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The role of public policies in fostering innovation and their implications for employment opportunities

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Ph.D Dissertation

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L’assenza può essere più potente della presenza

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INTRODUCTION
Towards a new industrial policy making approach

Shaping the industrial system on the pillars of innovation and technological change is considered as a unique occasion for jointly re-launching economic growth, contrasting environmental damage and improving employment opportunities. In the European context, the policy and academic debate on this topic is gaining increasing momentum, leading to relevant public investment and to the simultaneous implementation of policy programs[1] aimed at both fostering and addressing innovation activities towards more-sustainable patterns of development. Compared with a 30-years season of inactive industrial policies, this is shown to clearly mark an important turning point, especially in the Italian context, where a narrowed role of the public sector in supporting the industrial sector has been included among the main causes of the Italian competitiveness's gap with other European economies (Lucchese et al., 2016)[2].

Together with such a renewed attention towards industrial policies, a new conceptual approach of industrial policy making is finding its way. This modern view calls for a more proactive-entrepreneurial role of the public sector (Mazzucato, 2015) as well as a more holistic approach to innovation policies (Edquist, 2014). This goes beyond the narrow interpretation of the role of the State in supporting innovation and industrial development, usually associated

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1 In the context of Europe2020 strategy two main initiatives have been taken: "Innovation Union" (European Commission, 2010a) and "An integrated industrial policy for the globalization era" (European Commission 2010b). The former is aimed at ensuring the conditions for firms to innovate, while the latter is targeted at supporting manufacturing production's transition towards more-sustainable patterns of development.
In addition to other EU2020 initiatives, such as Horizon 2020 R&D program, COSME and Structural Funds, the "Industrial Compact" was issued in 2014 with the mission of returning industrial activities to 20% of GDP. This has been followed by the creation in 2015 of The European Fund for Strategic Investments (EFSI) and the subsequent launch of the 21 billion "Juncker Investment Plan".
In accordance with the renewed attention towards industrial policies aimed at revitalizing the European economy, Italy has carried out several measures to align its policies with the horizontal objectives of European programs, namely Horizon2020, the European Digital Agenda and the seven European Grand Challenges. More specifically, the measures to support Italian firms until 2020 in different fields such as R&D and innovation, internationalization, new entrepreneurship, local and production development are encompassed within the "Italy's Industria 4.0 Plan", which has been drawn up by a multi-stakeholder steering committee and explicitly avoids vertical or sector based measures in order to focus on "horizontal" actions directed at sustaining firms' innovative investments and promoting technological advances and productivity.

2 Over the Nineties, the huge loss of "big state-owned firms" has in fact downsized the Italian presence in the high-tech sector and, in addition, has reduced the necessity for private companies to grow in order to be competitive with the former (Antonelli et al., 2014; Munari et al., 2002). These facts encouraged the industrial system to develop through small-sized and low-tech focused firms, often grouped in industrial districts (Onida, 2004).

with a market-failures policy based perspective. Indeed, this traditional view depicts public sector as a mere fixing entity whose objective is to solve substantial market failures by providing the appropriate incentives to private firms to invest in innovative activities for the generation of technological and scientific knowledge (Arrow, 1962; Nelson, 1959). In this perspective, innovation is seen as a linear process going from research activities to the market introduction of new products or processes. Thus, the main policy issue is to increase the propensity of firms to invest in innovation activities, which is harmed by several factors: limited appropriability of research outputs, sunk costs in innovative investments, risks and the uncertainty associated with innovative investments. The central argument here is that the presence of different forms of market inefficiencies leads to a gap between the private and social returns of innovation. In order to balance such a trade-off, most of innovation policies adopted, mainly targeted towards private firms, take the form of supply-push incentives, such as grants, concessional loans and tax reliefs.

One of the main claim stemming from the new approach relies on the relevance attached to another class of innovation policies, namely demand-pull instruments. The central point is that public sector funding can, and actually often does, much more than fixing market failures (Mazzucato, 2015). For example, government funded the riskiest research and led to the most radical innovations (for instance internet technology and nanotechnology), by founding the early stage development of technologies through large scale and long-term investments. By creating new products and related markets, public sector can push forward the boundaries of technologies, drive industrial renewal and structural change processes rather than just incentivizing or stabilizing existing markets or sectors (Mazzucato, 2015).

On the other hand, going beyond the conception of innovation as a linear process by adopting an "holistic" perspective in the analysis of innovation, allowed the understanding of the role of innovation systems and of the importance of multiple actors involved in the knowledge generation process. This aspect has been largely emphasized by both institutional tradition of innovation studies (e.g., Freeman, 1987; Lundvall, 1992) and evolutionary theories (e.g., Metcalfe, 1995; Nelson and Winter, 1982)skills and artifacts and in each case there are different variety-generating mechanisms, different selection processes and different institutional structures. For policy purposes, the degree of connection between these different dimensions of technology is at the core of technology policy. In this paper I propose to sketch some general aspects of an emerging evolutionary perspective on technology policy. This perspective has developed out of the wide range of literature on innovation summarised by Freeman (1994 according to which, innovation is the result of the interactive process between many individual actors whose interactions are regulated by institutions, the interdependence between institutions (habits and practices), learning, and networks (Freeman, 1987) [3]. According to the holistic

3 The first theorization of the systemic nature of innovation comes from the seminal contribution by Chris

approach, “innovation is not just about basic research but is also about basic education, demand-side factors (such as innovation procurement and product quality requirements), creation of new organizations (such as the stimulation of entrepreneurship and the formation of policy organizations), interactive learning between organizations, the development of new regulations (e.g. for patents or public procurement), and incubators to support new companies and venture capital for innovation, to name a few of the most crucial elements” (Edquist, 2014). In that, the innovation process works as a “system” which encompasses “all important economic, social, political, organizational, institutional, and other factors that influence the development, diffusion, and use of innovations” (Edquist, 1997).

In other words, this approach rejects the idea of an optimal state of the system as an achievement target for policy, since it considers innovation policy as a process continuously on the run, whose interactive nature includes a plurality of public and private actors. The interaction process recognises the possibility of “system failure”, rather than “market-failure”, leading to low innovation performance due to a lack of coordination between the elements of the “innovation system”.

In this view, the traditional justifications linked to the market failure-based policies associated with R&D policies is enlarged by adding further goals associated with the recourse to public support for innovation, including the distribution of knowledge, the coordination of different agents and the possibility of increasing the cognitive capacity of firms.

Therefore, this perspective overrides the traditional view of innovation in terms of the market failure approach to R&D policy and puts more emphasis on the crucial role played by the institutions in creating, both jointly and individually (Metcalfe, 1995), the “proper” institutional conditions needed to sustain technological improvements and innovation (Nelson, 1993). Hence, compared to the traditional industrial technology frameworks, the holistic view of innovation provides a more complex setting for industrial policies by adding further economic and institutional elements concerned with learning as well as searching and

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Freeman (1987). In describing the congruence in Japanese society’s institutional networks interactions in managing new technologies, he emphasized four main innovation system elements. The first refers to the role of policy in creating comparative advantage by means of strategic industrial policies. The second involves the specific role of corporate R&D in order to assimilate external knowledge, while the third element relates to the importance of human capital in the successful implementation of large technological systems. Finally, the fourth factor is related to the conglomerate structure of Japanese industry, which is composed of large firms and, thus, able to internalize the externalities associated with innovations in supply chains. Many contributions since those of Freeman, have provided a number of particularly useful insights, enriching the systemic innovation theory. Lundvall (1992) draws attention to the role of non-R&D-based innovation, such as buying machinery, training of workers, or design, whose systemic interactions and complementarities have been deeply investigated within the innovation systems framework. Edquist and Johnson (1997) shed light on the role of institutions in shaping the innovation setting and coordinating the innovation process. They list the different types of institution that matter for innovation systems on the basis of a series of characteristics, i.e. formal versus informal (customs, traditions, and norms), basic (e.g., laying down basic arrangements on property rights, conflict management rules, etc.) versus supportive (the specific implementation of basic institutions), hard (binding, and policed) versus soft (more suggestive), and consciously or unconsciously designed.

exploring (Lundvall, 1992). Put simply, the central point of the modern view of innovation policy is that, in addition to all the instruments that are traditionally the domain of science and technology policy, the policy toolbox must also include a public research investment program and education-oriented policies, while paying, at the same time, particular attention to the general industrial and regional policy setting. Hence, industrial policies aiming at fostering the industrial transformation of the economies and at fuelling structural change processes based on the generation and adoption of new technology should consider a vast array of instruments combining supply-side measures along with other complementarity measures as well demand-pull instruments and systemic programs (Public R&D spending for universities and other public research institutions; funds for mission-oriented programs as defense, space, agriculture, health, energy or industrial technology, and general purpose technologies (GPTs); financing programs for tertiary education).

Building on these considerations, the present dissertation is intended to contribute to the policy and academic debates by providing a multifaced investigation on the links between different classes of public policies and innovation activities as well as their implications for employment opportunities. By focusing on the Italian industrial sector, the study is made by two main blocks for a total of three chapters. The first block looks at innovation “tout court” and emphases the concept of “policy” mix, while the second one points the attention on innovation with beneficial environmental effects by looking at its linkages with environmental and innovation policies and its effects in terms of employment growth at the firm level.

The structure has been systematized as follows:

1. **Chapter 1.** The first chapter provides an econometric investigation on the impact of both push and pull policy instruments on firms’ innovative investment. This appears to be a relevant issue from both academic and policy perspectives, considering that, despite of the frequent joint use of multiple instruments to stimulate innovative investment, most of empirical studies are focused on the impact of single policy instruments. In particular, a large scale, systematic evidence on the effects of public procurement on innovation activities based on quantitative policy evaluation techniques is still not available and, beyond the generalized optimism regarding its potential, the stimulating role of procurement on innovation could be affected by a considerable number of hindrances ranging from the low capabilities of the procuring organizations, the low degree of coordination along the national and local procurement chain to, more in general, the still predominant focus of procurement authorities on static-efficiency issues with respect to dynamic-efficiency objectives. By paying particular attention to the self-selection problem, such hampering factors will emerge from the impact evaluation exercise here proposed.

