production process, distribution method, or supporting activity. =0, otherwise.
Material Efficiency (Mater)	Changes in product or process that involve a decrease in the consumption of inputs (Considering just high and medium importance, we have transformed those values in a dummy variable (0 1)).
Energy Efficiency (Energy)	Changes in product or process that involves a decrease in the consumption of energy (Considering just high and medium importance, we have transformed those values in a dummy variable (0 1)).
Environment Responsiveness (Envir)	Changes in products or processes that reduce environmental damage of the firm's activity. (Considering just high and medium importance-. We have transformed those values in a dummy variable (0 1)).
Harrison model variables	
l	Employment growth rate between two periods (t and t-2)
g1eco	Sales growth due to old eco-products between two periods (t and t-2). See Appendix C for the calculation of this variable
π	Growth rate of the prices between two periods (t and t-2). We use prices at the industry level for deflation
d(eco)	Only process eco-innovation. This is a dummy variable created with the information collected in process innovation
g2eco	Sales growth due to new products eco-innovation between two periods (t and t-2). See Appendix C for the calculation of this variable
Instruments variables	
Range of goods and services (Rangegs)	=0 if the objective of increasing the range of products and services is not relevant =1 if high importance is assigned to this objective
Marketshare	=0 if it is not relevant for the company generate a higher market share =1 if high importance is assigned to this objective
Variables for specific analysis	
Skilled (l^{hs}) and Unskilled employment (l^{ls})	High Skill refers to employment growth with tertiary education, while low-skilled workers refer to employment growth without tertiary education. The growth rates are measure between two periods (t and t-2)
Dirty and Clean industries	Industrial classification of the sample following mainly Kunapatarowong and Martinez Ros (2016). See Table 1

Note:.
(1) The interaction of the "Innovation" and "Eco" variables have developed 6 Eco-Innovation variables: Prod -Mater, Prod- Energy, Prod -Envir, Proc -Mater, Proc -Energy, and Proc-Envir.
(2) We introduce instrument variables according to the original model Harrison et al. (2014) and Díaz et al. (2020).
Source: own elaboration.

Table A2
Descriptive statistics.

Dependent Variables	Mean	Std. Dev.	Min.	Max.
Employment Growth	-0.009	0.498	-0.999	52
Prod-Mater	0.134	0.312	0	1.439
Prod-Energy	0.137	0.316	0	1.471
Prod-Envir	0.112	0.290	0	1.391
Proc-Mater	0.114	0.318	0	1
Proc-Energy	0.108	0.310	0	1

(*continued on next page*)

Table A2 (*continued*)

Dependent Variables	Mean	Std. Dev.	Min.	Max.
Proc-Envir	0.106	0.307	0	1
Rangegs	2.104	1.084	0	3
Marketshare	1.947	1.107	0	3

Source: Own elaboration based on PITEC.

Table A3
Correlation matrix.

	Employment Growth	Prod-Mater	Prod-Energy	Prod-Envir	Proc-Mater	Proc-Energy	Proc-Envir	Rangegs	Marketshare
Employment Growth	1								
Prod-Mater	0.031	1							
Prod-Energy	0.054	0.817	1						
Prod-Envir	0.026	0.628	0.684	1					
Proc-Mater	-0.010	-0.152	-0.153	-0.137	1				
Proc-Energy	-0.009	-0.146	-0.147	-0.131	0.838	1			
Proc-Envir	-0.011	-0.143	-0.145	-0.129	0.711	0.733	1		
Rangegs	0.022	0.021	0.026	-0.007	-0.321	-0.311	-0.343	1	
Marketshare	0.036	-0.041	-0.028	-0.055	-0.290	-0.290	-0.321	0.640	1

Source: Own elaboration based on PITEC.

Table A4
Effects of eco-innovations on employment growth controlling by Non-eco variables.

