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The Greener the Better: Job Creation and Environmentally-Friendly Technological Change[1]

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Abstract

This paper investigates the link between environment related innovation and job creation at firm level. Employing Italian data on 4,507 manufacturing firms, matched with patent records for the period 2001-2008, we test whether "green" innovation, measured using 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 cost differential between generic and "green" innovation and endogeneity.

Keywords: Technological Change, Eco-Innovation, Employment
JEL: O33, Q55, J21

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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 last 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 and re-invigorating the need for further research.

Environmental protection is in fact a consolidate policy strategy in Europe since the very creation of the European Union (EU)[5]. By promoting the most ambitious and thorough piece of legislation in the world to foster sustainable growth[6], the EU further confirmed its willingness to deal with environmental concerns. Within the framework of the Lisbon Strategy first, and Europe 2020[7] after, EU policies aim at obtaining a "smart, sustainable, inclusive growth" with greater coordination of national and European policies.

Recently, the economic slow-down and persistent high unemployment in many European countries have caused several criticisms directed towards environmental policies. In particular, the impact of policy initiatives fostering the transition towards cleaner production has been severely questioned. Environmental legislation is often regarded as a burden impairing firms' competitiveness with potentially negative effects on employment.

This view is indeed unsupported by empirical evidences on the employment effects of environmental policies that, although limited, seem to point to a positive impact of environmental regulation on job creation (see Bozdek et al., 2008 and Morgenstern et al., 2002).

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[5] Already in 1987 the Treaty establishing the Union reported a dedicated section setting environmental protection objectives and principles.

[6]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 23April2009 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”.

[7]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 3 March 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.

The emergence of eco-innovation may create new challenges, but also great market opportunities coming from the need of satisfying the increasing sustainability awareness of both regulators and consumers. Understanding the effects of environmental innovation on employment at firm level is thus important 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.

Indeed, at firm level, it is yet to be determined whether environmental innovation may be seen as an opportunity to seek new markets or as a burden that may impair competitiveness and destroy jobs. Furthermore, it is still unclear whether or not environmental innovation may potentially yield different effects at firm level with respect to generic innovation, justifying dedicated streams of literature and policy attention. In our view, a careful investigation of this specific declination of technological change is crucial for a number of reasons. First, because of the relevance that environmental and climate change policies have nowadays in the political and economic debate. Secondly, because of the significant efforts devoted towards the development of cleaner technologies in times of public resource scarcity. Third, because any empirical evidence on the impact of eco-innovation on job creation may help to understand if it pays for firms to engage in green innovation.

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 towards cleaner technologies call for a greater effort in understanding the link between environment related innovation and employment. A better assessment of this aspect is particularly important to implement, if necessary, an effective environmental innovation policy in the future.

This paper tries to contribute to the debate shedding more light on the dynamics at play, 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 dataset that matches firm level data with patent records, we are able to distinguish between "green" and generic innovation and to assess the causal effect of environment related technological change on employment growth after controlling for firms' attitude towards generic innovation. 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 the literature on innovation and employment and contributing 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 previous studies using survey data based on a more discretional definition. Secondly we develop a reliable identification strategy thanks to the availability of a longer and consistent time series, allowing the set up 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 proxied using the measurement suggested by Harhoff and Thoma (2009). This further suggests the existence of a 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 paper 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 evidences 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 specific impact of eco-innovation on labour market outcomes is rather scant, but it 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 Hall et al., 2008; Harrison et al., 2008; Pianta, 2005). Process innovation has been generally associated to a labour-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 that may potentially explain different findings refers to the object of investigation performed either at firm or at the aggregate level. Firm-level analyses have been generally characterized by a “positive bias” (Vivarelli, 2011, 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 (Garcia et al., 2004; Hall et al., 2008; Harrison et al., 2008; König et al., 1995; Van Reenen, 1997). 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 labour 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 labour 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 labour 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., 2008).

Macro level analyses 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 labour saving and labour stimulating effect determined by a (potential) virtuous cycle that generates additional production and employment (Spiezia and Vivarelli 2002) is not straightforward. 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 heterogenous 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.

Within this context, studies on the relationships between environmental technologies 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-skills intensive industries and potentially positive effects on other industries.