2. **Chapter 2.** In this part of the dissertation, the attention is devoted at investigating the policy determinants of distinct “modes” of environmental innovation, as identified from a number of environmental goals by means of a clustering analysis. In so doing, the chapter brings together two research lines: the one underlighting the primary role of environmental and innovation policies in fostering the pace of introduction and diffusion of environmental technologies, and the other calling for a more “systemic” approach to environmental innovation. This study contributes to the literature in two ways. Firstly, consistent with the evolutionary perspective of innovation, it provides a novel framework of innovation modes, thus suggesting that firms pursue several approaches when engaging in eco-innovation. Secondly, a related contribution is that this research directly keys into the debate in the literature about the effectiveness of public policies in spurring EI, with the added insight to assess the effect of different policy tools in shaping distinct EI dynamics. Thus, an enriched and more nuanced view of environmental innovation processes is here provided, with important implications for theorizing about policies aiming to foster the transition towards increased sustainability.

3. **Chapter 3.** Devoted at assessing the employment impact of introducing green technologies, the third chapter presents the major novelty of considering the multifaced nature of environmental innovation, as detected in chapter 2. The analysis is performed within a not-parametric framework which allows to account for a key issue rooted in the evolutionary perspective. It namely refers to the fact that the impact of innovation-related growth drivers might be differentiated according to the pace at which a firm grows. To date, this kind of analysis have been mainly concentrated in the standard innovation field, with the main finding that the faster is the pace of growth the greater is the growth premium arising from innovative activities. The econometric exercise suggests that, regardless to the green technological trajectory followed by firms, the net employment effect of environmental innovation is always positive but only in certain cases statistically significant. This is of particular relevance for struggling firms where environmental innovation turns out to be a key candidate for overcoming the economic impasse while, on the contrary, fast-growing companies seem to fail in taking advantage from most of green orientations. This provides rationales for paying more attention to the potential role of public policies in disabling hampering factors, namely financial and knowledge barriers, that are responsible for preventing firms from engaging and successfully dealing with environmental innovation.

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Supply-side and demand-side innovation policies and their combination into policy mixes: new evidence from Italian microdata

Abstract

The contribution of the present paper is to provide an econometric investigation on the impact of both *push* and *pull* policy instruments on firms' innovative investment while controlling for a number of confounding factors. In so doing, policy tools are considered either as isolated or combined "treatments" within an impact evaluation framework. In parallel, the empirical analysis pays particular attention to the self-selection problem, basically linked to the strong self-selection and selectiveness affecting firms benefitting from public sustain.

Keywords: *Supply-Push Policies, Public Procurement, Selection-Bias, Hidden Treatment,Propensity Score Matching*

SECTION 1

Introduction

Since the end of the Second Word War, direct measures in supporting R&D were often implemented in concert with public procurement practices (Mowery, 2012), becoming the most adopted among other innovation tools (Aerts and Schmidt, 2008). These two instruments represented the central pillar of industrial policy in Europe during the all post-Second Word War period, when comprehensive sectoral programs and *mission-oriented* actions were put in place to sustain and enhance countries' domestic industry. However, during the Nineties, governments abandoned direct and selective measures to concentrate their policy efforts on more horizontal programs, mainly focused on SMEs and R&D tax credits (Lucchese et al., 2016).

Though *supply-side* horizontal measures to stimulate innovative investments still represent the core instruments of innovation policy in Europe (Cunningham et al., 2016), the potential role of *demand-side* innovation policies, and in particular of public procurement, is recently receiving increasing attention (Georghiou and Edler, 2007; EC, 2009; Izsak and Edler 2011; Uyarra 2013). Public procurement is supposed to ensure sufficient critical mass of demand to encourage innovative investments and facilitate interactions between users and potential suppliers, so that, procurement practices aimed at supporting innovation have been included in the policy agenda of both developed and emerging economies (Georghiou et al., 2010; OECD, 2011; Uyarra, 2013; Lember et al., 2013; Vecchiato and Roveda, 2014).

Namely, the integration of both *demand-pull* and *technology-push* measures along with other complementary tools constitutes the policy mix, whose efficacy depends not only on the effectiveness of single instruments but also on the quality of their interactions (Flanagan et al, 2011).

Despite the frequent joint use of multiple instruments to stimulate innovative investment, most of empirical studies are focused on the impact of single policy instruments. In particular, the evaluation of the impact of *supply-side* measures, in terms of input, output and behavioral additionality, represents a well-established field of research in innovation studies which provides a sound evidence on the efficacy, limits and advantages of these kind of tools (David et al. 2000; Cerulli, 2010; Cunningham et al., 2016). In contrast, the effects of *demand-side* policy measures, as public procurement, have been mainly investigated through qualitative cases studies (see for example Edquist and Hommen, 2000; Rolfstam, 2009; Uyarra and Flanagan, 2010; Flanagan et al., 2011; Brammer and Walker, 2011) and less explored by means of quantitative analyses (Crespi and Guarascio, 2018; Ghisetti 2017; Raiteri, 2018). In this respect, a large scale, systematic evidence on the effects of public procurement on innovation activities based on quantitative policy evaluation techniques is still not available. This appears to be a relevant issue from both academic and policy perspectives, considering that beyond the generalized optimism regarding its potential, the stimulating role of procurement on innovation could be affected by a considerable number of hindrances ranging from the low capabilities of the procuring organizations, the low degree of coordination along the national and local procurement chain to, more in general, the still predominant focus of procurement authorities on *static-efficiency* issues with respect to *dynamic-efficiency* objectives (Kattel and Lember, 2010).

The contribution of the present paper is to provide an econometric investigation on the impact of both *push* and *pull* policy instruments on firms' innovative investment controlling for a number of confounding factors. In particular, the present analysis evaluates the impact of both types of instruments either when used in isolation or in combination. This is done by performing an impact evaluation exercise on the effects of the interactions between *demand-pull* and *technology-push* policies.

In so doing I recognize that, from a policy evaluation perspective, looking at single policies within a policy mix context may lead to biased estimates, as the impact evaluation of a given policy turns out to be unbiased only when relevant confounding factors are accounted for. In particular, O aim to control for two main sources of biases. The first derives from the fact that, in addition to the effect stemming from the "focus" policy to be evaluated, other policies in the "mix" might influence the outcome variables (Guerzoni and Raiteri, 2015). The second, concerns the simultaneous access to different policy programs, which may signal that specific capabilities are owned by beneficiaries of multiple support policies, a source of selection bias that has to be taken into account in evaluating the interaction effects between different instruments.

The study is realized by carrying out a quasi-experimental analysis on a pulled dataset of 4,214 Italian manufacturing firms. Information is drawn from the 6th and 7th CIS waves and AIDA database, and covers the period 2010-2014. The empirical investigation is made of two stages focusing on two issues. The first is dedicated at investigating the impact of *supply-push* and *demand-pull* policies when taken both in combination and isolation. This allows to better control for potential "hidden treatment" impact arising when a confounding variable (that is not a firm's characteristic but an additional innovation policies) in not properly accounted for (Guerzoni and Raiteri, 2015). The second issue is designed to better evaluate the presence of relevant complementarity effects associated with the joint use of these two types of instruments by concentrating the analysis on a reduced, more homogenous, sample of firms.

The remainder of the paper is organized as follows. Section 2 provides a literature review on the impact of *supply-side* innovation policies on firms' innovativeness, by pointing the attention on findings emerging from "quasi experimental" studies. Then, by moving on *demand-pull* policies, it discusses the opportunities and limits of public procurement in stimulating demand-driven innovative investment (with a focus on the Italian context) and collects empirical evidences on the complementary effects between *supply-push* and *demand-pull* instruments. Section 3 defines the dataset, the operationalization of policy variables and the econometric strategy. Finally, Section 4 reports the results for the two stages and Section 5 summarizes the main insights emerging from the study, highlights the policy implications and outlines possible further research lines.

SECTION 2

Supply push policies

Supply-side innovation policies are classified as measures which directly and indirectly provide finance to support business R&D (Georghiou, 2003). Specifically, the direct support consists in grants or low-interest loans, while the indirect one takes the form of R&D tax credits. According to the classical view of public intervention, these types of instruments are mainly justified by the existence of market failures associated with innovative investment. These mainly originate from appropriability problems (Nelson, 1959; Arrow, 1962) and information asymmetries. The presence of financial barriers, makes R&D efforts highly dependent on firms' cash flow (Hall, 2002; Hall et al, 2016; Hottenrott and Peters, 2012; Schiantarelli, 1996) especially for small firms and those belonging to *high-tech* sectors (Canepa and Stoneman, 2003; Hottenrott and Peters, 2012). In this context, public support has the purpose to reduce the marginal cost of R&D by providing firms with sufficient funds to implement private innovative investments (Bronzini and Piselli, 2016). In particular, firms facing financial barriers tend to exploit direct funding to a greater extent than R&D tax credits, while the use of tax incentives is more diffused among firms fronting appropriability problems (Busom et al., 2014).

The empirical evidence on the impact of *supply-side* policies upon private innovation investment is mixed and heterogeneous across different types of measures (Mulligan et al., 2017) and different evaluation timing (Arque-Castells and Mohnen, 2015). However, while results from less recent literature were seriously affected by selection bias problems, a more recent stream of empirical studies addresses this issue by making use of quasi-experimental settings. The basic idea of this approach is to define the impact of a *treatment* (i.e. a specific innovation policy) as the difference reported in the target variable (i.e. innovative inputs and outputs) by looking at twin unites, treated and untreated (Rosenbaum and Rubin, 1983). Such an approach has been fruitfully adopted in order to control for the correlation of variables affecting the eligibility to a specific policy measure (size, sector, county, type of policy tool) and the measure itself (Huergo et al., 2016; Huergo and Moreno, 2017).

