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The greener the better? Job creation effects of environmentally-friendly technological change

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Abstract

This article investigates the link between environment-related innovation and job creation at firm level. Employing Italian data on 4507 manufacturing firms, matched with patent records for the period 2001–2008, we test whether “green” innovation, measured by the number of environment-related patents, has a positive effect on long-run employment growth that is specific with respect to non-environmental innovation. Results show a strong positive impact of “green” innovation on long-run job creation, substantially bigger than the effect of other innovations. Our findings are robust to a number of additional tests including controls for patents’ quality and cost differential between generic and “green” innovation and endogeneity.

JEL classification: O33, O55, J21

1. Introduction

The link between employment and innovation has been extensively investigated in the economic literature; however, the significance and direction of such relation are still among the most controversial topics in the economic and political debate. The past two decades have seen the emergence of novel forms of innovation due to the growing concerns regarding the environmental sustainability of the current production settings. Environment-related innovation, also called green or eco-innovation, has become a relevant phenomenon attracting the attention of scholars and policy makers for its potential to create new market opportunities, triggering a virtuous cycle of growth and employment. The reasons why eco-innovation should be beneficial for firms and for the economy are several. The key motivation lies in the potential exploitation of the opportunities associated to a new, growing market; the market for eco-friendly goods and services, in fact, represents nowadays around 2.5% of the European Union (EU) GDP and is expected to triple by 2030 (EU, 2011). Second, by inducing a more efficient and responsible use of resources, eco-innovation may improve the competitiveness of firms, and altogether their quality. Finally, since Europe is currently the market leader for environmental products, investing in environmental technologies and resource efficiency may help to create a long-lasting comparative advantage for European firms. Environmental protection is in fact a

consolidate policy strategy in Europe since the very creation of the EU.¹ Within the framework of the Lisbon Strategy first, and Europe 2020² after, EU policies aim at obtaining a “smart, sustainable, inclusive growth” with greater coordination of national and European policies.

Nonetheless, at firm level, the net effect of environmental innovation is still unclear and it has yet to be determined whether it may be seen as an opportunity to penetrate new markets, or as a burden that may impair competitiveness and destroy jobs. Furthermore, it is debatable whether environmental innovation may potentially yield different effects at firm level with respect to generic innovation, justifying dedicated streams of literature and policy attention. The lack of conclusive evidence, the increasing concerns regarding the levels of unemployment, and the risk of declining firms’ competitiveness in Europe—particularly in Italy—and the strong policy attention devoted to the transition toward cleaner technologies call for a greater effort in investigating the relation between environment-related innovation and employment. Understanding their link at firm level is crucial in order to predict how the market will adjust to the increasing relevance of the green economy and whether the benefits may outpace the costs associated to the shift in the dominant technological paradigms. A better assessment of this aspect is as well important to implement, if necessary, an effective environmental innovation policy in the future. Finally, this kind of analysis may offer more generalizable insights on the challenges and opportunities associated to changes in technological trajectories in industrialized economies.

This contributes to the existing debate, through a careful investigation of whether technological change, broadly related to sustainability and environmental aspects, has led to positive changes in employment outcomes at firm level in Italy. Using a novel data set that matches firm-level data with patent records, we are able to distinguish between firms performing “green” and/or generic innovation and to assess the causal effect of environment-related technological change on employment growth, after controlling for firms’ attitude toward generic innovation.³ This is, to the best of our knowledge, one of the few recent works providing fresh evidence on this relevant issue, trying to deal with the limitations that have traditionally affected previous studies on the link between innovation and employment and adding to the much more limited literature on the impact of eco-innovation. In this context our contribution is twofold. First, due to the nature of our data we are able to provide a consistent measure of environment-related innovation, overcoming the limitations of existing analyses that use survey data based on a more discretionary definition. Secondly, we develop a reliable identification strategy, thanks to the availability of a longer and consistent time series and the exploitation of a novel instrumental variable approach, allowing the setup of a credible econometric setting and to deal efficiently with the issues associated to the investigation of the causal relationship between job creation and eco-innovation.

We find that environmental innovation positively and significantly affects job creation to a greater extent than generic innovation. This result holds with respect to several robustness checks ranging from measurement to endogeneity concerns and it is robust also when controlling for cost differences between green and generic innovation as measured with the methodology popularized by Harhoff and Thoma (2009). This further suggests the existence of a

- 1 Already in 1987 the Treaty establishing the Union reported a dedicated section setting environmental protection objectives and principles. Among the many regulations and communications to tackle the issue of environmentally sustainable growth in place in the EU, here we recall: “Directive 2009/28/EC of the European Parliament and of the Council of 23 April 2009 on the promotion of the use of energy from renewable sources,” “Communication from the Commission to the Council and the European Parliament on EU policies and measures to reduce greenhouse gas emissions: towards a European Climate Change Programme (ECCP),” “Decision No 406/2009/EC of the European Parliament and of the Council of 23 April 2009 on the effort of Member States to reduce their greenhouse gas emissions to meet the Community’s greenhouse gas emission reduction commitments up to 2020.”
- 2 The Lisbon strategy was a development plan designed for the economy of the European Union between 2000 and 2010. It was defined by the European Council in Lisbon in March 2000, and has identified economic, social, and environmental sustainability as its core pillars for development. Europe 2020 is the natural prosecution of the Lisbon strategy. Europe 2020, proposed by the European Commission on March 3, 2010, covers the period 2010–2020. Horizon 2020 is the financial instrument that will help implementing the initiatives defined in Europe 2020 and will run from 2014 to 2020.
- 3 Note that by employing a proxy for innovation based on patents record we focus on firms developing green technologies in-house rather than on those organizations who adopt green technology/practices. In other words, our data do not provide information about firms that do not own patents but are still users of green technologies.

positive net effect in terms of jobs creation that persists also when differences in the amount of innovative inputs between green and generic innovation are taken into account.

The article is structured as follows: section 2 offers a review of the literature on the relationship between employment and technological change, underlying theoretical rationale and available empirical evidence on their link and trying to provide some additional insights with respect to the specific case of environmental-related innovation. Section 3 describes the methodology and the main estimation challenges, while section 4 presents the data used for the analysis. Section 5 shows and discusses our results and section 6 concludes.

2. Literature review

The literature on the impact of eco-innovation on labor market outcomes is nested on a large number of contributions looking at the link between technological innovation and employment. Despite the impressive research efforts on the topic, there is however no wide consensus on the direction and magnitude of the abovementioned relation. The emergence of heterogeneous results has been often justified in the light of several dimensions.

A key aspect regards the typology of innovation under analysis with particular respect to the distinction between process and product innovation and to their different impact on employment (among others [Pianta, 2005](#); [Hall et al., 2008](#); [Harrison et al., 2014](#)). Process innovation has been generally associated to a labor-saving impact causing employment reduction, the so called displacement effect, while product innovation has been linked to employment-stimulating outcomes based of virtuous cycles on increasing sales and revenues, the so-called compensation effect.

A second-order dimension refers to the scope of the analysis, which may concern either the firm or the aggregate level. Firm-level analyses have been generally characterized by a “positive bias” ([Vivarelli, 2014](#), see also [Chennels and van Reenen, 2002](#) for a survey). Most firm-level empirical studies in fact find a positive relationship between innovation and employment growth with a general consensus in the case of product innovation and less conclusive remarks for process innovation ([König et al., 1995](#); [Van Reenen, 1997](#); [Garcia et al., 2004](#); [Hall et al., 2008](#); [Harrison et al., 2014](#)). This is partially explained by the limited possibility to fully account for compensating mechanisms operating at broader sectoral and spatial level such as potential detrimental effects linked to displacement.

With few exceptions such as [Blechinger et al. \(1998\)](#) reporting evidence of labor displacement induced by process innovation, and [Van Reenen \(1997\)](#) finding that the impact of process innovations is small and not significant, the majority of existing firm-level analyses supports the existence of a positive, though less immediate, impact on employment also in the case of traditional labor-saving process innovation. Among others, [König et al. \(1995\)](#), [Smolny and Schneeweis \(1999\)](#), [Smolny \(2002\)](#), [Lachenmaier and Rottmann \(2011\)](#) report a positive and significant effect of process innovation on employment growth. Employment effects of process innovation are assumed to affect firms’ productivity lowering the amount of labor input and unit costs. However, in a dynamic perspective, lower prices might lead to higher demand and thus higher production, and consequently have a positive effect on employment. More straightforwardly in the case of product innovation, demand is expected to increase and employment is expected to grow ([Garcia et al., 2004](#), [Harrison et al., 2014](#)).

Analyses at aggregate level have looked at the innovation–employment link under a broader perspective, and despite providing a less accurate measure for innovative activities carried out by specific economic actors, they are able to account for broader spatial and sectoral dynamics. Also, in this context however the balance between labor-saving and labor-stimulating effects determined by a (potential) virtuous cycle that generates additional production and employment is not straightforward ([Spiezia and Vivarelli, 2002](#); [Gagliardi, 2014](#)). [Simonetti et al. \(2000\)](#) and [Tancioni and Simonetti \(2002\)](#) found no univocal effect of technological change on employment, while [Bogliacino and Vivarelli \(2012\)](#) focusing on 25 European countries over the period 1996–2005 find that technological change is positively correlated to employment growth. More recently, aggregate studies at country or sectoral level have exploited information on skills heterogeneity to tackle the emergence of heterogeneous results. Relevant contributions (among others, [Acemoglu, 2002](#) and [Goldin and Katz, 2007](#)) have documented the skill bias nature of technological change, arguing about its positive impact for the employment perspectives of high-skilled individuals and its negative correlation with employment outcomes for low-skilled people.

Beyond the large literature looking at the link between technological change and employment, recent studies have also focused on the emergence of specific technological paradigms. For instance, the information and communication technology (ICT) revolution has stimulated increasing research effort with the aim of disentangling the impact of

these technologies on job market outcomes. While early works have documented the stylized facts associated to ICT (Rosenberg, 1976; Dosi, 1982; Freeman *et al.*, 1982; David, 1985; Dosi *et al.*, 1988), more recent studies have investigated the extent to which these technologies are associated to distinctive trends in the job market. At firm level, ICT technologies have been associated to the so-called “skill biased organisational change” hypothesis (Bresnahan *et al.*, 2002; Piva *et al.*, 2005; Giuri *et al.*, 2008). These studies suggest IT technologies are complementary to novel workplace organization, including more decentralized decision-making and more self-managing teams, which favor skilled workers. In this context, “IT-enabled organizational change is important components of the skill-biased technical change” (Bresnahan *et al.*, 2002). At aggregate level, studies looking at the impact of ICT technologies have documented the progressive polarization of the workforce with middle-skilled occupations that have declined in respect to both higher- and low-skilled occupations (Spitz-Oener 2006; Goos and Manning 2007; Goos *et al.*, 2009; Michaels *et al.*, 2014; Autor and Dorn 2013).