	1	2	3
VARIABLES	RE	RE	RE
Proc-Mater	0.0494	–	–
	[0.049]	–	–
Proc-Mater_NO	0.0429	–	–
	[0.050]	–	–
Prod-Mater	1.2498***	–	–
	[0.182]	–	–
Prod-Mater_NO	1.0549***	–	–
	[0.110]	–	–
Proc-Energy	–	0.0544	–
	–	[0.047]	–
Proc-Energy_NO	–	0.0347	–
	–	[0.048]	–
Prod-Energy	–	1.2413***	–
	–	[0.176]	–
Prod-Energy_NO	–	1.0514***	–
	–	[0.104]	–
Proc-Envir	–	–	0.0349
	–	–	[0.044]
Proc-Envir_NO	–	–	0.0328
	–	–	[0.044]
Prod-Envir	–	–	1.2188***
	–	–	[0.166]
Prod-Envir_NO	–	–	1.0378***
	–	–	[0.105]
Constant	-0.0761	-0.0750	-0.0631
	[0.049]	[0.047]	[0.044]
Observations	22,259	22,259	22,259
Industrial Dummies	Yes	Yes	Yes
Time Dummies	Yes	Yes	Yes
Sargan test	1.819	2.072	2.066
P-value	0.769	0.722	0.724
First-stage for Non-Eco (Prod)	114.89	100.67	114.72
P-value	0.000	0.000	0.000
First-stage for Eco (Prod)	44.58	36.35	61.01
P-value	0.000	0.000	0.000
Number of ident	4489	4489	4489

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ Note: Robust standard errors in brackets.

Notes:.

(1) For this robustness check, we transform the green Harrison et al. (2014) model proposed in Section 3, and we build the following equation $l - g_1 - \pi = \alpha_0 + \alpha_1 d_{eco} + \alpha_2 d_{noeco} + \beta_1 g_{2eco} + \beta_2 g_{2noeco} + \varepsilon$.

(2) To create the new variables non-eco for g_2 and d, we compute a new dummy variable labelled "*noeco-dummy*"(takes the value of 1 if ecodummy=0, 0 otherwise), so we can distinguish between s_{eco} and s_{noeco}, which represent the percentage of green and non-green sales due to new products. Then, we computed non-green sales due to new products following this expression $g_{2noeco} \equiv s_{noeco}(1 + \hat{g})$ (g = *sales growth*). Finally, we multiply the "*noecodummy*" variable by "only process innovation" $d_{noeco} = d * noecodummy$ to get non-eco-process innovation.

(3) As we have a new endogenous variable, we include a new instrument "clients as a source of information" (=0 if

clients as a source of information is not relevant and =1 if high importance is assigned to this source). Therefore, the instrumental variables are increased range of goods and services, market share and clients as a source of information.

Appendix B. Harrison Model

The model assumes that a firm can produce old and new products in two periods of time. In the first period, all the products are old. Contrarily, firms can produce a combination of new and old products in the second period (Harrison et al., 2014).

$$Y_{it} = \theta_{it}F(K_{it}, L_{it}, M_{it})e^{\eta+\omega_{it}} \tag{B.1}$$

Where, K, L, and intermediate inputs M show constant returns to scale in the production of technology. θ captures all the factors –non-observables– that make a firm more productive than the average firm using the same technology.[14] The idiosyncrasy of the firm is represented by a fixed effect η and ω represents unanticipated productivity shocks[15] ($E(\omega_{it}) = 0$). The production function is composed by two equations with different technological productivity.

The employment equation is decomposed in two years. This equation minimizes cost in the production factors using Shephard's lemma.

$$\frac{\Delta L}{L} \cong -(\ln\theta_{12} - \ln\theta_{11}) + (lnY_{12} - \ln Y_{11}) + \frac{\theta_{11}}{\theta_{22}}\frac{Y_{22}}{Y_{11}} - (\omega_{12} - \omega_{11}) \tag{B.2}$$

Eq. (B.2) describes the growth of employment in logarithms considering four elements: (1) the change in the efficiency of old products in the production process $-(\ln\theta_{12} - \ln\theta_{11})$; (2) the rate of change of the demand of old products $(lnY_{12} - \ln Y_{11})$; (3) the increase of production related to new products $\frac{\theta_{11}}{\theta_{22}}\frac{Y_{22}}{Y_{11}}$; and (4) the impacts of non-technological perturbation of productivity $-(\omega_{12} - \omega_{11})$. Therefore, Eq. (B.2) can be expressed as follow:

$$l = \alpha_0 + \alpha_1 d + y_1 + \beta y_2 + u \tag{B.3}$$

The coefficient of y_1 is equal to one in Eq. (3). Therefore, equation B.3 can be expressed as Eq. (B.4).

$$l - y_1 = \alpha_0 + \alpha_1 d + \beta y_2 + u \tag{B.4}$$

where l stands for the employment growth rate over the period, y_1 and y_2 are the rates of output growth for old and for new products. The average efficiency growth in the production of the old product is captured by α_0 (negative). The effect of process innovation d[16] related to old products is measured by parameter α_1. In addition, d is equal to 1 whether the firm has implemented a process innovation not associated with a product innovation (process innovation only) and the parameter β captures the relative efficiency of the production of old and new products. Finally, u is the unobserved random disturbance ($u = -(\omega_{12} - \omega_{11}) + \xi$)[17] (Harrison et al., 2014).