Results provided by non-parametric marching analyses are, in general, less ambiguous than evidences stemmed from early studies (David et al, 2000), being the most of these in favor of the additionality hypothesis (see for example Almus and Czarnitzki, 2003; Czarnitzki and Licht, 2006), even if under specific conditions ranging from firm's characteristics (Bronzini and Iachini, 2014) to temporal dynamics (González and Pazó, 2008).

Considering that different measures to sustain innovative activities are often jointly implemented, another source of potential bias in estimating the effects of specific policies is related to the so-called "hidden effects". Hence, the empirical analyses based on quasi-experimental studies has started to consider also the interactions between different supply-side tools. For example, by using data from the 2005 Survey of Innovation from Statistics Canada, Bérubé and Mohnen (2009) find that firms benefiting from both R&D tax incentives and R&D subsidies are more innovative (in terms of number of innovations, world-first innovations and commercialization) than those only benefiting from R&D tax incentives. Drawing data from the Survey of (Italian) Manufacturing Firms (SMF) carried out by the Area Studi of Capitalia Bank 1989-2003, Carboni (2011) concludes that tax incentives appeared to be more effective than direct grants, although grants encourage the use of internal funding sources. Corchuelo Martínez-Azúa and Martínez-Ros (2009) collect 1.708 observations at the firm level from the Spanish Business Strategy Survey for 2001 and point out that R&D subsidized firms (especially SMEs) take more advantage from tax benefits when compared to not subsidized enterprises. Finally, by exploiting a dataset of 12.169 French companies covering the period 1993- 2009, Marino et al., (2016) propose a rich assessment of the public subsidies to R&D in absence or combination with the R&D tax credit. Their findings, based on categorical and continuous matching evaluation schemes, show that substitution between private and public funds may occur especially for medium-high levels of public subsidies under the regime of R&D tax credit.

Demand Pull policies

Growing emphasis has been recently attached to the use of *demand-side* innovation measures (Edler, 2013; Georghiou *et al*, 2014; OECD, 2011), and, particularly, to the adoption of public procurement (Edquist and Zabala-Iturriagagoitia, 2012) as a driving element of innovation. The main arguments sustaining the importance of demand as incentive of innovation stem from the pivotal contributions by Schmookler (1962) and Myers and Marquis (1969) with regard to the crucial importance of demand, or latent demand, in generating positive expectations of profitability from innovation investment (Antonelli and Gehringer, 2015; García-Quevedo et al., 2017).

These aspects have been recently emphasized by a flourishing literature on barriers to innovation associated with demand-related (i.e., lack of) incentives to invest in innovation (D'Este et al., 2012; Iammarino et al., 2009). Following this perspective, García-Quevedo et al. (2017) find evidence that positive expectations on the presence of adequate demand are a necessary condition to engage in R&D activities, showing that the perception of a lack of demand has a marked negative impact on both the decision to invest and on the amount of investment in R&D.

These results provide new support to the idea that public demand can operate as an effective tool in industrial and innovation policies (Filippetti and Archibugi, 2011; Chang and Andreoni, 2016). In particular, the main operative tool associated with public demand is public procurement, namely the direct purchase of goods and services by the public sector, which in the OCED area, represents almost 30% of national government spending and accounts for a share of above 12% of GDP[1]. By consolidating and creating markets, and thus reducing uncertainty, public demand provides strong incentives to come up with innovative solutions for the upgrading of product-related processes. In doing so, PP is supposed to be a key driver of technological upgrading (Uyarra and Flanagan, 2010; Edquist, 2015), whether the stimulation of innovations is an explicit goal of procurement (Innovative Public Procurement[2]) or not.

Demand-side instruments have been found to be effective when taken in combination with *supply-push* measures (Guerzoni and Raiteri, 2015), however, the actual role of PP in leading, or hindering, innovation is not clear enough from the empirical point of view, since the

1 Source: OECD - Government at a glance 2017 highlights (https://www.oecd.org/gov/government-at-a-glance-2017-highlights-en.pdf)

2 A well-developed discussion about innovation-related procurement has been provided by Edquist (2017). The scholar studies in deep the differences between "product procurement" and "functional procurement". The former are defined as those contracts that exactly require "which" innovative product/service has to be supplied. On the contrary, the latter are depicted as those contracts that describe "which function" the product/service should perform. Because of the lack of detailed information both at quantitative and qualitative level, an exhaustive consideration of the two types of public procurement contract is beyond the scope of this paper. Indeed, the focus is on the whole class of (PP) contract and a comprehensive class of innovation procurements contracts (IPP).

positive, but still anecdotal and case-study based empirical evidence does not investigate "how and under what conditions that impact of PP takes (or could potentially take) place" (Uyarra et al., 2014a). This aspect is extremely worth of note, because the success of PP definitely depends on "contextual" aspects reflecting national differences in the design, governance and implementation of PP as well as different objectives at country and sectoral level. In this respect, a recent stream of literature points out the existence of the country-specific breakdowns (Mourão and Cantu 2014, Uyarra et al. 2014b, Li et al., 2015, Rolfstam and Petersen 2011, Cepilovs 2013; Lember et al., 2014b) and systemic hindrances (Amann and Essig 2015; Georghiou et al. 2013; Rolfstam, 2012) affecting PP practices.

On the one hand, most countries have different and often contradictory ideas about the role of public procurement, especially in regard to the trade-off between static and dynamic efficiency (Nyiri et al., 2007). On the other hand, the effectiveness in devising and implementing PP policies is strictly connected to institutional capacities and coordination practices (Kattel and Lember, 2015) that governments often lack (Rolfstam, 2002; Lember et al. 2015). This aspect tends to be particularly problematic when sub-national institutions are responsible for the implementation of procurement contracts, as they may lack the internal capabilities to use PP as a strategic tool to sustain innovation (Albano and Sparro, 2010; Georghiou et al., 2013).

Such problems appear to be relevant in the Italian case, which is the one on which the present analysis is focused. In Italy the deliberate use of public procurement to sustain innovation activities is in fact limited and mainly concentrated in the healthcare sector (EC, 2014; Federsanità, 2015). For this reason, the Italian normative framework of the public procurement of innovation has been recently updated by the Low Decree 50/2016 and the tree-year plan AgID (Agenzia per l'Italia Digitale) for the digitalization of public services for citizens and enterprises, respectively. In this new context, the public purchasing of innovative goods has been largely enhanced by new instruments as, for example, the possibility of partnerships between public and private actors. However, the scarce exploitation of the new procurement-related tools has been currently claimed by AgiID which signals at least five serious deficiencies affecting the updated Italian PP framework:

I. Firstly, the low degree of clearness (need of a more divulgating language) and applicability (no mention of best practices and comparisons with other countries) recognized in the new schemes of contracts.
II. Secondly, the weak level of expertise showed by the procurement entities in acknowledging and managing the new instruments.
III. Thirdly, the short-term and static-efficiency vision of the tree-year plan AgID, which is still focused on saving-cost considerations instead of innovation goals, thus hampering the uptake of more risky and long-term projects usually associated with major innovation contents.

IV. Fourthly, the inefficient organization along the procurement chain due to an unclear allocation of responsibilities among the public institutions.
V. Fifthly, the low propensity to innovate due to the fact that the National Frame Contracts managed by Consip S.p.a - the Italian Public Procurement agency – has been designed within the broader Italian program for the rationalization of public spending in goods and services.

Evaluating the policy mix

In the evaluation of the effects of both *demand-pull* and *technology-push* tools it is important to take in consideration each source of confounding effects arising from extraneous variables *systematically* varying with the level of the treatment variable (Guerzoni and Raiteri, 2015). This consideration puts particular emphasis on the so-called "hidden effect" that, in the field of innovation studies, is usually associated with the contemporaneous presence of more than one policy tool. Moreover, by accounting for policy interaction effects it is possible to analyze the complementarity between *supply-push* and *demand-pull* measures, an issue viewed with increasing interest by both researchers and policy makers (Mohnen and Röller, 2005; Di Stefano et al., 2012).

In general, findings stemming from innovation literature do not confirm that combinations of instruments are always superior to a single instrument approach but provides evidences about how different instruments may lead to both synergies and conflicts, since they depend on the design features of the instruments in specific countries as well as the overall characteristics of a given "mix" (Magro and Wilson, 2013; Cantner et al., 2016; Kern et al., 2017; Costantini et al., 2017). More specifically, Aschhoff and Sofka (2009) perform a latent class tobit regression on a sample of 1.100 German firms in order to investigate the impact of different policy tools, i.e. regulation, R&D subsidies, knowledge spillover from university and public procurement, on the share of turnover sourcing from the development of innovations with market novelty during the three-year period 2000-2002. Their findings suggest that both public procurement and knowledge spillovers from universities exert a positive impact on innovation, especially for small firms placed in Western Germany. On the other hand, by focusing on innovation inputs, Guerzoni and Raiteri (2015) performed a quasi-experimental analysis on 4.992 European firms and evaluated the isolated and combined impact of R&D subsidies, tax credits and innovative public procurement on the probability of increasing R&D expenditures between the two-year period 2006-2008. Their results show that, when taken in interaction, innovative policies exert a greater impact compared to isolate policies. In particular, firms involving in both innovative procurement contracts and tax credit programs have the highest probability of increasing R&D expenditures.