The rationale behind this evidence lies in the theoretical contribution of Autor *et al.* (2003), which offers a more nuanced interpretation of the impact of technology in general (and computers in particular) on the labor market outcomes. In this context, computers are supposed to replace labor in routine tasks (tasks that can be expressed in step-by-step procedures or rules) and to complement (i.e. increase the productivity of) nonroutine tasks.

Surprisingly, given the increasing relevance in terms of policy attention and financial resources, other types of emerging technologies such as environment-related innovation has received less attention. The OECD has recently suggested that investing in green activities has significant job creation potential (OECD, 2011). Alternative studies have claimed that the employment benefit of green technologies has been overestimated, arguing that environmental policies, as initiatives aimed at providing incentives in environmental innovation, may have much less attractive labor market consequences (e.g. Michaels and Murphy, 2009; Morriss *et al.*, 2009; Hughes, 2011). Becker and Shadbegian (2008) examine the environmental product manufactures using a 1995 survey data for the United States, finding that they did not perform differently in terms of wage, employment, output, and exports than non-environmental product plants.

Within this context, studies on the relationship between environmental innovation and employment represent a more recent and relatively less developed strand of research. This literature is based on the seminal work by Pfeiffer and Rennings (2001) and Rennings and Zwick (2002). Pfeiffer and Rennings (2001), in line with the conventional literature on the link between employment and technological change, argue that the effects of environment-related innovations on employment depend on the types of innovation activities performed. Product innovation has been found to generate positive direct effect on employment, while the effects of process innovation are more ambiguous. Employment effects have also been found to be unevenly distributed across skills, with strong negative effects of environmental innovations on low-skill intensive industries and potentially positive effects on other industries.

Rennings and Zwick (2002), analyzing a sample of environmental-innovative firms for five EU countries in both manufacturing and service sectors, find that in most cases employment does not change as a consequence of eco-innovation. The evidence is stronger for manufacturing than services but results are generally at odds with the traditional skill biased hypothesis associated to technological change.

Rennings *et al.* (2004) show that environmental innovations in both products and services lead to positive outcomes in terms of employment (except for end-of-pipe innovation) and this finding has been recently confirmed by Horbach (2010), documenting a positive impact on employment of environment-related innovations for a sample of German firms. More interestingly, he finds a higher impact of eco-innovation with respect to generic innovation on employment.

On the other hand, Cainelli *et al.* (2011) find a negative link between environmental innovation and growth in employment and turnover in the short term, analyzing the Community Innovation Survey (CIS) sample of Italian firms, while Horbach and Rennings (2013), using data from the CIS 2008, document heterogeneous results distinguishing between different types of environmental technologies, such as process and product innovation, and material saving, energy savings, air emissions abatement, or recycling.

Licht and Peters (2013) survey the literature on the link between environmental innovation and employment and empirically test such link exploiting CISs data for 16 European countries, distinguishing between product and process innovation. They find a positive and significant effect on employment growth of product innovations, but no substantial difference between environmental and non-environmental innovation. According to their results, process innovation provides instead a little contribution in terms of employment growth.

Although insightful and besides the emergence of often conflicting results, all these studies have two main limitations. Firstly, it is not clear whether and through which channels environmental technologies affect employment differently than generic innovation. Also related to this issue, little insight is offered on the potentially different cost of carrying out environmental or non-environmental innovation.

Secondly, data used for the analyses are generally based on innovation surveys and as such are heavily influenced by the structure of the questionnaire. As remarked in [Horbach and Rennings \(2013\)](#), the CIS questionnaire defines innovation as the development or the adoption of a “new or significantly improved product, process, organizational method or marketing methods that creates environmental benefits compared to alternatives” (p. 160). A measure of environmental innovation relying on this definition may be highly discretionary and suffer from measurement problems and response bias. Furthermore, the time coverage of the CIS is limited and thus the analysis may not be able to capture medium-long term effects of eco-innovation.

[Table 1](#) summarizes the relevant literature described in the current section.

2.1 Conceptual framework

In testing for the direct effect of environment-related innovation on employment, we expect green technologies to have a positive effect on firm-level employment. Our hypothesis is grounded in the well-established theory of technology life cycle phases ([Consoli and Vona, 2015](#)). As noted by [Agarwal and Gort \(2002\)](#), according to its life cycle, a market bears a different range of challenges and opportunities. Both theory and empirical evidence support the view that technological opportunities greatly change from infancy to the maturity of a market: in the early years, the scope for innovation is at its highest, but as a product or a market becomes more mature, technological opportunities decrease. [Frankhauser et al. \(2008\)](#) detects a similar trail for the green sector, adopting a time horizon approach to predict the evolutionary path of the green sector, mostly related to its ability to generate new jobs. In the short run, a direct employment effect generates job losses in sectors adversely affected by climate change policies and new jobs in sectors taking advantage from these initiatives. In the long run, the positive effect outweighs the negative impact since innovation and the development of new technologies create opportunities for investment and growth (dynamic effect of climate policy). However, learning by doing usually helps to increase labor productivity, so the impact on jobs of introducing a new technology may be attenuated over time. In this view, environmental innovation is intended as an expanding sector yielding a potentially dramatic change in the production patterns. As such, it can be used as a blueprint for any other forms of innovation that possess similar attributes, thus providing relevant insights that can be generalized to other types of technological advances.

Nonetheless, the green sector has some specificities that are unprecedented in other technological sectors and that provide the rationale for dedicated analysis on the effects of green innovation. First of all, differently from other sectors, green innovation is linked to the reduction of negative externalities, in terms of less environmental degradation, for the society as a whole. Although there are still some skeptical economists, the majority of them nowadays recognize the need for some form of intervention to redirect production toward cleaner forms. As [Acemoglu et al. \(2012\)](#) note, in fact, clean and dirty inputs are highly substitutable, meaning that without immediate and decisive intervention, firms would not change their production patterns. Furthermore, as any other forms of innovation, environmental innovation is characterized by the presence of high switching costs (a typical example is renewable technologies), which may impair the attractiveness of the sector for investors. As a consequence, many countries and the EU more than others, have opted for various degrees of policy intervention to reduce environmental degradation. This implies that environmental technologies have exploded mainly because of a clear, long-term policy agenda that has contributed to a reduction in the level of uncertainty about future return from innovation and helped the coordination among actors.

A second specificity refers to the importance of knowledge spillovers linked to environmental technologies. As shown by [Dechezlepretre et al. \(2013\)](#), green technologies are characterized by substantially larger knowledge spillovers than substitute brown technologies and other recent radical technology fields such as robotics, biotechnology, nanotechnology, and 3D printing and in line with information technologies (ITs). While the presence of knowledge spillovers reduces the appropriability of the returns of technological innovations, it also suggests that environmental technologies enable the generation of a variety of complementary innovations, as they tend to be more general than other technology fields. As suggested by [Haupt et al. \(2007\)](#), a disproportionately high number of citations is also a signal that the technology field is in its early stage of the technology lifecycle.

Table 1. Summary of the related literature

Research themes	Studies	Main findings
Innovation and employment <i>Firm-level analyses</i>	Van Reenen (1997); Chennels and van Reenen (2002); Garcia <i>et al.</i> (2004); Pianta (2005); Hall <i>et al.</i> (2008); Vivarelli (2014); Harrison <i>et al.</i> (2014).	Process innovation: labor-saving impact (displacement effect) or nonsignificant impact on employment; Product innovation: employment-stimulating outcomes (compensation effect)
<i>Aggregate-level analyses</i>	König <i>et al.</i> (1995); Smolny and Schneeweis (1999); Smolny (2002); Lachenmaier and Rottmann (2011).	Positive and significant effect of process innovation on employment growth in a dynamic perspective.
	Simonetti <i>et al.</i> (2000); Spiezia and Vivarelli (2002); Tancioni and Simonetti (2002).	No univocal effect of technological change on employment
	Bogliacino and Vivarelli (2012)	Technological change is positively correlated to employment growth.
	Acemoglu (2002); Goldin and Katz (2007)	Skill biased technological change: positive impact for the employment perspectives of high-skilled individuals and negative correlation with employment outcomes for low-skilled people.
Emergence of technological paradigms <i>Firm-level analyses</i>	Gagliardi (2014)	Technological change is negatively correlated to employment outcomes when the spatial scale of labor market adjustments is taken into account.
	Rosenberg (1976); Dosi (1982); Freeman <i>et al.</i> (1982); David (1985); Dosi <i>et al.</i> (1988).	Analyses of stylized facts associated to the emergence of ICT.
<i>Macro-level analyses</i>	Piva <i>et al.</i> , 2005, Bresnahan <i>et al.</i> , 2002, Giuri <i>et al.</i> , 2008	“Skill biased organisational change”: IT technologies are complementary to novel workplace organization, favoring skilled workers.
Green growth and employment	Spitz-Oener (2006); Goos and Manning (2007); Goos <i>et al.</i> (2009); Michaels <i>et al.</i> (2014); Autor and Dorn (2013). Autor <i>et al.</i> (2003)	Job polarization: middle-skilled occupations have declined in respect to both higher- and low-skilled occupations. Computers replace labor in routine tasks and complement nonroutine tasks.
	OECD (2011)	Investing in the green sector associated to job creation potential.
Eco innovation and employment	Becker and Shadbegian (2008); Morriss <i>et al.</i> (2009); Michaels and Murphy (2009); Hughes (2011).	No difference between environmental and non-environmental products in terms of wage, employment, output, or exports.
	Pfeiffer and Rennings (2001); Rennings <i>et al.</i> (2004); Horbach (2010).	Product innovation generates positive direct effect on employment, while the effects of process innovation are more ambiguous (survey data on Germany).
	Rennings and Zwick (2002)	No employment effect of environmental innovation.
	Cainelli <i>et al.</i> (2011)	Negative effect of environmental innovation on employment (survey data on Italy).
	Horbach and Rennings (2013); Licht and Peters (2013)	Positive and significant effect of environmental innovation on employment (little contribution of process innovation).

A third element that explains the increased interest of firms toward the green sector is the growing attention paid by consumers to the environmental sustainability of the products they purchase. Firms are increasingly willing to switch their product mixes and production processes or inputs, in order to exploit new market opportunities. While this latter dimension, namely the *demand pull* effect, is common to other technological advances developed in the past few decades, the policy-driven lever, which also responds to the variety of potential positive spillovers associated with investments in green technologies, remains specific of green innovation.

3. Methodology

The investigation of the impact of green technological change on employment growth using firm-level data brings along a number of methodological challenges, ranging from measurement issues to model specification and endogeneity concerns. Each of them will be carefully addressed in this section to support the reliability of our findings.

3.1 Measurement issues

Measuring technological change at firm level is not an easy task. Recent studies have mainly exploited the availability of micro-data coming from innovation surveys. Most notably, the work of [Harrison *et al.* \(2014\)](#) refers to the third CIS to recover information on employment and sales between 1998 and 2000 and whether the firm has introduced process and product innovations during the period.