Rennings and Zwick (2002), analysing 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 Germany 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, analysing the Community Innovation Survey (CIS) sample of Italian firms while Horbach and Rennings (2013), using data from the Community Innovation Survey 2009 (CIS 2009) 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 Community Innovation Surveys 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 on 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 discretional 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.

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. (2008), refers to the third Community Innovation Survey (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, 2011, Horbach and Renning, 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) analysing manufacturing firms in Britain. The empirical investigation has been based on a novel dataset 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, p. 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 patents data as proxy for technological change. Despite 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 activities. 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.

3.2 Model specification

The key interest of this paper 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:

$$\Delta Empl_i^{T-t} = \beta_0 + \beta_1 Tech\_change_i^{T,t} + \beta_2 Green\_tech\_change_i^{T,t} + \delta X_i^t + \varepsilon_i \quad (1)$$

where $\Delta Empl$ is the dependent variable measuring the variation in employment for each firm i in the period T-t[8], *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. Additional controls for detailed sector of activity at 2 digits, and location (NUTS 1) are included. Our preferred specification also accounts for differences in the temporal window in which firm level information is available[9].

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'

[8] 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.

[9] The majority of firms are present for either eight (2001-2008) or seven years in our database (34% and 54% respectively). However a small proportion of them are observable for six (8%) or five (4%) years only. For some of them the 2001 information 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 four years lags controlling for the temporal window for which each firm is observed.

exit), prevent from the possibility to estimate the equation of interest in differences (i.e. controlling for time invariant firm fixed effects). Furthermore due to the typology 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 effects and economic performance. While the role of initial firm level conditions, determining the incentives to carry out technological investments, are netted 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. Despite being reasonable to assume both that investment decisions associated to inventions patented over the period 2001-2008 have been taken based on firms' conditions pre 2001[10], and that anticipation effects of future firm technological shocks are unlikely to affect substantially the decision to carry out technological investments (Harrison et al. 2008), there is still the 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 towards 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 labour productivity in specific sectors and geographical areas.

The existing literature has tried to address the abovementioned concerns associated to the endogeneity of technological change relying mainly on instrumental variables techniques and exploiting a range of possibilities. Harrison et al. (2008) 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

[10]Hypothesis that is also endorsed by the timing of the patenting procedure.

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, 2008). 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 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 US with that in UK and FDI inflows in UK with those in US respectively. Exploiting data on EPO patent applications count (for both non-environmental and environmental patents) for the period 1996-2004[11] filed by companies in Western Europe[12] in the same sector (4 digits 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)[13], 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

[11]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. (2009). 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).

[12]EU15 (excluding Italy) plus Norway and Switzerland.

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

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. 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 4,507 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 European Patent Office 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 bias[14] 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 to 2008. Real turnover (in euro) has been deflated by means of sector-specific deflators for gross output (Nace rev. 2, 2-digit, reference year 2000). ROI (Return On Investment) is the ratio between the EBIT (Earnings Before Interest and Taxes) and total assets, both in nominal terms. We also use the variation of cost for employees (labour 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, 4-digit) and age of the firm from the AIDA database. In our baseline specification we aggregate firms by macro-region (four NUTS1 regions) and 2-digit Nace sector. We excluded outliers based on having the

[14]Table 4 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).

value of the outcome variable three standard deviations greater than the third quartile or smaller than the first quartile (severe outliers)[15].

Environmental patents have been identified by means of a selection of environmentally-sound technologies prepared by the OECD[16] based on a list of relevant IPC and ECLA[17] classes. Environmentally-sound technologies 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. As robustness check, we identified environmental patents as those with IPC class available in the IPC Green Inventory[18] prepared by the WIPO[19] (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.

4.1 Tables and Figures

Table 1 reports some descriptive statistics for our variables of interest while Table 2 shows the distribution of observations and patent applications by sector and initial size. Table 3 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 different patenting behaviour of firms 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

[15]We also estimate our preferred specification on different samples that differ in the way outliers have been defined.
[16]Indicator for environmental technologies – ENV-TECH Indicator, http://www.oecd.org/env/consumption-innovation/indicator.htm.
[17]ECLA class ‘Y02 - Technologies or applications for mitigation or adaptation against climate change’.
[18]Costantini et al. (2013) find many non-environmental patents in the field of biofuels as defined by the selection of relevant IPC classes in the IPC Green Inventory.
[19] http://www.wipo.int/classifications/ipc/en/est/

relative to the distribution of firms that did not apply for patent in the 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 Baseline results

Table 5 reports the results of our OLS baseline estimates. In column 1 we include only our set of control variables. 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 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 per cent. The 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).

