Paper to be presented at
the DRUID16 20th Anniversary Conference
Copenhagen, June 13-15, 2016

Better Late Than Never: a longitudinal quantile regression approach to the interplay of green technology, employment and age

Riccardo Leoncini
University of Bologna
Department of Economics
riccardo.leoncini@unibo.it

Alberto Marzucchi
Catholic University of Milan
Dept. of International Economics, Institutions and Developme
alberto.marzucchi@unicatt.it

Sandro Montresor
Kore University of Enna
Faculty of Economics and Law
sandro.montresor@unikore.it

Francesco Rentocchini
f.rentocchini@soton.ac.uk
University of Southampton, Southampton Business School
f.rentocchini@soton.ac.uk

Ugo Rizzo
University of Ferrara
Dipartimento di Economia e Management
ugo.rizzo@unife.it

Abstract

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Jelcodes:L25,O33

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JEL Codes: L25; O33; Q55.

Key-words: green technologies; employment growth; age; growth rate distribution.

1. Introduction

The firms' capacity of growing over time is closely related to their ability of mastering their technological knowledge for the introduction of new products/services and processes, and of capturing the value of innovations (Mansfield 1962; Scherer 1965). Following the premises of the famous Gibrat's law (2003), innovation has been placed side by side with other determinants of firms' growth related to both their structural characteristics - e.g. age and size - and to their industry and institutional environment - e.g. market structure and geographical location - (Sutton 1998; Bottazzi & Secchi 2006; Cefis et al. 2007; Lotti et al. 2009; Coad 2007; Coad 2009; Lee 2010; Bottazzi et al. 2011; Coad & Holz 2012).

This picture of firms using their innovative capabilities to increase performance regardless of the environmental consequences of their production processes was radically changed by the debate in the aftermath of the 1972 Club of Rome's book on the limits to growth (Meadows et al. 1972), following which the issue became central. The recent emphasis posed by the Europe2020 strategy on smart and sustainable (as well as inclusive) patterns of growth has reinvigorated this focus, giving an important impetus to both the policy action and the academic debate on the issue. In particular, an increasing amount of literature has been produced on the role of eco-innovation in spurring growth, with a special emphasis on employment growth – especially in the light of the economic slow-down and the structural unemployment problems experienced by many European countries. At the macro-level, the job-creation impact of regulations aimed at spurring (among the other) the adoption of sustainable technologies has become a crucial exercise to support environmental policies, in particular within the European Lisbon Strategy (e.g. Bartik 2015; O'Riordan & Voisey 2013; Rogerson 2015). At the firm level, the relationship between green technologies and employment growth has increasingly been investigated by looking, on the one hand, at the trade-off between the opportunities of new markets and sustainability awareness and, on the other hand, at the possible related costs, in terms of both labour displacement and competitiveness losses (Gagliardi et al. 2016; Licht & Peters 2013).

This paper aims at shedding new light on the relationship between environmental technologies and employment growth, by paying novel attention to its entrepreneurial foundations. In particular, we claim that the employment effects, which have been recognised as characterising green technologies (e.g. Pfeiffer & Rennings 2001; Rennings & Zwick 2002), should be seen as integral part of a dynamic entrepreneurial process, which crucially depends on the firm's age and on the entrepreneurial capacity developed over its life span. In so doing, we suggest to integrate two streams of literature that have seen a disjoint progress so far. The former is related to the literature on "green entrepreneurship" (Hagedoorn 1996), focusing on the shift from green corporate entrepreneurship and intrapreneurship in the eco-renewal of large firms, to the role of individual entrepreneurs and small-scale firms in developing new ideas both sustainable and profitable. We then combine the previous stream with those industrial organisation and innovation studies, which have shown that "standard" innovation is a crucial driver of the performance of small and medium entrepreneurial firms (and especially young ones) (Rosenbusch et al. 2013; Schaltegger 2002; Dean & McMullen 2007); and, in particular, which have found that "age moderates the ways in which firms benefit from innovation" in terms of employment growth (Coad et al. 2016). Through the integration of these two bodies of literature, we also aim to recover in our analysis another important entrepreneurial aspect in addition to age, that is, the differential of growth opportunities entailed by the different levels of growth from which firms start exploiting the same technologies. Indeed, the fact that high growing firms (HGF), or "gazelles", lead the process of job-creation in economic systems (for a review, see Henrekson & Johansson 2010) has stimulated a fervid stream of literature that, making use of quantile estimations, has shown that the growth impact (mainly on revenues) of standard innovation is actually the highest for "superstar fast growth firms" (e.g. Coad & Rao 2008; Coad & Rao 2010). In spite of some newly emerged evidence on the role of green technologies for identifying HGFs (Colombelli et al. 2015), whether "green gazelles" could also lead to job creation has not been investigated yet, and represents a further elements of originality of the present paper.

We thus aim at obtaining new and more qualified evidence of the entrepreneurial nature of the process through which green technologies can create job at the firm level. More precisely, by using a novel patent-based longitudinal dataset comprising 5498 Italian firms over the period 2000-2008, we run quantile estimations of a model including the moderating role of age on the employment-growth impact of green technologies.