In a similar vein [Hall *et al.* \(2008\)](#), working on Italian manufacturing firms, used data coming from the Mediocredito-Capitalia surveys on sales per employee, growth rates of employment, and sales of old and new products for the period 1995–2003. Both databases allow to recover information on innovation activities carried out during the period under analysis (for both product and process innovation) and to relate them with changes in employment at firm level.

CIS data have been recently used also to look at the impact of environment-related innovation ([Cainelli *et al.*, 2011](#); [Horbach and Rennings, 2013](#); [Licht and Peters, 2013](#)) exploiting the availability of a dedicated section of the survey.

Besides the traditional problems associated to survey data in particular with respect to the credibility of the innovation measure, the key limitation in the context of the investigation of the link between technological change and employment outcomes is the availability of short time series (generally 2–3 years). The impact of technological change on firms' employment profiles is unlikely to be fully recoverable in a limited time span since the potential virtuous cycles of increasing sales, production, and employment need time to materialize.

To provide a more reliable investigation on the medium-long term impact of technological change in environment-related fields, we adopted an alternative data source that has been extensively used in the literature on technological change and employment, starting from the work of [Van Reenen \(1997\)](#) analyzing manufacturing firms in Britain. The empirical investigation has been based on a novel data set matching Italian firm-level information with records coming from the European Patent Office (EPO) and providing the possibility to attribute to each firm all inventions patented during the period 2001–2008. Patents, interpreted as “stock of blueprint technologies that can be actualized in the form of an innovation outcome when economic conditions are favourable” ([Van Reenen, 1997: 263](#)), allow to account for the technological knowledge gathered by each firm over time. In this context, the number of patented inventions during the period under analysis represents the recent stock of technological knowledge that each firm managed to accumulate. Furthermore and particularly relevant for this analysis, following the classification provided by the OECD (ENV-TECH), the sub-sample of environment-related patented inventions may be extrapolated from the full sample of patents, allowing to test for the existence of a specific effect on job creation coming from green technologies.

A number of preliminary considerations need to be highlighted with respect to the choice of patent data as proxy for technological change. First of all, the focus on patents implies that the paper investigates the link between employment and innovation with respect to firms who are the creator of new technologies rather than to the full sample of organizations that may use green technologies/practices in their production settings despite being not the owner of the invention. In principle, there are two channels that can influence employment in response to innovations: a direct effect on innovating firms, through the exploitation of market opportunities and higher investment, and an indirect effect on users of innovations, through process innovation and the demand for new skilled labor in order to adapt to

the use of new technologies. As highlighted in the literature, these two effects may yield different implications on employment. In particular, while the direct effect is usually associated with an increase in employment at firm level, the indirect effect on employment is ambiguous, as process innovation may be both labor saving or call for new, high-skilled labor in order to be properly implemented. Measuring innovation with patents allows to predominantly capture the direct effect of (eco-)innovation while provides very little information about its potential indirect effect.

Secondly, although being a widely used output measure, patents are likely to be skewed toward innovation in large firms and technologically intensive sectors. This may provide a significantly different perspective of analysis with respect to data coming from innovation surveys (especially the CIS), relying to a relevant proportion of small and medium enterprises and built in order to provide a balanced sample in terms of sector of activity. Furthermore patent data are notably more representative of product rather than process innovation, preventing from the possibility to address the two dimensions independently. With respect to this latter aspect it is important to bear in mind that our expectation on the sign of the relation between technological change, measured by means of patent data, and employment growth is strongly driven by previous findings. There is a general consensus on the existence of a positive link between product innovation and changes in employment (Peters, 2004; Hall *et al.*, 2008), while no clear evidence has been provided on the effect of process innovation. Given the nature of our proxy for technological change we expect a positive contribution to employment growth. Nonetheless the existence of a specific impact associated to environmental technologies, that is the focal object of our analysis, is less straightforward to assess, as well as still understudied within the existing literature.

Finally, it is widely acknowledged that patents differ substantially in their economic and technological value (i.e. quality), with few patents that are very valuable and many patents with little or no value (Schankerman and Pakes, 1986). The failure to account for the heterogeneity in the value across patents may give rise to substantial measurement errors and biased estimates. For this reason, we try to control also for these differences by employing a series of indicators of patent quality that will be described in section 4.

3.2 Model specification

The key interest of this article lies in the investigation of the potential job creation effect of green technological change. This implies accounting for this dimension while controlling for both firm-level characteristics, which may increase the likelihood of innovation, as well as firms' capability to develop other kinds of innovative activities that cannot be classified as environmentally friendly.

The estimation equation will take the following form:

$$\Delta Empl_i^{T-t} = \beta_0 + \beta_1 Tech_change_i^{T,t} + \beta_2 Green_tech_change_i^{T,t} + \delta X_t + \varepsilon_t \quad (1)$$

where $\Delta Empl$ is the dependent variable measuring the variation in employment for each firm i in the period $T-t$,⁴ $Tech_change$ is the number of non-environmental patents for firm i over the period T, t , $Green_tech_change$ is the number of green patents for firm i over the same time period, X is a vector of firm-level controls at the beginning of the period (t) and ε is a well-behaving error term. The vector X includes information on age, number of years since the first patent to proxy for technological path dependence, size measured in terms of initial turnover, and return on investment (ROI) to account for the financial performance of the firm. Finally, we control for detailed sector of activity at two digits, and location (NUTS 1). Our preferred specification also accounts for differences in the temporal window in which firm-level information is available.⁵

- 4 We here consider the difference between the logarithm of employees at the end of the period and the logarithm of employees at the beginning of the period.
- 5 The majority of firms are present for either 8 (2001–2008) or 7 years in our database (34% and 54%, respectively). However, a small proportion of them are observable for 6 (8%) or 5 (4%) years only. For some of them, information for year 2001 is not available, while others are reasonably firms that ceased their activities during the time period under analysis. Given the structure of the data, the restriction to those firms with full information for the whole time window 2001–2008 would have reduced significantly the number of observations. Due to all the above considerations, we decided to retain all firms and to run the regression on those for which the dependent variable can be constructed with at least 4 years' lags controlling for the temporal window for which each firm is observed.

Despite its simplicity, the above specification allows to test the hypothesis regarding the specific impact that green technologies may have in terms of job creation. In the evaluation of the reliability of our findings, it is important to highlight the possibility to control for detailed measures of firms' financial performance and additional information that are not common in alternative studies exploiting data from innovation surveys.

3.3 Endogeneity issues

The main concern within our estimation framework is the potential endogeneity of technological change. The characteristics of our data and the variability in the temporal window for which different firms are present in our database (due to both lacking information, especially for 2001, and firms' exit), prevent from the possibility to estimate the equation of interest in differences (i.e. controlling for time invariant firm fixed effects). The exploitation of the balanced dimension of our panel would in fact come at a great cost in terms of number of observations. Furthermore due to the characteristics of our measure of technological change we believe a pure difference in the number of patents between 2001 and 2008 would be a misleading proxy for firm technological trajectories, leading to a poor exploitation of the information available with respect to the stock of knowledge accumulated over time.

In the evaluation of the estimation strategy adopted, it has to be borne in mind that the decision to invest in innovation-enhancing technologies, bringing to the emergence of technological change as measured by the number of patents by firm, is generally taken in advance based on firm's specific productivity level and economic performance. While the role of initial firm-level conditions, determining the incentives to carry out technological investments, is factored out by controls included in the specification, it is still possible that unobserved productivity shocks over the period taken into account may shift firms' incentives to perform innovation-enhancing activities (Chennels and Van Reenen, 1999). This is a particularly relevant issue if we assume that investment decisions and the subsequent patenting output take place within the same time window or if we allow for the possibility of any anticipation effects of future technological shocks at firm level.

Two considerations need to be taken into account with respect to the above concerns. First, it is reasonable to assume that investment decisions associated to inventions patented over the period 2001–2008 have been taken based on firms' conditions pre-2001.⁶ Secondly, it is also plausible that anticipation effects of future firm technological shocks are unlikely to affect substantially the decision to carry out technological investments (Harrison *et al.*, 2014). Notwithstanding these clarifications, our estimation is still at risk of both simultaneity and reverse causality bias. If the investment decision and the realization of the innovation output take place during the time span 2001–2008 (especially for firms observed for a longer period), we may be unable to disentangle the sign of the causality (i.e. firms may shift toward different technologies in response to changes in the nature and typology of available workers). Furthermore we cannot exclude a priori the possibility that firms are stimulated to engage in innovation by the anticipation of future technological shocks, implying that they may decide to change their employment profile (e.g. hiring R&D personnel working on the development of such innovations) due to, for example, expected future increases in labor productivity.

The existing literature has tried to address the abovementioned concerns associated to the endogeneity of technological change relying mainly on Instrumental Variables (IV) techniques and exploiting a range of possibilities. Harrison *et al.* (2014) used information on the increased range of goods and services reported in the CIS questionnaire. Their identification strategy builds on the structure of the CIS questionnaire disentangling the reasons for the introduction of innovation. Due to the presence of two related questions referring to "increased market share" and "improved quality in goods and services" as alternative motivations to engage in technological innovation, the authors suggest that the "increased range of goods and services" variable must be interpreted as a "measure of the extent to which firm's innovation is associated with an increase in demand for reasons other than changes in product prices and quality" (Harrison *et al.*, 2014). As a result, they expect this instrument to be uncorrelated with both changes in the price of new products compared to old products and with productivity shocks. Despite the appealing rationale this identification strategy is questionable. Data exploited to construct the relevant instrument come from the same CIS wave reporting information on both innovation activities and motivations behind the innovation activities carried out over the period 1998–2000, as well as data on changes in employment during the same period. The risk of substantial simultaneity bias cannot be fully ruled out.

Hall *et al.* (2008) exploited data on R&D expenditures in the last year of the 3-year survey period, the same measure lagged 1 year (in the middle year of the survey period), the R&D employment intensity in the last year of the

6 Hypothesis that is also endorsed by the timing of the patenting procedure.

survey period, and a dummy variable for whether the firm assigned high or medium importance to developing a new product as the goal of its investment. Among this set of instruments, those taking advantage from information on R&D expenditures and employment intensity in the last year of the survey try to deal with the potential simultaneity bias referring to the end of their time window, but the lag is likely to be too limited to rule out any doubts regarding the existence of a significant time trend driving firms' investment decision.

In order to address the endogeneity concern for our measures of technological change, for both environmental and non-environmental technologies we adopt a novel identification approach taking advantage from the strategy popularized by Ellison *et al.* (2010) and Haskel *et al.* (2007), instrumenting the geographical concentration of economic activities in the United States with that in the UK and FDI inflows in the UK with those in the United States, respectively. Exploiting data on EPO patent applications count (for both non-environmental and environmental patents) for the period 1996–2004⁷ filed by companies in Western Europe⁸ in the same sector (four-digit NACE rev. 2), for the same size class (more or less than 250 employees in median value) and the same age class (more or less than 10 years),⁹ we instrument our proxies of technological change with comparable measures for a similar sample of European firms. The instrument relies on the idea that international technological trends (among technologically coherent countries) affect, for homogenous categories of firms (in terms of size, sector of activity, and age), the probability to engage in technological innovation and its intensity independently on shifts in firms' specific incentives. Coherently with previous contributions applying a similar strategy the exclusion restrictions for our IV implies that innovations developed by Western European firms in the same four-digit NACE sector do not directly impact on the evolution of employment in Italian firms. In other words, we assume that these technological innovations are not sufficiently global in scope to influence domestic firms directly. The focus on technology producers only and the legal rights associated with the patenting procedure reinforce the credibility of the abovementioned assumptions.