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 per cent, which should be compared to the increase driven by a non-environmental patent of about 0.58 per cent. Despite still positive and significant the magnitude of the regressor for non-environmental innovation is significantly lower.

The empirical analysis shows 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 that 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 10 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 preliminary evidence suggests a greater 'cost' for obtaining an environmental patent with respect to non-environmental innovations. In addition to 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 11 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[20]. 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 per cent to 12.8 per cent 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 further evidence reinforces our baseline claim on the additional job creation effect of environmental with respect to other forms 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

[20] 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.

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 patents[21] 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, the effect being greater for environmental than for non-environmental patents. Indeed the two measures recall different dimensions. While the flow of patents over the period of analysis proxies recent investments in innovation, past stock provides an indication for the accumulation of knowledge over time. The difference between the two measures, 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 (column 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 (4-digit Nace rev. 2 and NUTS3 in column 3), when assuming a non-linear 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).

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’ outliers[22] in terms of outcome variable (column 2), samples excluding the top and bottom 1% and 5% of the distribution of employment growth (columns 3 and 4) and a sample excluding influential observations based on Cook’s distance[23] (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

[21]Perpetual inventory method with 15 per cent depreciation rate.
[22]Above Q3+1.5*SD or below Q1-1.5*SD.
[23] We keep only observations with Cook’s distance smaller than 4/N.

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 impact 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 and discussed in section 3.

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 4-digit sector and for the same class of size and age computed for the time window 1996-2004.

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 both 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 bias. 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 favour 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 based also on patent statistics, is appropriate to control for this further problem some considerations have to be borne in mind. The aim of our instrumental variable 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 9, we observe a strong positive correlation between process and product innovation within each firm, suggesting that firms performing product innovation are also likely to perform process innovation and supporting our baseline reasoning regarding the fact that, despite more representative for product innovation, our regressor provides still 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 light, the propensity to introduce process innovations positively correlates with actual process innovation only. This evidence suggests that our instrumental variable 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

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[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 three years immediately prior.

[25] Sector at the 4-digit disaggregation (Nace Rev. 1.1), more or less that 250 employees, younger or older than 10 years.

endogeneity of the regressors of interest. Eco-innovation is associated to increasing employment at firm level suggesting that the labour saving effect is counterbalanced by virtuous cycles based on increasing productivity, revenues and further employment.

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 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.

In fact, the recent empirical research focusing on the segment of eco-innovation, stems from the belief that in the specific case of green technologies the potential in terms of job creation 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.

Despite these considerations, no conclusive evidences have been reached so far on the direction and magnitude of the effect and a number of criticisms have emerged over time. A clearer investigation of the impact of environment related innovation is indeed needed, in particular with respect to its link with employment perspectives.

This paper 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 towards cleaner forms of production 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 towards 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 consistent also when cost 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 in our period of analysis no relevant policies affecting environmental issues, with the notable exception of EU Emission Trading Scheme (refer to Ghisetti and Quatraro, 2013 for a deeper discussion of the environmental policy framework in Italy in the considered period) were in place in Italy. 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 labour 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, favouring the transition towards high value-added specializations and the exploitation of new market opportunities.

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Tables and Figures

Table 1 - 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
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
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 2 - Distribution of EPO patent applications (total and 'environmental')
by size and sectors

	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.

Table 3 - 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.

Table 4 - Full panel vs patenting firms

	Age	log(turn)	log(empl)	Empl gr	log(VA/L)	ROI
Difference	3.909***	1.152***	1.213***	-0.0817***	0.0862***	-0.000907
(no controls)	(0.233)	(0.0210)	(0.0207)	(0.0104)	(0.00635)	(0.00116)
Difference	3.550***	1.072***	1.070***	-0.0386***	0.0794***	-0.00667***
(controls: sect, year, prov)	(0.224)	(0.0204)	(0.0206)	(0.0104)	(0.00638)	(0.00119)
Difference	0.0576	0.0589***	0.141***	0.106***	-0.00956	0.00252**
(controls: sect, year, prov, size[a])	(0.224)	(0.00772)	(0.0104)	(0.0109)	(0.00659)	(0.00123)
N	49590	49590	49590	49590	49590	49590

[a] Size in terms of the logarithm of total asset

OLS estimates. Robust standard errors in parenthesis. * p<0.1, ** p<0.05, *** p<0.1.