However, it is not possible to estimate Eq. (B.3) because we cannot directly observe the output of either old or new products, y_1 or y_2, respectively. Instead, the available data are the growth sales, but the use of sales generates some issues because it includes prices for both new and old products. The problems are related to the unavailability of firm prices. To solve this problem, Harrison et al. (2014) suggest the use of the prices at the industrial level (π) to deflate the growth of sales due to old products. As results, we substitute g_1 for y_1 and g_2 for y_2. The Eq. (B.4) will be transformed in the following one (B.5):

$$l - g_1 - \pi = \alpha_0 + \alpha_1 d + \beta g_2 + \varepsilon_i \tag{B.5}$$

Where l is the employment growth between t and t-2. g_1 and g_2 are the sales growth due to old and new products (between t and t-2). d is a variable dummy that takes the value of 1 if the firm introduces a new process innovation not associated with a new product innovation, 0 otherwise ("only process innovation"). α_0 captures the average efficiency growth in the production of the old product (negative). α_1 is the parameter associated with "only process innovation" (negative), and β captures the relative efficiency of the production of old and new products (positive). If $\beta < 1$ means the new products are produced more efficiently than the old ones. ε_i is the error term.

Appendix C. Green Harrison model

Departing from the original Harrison et al. (2014) for the building of the variables:

$$l - g_1 - \pi = \alpha_0 + \alpha_1 d + \beta g_2 + \varepsilon_i \tag{C.1}$$

Where:

Nominal increased rates for all the products:

$$\widehat{g} \equiv \frac{(current\ sales\ old + current\ sales\ new) - past\ sales\ old}{past\ sales\ old} \tag{C.2}$$

Proportion of sales of new products:

$$s \equiv \frac{current\ sales\ new}{current\ sales\ old + current\ sales\ new} \tag{C.3}$$

Sales growth due to new products:

[14] The model assumed Hicks-neutral technological productivity captured by the parameter θ.

[15] This character captures all the non-observable changes of the productivity function that are not related to technological change, or in other words: industrial organization, work problems and so on.

[16] Process innovation is a binary variable.

[17] ξ represents many errors that are not correlated.

$$g_2 \equiv \frac{current\ sales\ new}{past\ sales\ old} = s(1+\widehat{g}) \tag{C.4}$$

Nominal sales growth due to old products:

$$\widehat{g_1} \equiv \frac{current\ sales\ old - past\ sales\ old}{past\ sales\ old} = \widehat{g} - g_2 \tag{C.5}$$

Real sales growth for all products:

$$g \equiv \widehat{g} - \pi \tag{C.6}$$

Real sales growth due to old products:

$$g_1 \equiv \widehat{g_1} - \pi \tag{C.7}$$

Now, we create the variables for the Green Harrison model

$$l - g_{1eco} - \pi = \alpha_0 + \alpha_1 d_{eco} + \beta g_{2eco} + \varepsilon_{ieco} \tag{C.8}$$

In addition, the variable*s*, which is the percentage of the sales due to new product (newmerc and newemp), must be multiplied by the eco-variables (material, energy and environment responsiveness). We depart form Eq. (B.3) and compute the new variables for g_1 y g_2.

$$s * ecodummy \equiv \left(\frac{current\ sales\ new}{current\ sales\ old + current\ sales\ new}\right) * ecodummy = s\_eco \tag{C.9}$$

Sales growth due to new products:

$$g_{2eco} \equiv \frac{current\ sales\ new}{past\ sales\ old} = s\_eco(1+\widehat{g}) \tag{C.10}$$

Nominal sales growth due to old products:

$$\widehat{g_{1eco}} \equiv \frac{current\ sales\ old - past\ sales\ old}{past\ sales\ old} = \widehat{g} - g_{2eco} \tag{C.11}$$

Real sales growth due to old products:

$$g_{1eco} \equiv \widehat{g_{1eco}} - \pi \tag{C.12}$$

Finally, to get eco-process innovation, we only multiply eco-variables (material, energy and environment responsiveness) by only process innovation.

$$d_{eco} = d * ecodummy \tag{C.13}$$

References

Aldieri, L., Vinci, C.P., 2018. Green economy and sustainable development: the economic impact of innovation on employment. Sustainability 10 (10), 3541.