The instrument is expected to be significantly and positively correlated with the regressor of interest, but uncorrelated with unobserved firm's productivity shocks.

4. Data

Our sample consists of 4507 Italian manufacturing firms. We selected these firms from a panel of 49,590 manufacturing firms in the AIDA (Bureau van Dijk) database based on the criterion that they should have applied for at least one patent at the EPO between 1977 and 2008. The link between firms in AIDA and applicants at the EPO is described in Lotti and Marin (2013). For each firm, we know the whole record of patent applications at the EPO for the period 1977–2008.

The focus on patenting companies (either in the considered period or before the period) allows relying on a homogeneous population of potentially innovative firms for which patenting is (or has been) a relevant tool to protect their inventions/innovations. This criterion may lead to a selection bias¹⁰ but it is also likely to substantially reduce the unobserved heterogeneity in patent propensity across firms. Given the object of the investigation (i.e. the potential specific effect on job creation attributable to environment-related technological change with respect to general innovation) the latter aspect is considered far more relevant than the former for the reliability of our estimation strategy.

We retrieved balance sheet and income statement information together with employees' headcount for each firm in our sample for the period 2001–2008. Real turnover (in euro) has been deflated by means of sector-specific

7 EPO patent applications have been retrieved from the matching between companies included into the Amadeus (Bureau van Dijk) and EPO patents released by Thoma *et al.* (2010). Information on size, age, and sector of activity has been taken from various editions of the Amadeus database while those on priority date and IPC class of patent applications come from the REGPAT (OECD) database (July 2013 release).

8 EU15 (excluding Italy) plus Norway and Switzerland.

9 Results are robust to changes in time window and the way in which size and age classes are defined.

10 Table A1 reports the difference (raw difference and difference controlling for some observable characteristics) in some relevant variables between our sample of patenting firms and the whole sample of firms in AIDA. Firms in our sample tend to be older, bigger (both in terms of turnover and employment), more productive (labour productivity) but with slower employment growth than other firms in AIDA. However, these differences tend to vanish when conditioning on sector, year, location (province), and, most importantly, on firm size (in terms of total asset).

deflators for gross output (NACE rev. 2, two-digit, reference year 2000). ROI is the ratio between the Earnings Before Interest and Taxes and total assets, both in nominal terms. We also use the variation of cost for employees (labor compensation) as an alternative way of measuring employment growth (in real terms, deflated with sector-specific deflators of value added). We obtained information on location (province—NUTS3), sector (NACE rev. 2, four-digit), and age of the firm from the AIDA database. In our baseline specification, we aggregate firms by macro-region (four NUTS1 regions) and two-digit NACE sector. We excluded outliers based on having the value of the outcome variable three standard deviations greater than the third quartile or smaller than the first quartile (severe outliers).¹¹

Environmental patents have been identified by means of the definition of environmentally sound technologies prepared by the OECD¹² based on a list of relevant IPC and ECLA¹³ classes. They include: general environmental management (pollution abatement, waste management, soil remediation, environmental monitoring), energy generation from renewable and non-fossil sources, combustion technologies with mitigation potential, technologies specific to climate change mitigation (e.g. CO₂ capture and storage), technologies with potential or indirect contribution to emissions mitigation, emission abatement and fuel efficiency in transportation, and energy efficiency in buildings and lighting. The full list of technology fields and IPC/ECLA classes employed to identify environmental patents are reported in Table A2 of Appendix 2.¹⁴

Finally, we account for heterogeneity in the value and relevance of patents by employing a series of indicators of patent quality in addition to the raw count of patents. We select six different measures of patent quality from the ones reviewed and defined by Squicciarini *et al.* (2013).¹⁵ Details on the measures of patent quality are reported in Appendix 1. Table 2 reports some descriptive statistics for our variables of interest, while Table 3 shows the distribution of observations and patent applications by sector and initial size. Table 4 reports the average values of our dependent variable by initial size and sector for different categories of patenting outcome during the considered period. Firms with at least one patent application in the period tend to grow, on average, substantially faster (or to shrink more slowly) than those without patents. This evidence is common for all size classes and most sectors, the only exception being sector CD (coke and refined petroleum products). Looking at firms with at least one environmental patent (*Env patent*), we observe an above-average long run growth rate of employment for all size classes, although this evidence is inconsistent for some sectors. The difference in performance for firms with heterogeneous patenting behavior is clearly visible in Figure 1, in which we plot the estimated kernel density of our dependent variable. The distribution of the long run growth of employment for firms with at least one patent in the period is slightly shifted to the right relative to the distribution of firms that did not apply for patent in the same period. Moreover, the distribution of long run growth for firms with at least one environmental patent is further shifted to the right, denoting an above-average growth in employment for firms active in the creation of green technologies. This descriptive evidence suggests a strong positive relationship between general patenting and job creation as well as a substantial premium for firms that are active in the field of environmental technologies.

5. Results

5.1 OLS estimates

Table 5 reports the results of our OLS baseline estimates. In column 1 we include our set of control variables only. Long run employment growth is positively related to firm's initial profitability (ROI); profitability is expected to stimulate new investments and, consequently, firm growth. The negative (raw) relationship between initial size and growth is a common finding in empirical analyses as well as the negative relationship between firm's age and firm's

- 11 We also estimate our preferred specification on different samples that differ in the way outliers have been defined.
- 12 Indicator for environmental technologies—ENV-TECH Indicator, <http://www.oecd.org/env/consumption-innovation/indicator.htm>.
- 13 ECLA class "Y02 - Technologies or applications for mitigation or adaptation against climate change."
- 14 As robustness check, we also identified environmental patents as those with IPC class available in the IPC Green Inventory developed by the WIPO (not reported but available upon request). The IPC Green Inventory, however, tends to include more patents than the ENV-TECH indicator, with greater risk of including non-environmental patents. Results when using this alternative measure tend to go in the same direction as the ones based on the more reliable OECD/ENV-TECH taxonomy but they are bigger in magnitude and more imprecise (greater standard errors).
- 15 Starting from 2013, the OECD complements the REGPAT Database, released every 6 months, with a database containing ready-to-use indicators of patent quality for EPO patent applications.

Table 2. Descriptive statistics

Variable	Mean	Median	Min	Max	SD
Tot patents (dummy)	0.6634	1	0	1	0.4726
Non-env patents (dummy)	0.6634	1	0	1	0.4726
Env patents (dummy)	0.0495	0	0	1	0.2169
ICT patents (dummy)	0.0233	0	0	1	0.1509
Tot patents (count)	2.5114	1	0	258	8.3023
Non-env patents (count)	2.3965	1	0	250	7.8733
Env patents (count)	0.1149	0	0	51	1.3446
ICT patents (count)	0.1036	0	0	30	1.0253
Stock tot patents	0.3841	0	0	38.8648	1.538
Stock non-env patents	0.3702	0	0	38.8648	1.4753
Stock env patents	0.0139	0	0	14.0222	0.2581
Empl growth	-0.0054	-0.0625	-2.7657	2.8034	0.6036
Empl cost growth	0.3172	0.2569	-6.9847	4.983	0.5988
Log (turnover)	16.0601	16.0002	10.625	21.1151	1.3961
ROI	0.0679	0.0564	-1.096	0.7094	0.078
AGE	26.1433	23	0	135	15.1769
Years since first patent	11.006	10	0	31	7.67

Table 3. Distribution of EPO patent applications (total and “environmental”) by size and sectors

Size/sector	N. firms	Tot patents	Av patents	Sh with patents	Tot env_pat	Av env_pat	Sh with env_pat
≤10 empl	546	572	1.05	0.65	20	0.04	0.03
11–50 empl	1634	2211	1.35	0.64	81	0.05	0.04
51–250 empl	1788	3998	2.24	0.67	134	0.07	0.05
251 + empl	539	4538	8.42	0.72	283	0.53	0.12
CA	104	133	1.28	0.59	3	0.03	0.02
CB	219	332	1.52	0.63	3	0.01	0.01
CC	137	186	1.36	0.62	6	0.04	0.04
CD	12	7	0.58	0.42	0	0.00	0.00
CE	219	774	3.53	0.63	36	0.16	0.08
CF	132	854	6.47	0.62	4	0.03	0.02
CG	494	1063	2.15	0.66	41	0.08	0.06
CH	842	1419	1.69	0.64	39	0.05	0.04
CI	237	565	2.38	0.73	44	0.19	0.07
CJ	318	904	2.84	0.69	60	0.19	0.08
CK	1260	3329	2.64	0.69	91	0.07	0.05
CL	188	1099	5.85	0.69	181	0.96	0.10
CM	345	654	1.90	0.65	10	0.03	0.03
Total	4507	11319	2.51	0.66	518	0.11	0.05

CA—food products, beverages, and tobacco products; CB—textiles, apparel, leather, and related products; CC—wood and paper products, and printing; CD—coke, and refined petroleum products; CE—chemicals and chemical products; CF—pharmaceuticals, medicinal chemical, and botanical products; CG—rubber and plastics products, and other non-metallic mineral products; CH—basic metals and fabricated metal products, except machinery and equipment; CI—computer, electronic, and optical products; CJ—electrical equipment; CK—machinery and equipment n.e.c.; CL—transport equipment; CM—other manufacturing, and repair and installation of machinery and equipment.

growth. Results are also consistent with respect to the control for patenting history since firms with a longer patenting history tend to grow slower.

In column 2 we add the total count of patents in the considered period. Sign, magnitude, and statistical significance of our controls remain unchanged but we find a strong positive effect of patenting outcome on long run employment growth. Each additional patent results, on average, in an increase of employment of about 0.72%. The

Table 4. Growth in employment by “patenting status” and size/sector

	No patent	At least one	Total	No env patent (but at least one patent)	Env patent
≤10 empl	0.49	0.67	0.60	0.66	0.74
11–50 empl	–0.13	0.06	–0.01	0.06	0.06
51–250 empl	–0.23	–0.12	–0.16	–0.12	–0.08
251 + empl	–0.17	–0.03	–0.07	–0.05	0.12
CA	–0.03	0.06	0.02	0.05	0.33
CB	–0.04	0.04	0.01	0.06	–0.42
CC	–0.10	0.19	0.08	0.19	0.07
CD	–0.27	–0.30	–0.28	–0.30	
CE	–0.13	0.03	–0.02	0.05	–0.06
CF	–0.18	–0.08	–0.12	–0.08	–0.04
CG	–0.03	0.11	0.06	0.11	0.14
CH	–0.10	0.04	–0.01	0.04	0.01
CI	–0.15	0.13	0.05	0.14	0.02
CJ	–0.15	0.08	0.01	0.07	0.21
CK	–0.11	–0.02	–0.05	–0.03	0.06
CL	0.04	0.23	0.17	0.19	0.46
CM	–0.01	0.11	0.07	0.11	–0.02
Total	–0.09	0.05	0.00	0.05	0.09

CA—food products, beverages, and tobacco products; CB—textiles, apparel, leather, and related products; CC—wood and paper products, and printing; CD—coke, and refined petroleum products; CE—chemicals and chemical products; CF—pharmaceuticals, medicinal chemical, and botanical products; CG—rubber and plastics products, and other non-metallic mineral products; CH—basic metals and fabricated metal products, except machinery and equipment; CI—computer, electronic, and optical products; CJ—electrical equipment; CK—machinery and equipment n.e.c.; CL—transport equipment; CM—other manufacturing, and repair and installation of machinery and equipment.