Building on the above considerations, I propose an evaluation exercise of the effects of both *demand-pull* and *supply-push* policy tools in shaping R&D investment of Italian firms. In so doing, I will try to tackle relevant issues related to selection bias and confounding factors, thus adopting a quasi-experimental empirical approach and distinguishing between cases in which *demand-pull* and *supply-push* policies act in isolation or in combination. In the next section I will provide details of data used for the empirical analysis and adopted methodology.

SECTION 3

Data and Methodology

The empirical analysis is based on firm-level data drawn from the 6th and 7th waves of the Italian Community Innovation Survey referring to the tree-year periods 2010-2012 and 2012-2014, respectively. The survey, developed by Eurostat according to the Oslo Manual and collected by Istat (Italian National Statistical Institute) every two-year, includes a representative sample of firms with at least 10 employees identified by a stratified random sampling, plus the whole population of firms with more than 249 employees. The CIS dataset has been integrated with balance-sheet data extracted from the AIDA-Bureau VanDijk database which provides information on firms' financial structure. After dropping non-innovative firms (for which relevant information on policies is missing), those operating in service sectors, and cleaning for missing information, the final pooled sample consists of 4.206 observations[3].

In comparison with previous CIS waves, CIS6 and CIS7 have made up a step forward regarding information on innovation policy instruments. In particular, a special section on public procurement (PP) and innovative public procurement (IPP) has been added in order to scrutinize two main aspects. Firstly, whether or not the innovative firm has been involved in a contract of public furniture and secondly, if so, whether or not the public contract explicitly required the engagement in innovation activities[4]. More specifically, in the present study traditional information on Supply Push (SP) policies[5] have been jointly analyzed with those related to PP and IPP within a quasi-experimental setting, where SP and PP and IPP instruments

3 As the policy target variable is represented by R&D investments, the focus has been put on manufacturing where the bulk of R&D expenditures by the world's developed economies is concentrated (David et al., 2000). Manufacturing firms have in fact been traditionally considered as technological forward, with R&D investment levels playing a primary role in explaining the innovation-related performance both at industry and firm-level.

4 At the best our knowledge, only Czarnitzki et al. (2018) attempted to exploit for the German case this information in a quantitative evaluation analysis. However, their analysis did not concern the simultaneous evaluation of different policy instruments.

5 Unfortunately, given the lack of more detailed information about the nature of the public aid received from innovative firms, I cannot distinguish between different types of instruments, i.e. public R&D subsidies, tax credits or loans.

are the treatment variables and private R&D investment the outcome variable[6].

The empirical strategy consists in a counter-factual analysis with the aim to "recreate" what would have happened to the same treated firm if it had not received the treatment.

Formally:

$$ATT\ (ATET) = E(Y_i^1 - Y_i^0 \mid T=1) \tag{1}$$

where and represent the outcome variable of the treated unit *i* with and without treatment, respectively.

In other words, the basic idea beyond this method is to compare the same unit in both states of the world, i.e. with or without treatment, by creating a hypothetical situation where the treated unit is untreated and then testing if there are significant differences in the mean of the variable of interest. Being the "counterfactual" situation not directly observable for the same unit, a "twin" unit is used as control. In this case, the average treatment effect on treated firms (ATET) is estimated by comparing differences on the mean of the target variable between the groups of treated and control, which are assumed to be identical to each other, except for the treatment.

This procedure works if, and only if, the two groups are perfectly randomized, which means that the probability of taking part to a policy program must be not correlated with individual characteristics of the firm.

Formally:

$$Y_i^1 ; Y_i^0 \quad T \tag{2}$$

Such assumption rarely holds, especially in our specific setting where the lack of randomization is very likely to arise because of the presence of two main sources of bias. The first one refers to the bias of "self-selectiveness" which affects those firms accessing to *supply-push* programs or winning a regular and/or innovative public procurement tender, or both. As a matter of fact, it is very likely that firms benefitting from one or more policy tools hold capability advantages (information network, research capabilities, financial soundness) over firms not involved in any policy program. This makes the former more prone to apply for policy program (as a grant or a public tender). Similarly, such a gap in capabilities between applicants and others

6 Following the bulk of previous literature, the present analysis focuses on R&D expenditures as the outcome variable. However, I acknowledge that R&D investment represents an input measure of innovation and that many innovation activities are not necessary linked to R&D. Hence, I also test the impact of our focus variables on an outcome variable, i.e. the share of turnover achieved with new products. Results remain largely confirmed.

leads to the second bias, the so-called "picking the winner" effect (Cantner and Kösters, 2012). This takes place when public agencies select firms that are already more performing than others with the aim to maximize the probability of success of their policies (Almus and Czarnitzki, 2003; Antonelli and Crespi, 2013). Both arguments provide valid rationales for hypothesizing that treatments cannot be randomly assigned because the odd of getting treated relies on a set of characteristics (X) that drive the "self-selection" as well as the selection by public agencies.

Formally:

$$E_x \{Y^1 - Y^0 \mid T=1|X\} \tag{3}$$

In such a situation, the comparison between treated and untreated requires to make the same kind of manipulation in order to balance the differences arisen from every potential source of bias (Aerts and Schmidt, 2008) and restore the independence assumption.

Formally:

$$E_x \{Y^1 - Y^0 \mid T=1|X\} = E_x \{Y^0 \mid T=1|X\} = E_{(X,T=1)} \{E(Y \mid T=1;X)\} - E_{(X,T=1)} \{E(Y \mid T=0;X)\} = m_{1,1}(X) - m_{1,1}(X) \tag{4}$$

where are functions of the observables, namely Y, T, X, that can be estimated by adopting non parametric approaches. A valid option is to use the "propensity score matching technique" consisting of a randomized ex-post experiment where a reliable control group of non-treated individuals is identified. As shown in Cerulli, (2010) this method has been widely used to assess the effects of public sustain, mainly direct support, on business R&D or other outcomes. More specifically, the units belonging to the control group appear very similar to the treated units for all the observable pretreatment characteristics, that are considered relevant in influencing the probability of being treated (Heckman et al., 1998; Heckman and Navarro-Lozano, 2004). This group is used as a substitute for the non-observable counterfactual group (Caliendo and Kopeinig, 2008). More in detail, such procedure condenses the vector of relevant pre-treatment characteristics into a single scalar index, called the propensity score, which represents the probability of being treated, given the relevant covariates (Rosenbaum and Rubin, 1983). At a given value of the propensity score, the exposure to treatment should be random and therefore both treated and control units should be on average observationally identical.

In addition to the self-selectiveness and the selection process by public agencies, another source of bias in policy evaluation exercises is represented by the "hidden treatment effect". Specifically, it consists of a confounding factor arising when the effect of a treatment is estimated without taking into account its potential interactions with other treatments aimed at the same goal and operating in the same environment. Such a problem appears to be relevant in the present analysis since the innovation policy mix is usually made of several policy measures, including both *supply-push* (SP) and *demand-pull* (PP/IPP) instruments. As previously argued, the probability for the same firm of being involved in a double treatment scenario is not negligible, leading to biased policy effect estimates when hidden effects are not properly taken into account. In the examined cases, as reported in Table 1, among the 4.206 firms belonging to the whole sample, 1.165 received only public sustain by governments, 382 have been involved only in contracts of public furniture, while the remaining 321 treated firms have been interested by both public incentives for innovation and public procurement contracts. Moreover, among firms with IPP contracts 75 of them where involved in both IPP activities and supply push instruments, while 55 firms benefited only of IPP stimuli[7].

Thus, in order to eliminate possible sources of bias due to hidden treatment effects each treatment variable has been considered both in isolation and in combination.

TABLE 1. DESCRIPTION OF THE TREATMENTS

Treatment	Treated	Control	Description
SP_Only	1.165	75	Firms receiving only direct/indirect public sustain
PP_Only	382	2.338	Firms receiving only public procurement contract
SP&PP	321	2.338	Firms receiving direct/indirect public sustain and public procurement contract
IPP_Only	55	2.338	Firms receiving only innovative public procurement contract
SP&IPP	75	2.338	Firms receiving direct/indirect public sustain and innovative public procurement contract

In the first step of analysis I compare the average treatment effect (ATT) on the outcome variable (Y) deriving from different four treatments (namely SP_Only, PP_Only, SP&PP, SP&IPP) with the same baseline scenario characterized by the absence of any treatment.

Formally, for a given treatment *m*:

$$ATT\ (ATET) = E(Y_i^1 - Y_i^0 \mid m)=1 \qquad (5)$$

where Y_i^1 represents the outcome variable under the treatment program of interest *m* and Y_i^0 is referring to the outcome variable in absence of any type of treatment. Hence, each treated

7 I acknowledge the limited relevance of the sample of firms involved in IPP. The results presented in this paper should be intended as a first attempt to provide evidence on this specific type of PP contracts, which has been rarely studied in a quantitative policy evaluation context of analysis.

group is compared with the same control group composed by those firms characterized by the total absence of treatment.

In this first step of the analysis I can evaluate whether the effect of distinct or combined policies is positive and significant or not. However, the evaluation of the potential complementarities between different types of instruments is complicated by additional selection bias sources that may affect the estimation of the impact for jointly treated firms. Here, I argue that firms able to access both PP and SP policies might be structurally dissimilar from those not involved in any treatment as the two groups might well differ from each other in terms of capabilities and structural characteristics. This condition increases the heterogeneity among units and makes the two groups (treated and control) too different to be comparable even after matching (Ghisetti, 2018). Hence, a feasible way to correctly identify the existence of complementarities between distinct instruments could be to compare the double treated units with a reduced group of controls which is obtained by restricting the analysis to firms with at least one treatment and dropping the initial controls (firms not benefitting from any type of public policies). This may allow to increase the level of firms' homogeneity in the two groups (treated and control) as once treated units are supposed to be more similar to the double treated ones. Such a procedure is followed in our second step of analysis, when the ATET of jointly treated firms is compared with three control groups : (1) a control group made of firms receiving a single treatment, thus without distinguishing between SP and PP policies; (2) a control group comprising firms only benefitting from SP policies; (3) a control group formed by recipients of only PP policies.