Results confirm the superior capacity of job creation displayed by green vs. brown technologies in previous studies (Gagliardi et al. 2016), but with the exception of the slowest and fastest growing firms. Quite at odds with the evidence on the job-impact of the so-called "gazelles", this suggests an employment-creation effect of green technologies limited to moderately growing firms. As far as the fastest ones are concerned, a growth differential for green over brown have technologies does not emerge. This is confirmed by the fact that middle-fast growing firms are also the only ones, on which age plays a moderating role of the growth impact of green technologies, although somehow inconsistently with the green-entrepreneurship literature, this moderation effect is rather negative. While naturally disadvantaged with respect to the younger ones, in the capacity of starting up green entrepreneurial ventures, older firms seem to counterbalance this gap with greater incentives (i.e. higher needs of green-renewal of old plants) and/or capacities (i.e. longer experience in dealing with complexity) than younger ones in exploiting the growth potential of green technologies.

The rest of paper is structured as follows. Section 2 explores more extensively the background literature. Section 3 presents the empirical application. Section 4 illustrates and presents the results. Section 5 concludes.

2. Background literature

Quite surprisingly, given its importance in the current policy debate on smart and sustainable growth strategies, the role of eco-innovations and green technologies in spurring job creation is quite under-investigated at the micro-level. If we compare the number of studies focused on this relationship with those available on the employment impact of "standard" innovations, a strong contrast emerges. On the one hand, in spite of the limits of many of these contributions (such as selection bias and measurement errors, see Haltiwanger et al. 2013 for a discussion), technological innovations are generally recognised to make firms increase employment, by overcoming possible labour-saving effects from their introduction (e.g. Harrison et al., 2014, see Vivarelli 2007 for a survey). On the other hand, the evidence on a similar role of green technologies is scanty and mainly relies on survey-based, cross-sectional data, whose results can be generalised only with extreme cautiousness. In spite of some notable exceptions - of an absent (Rennings & Zwick 2002), if not even negative (Cainelli et al. 2011) impact (at least in the short-run) - eco-innovations have been generally found to exert a positive effect on employment, but to an extent much more dependent on their fields of applications (e.g. end-of-pipe vs. cleaner-technologies) than for the kind of standard innovations, and with little evidence of a differential impact between green and "brown" (that is, non-green) technologies (Pfeiffer & Rennings 2001; Rennings et al. 2004; Horbach 2010; Horbach & Rennings 2013; Licht & Peters 2013). A notable exception in this last respect is represented by the recent work by Gagliardi et al. (2016), based on longitudinal patent-based data for Italy (2001-2008). Quite robustly, eco-innovations, which are interestingly found to have higher costs than generic ones, boost firms' employment growth over and above their attitude towards innovation.

This last differential analysis is indeed a crucial issue, for a fuller evaluation of the employment effect entailed by the transition towards cleaner forms of production, rather than by the "simple" adoption of green-techs *per se*. Furthermore, it is important for an actual understanding of the channels through which environmental technologies affect employment, even irrespectively from the inner act of their adoption, which is of course common to brown technologies too.

The comparative impact of green and brown technologies on employment growth is also among the objectives of our own study. In particular, following this thin but emerging literature, we expect the impact of the former to be larger than that of the latter, claiming that investments in environment-related technological fields allow firms to pursue "win-win" – environmental and extra-environmental – strategies, with a "multiplicated" performance impact vis a vis to generic technological investments (Porter & Van-der-Linde 1995; Porter & Van der Linde 1995; Ambec & Lanoie 2008).

We also enrich this analysis with some important elements of novelty. First of all, we look at job creation as an entrepreneurial process that crucially depends on the age at which the firm exploits technologies in order to growth. As is well known, this is a recognised argument in the industrial organisational literature, with a twofold specification. On the one hand, age has been found (along with size) to be an important determinant of the firm's growth potential, with large (though not yet conclusive) evidence of younger firms to be more dynamic and thus more effective in spurring growth (Haltiwanger et al. 2013, Lawless 2014). On the other hand, and with greater relevance for our research question, age has emerged (along with other characteristics) as a crucial moderating factor of the impact of innovative activity on firms' employment growth (as for instance it is clear from the introduction of the special issue published in 2014 by SBE (Audretsch et al. 2014)). This holds particularly true for employment growth, as has been recently shown by Coad et al. (2016), who found that young firms obtain more employment growth per unit of standard innovations (i.e., R&D expenditure).