Aldieri, L., Kotsemir, M., Vinci, C.P., 2019a. The impact of environmental innovations on job-creation process: an empirical investigation for Russian regions. Environ. Econ. Policy Stud. 21 (2), 285–306.

Aldieri, L., Carlucci, F., Cirà, A., Ioppolo, G., Vinci, C.P., 2019b. Is green innovation an opportunity or a threat to employment? An empirical analysis of three main industrialized areas: the USA, Japan and Europe. J. Clean. Prod. 214, 758–766.

Al-Ayouty, I., Hassaballa, H., Rizk, R., 2017. Clean manufacturing industries and environmental quality: the case of Egypt. Environ. Dev. 21, 19–25.

Audretsch, D.B., Coad, A., Segarra, A., 2014. Firm growth and innovation. Small Bus. Econ. 43 (4), 743–749.

Benavente, J.M., Lauterbach, R., 2008. Technological innovation and employment: complements or substitutes? Eu. J. Dev. Res. 20 (2), 318–329.

Blanchflower, D.G., Burgess, S.M., 1999. New technology and jobs: comparative evidence from a two country study. Econ. Innov. New Technol. 8 (1–2), 23–44.

Burger, M., Stavropoulos, S., Ramkumar, S., Dufourmont, J., van Oortd, F., 2019. The heterogeneous skill-base of circular economy employment. Res. Policy 48 (1), 248–261.

Cainelli, G., Mazzanti, M., Zoboli, R., 2011. Environmentally oriented innovative strategies and firm performance in services. Micro-evidence from Italy. Int. Rev. Appl. Econ. 25 (1), 61–85.

Calvino, F., Virgillito, M.E., 2018. The innovation-employment nexus: a critical survey of theory and empirics. J. Econ. Surveys 32 (1), 83–117.

Caravella, S., Crespi, F., 2022. On the growth impact of different eco-innovation business strategies. Econ. Politica 39, 657–683.

Coad, A., Hölzl, W., 2011. Firm growth: empirical analysis. M. Dietrich & J. Krafft (Eds.). Handbook on the Economics and Theory of the Firm. Edward Elgar, Cheltenham.

Colombelli, A., Krafft, J., Quatraro, F., 2021. Firms' growth, green gazelles and eco-innovation: evidence from a sample of European firms. Small Bus. Econ. 56, 1721–1738.

Costantini, V., Crespi, F., Paglialunga, E., 2018. The employment impact of private and public actions for energy efficiency: evidence from European industries. Energy Policy 119, 250–267.

Crespi, F., 2016. Policy complexity and the green transformation of the economies as an emergent system property. Environ. Econ. Policy Stud. 18 (2), 143–157.

Crespi, G., Tacsir, E., Pereira, M., 2019. Effects of innovation on employment in Latin America. Ind. Corp. Change 28 (1), 139–159.

Dachs, B., Hud, M., Koehler, C., Peters, B., 2016. Employment Effects of Innovations Over the Business cycle: Firm-Level Evidence from European Countries. Zentrum für Europäische Wirtschaftsforschung (ZEW), Mannheim. ZEW Discussion Papers, No. 16-076. https://nbn-resolving.de/urn:nbn:de:bsz:180-madoc-415893.

Dachs, B., Peters, B., 2014. Innovation, employment growth, and foreign ownership of firms: a European perspective. Res. Policy 43 (1), 214–232.

De Elejalde, R., Giuliodori, D., Stucchi, R., 2015. Employment and innovation: firm-level evidence from Argentina. Emerg. Mark. Finance Trade 51 (1), 27–47.

Demirel, P., Danisman, G.O., 2019. Eco-innovation and firm growth in the circular economy: evidence from European small- and medium-sized enterprises. Bus. Strategy Environ. 28 (8), 1608–1618.

Díaz, G.A., Barge-Gil, A., Heijs, J., 2020. The effect of innovation on skilled and unskilled workers during bad times. Struct. Change Econ. Dyn. 52, 41–158.