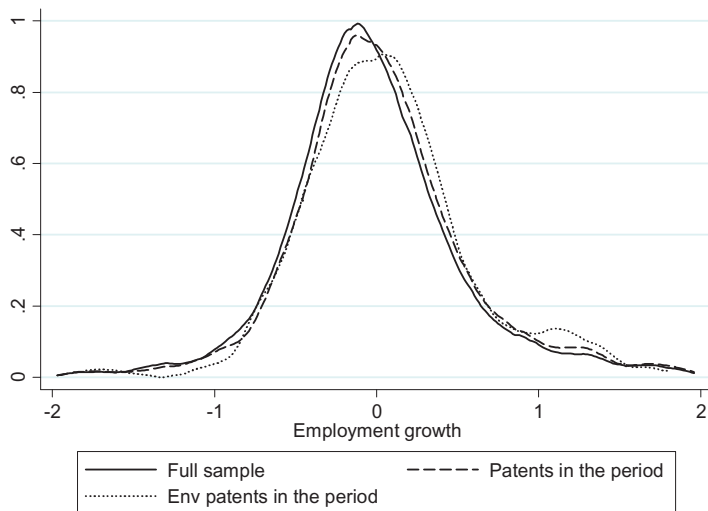


Figure 1. Distribution of employment growth by “patenting status”.

positive sign is consistent with most of the existing recent contributions investigating the link between product innovation and employment. As discussed in the previous section, even though our measure of innovation output (patent count) includes both product and process innovations, product innovations tend to be over-represented relative to process innovations (Arundel and Kabla, 1998).

Table 5. OLS results

	(1)	(2)	(3)	(4)	(5)
Log (turnover)	-0.0697*** (0.00774)	-0.0799*** (0.00813)	-0.0794*** (0.00807)	-0.0801*** (0.00812)	-0.0732*** (0.00785)
ROI	0.564*** (0.128)	0.565*** (0.126)	0.576*** (0.126)	0.566*** (0.126)	0.572*** (0.128)
AGE	-0.00562*** (0.000643)	-0.00537*** (0.000635)	-0.00536*** (0.000633)	-0.00539*** (0.000637)	-0.00554*** (0.000643)
Years since first patent	-0.00952*** (0.00114)	-0.00990*** (0.00113)	-0.00989*** (0.00112)	-0.00976*** (0.00113)	-0.00976*** (0.00114)
Tot patents (count)		0.00721*** (0.00190)			
Non-env patents (count)			0.00585*** (0.00173)	0.00649*** (0.00184)	
Env patents (count)			0.0272*** (0.00715)		
Non-env / non-ICT patents (count)					
ICT patents (count)					
Env patents (dummy)				0.0898** (0.0394)	
Stock non-env patents					0.0140*** (0.00511)
Stock env patents					0.0540*** (0.0181)
N	4507	4507	4507	4507	4507
R squared	0.125	0.134	0.136	0.134	0.127
F	13.92	13.96	14.04	13.68	13.60

Dependent variable: long run change in employee headcounts. OLS estimates. Robust standard errors in parenthesis. * $P < 0.1$, ** $P < 0.05$, *** $P < 0.01$. Sector dummies (two-digit), regional dummies (NUTS1), and time window dummies included.

In column 3, we split our measure of overall innovation into “green” innovations (*Env patents (count)*) and other innovations (*Non-env patents (count)*). We find a big and statistically significant effect of “green” innovation on employment growth. Applying for one additional “green” patent results in an average increase of long run employment of about 2.7%, which should be compared to the increase driven by a non-environmental patent of about 0.58%. Despite still positive and significant, the magnitude of the regressor for non-environmental innovation is significantly lower.

All in all, results based on OLS estimates show that environment-related technological change is associated to employment growth in Italian firms. This implies that investments in green technologies are likely to generate a (gross) return in terms of employment growth that is substantially bigger (more than four times) than the return of non-environmental technologies. In interpreting this result it is important to bear in mind two caveats.

First, our baseline results do not account for differences in patents’ quality. If environmental patents differ systematically from others in terms of quality, this may drive substantially our results. [Table A4](#) in the Appendix 2 reports average measures of patent quality for environmental and non-environmental patents. We observe that, with the only exception of patent family size, environmental patents tend to be of higher “quality” than non-environmental patents, especially when considering forward citations (in line with [Dechezpretre et al., 2013](#)) and scope. This difference may partially explain the greater job creation effect of environmental patents providing additional evidence on the rationale behind our empirical results.

Second, our estimation does not control for the cost of different innovations. Indeed, it could be the case that the cost for obtaining green patents is different from the cost for obtaining other patents. If cost differentials are significant, the net effect on employment can be overestimated in particular with respect to the impact of non-environmental innovation. Unfortunately, it is difficult to recover reliable information on the cost of the innovative process; however,

we try to shed some light on this dimension by comparing the number of inventors associated with our sample of green and non-green patents. As suggested by Harhoff and Thoma (2009), the number of inventors needed to obtain a patent is a good proxy for R&D investment, due to the relevance of wages for researchers in overall R&D expenditure. Table A5 in the Appendix 2 shows some descriptive statistics on inventors count for our sample of patents. On average, each patent requires 1.88 inventors, while one environmental patent requires on average 2.1 inventors. The distribution is quite skewed, with more than half of non-environmental patents requiring just one inventor. This evidence suggests a greater “cost” for obtaining an environmental patent with respect to non-environmental innovations. In evaluating this claim it is however important to highlight that the number of inventors per patent is likely to be specific to each technology field. This implies that part of the difference in the number of inventors may be explained by characteristics other than the simple environmental versus non-environmental dichotomy. In Table A6 in the Appendix 2 we investigate the extent to which environmental patents require, on average, more inventors than other patents when controlling for year dummies and technology fields covered by the patent.¹⁶ Evidence confirms that, on average, environmental patents require more inventors than other patents even after controlling for technology fields. The difference ranges between 0.088 (but not statistically significant) and 0.24 inventors, which corresponds, in percentage terms, to a range going from about 4.7% to 12.8% more inventors than non-environmental patents. When comparing estimated cost differentials and estimated return differentials, however, the gap in net returns between environmental and non-environmental patents remains remarkable, suggesting that, despite requiring a greater innovative effort, eco-innovations are still likely to yield a significant return in terms of employment effects. This evidence reinforces our baseline claim on the additional job creation effect of environmental with respect to other forms of innovation.

5.2 Robustness checks

The reliability of our results is further tested through a number of robustness checks. Our baseline results are confirmed in their sign and significance when focusing on the extensive margin only (column 4 of Table 5, binary indicator of whether the firm applies for at least one “green” patent), in which the effect remains positive despite the slight reduction in the level of significance. In column 5 of the same table, we include the stock of patents¹⁷ prior to the initial year, for both non-environmental patents and environmental patents. Past patenting performance affects employment dynamics similarly to current patenting, with both patent stocks having a positive effect on employment growth and the effect being greater for environmental than for non-environmental patents. Indeed the two measures recall different dimensions. Whereas the flow of patents over the period of analysis proxies recent investments in innovation, past stocks provide an indication for the accumulation of knowledge over time. The difference between the two measures, which are traditionally highly correlated since novel innovations are more likely to emerge from cumulative patterns, may be more relevant in the case of environmental technologies. Innovative efforts in this context increased significantly in recent years, and a number of firms have grown in size or entered the market, thanks to the new opportunities associated to the “green economy.” Past stocks may substantially underestimate this dimension, implying a weaker explanatory power for green innovation than for generic innovation. This hypothesis finds some suggestive evidence in terms of R squared that shrinks sensibly when using stock measures (column 5, Table 5—R squared of 0.127) instead of flow measures (column 3, Table 5—R squared of 0.136).

Table 6 performs some additional robustness checks. Results tend to be robust to the omissions of control variables (columns 1 and 2) even though the estimated return of non-environmental patents in terms of job creation turns out to be substantially underestimated relative to our baseline results. No substantial difference in the effect of our variables of interest is found when adding more detailed dummy variables (four-digit NACE rev. 2 and NUTS3 in column 3), when assuming a nonlinear relationship between initial size and employment growth (column 4), when using initial size expressed in terms of employees (column 5), and when using the growth rate of total compensation to employees as an alternative measure of employment growth (column 6).

16 We classify patents by technology fields based on the classification provided by Schmoch (2008), which identifies 35 technology fields, further aggregated into 5 macro-fields.

17 Perpetual inventory method with 15% depreciation rate.

Table 6. Robustness checks: alternative specifications

	(1) No controls	(2) Only dummies	(3) Dummies “demanding”	(4) Square size	(5) Size: employees	(6) Dep: empl_cost	(7) Comparison with ICT
Non-env patents (count)	0.00144 (0.000906)	0.00187* (0.000997)	0.00686*** (0.00157)	0.00385*** (0.00148)	0.00759*** (0.00205)	0.00509*** (0.00189)	
Env patents (count)	0.0290*** (0.00792)	0.0257*** (0.00791)	0.0262*** (0.00787)	0.0265*** (0.00820)	0.0282*** (0.00671)	0.0293*** (0.00812)	0.0262*** (0.00634)
Log (turnover)			-0.0870*** (0.00849)	-1.095*** (0.132)		-0.102*** (0.00826)	-0.0797*** (0.00807)
ROI			0.512*** (0.128)	0.646*** (0.126)	0.371*** (0.124)	0.704*** (0.116)	0.581*** (0.126)
AGE			-0.00492*** (0.000686)	-0.00497*** (0.000623)	-0.00344*** (0.000619)	-0.00497*** (0.000587)	-0.00535*** (0.000633)
Years since first patent			-0.00909*** (0.00117)	-0.00988*** (0.00111)	-0.00755*** (0.00110)	-0.00985*** (0.00109)	-0.00991*** (0.00112)
Log (turnover) squared				0.0314*** (0.00403)			
Log (employees)					-0.142*** (0.00920)		
Non-env / non-ICT patents (count)							0.00550*** (0.00175)
ICT patents (count)							0.0172* (0.0105)
Sect. dummies (two-digit)	No	Yes	No	Yes	Yes	Yes	Yes
Sect. dummies (four-digit)	No	No	Yes	No	No	No	No
Reg. dummies (NUTS1)	No	Yes	No	Yes	Yes	Yes	Yes
Reg. dummies (NUTS3)	No	No	Yes	No	No	No	No
Time window dummies	No	Yes	Yes	Yes	Yes	Yes	Yes
N	4507	4507	4507	4507	4507	4477	4507
R squared	0.00511	0.0429	0.233	0.155	0.187	0.163	0.137
F	9.081	5.466		14.86	17.21	20.45	13.87

Dependent variable: long run change in employee headcounts (except last column). OLS estimates. Robust standard errors in parenthesis.