Once again, in contrast with this body of literature, the role of age for the job creation of green technologies has received little attention. To be sure, attention has nearly exclusively concentrated on processes of eco- and, more in general, sustainable entrepreneurship – the so-called "ecopreneurs" (Schaltegger 2002) – in which the adoption of environmental innovations is typically located in, though not limited to, the start-up phase of a company (Dean & McMullen 2007). In spite of the uncertainty about the entrepreneurship's role in this area (Hall et al. 2010, p.439), these "early-age" eco-innovators have actually been found to have an advantage in terms of economic performance, in particular in their being small 'Davids' that challenge the large incumbent companies, or 'Goliaths' (Hockerts & Wustenhagen 2010). However, little is known about the green-technologies application of the wide spectrum of innovation and learning mechanisms with respect to which, young (and not just started-up) companies differ from old ones in the standard technology literature (Jovanovic 1982; Ericson & Pakes 1995). In particular, a green extension is missing, and would be instead extremely interesting, for the age-specific capacity of evaluating technological uncertainty/risk and the marketability of undertaken innovations (Audretsch 1995; Taymaz 2005) – with respect to which older firms could be claimed to be advantaged – and of the capacity of overcoming organisational inertia in setting innovations at work, and in taking stock of previous mistakes in doing the same (Majumdar 1997; Sorensen & Stuart 2000; Criscuolo et al. 2012) – with respect to which younger firms would be better placed. Furthermore, although it has not captured attention yet, also with respect to eco-innovations, age could involve differences in the extent to which firms are capable of strengthening their available resources (e.g. through economies of scale) to increase their economic green-returns, as well as in their capacity (e.g. through reputation and market position) of setting alliances to source resources externally for that to happen (Herriott et al. 1985; Levitt & March 1988). All of these mechanisms make the comparison between young and old companies in the capacity of taking stock of green technologies more balanced than it could be for brown ones. Furthermore, in the same direction we are also led by few papers that have recently investigated the learning mechanisms and modes of eco-innovations (Ghisetti et al. 2015; Marzucchi & Montresor 2015). Indeed, eco-innovations differ from standard ones in many of the respects – e.g. external knowledge search and internal knowledge exploitation – with respect to which younger firms have been often claimed to be more capable of spurring employment growth.

In synthesis, while we think that considering age as an additional regressor in investigating the job-creation impact of green (and brown) technologies is important, as well as its interaction with the latter, we do not have firm expectations about the sign of its estimation.

A second element of novelty that we bring in our analysis is related to its entrepreneurial foundations, that is, to the level of growth from which firms start in exploiting their green-technologies and obtaining their employment impact. This is also a largely debated issue in industrial organisation and, in particular, in a recent stream of literature that has shown how innovation has a different growth impact for firms running at different pace. Coad & Rao (2008), for example, have found that the revenue growth impact of standard innovation is the highest for "superstar fast growth firms" (e.g. Coad & Rao 2008; Coad & Rao 2010).

More relevant for our own studies are the results of Coad et al., (2016), who show that the fastest firms benefit from standard innovation in terms of employment growth, while this return is even negative for the slowest ones of the distribution. These results are consistent with an innovation-adapted version (Birch 1981), according to which the so-called "gazelles", or HGF, would create most of the job in an economic system. Once more, this thesis has been only limitedly investigated with respect to eco-innovations, but mainly to address the role of green technologies in making the "green-gazelles" run, rather than to ascertain their capacity to engender higher employment growth.

In the paper we tackle this issue by resorting to quantile regression techniques (Koenker et al. 1978; Koenker & Hallock 2001). This methodological choice appears opportune also for addressing the impact of other firm-specific aspects that concur with age in accounting for the employment-growth potential of green-technologies. Indeed, the most recent literature (e.g. Distante et al. 2014) has shown that quantile estimates can help in better disentangling the intertwining between age and size in determining firms' growth: an issue on which earlier studies were unable to provide conclusive evidence (see, for instance, Dunne et al. 1989; Dunne & Hughes 1994; Lotti et al. 2003 for positive findinngs and Haltiwanger et al. 2013 for negative ones).

3. Data and Methods

3.1 Data

The empirical analysis is based on a longitudinal dataset comprising 5498 Italian manufacturing companies observed over the period 2000-2008. It combines data from three different sources. Our first source of data is the ASIA database of the Italian National Statistical Office (ISTAT) that contains information on the structural characteristics of the population of Italian companies. We retrieve information relating to the industrial sector, the number of employees and the date of birth for the population of Italian business firms over the period 2000-2011. Due to data availability of the other relevant data sources, we restrict the period of interest to the 2000-2008. Moreover, building upon other firm-level studies (Geroski et al. 2010; Mata & Portugal 2002; Coad & Rao 2011) we consider a firm to be ceased if absent from the records for three consecutive years. Our second source of data refers to balance sheet information - investment in tangible and intangible assets - obtained from the Bureau van Dijk AIDA database for the period 2000-2008. Lastly, we rely on the Worldwide Patent Statistical Database (PATSTAT) to retrieve patent data information. We use information from PATSTAT relating to the names of the assignees, the filing date and technological classes, as identified by the International Patent Classification (IPC), of patent filings.

We combine information collected from the three data sources described above and restrict our sample to manufacturing companies (Section D of NACE Rev. 1.1) that filed at least one patent application in the period 1977-2008. Our resulting sample is an unbalanced panel comprising 5498 firms observed over the period 2000-2008.