Figure 1 - Distribution of employment growth by 'patenting status'

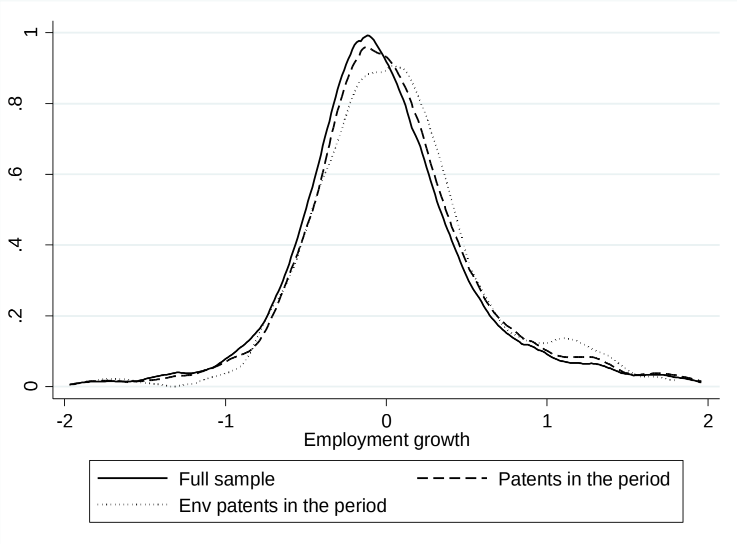

Table 5 - Baseline results

	(1)	(2)	(3)	(4)	(5)
log(turnover)	-0.0697***	-0.0799***	-0.0794***	-0.0801***	-0.0732***
	(0.00774)	(0.00813)	(0.00807)	(0.00812)	(0.00785)
ROI	0.564***	0.565***	0.576***	0.566***	0.572***
	(0.128)	(0.126)	(0.126)	(0.126)	(0.128)
AGE	-0.00562***	-0.00537***	-0.00536***	-0.00539***	-0.00554***
	(0.000643)	(0.000635)	(0.000633)	(0.000637)	(0.000643)
Years since first patent	-0.00952***	-0.00990***	-0.00989***	-0.00976***	-0.00976***
	(0.00114)	(0.00113)	(0.00112)	(0.00113)	(0.00114)
Tot patents (count)		0.00721***			
		(0.00190)			
Non-env patents (count)			0.00585***	0.00649***	
			(0.00173)	(0.00184)	
Env patents (count)			0.0272***		
			(0.00715)		
Env patents (dummy)				0.0898**	
				(0.0394)	
Stock non-env patents					0.0140***
					(0.00511)
Stock env patents					0.0540***
					(0.0181)
Sect. dummies (2-digit)	Yes	Yes	Yes	Yes	Yes
Reg. dummies (NUTS1)	Yes	Yes	Yes	Yes	Yes
Time window dummies	Yes	Yes	Yes	Yes	Yes
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<0.1.

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
Non-env patents (count)	0.00144	0.00187*	0.00686***	0.00385***	0.00759***	0.00509***
	(0.000906)	(0.000997)	(0.00157)	(0.00148)	(0.00205)	(0.00189)
Env patents (count)	0.0290***	0.0257***	0.0262***	0.0265***	0.0282***	0.0293***
	(0.00792)	(0.00791)	(0.00787)	(0.00820)	(0.00671)	(0.00812)
log(turnover)			-0.0870***	-1.095***		-0.102***
			(0.00849)	(0.132)		(0.00826)
ROI			0.512***	0.646***	0.371***	0.704***
			(0.128)	(0.126)	(0.124)	(0.116)
AGE			-0.00492***	-0.00497***	-0.00344***	-0.00497***
			(0.000686)	(0.000623)	(0.000619)	(0.000587)
Years since first patent			-0.00909***	-0.00988***	-0.00755***	-0.00985***
			(0.00117)	(0.00111)	(0.00110)	(0.00109)
log(turnover) squared				0.0314***		
				(0.00403)		
log(employees)					-0.142***	
					(0.00920)	
Sect. dummies (2-digit)	No	Yes	No	Yes	Yes	Yes
Sect. dummies (4-digit)	No	No	Yes	No	No	No
Reg. dummies (NUTS1)	No	Yes	No	Yes	Yes	Yes
Reg. dummies (NUTS3)	No	No	Yes	No	No	No
Time window dummies	No	Yes	Yes	Yes	Yes	
N	4507	4507	4507	4507	4507	4477
R squared	0.00511	0.0429	0.233	0.155	0.187	0.163
F	9.081	5.466		14.86	17.21	20.45

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<0.1.