* $P < 0.1$, ** $P < 0.05$, *** $P < 0.01$.

Finally, we compare the return of environmental patents in terms of job creation (or destruction) with the one of other specific fields which have experienced a rapid development in the past decades, such as ICTs.¹⁸ The specification reported in column 7 highlights that the link between ICT patents and job creation is statistically significant only at the 10% level but the magnitude (1.7% increase in employment for each additional ICT patent) is only slightly smaller than for environmental patents and still well above the job creation potential of other “general” patents.¹⁹ Therefore the impact of green technology remains positive and significant also when compared with other emerging fields.

Finally, Table 7 reports the results of our preferred specification for different samples based on alternative ways of identifying outliers. We use the whole potential sample of firms (column 1), a sample which excludes both “severe” and “mild” outliers²⁰ in terms of outcome variable (column 2), samples excluding the top and bottom 1% and

18 Patents in these fields have been selected following the taxonomy proposed by Schmoch (2008) who identifies 35 different technology fields based on the IPC class of patents. Out of these 35 technology fields, Schmoch (2008) suggests that “A combination of the fields 3 to 7 [3 Telecommunications, 4 Digital communication, 5 Basic communication processes, 6 Computer technology, 7 IT methods for management.] represents information technology in general”. Relevant IPC classes are reported in Table A3 in the Appendix 2.

19 We thank an anonymous referee for suggesting this further check.

20 Above $Q3+1.5*SD$ or below $Q1-1.5*SD$.

Table 7. Robustness checks: alternative samples

	(1) All observations (including severe outliers)	(2) Mild outliers excluded	(3) Top/bottom 1% excluded	(4) Top/bottom 5% excluded	(5) No influential observations (Cook's dist)	(6) Regression robust to outliers
Non-env patents (count)	0.00816*** (0.00242)	0.00414*** (0.00129)	0.00575*** (0.00176)	0.00352*** (0.00115)	0.00947*** (0.00131)	0.00456*** (0.000887)
Env patents (count)	0.0278*** (0.00666)	0.0208*** (0.00362)	0.0271*** (0.00716)	0.0189*** (0.00374)	0.0282*** (0.0107)	0.0261*** (0.00508)
Log (turnover)	-0.118*** (0.0133)	-0.0347*** (0.00623)	-0.0749*** (0.00799)	-0.0312*** (0.00542)	-0.0718*** (0.00689)	-0.0354*** (0.00523)
ROI	0.553*** (0.141)	0.623*** (0.0992)	0.470*** (0.123)	0.463*** (0.0874)	0.533*** (0.111)	0.698*** (0.0844)
AGE	-0.00541*** (0.000816)	-0.00460*** (0.000525)	-0.00588*** (0.000668)	-0.00452*** (0.000463)	-0.00543*** (0.000519)	-0.00459*** (0.000467)
Years since first patent	-0.00759*** (0.00155)	-0.00822*** (0.000920)	-0.00885*** (0.00114)	-0.00661*** (0.000805)	-0.00912*** (0.000963)	-0.00773*** (0.000895)
N	4559	4357	4495	4150	4351	4559
R squared	0.124	0.122	0.132	0.128	0.148	0.138
F	10.73	14.20	12.99	14.22	19.70	17.59

Dependent variable: long run change in employee headcounts. OLS estimates. Robust standard errors in parenthesis.

* $P < 0.1$, ** $P < 0.05$, *** $P < 0.01$. Sector dummies (two-digit), regional dummies (NUTS1), and time window dummies included.

5% of the distribution of employment growth (columns 3 and 4) and a sample excluding influential observations based on Cook's distance²¹ (column 5). Finally, column 6 reports the results for the whole sample obtained with robust regression, in which observations are weighted by a measure negatively related to their influence on the results. The estimated coefficients for our variables of interest and main controls remain stable across all different samples as well as in the robust regression, with somewhat weaker results in some cases, suggesting that our results are not driven by the composition of the sample.

5.3 Instrumental variables

Despite the promising stability of our results with respect to a number of robustness checks, a more careful analysis of the potential role of endogeneity concerns is still needed. As acknowledged in section 3, there are a number of considerations that may question the causality between technological change and employment, ranging from simultaneity to reverse causality biases. To deal with them we adopted the identification strategy based on an Instrumental Variable (IV) approach as discussed in section 3.3 (Table 8).

We re-estimated the relation of interest using as instrument the count of patents by firms (for total and environmental-related patents, respectively) in Western Europe in the same four-digit sector and for the same class of size and age computed for the time window 1996–2004. In selecting the time window for the creation of our IV, we had to consider a variety of issues. It should be long enough to describe long run international technology trends. However, the period should be close enough to our reference period to be a reliable indicator of current technology trends. Data on patents in Thoma *et al.* (2010) have an excellent coverage up to the year 2000, while the coverage for 2005 is already very poor.²² On the other hand, data availability on firm-level information coming from the Amadeus (Bureau van Dijk) database²³ is hardly available before 1996.

21 We keep only observations with Cook's distance smaller than 4/N.

22 Thoma *et al.* (2010) matched 27,093 EPO patent applications in 2000, while only 1660 patent applications were matched to firms in Amadeus in 2005.

23 We used three different releases: September 2006, March 2009, and April 2013.

Table 8. Instrumental variables (non-environmental and environmental patents)

	OLS	IV	First stage (non-env patents)	First stage (env patent)
Non-env patents (count)	0.00585*** (0.00173)	0.0216* (0.0112)		
Env patents (count)	0.0272*** (0.00715)	0.138** (0.0682)		
Log (turnover)	-0.0794*** (0.00807)	-0.108*** (0.0156)	1.203*** (0.0913)	0.0529*** (0.0160)
ROI	0.576*** (0.126)	0.629*** (0.121)	0.489 (1.453)	-0.490* (0.255)
AGE	-0.00536*** (0.000633)	-0.00459*** (0.000720)	-0.0290*** (0.00809)	-0.00184 (0.00142)
Years since first patent	-0.00989*** (0.00112)	-0.0110*** (0.00133)	0.0486*** (0.0155)	0.00294 (0.00271)
Non-env patents in EU for same sect/size/age			0.00507*** (0.000705)	0.0000219 (0.000124)
Env patents in EU for same sect/size/age			-0.0123* (0.00667)	0.00673*** (0.00117)
N	4507	4507	4507	4507
R squared	0.136	0.0164	0.0916	0.0439
F	14.04	14.20	10.98	5.000
Test of excluded instrument (F)			30.32***	26.43***
Anderson underidentification (Chi ²)		42.94***		
Cragg–Donald weak instrument test (F)		21.47		
Stock–Yogo weak ID critical value (10% max IV size)		7.03		
Anderson–Rubin weak instrument test (F)		7.385***		
Anderson–Rubin weak instrument test (Chi ²)		14.91**		
Wu–Hausman exogeneity test (F)		4.464**		
Durbin–Wu–Hausman exogeneity test (F)		8.999**		
Pagan–Hall heterosk. test (Chi ²)		52.38		

Dependent variable: long run change in employee headcounts. OLS and IV estimates. Standard errors in parenthesis.

* $P < 0.1$, ** $P < 0.05$, *** $P < 0.01$. Sector dummies (two-digit), regional dummies (NUTS1), and time window dummies included.

For identification purposes, we need at least two instruments to deal with two endogenous explanatory variables. We use the same kind of instrument for both non-environmental and environmental patent counts, where the instrument for “green” patents is constructed following the same logic as the instrument for total patents but considering “green” patents only. In the first stage, each instrument positively and strongly correlates with its corresponding endogenous variable, as expected. However, while no relationship is found between non-environmental patents in Western European firms and “green” patents, a weak negative relationship is found between “green” patents in Western European firms and non-environmental patents. The first stage also supports the evidence that instruments are sufficiently strong (as indicated by the F test on excluded instruments, by the Cragg–Donald test statistics, well above the Stock–Yogo critical value for 10% bias and Anderson–Rubin test) ruling out any doubts regarding the presence of weak instrument biases. Furthermore, the null hypothesis of exogeneity is rejected by the Wu–Hausman and Durbin–Wu–Hausman tests, while the null hypothesis of homoskedasticity cannot be rejected (Pagan–Hall test of homoskedasticity). Regarding our parameters of interest, non-environmental patents turn out to be only weakly significant (at 10% level), while the effect of “green” patents remains positive and significant. Moreover, the point estimate for “green” patents is substantially larger in magnitude (about five times larger) than the one estimated with OLS, supporting the existence of a downward bias for OLS estimates. This suggests that, besides the problems of reverse causality and simultaneity, our OLS results suffer also from a measurement bias associated to the difficulties in disentangling the potentially heterogeneous effect of process with respect to product innovation. This consideration is justified in light of the large literature on the different effects of product and process innovation on job creation,

suggesting a generally negative effect of process innovation on employment. As already discussed, our proxy for technological change (patents) is likely to underestimate process innovations in favor of product innovations explaining the large positive effect. Nonetheless, a certain correlation between the two dimensions may still persist at firm level, and this may lower the magnitude of the overall coefficient, generating a certain degree of attenuation bias.

In justifying why our instrument, despite also based on patent statistics, is appropriate to control for this problem, some considerations have to be borne in mind. The aim of our IV approach is to capture innovation trends, or propensity to innovate, for specific segments of firms during a specific time trend. We suggest that the propensity to innovate is correlated with patents outcomes for homogeneous categories of firms but not necessarily correlated with specific unobservable factors such as the probability to perform process more than product innovation at firm level, even though a positive correlation between patent outcome and process innovation within each single firm is expected. We check these assumptions using survey data for Italian firms from another source that allows us to distinguish between product and process innovation.²⁴ For each firm, we compute the share of firms in other Italian regions (NUTS1) within the same sector, age class, and size class.²⁵ From Table A7 in the Appendix 2, we observe a significant positive correlation between process and product innovation within each firm, suggesting that firms performing product innovation are also likely to perform process innovation. This evidence also supports our baseline claim regarding the fact that, despite more representative for product innovation, our regressor may still provide an indicative measure also for process innovation. However, the propensity to introduce product innovations by homogeneous categories of firms is positively correlated with actual product innovation but uncorrelated with actual process innovation. In the same vein, the propensity to introduce process innovations positively correlates with actual process innovation only. This evidence suggests that our IV approach is likely to isolate the effect of product innovation from that of process innovation, explaining the significant increase in the coefficient for our regressor of interest in the second-stage regression.