3.2 Methodology

As discussed in the theoretical section, we are interested in examining the relationship between "being green" and firm growth, as well as the moderating effect of firm's age on this relationship. More formally the relationship we investigate is the following:

$$Growth_{it} = \alpha + \beta_1 Pat\ Green_{i,t-1} + \beta_2 Pat\ Brown_{i,t-1} + \beta_3 Age_{i,t-1} + \beta_4 (Pat\ Green\ X\ Age)_{i,t-1} + \beta_5 (Pat\ Brown\ X\ Age)_{i,t-1} + \boldsymbol{z}'_{i,t-1}\gamma + \boldsymbol{d}'_t\delta + \mu_i + \varepsilon_{it} \quad (1)$$

Where $\boldsymbol{d}_t$ indicates a series of time controls; $\boldsymbol{z}_{i,t-1}$ is a vector of firm-specific control variables; μ_i denotes the unobserved firm specific effects and $\varepsilon_{i,t}$ is the error term.

Building upon the approach adopted in several empirical works, which focus the relationship between growth and innovation, we employ a quantile regression approach (Coad & Rao 2008; Kesidou & Demirel 2012). When investigating firms growth, quantile analysis is to be preferred to standard least squares for a number of reasons (Buchinsky 1998). First, the distribution of growth rates is recognised to be highly non-linear and considerably heavy-tailed (Bottazzi & Secchi 2003). The quantile approach allows for a richer characterization of the data and helps to disentangle the relationship between our independent variables and firm growth at different quantiles of the distribution of the rates of growth, rather than at conditional mean only. As a consequence of this, a second advantage of the quantile method is that no distributional assumption is needed on the form of the relationship between the independent and dependent variables. Third, the quantile approach provides a more robust and efficient alternative to OLS when the error term is non-normal. Finally, quantile regression is robust to outliers.

We contribute to the above empirical literature by controlling for problems arising from unobserved heterogeneity. Most of the applied literature adopting a quantile regression approach has done so in a cross-sectional setting and, for this reason, has been unable to control for problems of endogeneity arising from unobserved heterogeneity. Conversely, we follow recent developments in a stream of the applied econometrics literature trying to overcome this major limitation (Koenker 2004; Galvao 2011; Canay 2011). Specifically, we implement the procedure suggested by Canay (2011), who develops a method to estimate fixed effects quantile regression for panel data. The solution proposed consists of a two-steps estimator. In the first step, we estimate equation (1) above as a standard linear panel regression model via the within estimator (Wooldridge 2010). From this, we obtain the predicted value depurated from the unobserved heterogeneity component:

$$\hat{y}_{it} = Growth_{it} - \hat{\mu}_i$$

Where $\hat{\mu}_i = E[Growth_{it} - \widehat{Growth}_{it}]$ is an estimate of the unobserved heterogeneity term. At the second step, a standard quantile regression model is implemented where the transformed dependent variable above ($\hat{y}_{it}$) is regressed on our relevant independent variables (Koenker & Hallock 2001). Robust standard errors are obtained via bootstrap replications (1000 replications).

To sum up, exploiting the panel nature of our data, we investigate our research questions with a set of quantile fixed effects regressions that control for unobserved heterogeneity. Our main focus is on whether firm's growth is affected by firm's age, the orientation of the firm toward green technologies and the interaction between the two.

3.3 Variables

We measure company growth using data on the number of employees retrieved by ASIA. Specifically, our dependent variable is the growth rate of employees. Employees' growth is considered to be the most accurate measure of firm performance in the early stages after the firm's constitution (Clarysse et al. 2011). As a consequence, given the objective of this work is to study the relationship between green technologies and firms growth, with particular emphasis on the effect of green technologies for young companies, growth of employees represent the most appropriate growth measure. Building upon previous works in the field, growth of employees is calculated as the difference between the logarithm of employees at year t and the logarithm of employees at year $t\text{-}1$ (Coad & Rao 2006; Coad 2010; Wennberg et al. 2011). In order to remove common time trends for firms operating in the same sector (e.g. inflation, business cycles, etc.) we normalize growth rates subtracting, for each year, the sectoral mean growth rate of the NACE Rev. 1.1 2-digit sector (Bottazzi et al. 2011; Coad & Rao 2010).[1]

Our main independent variables refer to the investment in green and brown technologies, that is, the amounts of investments in environmentally friendly and non-environmentally friendly

[1] We also run the estimates using non-normalised growth rates and growth rates normalised at NACE Rev. 1.1 4-digit sectors. All attempts (available from the authors upon request) yield results that are not qualitatively different from the ones presented here.

technologies. Most of the recent research dealing with environmental innovation has relied upon patent data as they are a more robust indicator of environmental innovation compared to questionnaire-based measures (Arundel & Kemp 2009; Berrone et al. 2013). As described in the data section, we retrieve information on the patenting activities of the companies contained in our sample from PATSTAT for the period 1977-2008. We define patents as having environmental content ("Green" patents) if they are part of the classification provided by the OECD Indicator of Environmental Technologies (OECD 2015). OECD classification lists IPC subclasses that are considered to describe environmentally friendly technologies and has been increasingly adopted in recent works trying to identify technologies having an environmental content (Nesta et al. 2014).