The propensity score matching

In order to artificially create the counterfactual situation depicting the outcome of the treated under the untreated condition, the best pairs of treated and control firms have been identified by exploiting the propensity score matching for each of the four treatments on the basis of the pretreatment characteristics (X) retaining to affect both the treatments and the target variable. To provide unbiased estimated of ATT by using the generalized propensity score estimator, three assumptions need to be satisfied. The first is the conditional independence condition (CIA), also known as "confoundedness" assumption, which requires that all the systematic differences between "treated" and "untreated" units are removed through the *observable* variables identified as covariates (X)[8]. In other words, once it is controlled by the set of X, the potential outcomes are independent from treatment assignment. Given the difficulty to directly verify this strong assumption, I select all the covariates that could allow the condition to hold. The second condition is the SUTVA (Rubin, 1978), i.e. stable unit treatment value assumption,

8 The implications of CIA are discussed in Cerulli (2015).

which assumes that treatment applied to one unit does not affect the outcome for another unit. Finally, the third condition refers to the "common support" assumption according to which covariates themselves (X) should not perfectly predict the probability of receiving one specific treatment. The satisfaction of all these conditions allows the generalized propensity score matching estimator to consistently estimate the ATT.

The focus variable capturing the "input additionality" in the present analysis is represented by the total expenditures in internal and external R&D activities over the three-year period, whose use is very common in the literature (e.g Almus and Czarnitzki, 2003; Carboni, 2011; Mulligan et al., 2017). This amount has been divided by the mean of turnover referring to the same time window (R&D $_{\text{Turnover}}$) since expressing target-variables in ratios instead of levels allows for the reduction of collinearity with firms' size (Carboni, 2011) and ensures less volatile results (Cerulli and Potì, 2012).

The covariates adopted for the implementation of the propensity score method have been identified according to those aspects recognized by the literature as relevant in influencing both the participation to *push* and *pull* innovation policy programs as well as stimulating private R&D expenditures[9]. The summary statistics have been reported in Table 2. To properly control for firms' propensity in investing in R&D, a measure of financial constraints proxied by the bank interest paid by firms on their bank loans (*Bank_rate*) has been included among the regressors[10]. Many theoretical arguments justify the close relationship between financial constraints and R&D expenditures through the "financing gap hypothesis", according to which most R&D projects are founded by firms' internal resources instead of external ones. This is due to the difficulties faced by external investors in assigning the right value to the intangible assets created by R&D efforts and thus, in distinguishing good projects from bad ones. As a result, financial institutes could be reluctant towards R&D investments with the effect to create financial constraints and credit rationing (Bond and Meghir, 1994; Fazzari et al., 1988; Hoshi et al., 1991), by making R&D investments more sensitive to firms' internal financial resources (Hall, 2002; Hall and Lerner, 2009; Hall et al., 2016; Scellato, 2007). In case of liquidity constraints, the additional public financing works as an exogenous injection of cash-flow thus producing a positive increase of R&D expenditures (Cerulli and Potì, 2012). In this framework, financial constraints represent one of the main rationales beyond government intervention (Takalo and Tanayama, 2010) since firms affected by financial/liquidity constraints have been found particularly oriented towards government funding (Lach, 2002; Gonzalez *et al.,* 2005; Czarnitzki and Toole, 2007; Hyytinen and Toivanen, 2005). To construct the DEB variable, the logarithmic transformation has been applied to the interest rate variable by adding one to

9 A critical discussion of the empirical literature on the driving factors of R&D is provided by Becker (2013).

10 Other measures typically used for financial constraints (as for instance indebtedness represented by bank debts) are not adopted because they are missing for many observations.

avoid dropping zeros. A second regressor (*LogTurnover*$_{t-3}$), measured here by the logarithm of turnover referring to the first year of each three-year period considered, aims at capturing the influence of firms' dimension. In line with the "financing gap' hypothesis" sustaining the importance of internal financial resources in stimulating R&D investments, bigger firms tend to have larger cash flows. In addition, large firms could have more possibilities to engage in innovation activities thanks to better organization, easier access to financial markets and better opportunities to overcome the innovation-related barriers (Savignac, 2008; Pellegrino and Savona, 2013). In the same vein, I further control for group affiliation (*Group)* which may influence the amount of resources available to engage in R&D for affiliated firms, as well as their capacity to route the procedure for being engaged in public programs (González et al., 2005; Hussinger, 2008; Aristei et al., 2015).

Furthermore, in order to take into account the relevance played by specialized human capital in firms' knowledge capabilities, I include the variable *Empud* as the share of graduated employees on total employees (Piva and Vivarelli, 2009). The rationale for the inclusion of such variable is also strictly linked to the self-selection bias due to higher capabilities required to firms to be involved in policy programs (Huergo and Moreno, 2017). For the same reasons, an export dummy (*Export*) has also been included among the regressors, as firms operating in international markets might show higher innovative propensity than national market focused enterprises (Arnold and Hussinger, 2005) and could have higher capabilities in dealing with bureaucratic procedures compared with non-exporters (Takalo *et al.,* 2013). In addition, since more capital-intensive firms may have higher commitments to innovation than more *labour-intensive* ones (Carboni, 2011), a capital intensity variable is included. It is measured as the logarithm of the ratio between capital assets and turnover ($LogK_{Turnover\_t-3}$) referring to the first year of each tree-year period considered.

Finally, regional dummies and seven sectoral dummies[11] have been included to account for the unobservable effects due to territorial and sectoral heterogeneities.

11 The seven sector dummies included are CA, CB, CC, CD-CG, CH, CI-CL and CM (Statistical classification of economic activities in the European Community (NACE) Second Revision.

TABLE 2. SUMMARY STATISTICS

Variable	Obs.	Mean	Std. Dev.
Bank_rate	4,206	2.308	1.504
LogTurnover$_{t\text{-}3}$	4,206	17.123	1.695
Group	4,206	.72070	.449
Empud	4,206	2.602	1.537
Export	4,206	.900	.299
LogK$_{Turnover\_t\text{-}3}$	4,206	8.479	2.036
R&D$_{Turnove}$ *(%)*	4,206	2.389	5.910

SECTION 4

Results from the first-matching analysis

Table 3 shows the descriptive statistics for a total of 4.206 innovative firms belonging to the pulled sample. There are some interesting differences between non-treated firms (2.338 firms not participating in any policy program) and firms involved in the four different treatments identified, whose significance is confirmed by the results provided from tests on mean differences. For instance, when compared with the control group (T=0), firms that receive public sustain for innovation activities are found to pay higher interest rates, are larger and more oriented towards international markets, report a higher percentage of employee with tertiary education, are more capital-intensive and, finally, devote more resources to R&D activities. With respect to the same group of control firms (T=0), firms exclusively involved in PP contracts show a lower interest rate, count more graduated on their total workforce and show a major propensity to export. Finally, by focusing on the double treatment referring to the firms involved in both SP programs and PP contracts, the sharpest differences between them and the controls are related to the size, the group belonging, the number of graduated, the capital intensity and the higher propensity to engage in R&D expenditures. The same differences hold also for the subsample composed by firms receiving the double SP&IPP treatment.

TABLE 3. DESCRIPTIVE STATISTICS

	NOT TREATED	**TREATED**				
Variables		**SP_Only**	**PP_Only**	**SP&PP**	**IPP_Only**	**SP&IPP**
Bank_rate	2.27	2.45*	1.99*	2.29	1.78*	2.25
$LogTurnover_{t-3}$	16.95	17.25*	17.16*	17.77*	17.22	18.12*
Group	0.69	0.73*	0.76*	0.77*	0.87*	0.84*
Empud	2.40	2.65*	3.02*	3.34*	3.45*	3.74*
Export	0.89	0.94*	0.81*	0.90	0.83	0.90
$LogK_{Turnover\_t-3}$	8.28	8.74*	8.38	8.99*	8.40	9.37*
$R\&D_{Turnove}$ *(%)*	1.84	3.23*	1.57	4.21*	2.37	6.15*
N	**2.338**	**1.165**	**382**	**321**	**55**	**75**

* Variable mean differences between different groups of treated and control group (2.229 untreated firms) are statistically different from zero (t-test p-value < 0.05)

For the estimation of the propensity score referring to each treatment, I implement four logit models in order to compute the conditional probability of receiving the *m* treatment given the above set of covariates (X) by using T=0 as baseline.

As shown in Table 4, the major driver of the probability of being treated are firms' capabilities (*Empud*). The indicator is positively and significantly associated with all the treatments and its magnitude increases when the policies are taken in combination. Firms that face a higher rate of interest (*Bank_rate)* have higher odds of receiving both only financial incentives as well as the double treatment. Furthermore, the greater is the initial size ($LogTurnover_{t-3}$), the higher is the probability of being jointly treated. In addition, firms belonging to a group (*Group*) are less likely to get into the double treatment. Finally, more capital-intensive companies show major odds of receiving SP sustain, while export activities (*Export*) are positively associated with been involved only in a SP program and negatively related to the PP treatment, even when "innovative" (IPP).