Results for our instrumental variable estimation confirm that the positive and significant relation between environmental technological change and employment growth remains consistent also after accounting for the endogeneity of the regressors of interest. Eco-innovation is associated to increasing employment at firm level, suggesting that the labor saving effect is counterbalanced by virtuous cycles based on increasing productivity, revenues, and further employment.

5.4 Indicators of patent quality

As discussed in section 3.1, the raw count of patents fails to account for the heterogeneity in the value of patents, leading to measurement errors and, consequently, to biased estimates. Moreover, this measurement error could systematically underestimate the relevance of specific technology fields. As we have noticed in Table A4, environmental patents are, on average, of greater quality. For this reason, the differential positive effect of environmental patents on job creation may be explained by differences along this dimension.

To reduce the risk of measurement error and to account for systematic differences in patent quality across technology fields, we replicate our analysis for the six different indicators of patent quality described in Appendix 1. In Tables 9 and 10 we report the results of our preferred specification (both OLS and IV). OLS results confirm the positive effect of patenting on job creation and a substantial premium for environmental patents relative to patents in other technology fields. This result is generally confirmed when instrumenting quality-adjusted patents with the same IV used for patent count.²⁶ The effect of quality-adjusted environmental patents remains significant for all measures of patent quality and substantially greater in magnitude when compared to quality-adjusted non-environmental patents, that turn out to be statistically insignificant when considering forward citations, number of claims, and radicalness. As with the simple count, OLS substantially underestimate the effect of both environmental and non-environmental patents. The job creation potential of quality-adjusted environmental patents is about six to seven times bigger than the one of quality-adjusted non-environmental patents, in line with the estimates based on raw patent count, for all measures except forward citations (with a slightly smaller difference) and patent family size (with a substantially larger difference). All in all, the job creation

24 We use the 7th, 8th, 9th and 10th waves of the “Survey on Manufacturing Firms” conducted by Unicredit (an Italian commercial bank, formerly known as Mediocredito-Capitalia). These four surveys were carried out in 1998, 2001, 2004, and 2007, respectively, using questionnaires administered to a representative sample of Italian manufacturing firms. Each survey covered the 3 years immediately prior.

25 Sector at the four-digit disaggregation (Nace rev. 2), more or less that 250 employees, younger or older than 10 years.

26 IVs work pretty well for most measures, with the only remarkable exception of forward citations, for which instruments are particularly weak.

Table 9. Measures of patent quality (I)

	OLS	IV	First stage (non-env patents)	First stage (env patent)
Citations (5-years forward)				
Non-env patents (fwd citations 5-years)	0.00940*** (0.00321)	0.155 (0.0962)		
Env patents (fwd citations 5-years)	0.0325*** (0.0118)	0.575* (0.336)		
Non-env patents in EU for same sect/size/age			0.000960*** (0.000344)	-0.0000635 (0.0000907)
Env patents in EU for same sect/size/age			-0.00463 (0.00325)	0.00241*** (0.000858)
N	4507	4507	4507	4507
F	13.70	5.267	5.643	3.236
Test of excluded instrument (F)			3.94**	4.64***
Cragg–Donald weak instrument test (F)		3.161		
Stock–Yogo weak ID critical value (10% max IV size)		7.03		
Wu–Hausman exogeneity test (F)		6.604***		
Durbin–Wu–Hausman exogeneity test (F)		13.30***		
Number of claims				
Non-env patents (# of claims)	0.000167 (0.000102)	0.00119 (0.000914)		
Env patents (# of claims)	0.00189*** (0.000628)	0.00839* (0.00429)		
Non-env patents in EU for same sect/size/age			0.0703*** (0.0147)	0.00347** (0.00176)
Env patents in EU for same sect/size/age			-0.163 (0.139)	0.102*** (0.0166)
N	4507	4507	4507	4507
F	13.59	13.77	6.405	5.697
Test of excluded instrument (F)			13.49***	43.05***
Cragg–Donald weak instrument test (F)		9.962		
Stock–Yogo weak ID critical value (10% max IV size)		7.03		
Wu–Hausman exogeneity test (F)		4.923***		
Durbin–Wu–Hausman exogeneity test (F)		9.922***		
Patent family size				
Non-env patents (patent family size)	0.000555*** (0.000159)	0.00209* (0.00118)		
Env patents (patent family size)	0.00488*** (0.00186)	0.0375** (0.0148)		
Non-env patents in EU for same sect/size/age			0.0499*** (0.00557)	0.000225 (0.000654)
Env patents in EU for same sect/size/age			-0.210*** (0.0527)	0.0294*** (0.00619)
N	4507	4507	4507	4507
F	13.86	13.21	11.37	3.972
Test of excluded instrument (F)			41.50***	18.96***
Cragg–Donald weak instrument test (F)		18.69		
Stock–Yogo weak ID critical value (10% max IV size)		7.03		
Wu–Hausman exogeneity test (F)		5.092***		
Durbin–Wu–Hausman exogeneity test (F)		10.26**		

Dependent variable: long run change in employee headcounts. OLS and IV estimates. Standard errors in parenthesis.

* $P < 0.1$, ** $P < 0.05$, *** $P < 0.01$. Sector dummies (two-digit), regional dummies (NUTS1), and time window dummies included.

Table 10. Measures of patent quality (III)

	OLS	IV	First stage (non-env patents)	First stage (env patent)
Patent scope				
Non-env patents (scope)	0.00294*** (0.000870)	0.0104* (0.00574)		
Env patents (scope)	0.0159*** (0.00470)	0.0710** (0.0286)		
Non-env patents in EU for same sect/size/age			0.00980*** (0.00125)	0.000154 (0.000208)
Env patents in EU for same sect/size/age			-0.0359*** (0.0118)	0.0146*** (0.00197)
N	4507	4507	4507	4507
F	13.91	14.71	10.76	6.046
Test of excluded instrument (F)			32.71***	47.61***
Cragg-Donald weak instrument test (F)		30.88		
Stock-Yogo weak ID critical value (10% max IV size)		7.03		
Wu-Hausman exogeneity test (F)		4.323**		
Durbin-Wu-Hausman exogeneity test (F)		8.714**		
Patent originality				
Non-env patents (originality)	0.00813*** (0.00234)	0.0304* (0.0157)		
Env patents (originality)	0.0365*** (0.00975)	0.181** (0.0847)		
Non-env patents in EU for same sect/size/age			0.00358*** (0.000471)	0.0000211 (0.0000908)
Env patents in EU for same sect/size/age			-0.00976** (0.00445)	0.00531*** (0.000859)
N	4507	4507	4507	4507
F	14.08	14.33	10.83	5.361
Test of excluded instrument (F)			33.08***	30.65***
Cragg-Donald weak instrument test (F)		25.99		
Stock-Yogo weak ID critical value (10% max IV size)		7.03		
Wu-Hausman exogeneity test (F)		4.471**		
Durbin-Wu-Hausman exogeneity test (F)		9.012**		
Patent radicalness				
Non-env patents (radicalness)	0.0181*** (0.00553)	0.0622 (0.0405)		
Env patents (radicalness)	0.0802*** (0.0309)	0.426* (0.218)		
Non-env patents in EU for same sect/size/age			0.00149*** (0.000208)	0.0000472 (0.0000335)
Env patents in EU for same sect/size/age			-0.00317 (0.00197)	0.00202*** (0.000317)
N	4507	4507	4507	4507
F	13.82	14.58	10.41	5.689
Test of excluded instrument (F)			30.85***	40.99***
Cragg-Donald weak instrument test (F)		23.45		
Stock-Yogo weak ID critical value (10% max IV size)		7.03		
Wu-Hausman exogeneity test (F)		4.485**		
Durbin-Wu-Hausman exogeneity test (F)		9.040**		

Dependent variable: long run change in employee headcounts. OLS and IV estimates. Standard errors in parenthesis. * $P < 0.1$, ** $P < 0.05$, *** $P < 0.01$. Sector dummies (two-digit), regional dummies (NUTS1), and time window dummies included.

potential of innovation and the substantial premium for green innovation is confirmed when controlling for quality of patents. This further suggests that the greater job creation potential of environmental patents goes beyond differences in the quality.

5.5 Discussion

The results of the empirical analysis show that environment-related technological change is associated to employment growth in Italian firms. Data suggest that investments in green technologies in the sample and for the period considered have been able to generate a return in terms of employment growth that is substantially bigger than the return of non-environmental technologies. Based on our empirical evidence, part of this effect may be explained by differences in patents' quality. However, despite environmental patents have been generally found of better quality, a substantial premium for green innovation is confirmed. Consistently with this, green innovations also appear to be on average more "expensive" than other innovations. Nonetheless, also in this case the employment premium associated to green technologies remains consistent.

Our main results are robust to a number of checks, including endogeneity concerns. Environment-related innovations have generated significant positive effects in terms of job creation. This evidence supports the interest and effort devoted to the development of these technologies in recent years. We argue that these results should be interpreted in the light of the technology life cycle theory. Firms that operate in markets at their early stage of maturity are able to exploit better market and technological opportunities. Green technologies are thus characterized by a greater potential with respect to different and more mature technologies. Investments in this context are likely to have a more disruptive effect in terms of employment gains for those firms, regions, and countries that have been able to keep climbing the innovation ladder. Given this evidence the uneven diffusion of environment-related technologies across time and across geographical areas also represents a potential source of long-lasting competitive advantage.

6. Concluding remarks

The increasing level of unemployment in Europe and the growing attention on the potential of the green economy as one of the possible way out from economic stagnation has reinvigorated the attention on the link between innovation and employment. Policy makers have substantially supported investments in environmental-related technologies since green innovation is expected to create new market opportunities stimulating further employment and growth.

Coherently, the recent empirical research focusing on the segment of eco-innovation stems from the belief that the potential in terms of job creation of green technologies is particularly relevant. In this context, technological change, creating opportunities for the formation of new industries through processes of industrial branching, may generate greater and faster growth rates due to higher incentives in terms of entry or expansions of incumbent firms operating in related industries. Moreover, the fact that environmental technologies are mostly "young" technologies implies that the stock of fixed capital cumulated in these fields is likely to be still small, leaving many routine tasks to be carried out by the workforce, at least in the short and medium run.

This article contributes to the existing literature, providing a comprehensive investigation of the link between environmental technological change and employment outcome in the case of Italian firms. Results show that the emergence of eco-innovation stimulating the transition toward cleaner forms of production and consumption has contributed substantially to employment growth over the period 2001–2008. This evidence is robust to a number of checks including controlling for the potential endogeneity of the regressors of interest. Most of all, from our results it emerges that eco-innovation boosted employment growth in Italian firms over and above their attitude toward generic innovation. This implies that investments in technological innovation in environment-related fields have had per se a beneficial impact that is independent on firms' capability to develop any other form of innovation outcome. Interestingly, this impact remains remarkable also when cost and quality differentials across different typologies of innovations are taken into account.