Table 7 - Robustness checks: alternative samples

	(1) All observations (incl sev outliers)	(2) Mild outl 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***	0.00414***	0.00575***	0.00352***	0.00947***	0.00456***
	(0.00242)	(0.00129)	(0.00176)	(0.00115)	(0.00131)	(0.000887)
Env patents (count)	0.0278***	0.0208***	0.0271***	0.0189***	0.0282***	0.0261***
	(0.00666)	(0.00362)	(0.00716)	(0.00374)	(0.0107)	(0.00508)
log(turnover)	-0.118***	-0.0347***	-0.0749***	-0.0312***	-0.0718***	-0.0354***
	(0.0133)	(0.00623)	(0.00799)	(0.00542)	(0.00689)	(0.00523)
ROI	0.553***	0.623***	0.470***	0.463***	0.533***	0.698***
	(0.141)	(0.0992)	(0.123)	(0.0874)	(0.111)	(0.0844)
AGE	-0.00541***	-0.00460***	-0.00588***	-0.00452***	-0.00543***	-0.00459***
	(0.000816)	(0.000525)	(0.000668)	(0.000463)	(0.000519)	(0.000467)
Years since first patent	-0.00759***	-0.00822***	-0.00885***	-0.00661***	-0.00912***	-0.00773***
	(0.00155)	(0.000920)	(0.00114)	(0.000805)	(0.000963)	(0.000895)
Sect. dummies (2-digit)	Yes	Yes	Yes	Yes	Yes	Yes
Reg. dummies (NUTS1)	Yes	Yes	Yes	Yes	Yes	Yes
Time window dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	4559	4357	4495	4150	4351	4559
r2	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<0.1.

Table 8 - Instrumental variables (total and environmental patents)

	OLS	IV	First stage (Tot patents)	First stage (env patent)
Non-env patents (count)	0.00585***	0.0216*		
	(0.00173)	(0.0112)		
Env patents (count)	0.0272***	0.138**		
	(0.00715)	(0.0682)		
log(turnover)	-0.0794***	-0.108***	1.203***	0.0529***
	(0.00807)	(0.0156)	(0.0913)	(0.0160)
ROI	0.576***	0.629***	0.489	-0.490*
	(0.126)	(0.121)	(1.453)	(0.255)
AGE	-0.00536***	-0.00459***	-0.0290***	-0.00184
	(0.000633)	(0.000720)	(0.00809)	(0.00142)
Years since first patent	-0.00989***	-0.0110***	0.0486***	0.00294
	(0.00112)	(0.00133)	(0.0155)	(0.00271)
Non-env patents in EU for			0.00507***	0.0000219
same sect/size/age			(0.000705)	(0.000124)
Env patents in EU for			-0.0123*	0.00673***
same sect/size/age			(0.00667)	(0.00117)
Sect. dummies (2-digit)	Yes	Yes	Yes	Yes
Reg. dummies (NUTS1)	Yes	Yes	Yes	Yes
Time window dummies	Yes	Yes	Yes	Yes
N	4507	4507	4507	4507
R squared	0.136	0.0164	0.0916	0.0439
F	14.04	14.20	10.98	5.000
Anderson underidentification (chi2)		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 (chi2)		14.91***		
Wu-Hausman exogeneity test (F)		4.464**		
Durbin-Wu-Hausman exogeneity test (F)		8.999**		
Pagan-Hall heterosk. test (chi2)		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<0.1.

Appendix

Table 9 – 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

Table 10 – 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 11 – Average inventors by patent (controlling for technology field)

Dep: inventors count by patent	(1)	(2)	(3)
Env patent (0/1)	0.240***	0.0881	0.215***
	(0.0571)	(0.0604)	(0.0667)
Dummies 5-tech	No	Yes	No
Dummies 35-tech	No	No	Yes
Year dummies	Yes	Yes	Yes
N	11342	11342	11342
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<0.1. Average inventors (all patents): 1.88