TABLE 4. PROPENSITY SCORE ESTIMATES

	SP_Only	PP_Only	SP&PP	IPP_Only	SP&IPP
Bank_rate	0.0890*** (3.39)	-0.0569 (-1.46)	0.140** (3.12)	-0.112 (-1.21)	0.166 (1.88)
$LogTurnover_{t-3}$	-0.0297 (-0.66)	0.0436 (0.70)	0.330*** (4.38)	-0.0972 (-0.86)	0.363* (2.39)
Group	-0.101 (-1.04)	0.0785 (0.50)	-0.468** (-2.68)	0.732 (1.61)	-0.352 (-0.93)
Empud	0.0752** (2.77)	0.229*** (5.82)	0.296*** (6.65)	0.343*** (3.74)	0.467*** (5.32)
Export	0.375* (2.52)	-0.782*** (-4.63)	-0.426 (-1.83)	-1.052* (-2.39)	-0.863 (-1.84)
$LogK_{Turnover\_t-3}$	0.119*** (3.43)	0.00820 (0.18)	-0.00523 (-0.09)	0.0737 (0.70)	0.106 (0.90)
Sectoral dummies	Yes	Yes	Yes	Yes	Yes
Geographical dummies	Yes	Yes	Yes	Yes	Yes
Observation	3503	2720	2659	2393	2413
Pseudo_Rsquare	0.0246	0.0584	0.1019	0.1162	0.1802

Standard errors in parentheses. ***, **, * denote 1%, 5% and 10% levels of significance, respectively

The results for the first matching procedure are reported in Table 5. To better balance the *trade-off* between bias and efficiency different algorithms have been used (Caliendo and Kopeinig, 2006). Considering that the dimension of the control group largely exceeds that of the treated group, the 5NNM method has been chosen in order to increase the efficiency of the estimates. This technique consists in the identification of five observations which are closest to the treated unit in term of propensity score values. The goodness of the matching performance referring to the ability of the matching procedure to balance the distribution of the co-variates in both treated and control groups is provided by the fact that in the matched sample the standardized differences are all close to zero, and the variance ratios are all close to one. Furthermore, the graphs reported in the Appendix confirm the goodness of the matching procedure. Firstly, the distribution of the estimated propensity score before and after the pairing procedure signals the good quality of the procedure given the significant reduction in the dissimilarities between treated and control distributions after the matching. Secondly, the evidence that the overlap assumption is not violated is provided by the figures showing that for each treatment, the estimated densities have most of their respective masses in regions in which they overlap.

In addition, the validity of the matching procedure is supported by all tests for matching quality (see the figures A1-A5 reported in the Appendix). Firstly, the reduction of the mean standardized bias falls below 5% threshold in most of the cases, a condition which is already a sufficient to ensure the success of the pairing procedure (Rosenbaum and Rubin, 1985). Secondly, the pseudo R-square values are lower for matched firms when compared with unmatched ones. This evidence, suggesting that less variance is explained by the set of covariates in the matched firms, implies that the treated and untreated units are very similar to each other (Sianesi, 2004). Thirdly, the log-likelihood ratio tests on differences in covariates means are rejected before the matching and not rejected after the matching, showing that all *p-values* are lower than 0.05 (Ghisetti, 2017).

Interesting findings emerge from the results provided by the selected algorithm (5NN) and reported in Table 5. Since the outcome variable is expressed as the ratio between total R&D expenditures and turnover, the interpretation of the average effect of being involved in one of the three treatments *vs* the case of zero treatment, is almost immediate. Looking at isolated treatments I find that the average effect of receiving only public sustain funding (*SP_Only*) is statistically significant (the treatment increases the R&D/turnover ratio by 1.12 p.p.), suggesting that *technology-push* policies exert an additional impact on firms' private R&D investments. With regard to firms exclusively involved in PP contracts (*PP_Only),* the difference in the outcome recorded by treated and untreated units is negative and weakly significant. Similarly, when compared with the same control group, firms involved exclusively in the IPP procurement contract (*IPP_Only*) show a lower ratio of R&D on turnover, although this difference turns out to be not significant. To check for the robustness of our analysis, I implement four alternative algorithms, i.e. 1NNM, 3NNM, 3NNM with caliper and the Kernel method (Tables 6). In most cases, results remain unchanged with respect to both the significance and the sign of the impact. The only exception is represented by the narrowest group of treated, i. e. the *IPP_Only* sample, whose coefficients and signs change across the alternative algorithms but never gain significance. Finally, by focusing on simultaneous treatments, the most important finding concerns the average impact associated with the probability of being involved in the double treatment, i.e. *SP and PP,* which is higher than that associated with the *SP_Only* treatment. In fact, for double treated firms the ratio between R&D expenditures and turnover is 2,09 p.p. higher than that recorded for untreated firms. These results are confirmed by the estimates obtained by looking at the IPP policy. The double treatment referring to the variable *SP&IPP* determines an additional effect of 3.63% on the amount of R&D expenditure on turnover, which is remarkably high.

TABLE 5. RESULTS FROM 5NNM

Treatment	Coef. ATET(ATT)	S.E.	Z	P>|z|
SP_Only	1.126904***	.246545	4.57	0.000
PP_Only	-.4008825*	.238634	-1.68	0.093
SP&PP	2.090004***	.4261198	4.90	0.000
IPP_Only	-1.440802	1.503507	-0.96	0.338
SP&IPP	3.636453***	1.016387	3.58	0.000

* p< 0.1, ** p< 0.05, *** p< 0.01

These findings are comparable across the alternatives matching algorithms selected. 1NNM, 3NNM and Kernel algorithms (1000 repetitions) do not change the significance and the sign of the impact of different treatments on the outcome (Table 6).

These results offer the following insights. First, the impact exerted by *technology-push* policies when taken in isolation is positive and significant. This evidence is in line with previous literature and it is robust with respect to the confounding factors source of bias. On the other hand, the whole PP category does not result itself to produce an additional effect on the target variable. On the contrary, the effect is slightly negative suggesting that firms benefiting only from PP contracts appear to have less incentives to compete on markets through innovative investments. This might happen when the public sector assures a sufficient level of demand to firms, regardless the innovative content of the goods or services provided. Such an outcome confirms the non-obvious link between PP and innovation activities in countries like Italy, where the objectives and capabilities of contracting authorities are not favorable to generating innovation enhancing effects deriving from public demand. Finally, the evidence from the *first-stage* of analysis would suggest that, in line with the evidence provided by Guerzoni and Raiteri (2015), complementarity effects between the *push* and *pull* tools positively shape R&D investments. However, I claim that this result might suffer from selection bias as previously argued. This issue is discussed in the next section.

TABLE 6. ROBUSTNESS

Treatment	1NNM	3NNM[a]	KERNEL 1 NNM[b]
SP_Only	.923797***	.9749264**	.923797***
PP_Only	-.0519058	-.397396*	-.0519058
SP&PP	2.240973***	2.169847***	2.240973***
IPP_Only	-2.467.046	-.8842317	.3971646
SP&IPP	4.109721***	4.109721***	4.109721***

* p< 0.1, ** p< 0.05, *** p< 0.01

a The same algorithm (3NNM) has been implemented by imposing the "caliper" threshold (0.25 times the standard deviation of the propensity scores recovered with the multinomial logit models) which imposes a tolerance level on the maximum propensity score distance to avoid bad matches. Results remain unchanged.

b Bootstrapped standard error, 1000 repetitions.

Results from the second-matching analysis

In this stage of the analysis I evaluate the effect of the double SP&PP treatment on innovation (321 cases) by considering three groups of controls that are made of: 1.547 firms with one treatment (1), either SP or PP; 1.165 firms benefitting only from SP instruments (2) and 383 involved only in PP contracts (3). Such a further investigation is highly recommended for a better control of selection-bias issues. Indeed, there is reason to believe that, compared to companies that do not participate in SP or PP policy programs (T=0), firms involved in at least a single policy (SP or PP) are more close to those getting into a double policy treatment (SP&PP) in terms of research capabilities, network interactions and structural characteristics. Building on these considerations, the purpose of this second stage is reducing "*ex ante*" the heterogeneity among firms by performing the analysis on more homogeneous samples of treated and controls.

However, considering that between the double treated and the new controls some differences still persist (especially when looking at the size, firms' capabilities, capital-intensity and propensity to engage in R&D expenditures, as shown in in Table 7), a PSM analysis is needed also in this case.

TABLE 7. DESCRIPTIVE STATISTICS

Variables	**Treated**	**Control Group**		
		Sample (1)	**Sample (2)**	**Sample (3)**
	SP&PP	**All *firms with 1 treatment***	***Firms involved in SP programs***	***Firms with PP contracts***
Bank_rate	2.30	2.34	2.46	**2.01***
LogTurnover$_{t-3}$	17.77	**17.24***	**17.26***	**17.17***
Group	0.77	0.74	0.73	0.76
Empud	3.33	**3.74***	**2.65***	**3.02***
Export	0.90	0.91	0.93	**0.81***
LogK$_{Turnover_t-3}$	8.99	**8.65***	8.74	**8.38***
R&D$_{Turnove}$ (%)	4.22	2.78	**3.23***	**1.52***
N	**321**	**1,547**	**1,165**	**383**

* Variable mean differences between different groups of treated and control group (2.228 untreated firms) are statistically different from zero (t-test p-value < 0.05).

The propensity score referring to the double treatment SP&PP is calculated by implementing three logit models on three different sample: firms with one of the two types of treatment (1); firms involved in SP programs (2); firms with PP contracts programs (3). This allows for the computation of the conditional probability of receiving both treatments for firms already involved in a policy program (1), by further distinguishing between SP (2) and PP tools (3), given the same set of covariates X applied in the first stage.