Technological investment variables are defined as stocks (rather than flows) because we expect a firm's rate of investment in technology to be affected by the cumulated stocks of investment and not just by current or lagged flows (Bloom & Van Reenen 2002; Hall et al. 2005). In this framework, we follow the literature and we compute all the stocks variables using the perpetual inventory method and assuming a constant value of the depreciation rate of 0.15 (Blundell et al. 1995; Hall 1993).[2] Specifically, the stocks variables are $Pat\ Green_{i,t-1}$, which is the logarithm of the stock of environmentally friendly technologies (plus 1), filed by the firm *i* at year *t-1*. $Pat\ Brown_{i,t-1}$ measures instead the logarithm of the stock of non-environmentally friendly technologies (plus 1), filed by firm *i* in year *t-1*. Our third explanatory variable is $Age_{i,t-1}$ which measures the (log transformed) age of the company *i* at time *t-1*.

We then control for a set of variables that are often included in growth rate regression models. These are: the number of employees (*Emp*), investment both in physical (*Inv Tang*) and intangible (*Inv Intang*) capital, and the Herfindahl-Hirschman index (*HH index*). Investments are recognized as important explanatory factor when explaining firms' growth (Hall 1987). $Inv\ Tang_{i,t-1}$ ($Inv\ Intang_{i,t1}$) are calculated as the yearly net acquisition of tangible (intangible) assets plus the amortization[3] (Grazzi et al., 2015). These two indicators are measured in thousands of euros, and together with the number of employees, are log transformed (plus 1). Also, Herfindahl-Hirschman index is a popular measure of industry concentration and has been found to play a relevant role with respect to firms' performance (Kaniovski & Peneder 2008). $HH\ index_{jt}$ is sum of the square of the turnover shares of firms operating in (NACE Rev.1.1) industry *j* at time *t*.

[2] Patent stocks are calculated through the formula: $K_t = K_{t-1} * (1 - \delta) + P_t$ where K_t is the stock of patents at year *t*, δ is the depreciation rate, and P_t is the number of new patents in year *t*.

[3] Investment values were deflated: the deflator was constructed by dividing current prices to chained-linked prices (reference year 2005) at the higher level of disaggregation as provided by Istat (aggregation of Nace 2-digit industrial levels).

Finally we include a set of eight dummy variables to control for year effects. Table 1 briefly describes the variables included in the analysis and their sources.

Descriptive statistics of the variables employed in the empirical exercise are reported in Table 2. The table shows that the average firm in our sample is 24 years old and has 171 employees. As for the technological activity of the companies contained in our sample, we notice that firms tend to file disproportionately more patents in non-green technologies compared to green technologies. However, the value of the standard deviation of both green and non-green patent variables is rather high and we expect a high variance in these variables along firm's age. For this purpose, Table 3 compares the stock of green and non-green patents for different age classes. The table shows that, while non-green inventive activity is monotone increasing in age classes, a U-shaped relationship is apparent between green inventive activity and age classes. Specifically, firms in the '0-10' and '50 over' age classes show a value of the stock of green patents which is significantly higher compared to firms in '10-20' and '20-50' age classes. In the following section, the empirical exercise studies the relationship between green and non-green inventive activity and growth across firm's age.

Table 4 reports the bivariate correlations for the variables considered in the analysis. There is no indication of significant multi-collinearity amongst the independent variables (i.e. the Variance Inflation Factor ranges from 1.02 to 2.62, well below the threshold level of 5).

4. Results

The results emerging from the quantile fixed effect estimates are presented in Table 5 and Table 6. Table 5 focuses on the impact of green and brown technologies on firm's employment-growth. Table 6 instead shows the results of incorporating in the model the role of age as a moderating factor of the relationship between environmental (or non- environmental) patents and job creation.

Before coming to the core of our analysis, we briefly present the results concerning the controls employed in our econometric specification. As expected in the industrial organization literature, both tangible and intangible investments significantly drive firm growth, suggesting its reliance on a capital endowment of different kind. Furthermore, an increase in market competition also seems to favour growth at the firm level, as it is noticeable in the negative coefficients of the HH index, which is significant from 10^{th} to 75^{th} percentile. Quite interestingly, market concentration does not affect job creation for firms located at the highest extreme of the distribution (90th percentile), whose growth "super-star" status does not seem to benefit from any competition effects.