Fernández, S., Torrecillas, C., Labra, R.E., 2021. Drivers of eco-innovation in developing countries: the case of Chilean firms. Technol. Forecast. Soc. Change 170, 120902.

Freeman, C., Soete, L., 1987. Technical Change and Full Employment. Basil Blackwell.

Gagliardi, L., Marin, G., Miriello, C., 2016. The greener the better? Job creation effects of environmentally friendly technological change. Ind. Corp. Change 25 (5), 779–807.

García-Marco, T., Zouaghi, F., Sánchez, M., 2020. Do firms with different levels of environmental regulatory pressure behave differently regarding complementarity among innovation practices? Bus. Strategy Environ. 29 (4), 1684–1694.

Ghisetti, C., 2018. On the economic returns of eco-innovation: where do we stand? J. Horbach & C. Reif (Eds.). New Developments in Eco-Innovation Research. Springer, Cham, Switzerland, pp. 55–79.

Goos, M., Manning, A., Salomons, A., 2014. Explaining job polarization: routine-biased technological change and offshoring. Am. Econ. Rev. 104 (8), 2509–2526.

Greenan, N., Guellec, D., 2000. Technological innovation and employment reallocation. Labour 14 (4), 547–590.

Griliches, Z., 1969. Capital-skill complementarity. Rev. Econ. Stat. 465–468.

Hall, B.H., Mairesse, J., Turner, L., 2008. Employment, innovation, and productivity: evidence from Italian microdata. J Eur. Econ. Assoc. 6 (4), 795–827.