TABLE 8 - PROPENSITY SCORE ESTIMATES. PROBABILITY OF BEING DOUBLE TREATED

	Sample (1) **All *firms with 1 treatment***	**Sample (2)** ***Firms involved in SP programs***	**Sample (3)** ***Firms with PP contracts***
Bank_rate	0.0959* (2.08)	0.0531 (1.09)	0.214*** (3.73)
LogTurnover$_{t-3}$	0.294*** (4.05)	0.391*** (4.79)	0.216* (2.38)
Group	-0.464* (-2.54)	-0.404* (-2.13)	-0.601* (-2.55)
Empud	0.196*** (4.22)	0.264*** (5.25)	0.0670 (1.16)
Export	0.375* (2.52)	-0.863 (-1.84)	-0.426 (-1.83)
LogK$_{Turnover\_t-3}$	-0.0847 (2.03)	-0.190** (3.01)	0.0445 (0.90)
Sectoral dummies	yes	yes	yes
Geographical dummies	yes	yes	yes
Observation	1,868	1,486	703
Pseudo_Rsquare	0.0489	0.0776	0.0655

t statistics in parentheses; * p< 0.1, ** p< 0.05, *** p< 0.01

As shown in Table 8, the major drivers of the probability of receiving a second treatment for firms already involved in one policy instrument are size (*LogTurnover*$_{t-3}$) and the quality of personnel capabilities (*Empud*). A weak but positive impact is also displayed by *Bank_rate* and *Export* variables, while a negative and weakly significant correlation is found for the variable *Group*. However, when accounting for the type of policy in which a unit is already involved, I observe that the positive impact of size and firms' capabilities mainly hold for firms already involved in SP programs (2), where the probability of receiving the PP treatment is also found to increase when the capital-intensity (*LogK*$_{Turnover\_t-3}$) decreases. In contrast, firms benefitting from PP contracts seem to increase their odd of getting into a SP measure when paying higher interest rate.

The goodness of the new matching performance is provided by Figures A8-A10 and tests (Table A12) for matching quality reported in the Appendix. Table 9 shows results from the selected algorithm (5NNM) and provides also calculations from the alternatives matching algorithms (1NNM, 3NNM and Kernel algorithms) included as robustness checks. Results remain unchanged along all different options in most of the cases.

TABLE 9 - RESULTS & ROBUSTNESS

Control group	Algorithm	Coef. ATET	S.E.	Z	P>|z|
Firms with 1 Treatment (1)	5NNM	1.344878***	.4069606	3.30	0.001
	1NNM	1.365652***	.456462	2.99	0.003
	3NNM	1.496027***	.4078093	3.67	0.000
	KERNEL (1NN)[a]	1.365652**	.5747319	2.38	0.017
Only_SP (2)	5NNM	.7631378*	.4337044	1.76	0.078
	1NNM	.8828199	.5398282	1.64	0.102
	3NNM	.904991**	.4532852	2.00	0.046
	KERNEL (1NN)[a]	.8828199	.7385073	1.20	0.232
Only_PP (3)	5NNM	2.584441***	.3904182	6.62	0.000
	3 NNM	2.402056***	.4377315	5.49	0.000
	1 NNM	2.64049***	.3907199	6.76	0.000
	Kernel (1NN)[a]	2.402056***	.4598702	5.22	0.000

* $p< 0.1$, ** $p< 0.05$, *** $p< 0.01$

[a] Bootstrapped standard errors, 100 repetitions;

Interestingly, by reducing the control sample to firms involved in one policy treatment (1), thus not distinguishing between SP and PP policies, I find that those getting into the double treatment show a higher propensity to engage in R&D expenditures over their once-treated peers (+ 1.34 p.p.). However, when narrowing the controls to group (2) and (3), I observe a reduction in this estimated effect. Firms involved in SP programs (2) receive from the PP treatment only a marginal, and weakly significant, stimulus for increasing their R&D expenditures. On the other hand, the amount of R&D expenditures reported by double treated companies significantly increases (+ 2.58 p.p). when compared with SP controls (3). Hence, there is reason to believe that the strong effect associated with the double treatment SP&PP in the first stage of the analysis was mainly driven by the selection bias arising from the involvement in both treatments. Moreover, while the relevant role of SP policies in fostering firms' R&D expenditures decisions is here confirmed, the complementarity effects between the two types of instruments appear to be limited. This latter evidence might be explained by the arguments outlined in section 3, suggesting that only under specific circumstances PP might represent a powerful engine of innovation investment, which may differ across countries and sectors.

SECTION 5

Conclusions

The present paper investigated the joint and isolated impact of *supply-side* and *demand-side* measures on firms' R&D investments. In so doing the paper contribute to the existing literature by enlarging the quantitative evidence on the effectiveness of both types of policies thanks to the fresh information provided by the Italian Community Innovation Survey. Moreover, from a methodological perspective, the proposed analysis complements previous evidence by paying particular attention to selection-bias issues that might affect the reliability of results. From the two-stage counterfactual analysis, two main findings have emerged. Firstly, consistently with previous literature, the effectiveness of SP in spurring innovation activities has been confirmed also after controlling for the presence of *demand-pull* instruments as potential source of bias. This means that, regardless to the presence of *demand-pull* instruments, in absence of public funding (grants, soft loans, tax reliefs) the amount of privately funded R&D would have been smaller.

Secondly, the role of PP as innovation-enhancing instrument turns out to be largely ineffective both when considered in isolation and in combination with SP policies. Considering the renovate emphasis recently attached to the public demand as lever of innovation, this result may be striking at first. However, rationales for this finding are provided by the marginal role that PP currently plays in the innovation policy arena. To be an *effective innovation-inducing* tool, PP has in fact to overcome a considerable number of barriers at administrative level, that are basically due to the lack of institutional capacities and coordination practices among procuring entities (Kattel and Lember, 2015; Lember et al. 2015; Rolfstam; Amann and Essig, 2015; Georghiou et al., 2013; Albano and Sparro, 2010). More in general, in many countries like Italy, PP appears to be still far from being that "radical" policy (Iossa et al., 2017) able to allow for huge transformative innovations by stimulating an adequate demand of technological knowledge (Nyiri et al. 2007; Kattel and Mazzucato, 2018). In this way PP appears to represent an "incremental" practice mainly based on management-inspired performances (Verhoest et al. 2011) and typically issued at the achievement of short-term efficiency gains through minimum risk-taking and maximum competition (Kattel and Lember 2010).

From a policy perspective our results suggest that although increasing importance has been recognized to procurement as a way to stimulate innovation, when this instrument is not specifically designed to this aim its effectiveness appears to be limited. In this respect a change in the vision of PP agencies in order to sustain the undertaking of more innovative, risky and long-term projects and, to invest in internal skill building practices appear to be needed.

In conclusion, it has to be recognized that additional research is needed to further investigate the examined issues. Firstly, it would be interesting to compare the results obtained in the Italian case with those of other countries. Secondly, concerning SP instruments, it would be worth to distinguish between different tools, in particular public R&D subsidies, tax credits or loans. Moreover, it would be interesting to evaluate the impact of different instruments by having information on the monetary amount of both PP contracts and SP incentives. Finally, the use of data with qualitative information on the tender would allow for a better identification and comprehension of the mechanism related to the PP and innovation nexus.

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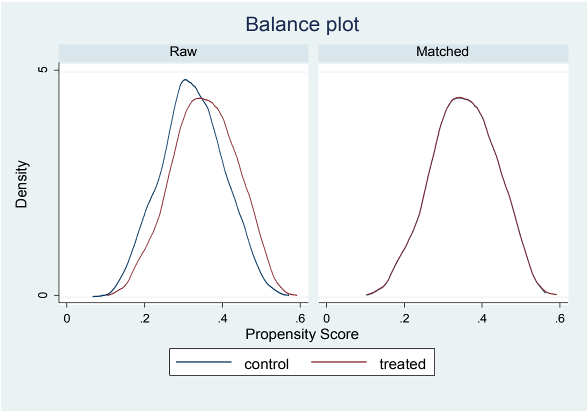
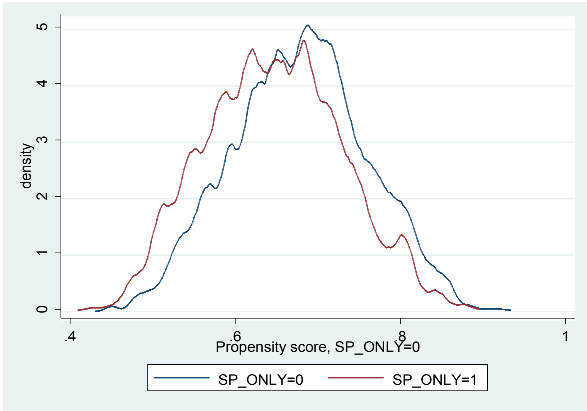
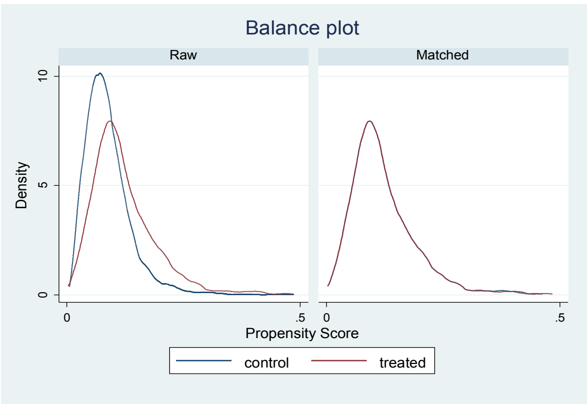
Appendix

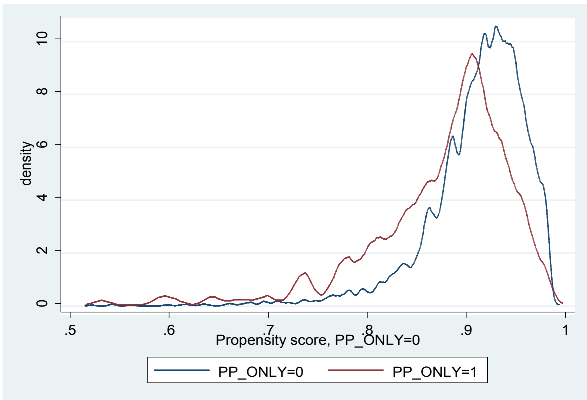
Figures A1 - Distributions of the propensity score (left) and overlap assumption (right) for the treated and the not-treated group before (blue line) and after (red line) the matching for T=SP_Only