As for the standard IO regressors, the firm's (initial) size confirms its role of growth driver. In particular, smaller companies in the sample show higher growth opportunities and capacities, in line with the entrepreneurship literature. As far as age is concerned, instead, when the distinction between green and brown technologies is introduced among the explanatory variables the way we do, the results of the standard literature on the growth advantages of newly/recently created companies (Coad et al. 2013; Barba Navaretti et al. 2014) are not confirmed and even reversed. Indeed, older companies grow more than younger ones, as the positive and significant effect of firm's age on firm growth holds across all quantiles. While the specificities of our sample (i.e. innovation-oriented Italian firms) could account for this result to a certain extent, the benefits accruing to firms with age appear to more than compensate its disadvantages in our case. The fact that older firms are more transparent than younger in informational terms and thus more attractive in terms of financing options for growth (e.g. public equity and long-term debt vs. insider funding (Gregory et al. 2005; Hartarska & Gonzalez-Vega 2006) is a first aspect to consider in the financial realm. Second, the plethora of experience advantages that have been associated to firm maturity should be recalled here, in particular those in accessing new and foreign markets, although the learning impediments of getting older could contrast them (e.g. Autio et al. 2000).

The previous results on the controls are very useful in interpreting those on the focal technology variables of our exercise. The positive and significant coefficients of both *Pat Green* and *Pat Brown* across the whole set of percentiles extend to the green realm, the role of technology as a driver of firm growth. Although eco-innovations may have higher cost (Gagliardi et al. 2016), our evidence points to an increased economic performance induced by green technologies, which translates into firm growth. This resonates well with the emerging evidence on the business-environmental win-win situations enhanced by environmental practices, which can either increase the value of products (e.g. through market penetration and product differentiation) or reduce production costs (e.g. through resource and material efficiency) (Ambec & Lanoie 2008).

But, what is the role of green technologies when compared to non-green ones? Addressing this question is crucial to ascertain whether green technologies provide a growth premium with respect to standard technologies or if, instead, the effect of green and non-green patents is not different. We thus analyse the difference in the coefficients of *Pat Green* and *Pat Brown*. There emerges that for the 25th, 50th and 75th percentiles green technologies exert a significantly higher effect (at 1% level of confidence) on growth than standard technologies. This does not occur for extreme percentiles (10th and 90th), for which green and brown patents have a statistically comparable effect on growth. This is a first and quite important result of our study. It confirms the idea that green technologies provide firms with opportunities for job creation that extend beyond those offered by brown technologies (Gagliardi et al. 2016). Moreover, we better qualify this idea, as the growth premium of green over brown technologies is not for all. Indeed, it seems to fade away when innovation efforts are pursued either to survive (struggling firms) or to stay among the growth "superstars" (gazelles).

The picture emerging from the previous results appears more nuanced when we introduce interaction terms to capture the interplay between technology, both green and brown, and firm's age in driving employment growth (Table 6). First, while the effect of *Pat Green, per se,* is never significant, the impact of *Pat Brown* remains positive and significant, except for the 10th percentile, where growth rates are largely negative. Hence, only brown technologies *per se* exert a positive effect on firm growth, while that of green ones disappears. In fact, it is only when *Pat Green* is interacted with *Age* that the effect becomes significant and positive, even with the exclusion of the percentile made of struggling firms. This is the second important result of our study, whose interest is reinforced when we consider the controls (see above). Not only grow older firms faster, but they also have an exclusive capacity of exploiting the opportunities of green technologies and turn them into employment growth,

At the outset, this result seems to corroborate and extend to the green realm, previous arguments about the higher capacity of older firms to evaluate the uncertainty/risk and the actual marketability of their innovations (Audretsch 1995; Taymaz 2005). And this is true irrespective of their likely disadvantages in terms of organisational inertia and learning impediments (Majumdar 1997; Sorensen & Stuart 2000; Criscuolo et al. 2012). Moreover, older firms show higher capacity to exploit economies of scale for increasing their innovation returns, as well as in setting alliances to source externally resources for innovative activity (Herriott et al. 1985; Levitt & March 1988). Finally, mature firms have arguably acquired a more diversified experience in dealing with technology over time, to turn the adoption of eco-innovations into growth.

All of the previous "general" aspects should be integrated by considering the specific nature of green technologies and the specific evidence obtained so far. To start with, older firms may have greater pressures and incentives of renewing in an eco-sustainable manner their older capital vintages, in addition to those common with younger ones for investing into new sustainable ones.

Second, maturity can give firms more chances to grasp the higher complexity of, typically multi-purpose, eco-innovations (e.g. joining production, environmental and institutional objectives) and relying on diverse knowledge (Ghisetti et al. 2015). Third, a better access to finance (Schneider & Veugelers 2010) can allow older firms to face the higher cost of eco-innovations without crowding out other growth-driving investments (Gagliardi et al. 2016). Last, but not least, the higher uncertainty that characterises the newest green technologies could constitute the well-known "liability of newness" (Freeman et al. 1983), which imposes a higher risk of failure on young green companies with respect to standard (brown) technologies.

Indeed, while positive with respect to older firms, the implications of our result for the issue of entrepreneurial growth are quite discouraging. Our evidence suggests that green innovations do not offer a viable strategy for the growth of young firms, at least in the short run, given the additional efforts of time and money - like those associated to signalling, labelling and certification - which are often required to extract value out of the investment in green innovations, (Ambec & Lanoie 2008). When attempting to pursue the heavily uncertain path of growth (e.g. Coad et al. 2013), young companies may have instead some short-term gains from standard innovations, which do not target external benefits associated to environmental protection and are arguably less distant from the traditional industrial knowledge base (Ghisetti et al. 2015). Quite interestingly, this occurs for the central quantiles of the distribution, as noticeable from the negative and significant coefficients of the interaction term *Pat Brown X Age* in the 25^{th} and 50^{th} percentile, while for fast growing or struggling companies, age does not moderate the growth-driving effect of standard innovation.