Harrison, R., Jaumandreu, J., Mairesse, J., Peters, B., 2014. Does innovation stimulate employment? A firm-level analysis using comparable micro-data from four European countries. Int. J. Ind. Organ. 35, 29–43.
Horbach, J., 2010. The impact of innovation activities on employment in the environmental sector-empirical results for Germany at the firm level. J. Econ. Stat. 230 (4), 403–419.
Horbach, J., Janser, M., 2016. The role of innovation and agglomeration for employment growth in the environmental sector. Ind. Innov. 23 (6), 488–511.
Horbach, J., Rammer, C., 2018. Energy transition in Germany and regional spill-overs: the diffusion of renewable energy in firms. Energy Policy 121, 404–414.
Horbach, J., Rammer, C., 2020. Circular economy innovations, growth and employment at the firm level: empirical evidence from Germany. J. Ind. Ecol. 24 (3), 615–625.
Horbach, J., Rammer, C., Rennings, K., 2012. Determinants of eco-innovations by type of environmental impact—The role of regulatory push/pull, technology push and market pull. Ecol. Econ. 78, 112–122.
Horbach, J., Rennings, K., 2013. Environmental innovation and employment dynamics in different technology fields–an analysis based on the German Community Innovation Survey 2009. J. Clean. Prod. 57, 158–165.
Hou, J., Huang, C., Licht, G., Mairesse, J., Mohnen, P., Mulkay, B., Peters, B., Wu, Y., Zhao, Y., Zhen, F., 2019. Does innovation stimulate employment? Evidence from China, France, Germany, and The Netherlands. In: Ind. Corp. Change, 28, pp. 109–121. https://doi.org/10.1093/icc/dty065. Pages.
Jaimovich, N., Siu, H.E., 2020. Job polarization and jobless recoveries. Rev. Econ. Stat. 102 (1), 129–147.
Janahi, N.A., Durugbo, C.M., Al-Jayyousi, O.R., 2021. Eco-innovation strategy in manufacturing: a systematic review. Clean. Eng. Technol. 5, 100343.
Kunapatarawong, R., Martínez-Ros, E., 2016. Towards green growth: how does green innovation affect employment? Res. Policy 45 (6), 1218–1232.
Léger, P. (2016). Eco-innovation observatory: Country Profile 2014-2015; Spain. European Commission. Available at: https://green-business.ec.europa.eu/eco-innovation_en.
Leo, M., Steiner, M., 1994. Innovation and employment in services. Int. J. Serv. Ind. Manag. 5 (3), 49–63.
Leoncini, R., Marzucchi, A., Montresor, S., Rentocchini, F., Rizzo, U., 2019. Better late than never': the interplay between green technology and age for firm growth. Small Bus. Econ. 52 (4), 891–904.
Licht, G.; Peters, B. 2014. Do green innovations stimulate employment? Firm-level evidence from Germany (No. 53). WWWforEurope Working Paper. WIFO Studies.
Madaleno, M., Robaina, M., Dias, M.F., Meireles, M., 2020. Dimension effects in the relationship between eco-innovation and firm performance: a European comparison. Energy Rep. 6, 631–637.
Mairesse, J., Wu, Y., 2019. Impacts of innovation, export, and other factors on firm employment growth in Chinese manufacturing industries. Ind. Corp. Change 28 (1), 123–138.
McDonagh, P., Prothero, A., 2014. Sustainability marketing research: past, present, and future. J. Mark. Manag. 30 (11–12), 1186–1219.
Nelson, R.R., Phelps, E.S., 1966. Investment in humans, technological diffusion, and economic growth. Am. Econ. Rev. 56, 69–75.
Pawłowski, A., Yu, R., 2017. The effect of environmental innovation on employment level: evidence from China's manufacturing industries. Problemy Ekorozwoju : Prob. Sustain. Develop. 12 (1), 7–14.
Pérez Fernández de Retana, M., Buenetxea Aizpuru, E., 2020. Eco-innovation observatory: Country Profile 2018-2019; Spain. European Commission. Available at: https://green-business.ec.europa.eu/eco-innovation_en.
Pfeiffer, F., Rennings, K., 2001. Employment impacts of cleaner production–evidence from a German study using case studies and surveys. Bus. Strategy Environ. 10 (3), 161–175.
Pianta, M., 2005. Innovation and employment. J. Fagerberg, D. Mowery, & R. Nelson (Eds.). The Oxford Handbook of Innovation. Oxford University Press, pp. 568–597. https://ora.uniurb.it/handle/11576/1889692.
Pizarro, F.B.R., 2013. Innovación y empleo en las empresas manufactureras españolas. Documentos De Trabajo De La Facultad De Ciencias Económicas y Empresariales, N °.7, 2013 41 Pags.
Porter, M.E., Van der Linde, C., 1995. Toward a new conception of the environment-competitiveness relationship. J. Econ. Perspect. 9 (4), 97–118.
Rennings, K., Zwick, T., 2002. Employment impact of cleaner production on the firm level: empirical evidence from a survey in five European countries. Int. J. Innov. Manag. 6 (3), 319–342.
Rennings, K., Ziegler, A., Zwick, T., 2004. The effect of environmental innovations on employment changes: an econometric analysis. Bus. Strategy Environ. 13, 374–387.
Sachs, J.D., Kroll, C., Lafortune, G., Fuller, G., Woelm, F., 2022. Sustainable development report 2022. Cambridge University Press.
Shan, W., Wang, J., 2019. The effect of environmental performance on employment: evidence from China's manufacturing industries. Int. J. Environ. Res. Public Health 16 (12), 2232.
Stoever, J., Weche, J.P., 2018. Environmental regulation and sustainable competitiveness: evaluating the role of firm-level green investments in the context of the porter hypothesis. Environ. Resour. Econ. 70, 429–455.
Sun, Z.Q., Yoon, S.J., 2022. What makes people pay premium price for eco-friendly products? The effects of ethical consumption consciousness, CSR, and product quality. Sustainability 14 (23), 15513.
Torrecillas, C., Fernández, S., 2022. Exports and outward FDI as drivers of eco-innovations. An analysis based on Spanish manufacturing firms. J. Clean. Prod. 349, 131243.
Torrecillas, C., Fernández, S., García-García, C., 2023. Drivers to increase eco-efficiencies in Uruguay, Peru, and Panama. Energy Policy 183, 113832.
Triguero, A., Cuerva, M.C., Álvarez-Aledo, C., 2017. Environmental innovation and employment: drivers and synergies. Sustainability 9, 2057.
Triguero, A., Fernández, S., Sáez-Martinez, F.J., 2018. Inbound open innovative strategies and eco-innovation in the Spanish food and beverage industry. Sustain. Prod. Consum. 15, 49–64.
Violante, G.L. (2008). Skill-biased technical change. New Palgrave Dictionary of Economics, 2.
Vivarelli, M., 1995. The Economics of Technology and Employment: Theory and Empirical Evidence. Edward Elgar Publishing.
Vivarelli, M., 2014. Innovation, employment and skills in advanced and developing countries: a survey of economic literature. J. Econ. Issues 48 (1), 123–154.
Wendler, T., 2019. About the relationship between green technology and material usage. Environ. Resour. Econ. 74, 1383–1423.