Related to this latter issue and in evaluating the reliability of our results, it is also important to consider that, with some exceptions,²⁷ in our period of analysis there were relatively few policies concerned with environmental issues.

27 Notable exceptions are the EU Emission Trading Scheme and the feed-in tariff scheme for renewable generation from solar energy. Refer to [Ghisetti and Quatraro \(2013\)](#) for a deeper discussion of the environmental policy framework in Italy in the considered period.

This implies the absence of systematic incentives lowering at firm level the cost of performing environmental with respect to generic innovation.

The main limitation of our analysis remains related to the fact that while providing a reliable investigation on the direct effect of eco-innovation at firm level, our setting is unable to fully capture broader sectoral and spatial dynamics.

Despite that and although requiring some degrees of caution in developing comprehensive policy implications, it is still possible to make some considerations. According to our findings, Italian firms that have engaged into green innovation have experienced a substantial employment growth, demonstrating that the potential compensating mechanisms based on virtuous cycles of increasing productivity and revenues have outpaced any labor-saving effects at firm level. Our results suggest that there are significant opportunities associated to environment-related business activities, and firms that have been able to take advantage of them are those experiencing the best performance in terms of employment growth. In this perspective, supporting investments in environmental technologies may come up to be a reasonable policy option in order to cope with the challenges associated to periods of economic downturn, favoring the transition toward high value-added specializations and the exploitation of new market opportunities.

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Appendix 1—Measures of patent quality

This appendix describes the set of indicators of patent quality that we employ for the estimates discussed in section 5.4. The most used proxy of patent quality is the number of forward citations received by a patent (Trajtenberg, 1990; Harhoff *et al.*, 1999; Hall *et al.*, 2005). The idea behind the use of citations as a proxy of patent quality is that citations represent the technological relevance of a patent in terms of potential development of related technologies. We count forward citation within 5 years from the publication. This choice could create some inconsistency when dealing with recent patents, due to the lag between priority, application, and publication (typically 18 months between application and publication for the EPO) of both cited and citing patents. This limits substantially the reliability of the indicator for patents filled in the second half of the 2000s (truncation issue, Hall *et al.*, 2005), for which we underestimate the actual number of forward citations. Moreover, it has been acknowledged that most of citations in EPO patents are added by examiners rather than by inventors (Michel and Bettles, 2001), further limiting the use of this indicator for EPO patents.

The second indicator is the count of claims contained in the patent. Claims define the technology aspects that are protected by the patent and, according to Tong and Davidson (1994), their number is positively correlated with the expected value of the patent.

The third indicator measures the size of the patent family of each patent, that is, the number of patent offices in which the invention has applied for protection. Due to the costs linked to extending the protection to multiple patent offices, only inventions that are expected to be sufficiently valuable are likely to be protected in many countries (Lanjouw *et al.*, 1998).

The fourth indicator is a proxy on the technological breadth of patents (scope), which is measured as the number of four-digit IPC classes that are listed in the patent. The idea, put forward and confirmed empirically by Lerner (1994), is that firms active in many technological fields are also the ones that are valued the most.

The fifth indicator measures the originality of the patent that is the extent to which the patent relies on (i.e. cites) technologies that do not pertain to its technological field. The indicator, initially proposed by Hall *et al.* (2001), is based on sum of square of the share of citations made (backward citations) to patents in IPC classes different from the ones listed in the citing patents.

Finally, we employ the measure of radicalness proposed by Shane (2001). The measure, described in Squicciarini *et al.* (2013), is based on the extent to which the patent is cited (forward citations) by patents pertaining to IPC classes not listed in the original patent. Being based on forward citations, the indicator of radicalness is likely to be affected by the same limitations as the indicator of forward citations.

Appendix 2

Table A1. Full panel vs. patenting firms

	Age	Log (turn)	Log (empl)	Empl growth	Log (VA/L)	ROI
Difference (no controls)	3.909*** (0.233)	1.152*** (0.0210)	1.213*** (0.0207)	−0.0817*** (0.0104)	0.0862*** (0.00635)	−0.000907 (0.00116)
Difference (controls: sect, year, prov)	3.550*** (0.224)	1.072*** (0.0204)	1.070*** (0.0206)	−0.0386*** (0.0104)	0.0794*** (0.00638)	−0.00667*** (0.00119)
Difference (controls: sect, year, prov, size ^a)	0.0576 (0.224)	0.0589*** (0.00772)	0.141*** (0.0104)	0.106*** (0.0109)	−0.00956 (0.00659)	0.00252** (0.00123)
N	49,590	49,590	49,590	49,590	49,590	49,590

^aSize in terms of the logarithm of total asset.

OLS estimates. Robust standard errors in parenthesis. * $P < 0.1$, ** $P < 0.05$, *** $P < 0.01$.

Table A2. Technology classes for environmental patents

Technology class	Description	IPC/ECLA Class
General environmental management	Air pollution abatement	B01D46, B01D47, B01D49, B01D50, B01D51, B01D53/34-72, B03C3, C10L10/02, C10L10/06, C21B7/22, C21C5/38, F01N3, F01N5, F01N7, F01N9, F23B80, F23C9, F23G7/06, F23J15, F27B1/18
	Water pollution abatement	B63J4, C02F, C05F7, C09K3/32, E02B15/04-06, E02B15/10, E03B3, E03C1/12, E03F
	Solid waste collection	E01H15, B65F
	Material recovery, recycling and re-use	A23K1806-10, A43B1/12, A43B21/14, B03B9/06, B22F8, B29B7/66, B29B17, B30B9/32, B62D67, B65H73, B65D65/46, C03B1/02, C03C6/02, C03C6/08, C04B7/24-30, C04B11/26, C04B18/04-10, C04B33/132, C08J11, C09K11/01, C10M175, C22B7, C22B19/28-30, C22B25/06, D01G11, D21B1/08-10, D21B1/32, D21C5/02, D21H17/01, H01B15/00, H01J9/52, H01M6/52, H01M10/54
	Fertilizers from waste	C05F1, C05F5, C05F7, C05F9, C05F17
	Incineration and energy recovery	C10L5/46-48, F23G5, F23G7
	Waste management n.e.c.	B09B, C10G1/10, A61L11
	Soil remediation	B09C
	Environmental monitoring	F01N11, G08B21/12-14
	Energy generation from renewable and non-fossil sources	Wind energy
Solar thermal energy		Y02E10/4
Solar photovoltaic (PV) energy		Y02E10/5
Solar thermal-PV hybrids		Y02E10/6
Geothermal energy		Y02E10/1
Marine energy		Y02E10/3
Hydro energy		Y02E10/2
Biofuels		Y02E50/1
Combustion technologies with mitigation potential	Fuel from waste	Y02E50/3
	Technologies for improved output efficiency (combined combustion)	Y02E20/1
	Technologies for improved input efficiency	Y02E20/03
Climate change mitigation	CO2 capture or storage	Y02C10
	Capture or disposal of greenhouse gases other than CO2	Y02C20
Potential or indirect contribution to emissions mitigation	Energy storage	Y02E60/1
	Hydrogen technology	Y02E60/3
	Fuel cells	Y02E60/5
Emissions abatement and fuel efficiency in transportation	Integrated emissions control	F02B47/06, F02M3/02-055, F02M23, F02M25, F02M67, F01N9, F02D41, F02D43, F02D45, F01N11, G01M15/10, F02M39-71, F02P5, F02M27, F02M31/02-18
	Post-combustion emissions control	F01M13/02-04, F01N5, F02B47/08-10, F02D21/06-10, F02M25/07, F01N11, G01M15/10, F01N3/26, B01D53/92, B01D53/94, B01D53/96, B01J23/38-46, F01N3/08-34, B01D41, B01D46, F01N3/01, F01N3/02-035, B60, B62D
	Technologies specific to propulsion usin electric motor	B60K1, B60L7/10-20, B60L11, B60L15, B60R16/033, B60R16/04, B60S5/06, B60W10/08, B60W10/26, B60W10/28, B60K16, B60L8
		B60K6, B60W20

(continued)

Table A2. Continued

Technology class	Description	IPC/ECLA Class
Energy efficiency in buildings and lighting	Technologies specific to hybrid propulsion	
	Fuel efficiency-improving vehicle design	B62D35/00, B62D37/02, B60C23/00, B60T1/10, B60G13/14, B60K31/00, B60W30/10-20
	Insulation	E04B1/62, 04B1/74-78, 04B1/88, E06B3/66-677, E06B3/24
	Heating	F24D3/08, F24D3/18, F24D5/12, F24D11/02, F24D15/04, F24D17/02, F24F12, F25B29, F25B30
	Lighting	H01J61, H05B33

Table A3. Technology classes for ICT patents (source: [Schmoch, 2008](#))

Technology class	Description	IPC Class
3	Telecommunications	G08C, H01P, H01Q, H04B, H04H, H04J, H04K, H04M, H04N-001, H04N-007, H04N-011, H04Q
4	Digital communication	H04L
5	Basic communication processes	H03#
6	Computer technology	(G06# not G06Q), G11C, G10L
7	IT methods for management	G06Q

Table A4. Difference in patent quality between environmental and non-environmental patents

	Citations	Claims	Family size	Scope	Originality	Radicalness
Non-env patents	0.313	14.095	5.334	1.551	0.610	0.289
Env patents	0.491	14.512	4.870	1.912	0.698	0.313
Average	0.321	14.114	5.313	1.568	0.614	0.290

Table A5. Inventors by patent category (descriptive statistics)

	Mean	Min	Q1	Median	Q3	Max	SD
Env patents	1.87	1	1	1	2	13	1.34
Non-env patents	2.10	1	1	2	3	7	1.27
Total	1.88	1	1	1	2	13	1.33

Table A6. Average inventors by patent (controlling for technology field)

Dep: inventors count by patent	(1)	(2)	(3)
Env patent (0/1)	0.240*** (0.0571)	0.0881 (0.0604)	0.215*** (0.0667)
Dummies 5-tech	No	Yes	No
Dummies 35-tech	No	No	Yes
Year dummies	Yes	Yes	Yes
N	11,342	11,342	11,342
F	2.843	116.6	48.97
R squared	0.00187	0.159	0.261

OLS estimates. Robust standard errors in parenthesis.

* $P < 0.1$, ** $P < 0.05$, *** $P < 0.01$. Average inventors (all patents): 1.88.

Table A7. Correlation matrix between actual innovation outcome and propensity to innovate (source: own elaborations on Capitalia-Mediocredito-Unicredit surveys)

	Product inno (firm)	Process inno (firm)	Product inno (sect-age-size)	Process inno (sect-age-size)
Product inno (firm)	1			
Process inno (firm)	0.2876*	1		
Product inno (sect-age-size)	0.1432*	0.0173	1	
Process inno (sect-age-size)	0.0006	0.1244*	0.2328*	1

$N = 16,313$; * P -value < 0.01 .