5. Conclusions

The relationship between the firms' engagement in green technologies and their resulting employment growth, has been quite overlooked by the ecologically-oriented literature, and constitutes the central topic of this paper. In order to shed some light on the debate on whether green technologies can benefit firms with a growth premium with respect to those adopting brown technologies, we propose an econometric strategy based on a longitudinal quantile regression of a novel sample of more that 5 thousands Italian innovative firms observed over the period 2000-08.

Our results confirm the very important role of technology, both green and brown, in creating employment opportunities, thus confirming the previous literature on the topic. Moreover, a very important role at this regard is constituted by the industrial structure of the industry the firms are located, as both investments (tangible and intangible) and the industry concentration have a quite important role (evidently with different impacts and directions) on how firms can benefit from their technological resources. However, when the analysis is made more detailed, and several quantiles are examined rather than the conditional average, the results obtained seem a bit ambivalent. On the one side, we find confirmation of the existence of such a superior capacity to create jobs by recurring to green technologies. This seems to us a very important result, as, according to our estimates, it involves the vast majority of the firms in our sample, covering the central (and biggest chunk of the) percentiles of our firms' distribution. Therefore, 'around average' growing forms seems to be capable of benefitting from the adoption of sustainable technologies confirming that green technologies need not to be particularly sophisticated in order to be 'palatable' for average firms. However, we found scarce if no, evidence about the peculiar role of the so-called "gazelles": they seem to pay their role in experimenting with new technologies and thus seems unable to benefit from them, at least in terms of employment growth. Moreover, is we coupled this result to that about the slowest portion of our sample, which showed a similar pattern, we seem to support the claim that the impact on job creation of green technologies, being limited to moderately growing firms, implies that in order to impact employment, firms adopting green technologies must have already overcome the problems related to low rates of growth, and should be in the position to try and exploit the technological opportunities (and the related employment effects) that the fastest firms have possibly already exhausted.

A further confirmation of this picture comes when the moderating role of age is also considered. In this case, in fact, we find additional evidence on the fact that middle-fast growing firms are also the only ones, on which age plays a moderating role of the growth impact of green technologies. Moreover, and somehow inconsistently with the literature on green entrepreneurship, this moderation effect is however negative.

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Table 1: Variables description

Variable name	Description	Source
$Growth_{it}$	growth of employees of firm *i* in year *t* ($lnsize_{it} – lnsize_{it-1}$)	ASIA Istat
Pat $Green_{it}$	stock of green patents of firm *i* in year *t* (log transformed)	PATSTAT
Pat $Brown_{it}$	stock of non-green patents of firm *i* in year *t* (log transformed)	PATSTAT
Age_{it}	number of years since constitution of firm *i* in year *t* (log transformed)	ASIA Istat
Emp_{it}	number of employees of firm *i* in year *t* (log transformed)	ASIA Istat
Inv $Tang_{it}$	investment in physical capital of firm *i* in year *t* (log transformed)	AIDA BvD
Inv $Intang_{it}$	investment in intangible capital of firm *i* in year *t* (log transformed)	AIDA BvD
HH $index_{jt}$	Herfindahl–Hirschman Index for industry *j* in year *t*	AIDA BvD

Table 2: Descriptive statistics (n=30670)

Variable	Mean	Median	S.D.	Min	Max
Growth	-0.006	-0.024	0.225	-4.336	5.945
Pat Green	0.143	0.000	1.223	0.000	43.329
Pat Brown	2.123	0.614	15.027	0.000	961.138
Age	23.949	24	13.622	1.000	141
Emp	171.510	53	675.774	0.080	29144
Inv Tang	2854.694	297.096	29183.460	0.001	3115048
Inv Intang	1031.039	48.698	15892.520	0.001	1617583
HH index	0.026	0.007	0.063	0.000	0.988

All values are reported before log-transformation.

Table 3: Sample firms patenting propensity at different age classes (n=30670)

Variable	Age 0-10	Age 10-20	Age 20-50	Age 50over	ANOVA (F test)
Pat Green	0.187	0.110	0.136	0.274	8.21***
Pat Brown	1.566	1.659	2.469	2.783	8.48***

All values are reported before log-transformation.

Table 4: Correlation matrix (n=30670)

	Growth	Pat Green	Pat Brown	Age	Emp	Inv Tang	Inv Intang
Pat Green	0.001						
Pat Brown	-0.0249	0.2571					
Age	-0.1264	0.0095	0.1033				
Emp	-0.1741	0.1811	0.3652	0.302			
Inv Tang	-0.0103	0.1586	0.2815	0.2115	0.7361		
Inv Intang	0.0078	0.144	0.3109	0.0644	0.5068	0.4613	
HH index	-0.0121	0.063	0.0677	0.0252	0.1203	0.1142	0.0889

Table 5: Quantile regression with fixed effects: firm growth's determinants

	[1]	[2]				
	Linear Panel FE	Quantile FE				
		q10	*q25*	*q50*	*q75*	*q90*
Age	0.0818***	0.0991***	0.0882***	0.0808***	0.0735***	0.0609***
	[0.0180]	[0.0021]	[0.0011]	[0.0007]	[0.0011]	[0.0023]
Pat Green	0.0256**	0.0161**	0.0242***	0.0226***	0.0267***	0.0262***
	[0.0114]	[0.0066]	[0.0025]	[0.0017]	[0.0025]	[0.0055]
Pat Brown	0.0139***	0.0086***	0.0133***	0.0144***	0.0146***	0.0196***
	[0.0054]	[0.0022]	[0.0009]	[0.0007]	[0.0010]	[0.0022]
Emp	-0.4506***	-0.4203***	-0.4330***	-0.4432***	-0.4540***	-0.4691***
	[0.0234]	[0.0017]	[0.0009]	[0.0007]	[0.0011]	[0.0018]
Inv Intang	0.0051***	-0.0007	0.0019***	0.0037***	0.0055***	0.0081***
	[0.0009]	[0.0006]	[0.0003]	[0.0002]	[0.0004]	[0.0005]
Inv Tang	0.0203***	0.0159***	0.0154***	0.0157***	0.0173***	0.0210***
	[0.0023]	[0.0010]	[0.0006]	[0.0004]	[0.0006]	[0.0011]
HH index	-0.0527	-0.1295***	-0.0760***	-0.0394***	-0.0245***	-0.0212
	[0.0322]	[0.0271]	[0.0126]	[0.0067]	[0.0089]	[0.0222]
Constant	1.2378***	1.0834***	1.2082***	1.3064***	1.3930***	1.4909***
	[0.0814]	[0.0107]	[0.0061]	[0.0043]	[0.0070]	[0.0122]
Firm-year obs	30670			30670		
Firm obs	5498			5498		

* p<0.10, ** p<0.05, *** p<0.01. Year dummy variables have been included in all models. For the second model, bootstrapped standard errors are reported in parenthesis. They are based on 1000 replications of the data.

Table 6: Quantile regression with fixed effects: firm growth's determinants – interaction effects

	[1]	[2]				
	Linear Panel FE	Quantile FE				
		q10	*q25*	*q50*	*q75*	*q90*
Age	0.0817***	0.0984***	0.0875***	0.0801***	0.0721***	0.0607***
	[0.0181]	[0.0028]	[0.0014]	[0.0008]	[0.0014]	[0.0028]
Pat Green	-0.0068	0.0237	-0.0001	-0.0076	-0.0158	-0.0371
	[0.0481]	[0.0190]	[0.0089]	[0.0050]	[0.0102]	[0.0252]
Pat Brown	0.0243	0.0108	0.0202***	0.0213***	0.0194***	0.0286***
	[0.0238]	[0.0094]	[0.0043]	[0.0027]	[0.0044]	[0.0106]
Pat Green X Age	0.0106	-0.0009	0.0077***	0.0100***	0.0137***	0.0203***
	[0.0149]	[0.0059]	[0.0029]	[0.0017]	[0.0031]	[0.0077]
Pat Brown X Age	-0.0035	-0.0007	-0.0023*	-0.0024***	-0.0017	-0.0031
	[0.0074]	[0.0029]	[0.0013]	[0.0008]	[0.0014]	[0.0033]
Emp	-0.4506***	-0.4207***	-0.4331***	-0.4432***	-0.4539***	-0.4692***
	[0.0234]	[0.0017]	[0.0009]	[0.0008]	[0.0011]	[0.0018]
Inv Intang	0.0051***	-0.0007	0.0019***	0.0037***	0.0055***	0.0081***
	[0.0009]	[0.0006]	[0.0003]	[0.0002]	[0.0004]	[0.0005]
Inv Tang	0.0203***	0.0160***	0.0154***	0.0157***	0.0172***	0.0210***
	[0.0023]	[0.0011]	[0.0006]	[0.0004]	[0.0006]	[0.0010]
HH index	-0.0527	-0.1342***	-0.0760***	-0.0408***	-0.0242***	-0.0209
	[0.0323]	[0.0276]	[0.0128]	[0.0071]	[0.0086]	[0.0214]
Constant	1.2660***	1.0857***	1.2106***	1.3091***	1.3985***	1.4924***
	[0.0859]	[0.0128]	[0.0067]	[0.0045]	[0.0075]	[0.0130]
Firm-year obs	30670	30670				
Firm obs	5498	5498				

* p<0.10, ** p<0.05, *** p<0.01. Year dummy variables have been included in all models. For the second model, bootstrapped standard errors are reported in parenthesis. They are based on 1000 replications of the data.