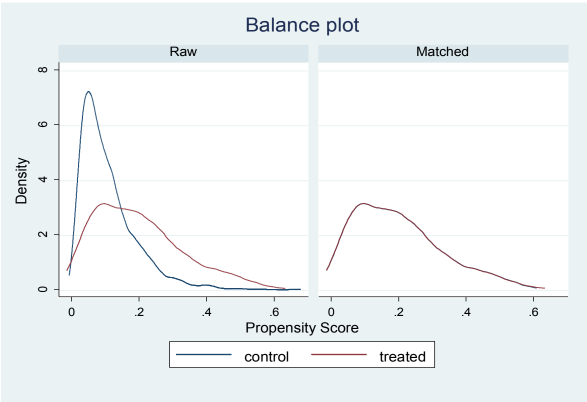


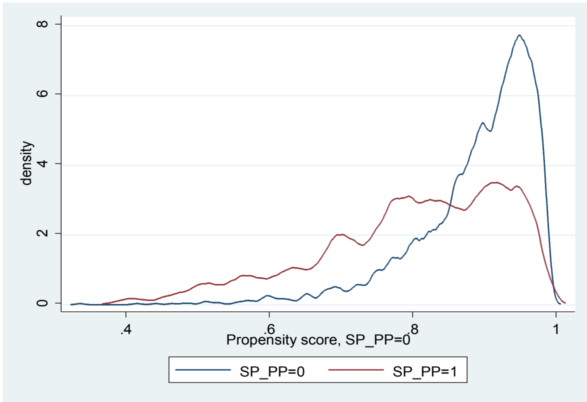
Figures A2 - Distributions of the propensity score (left) and overlap assumption (right) for the treated and the not-treated group before (blue line) and after (red line) the matching for T=PP_Only



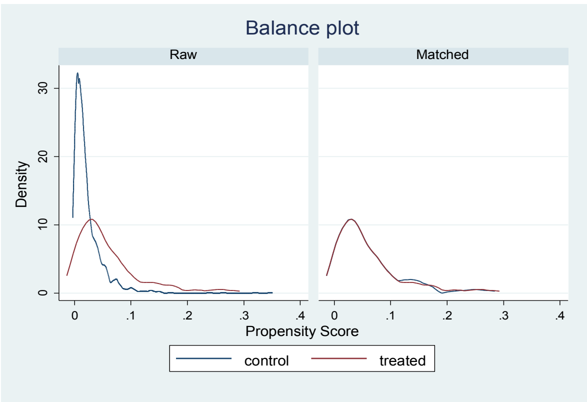


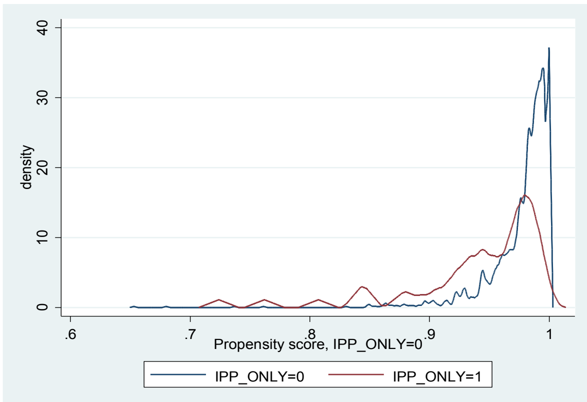
Figures A3 - Distributions of the propensity score (left) and overlap assumption (right) for the treated and the not-treated group before (blue line) and after (red line) the matching for T=SP&PP



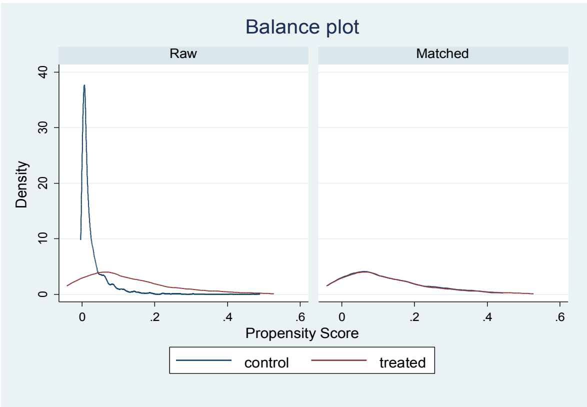


Figures A4 - Distributions of the propensity score (left) and overlap assumption (right) for the treated and the not-treated group before (blue line) and after (red line) the matching for T=IPP _Only





Figures A5 - Distributions of the propensity score (left) and overlap assumption (right) for the treated and the not-treated group before (blue line) and after (red line) the matching for T=SP&IPP



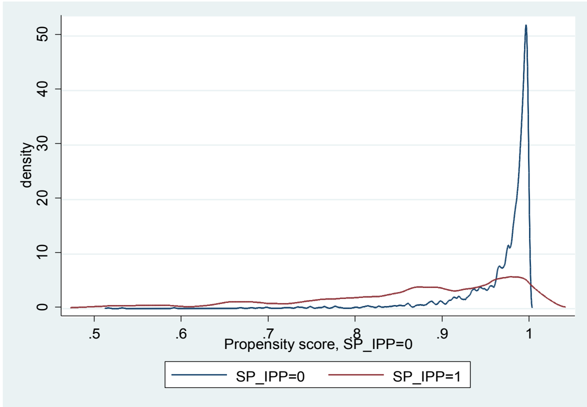


TABLE A6. RESULTS OBTAIN USING THE PSMATCH2 COMMAND (FIRST-MATCHING PROCEDURE)

Treatment	Treated	Controls	Difference (ATT)	S.E	T stat
SP_Only	3.12189614	1.80270788	**1.31918826**	.234064546	5.63
PP_Only	1.52767652	1.80270788	**-.533309892**	.236677772	-2.25
SP&PP	4.21661893	1.80270788	**2.31135225**	.438321731	5.27
IPP_Only	2.37477073	1.80270788	**-1.85636263**	.63827821	-2.91
SP&IPP	6.1547905	1.80270788	**4.33391385**	.998173983	4.34

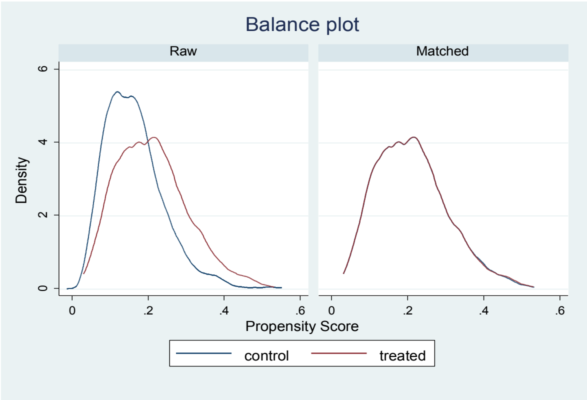
Note: the main disadvantage of psmatch2 over teffects is that the latter does not take into account the fact that propensity scores are estimated rather than known when calculating standard errors.

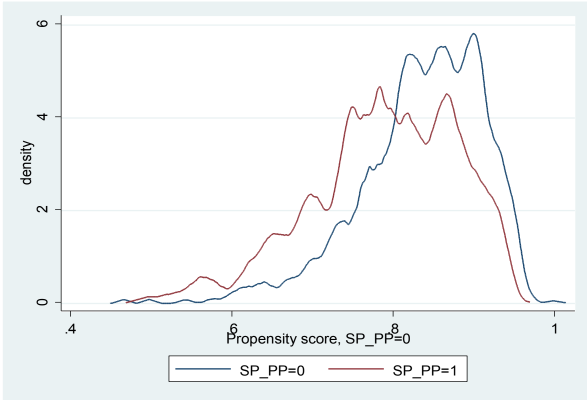
TABLE A7. BALANCE OF THE FIRST-MATCHING PROCEDURE

Treatment	Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias
SP_Only	Unmatched	0.025	109.18	0.000	10.0	8.8
	Matched	**0.000**	**0.98**	**1.000**	**0.9**	**1.0**
PP_Only	Unmatched	0.057	126.63	0.000	15.3	13.1
	Matched	**0.002**	**2.01**	**1.000**	**2.5**	**2.6**
SP&PP	Unmatched	0.099	193.50	0.000	19.9	11.8
	Matched	**0.004**	**3.35**	**0.998**	**3.1**	**3.5**
IPP_Only	Unmatched	0.092	46.81	0.000	24.5	16.7
	Matched	**0.012**	**2.83**	**1.000**	**4.6**	**4.7**
SP&IPP	Unmatched	0.168	112.08	0.000	30.9	29.1
	Matched	**0.016**	**3.35**	**0.998**	**5.1**	**4.8**

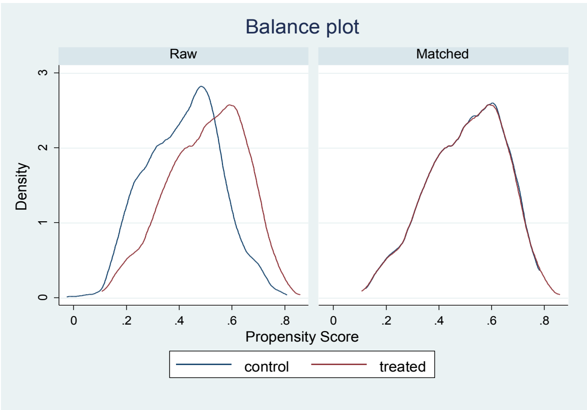
Note: Balancing tests obtained after running the psmatch2 command.

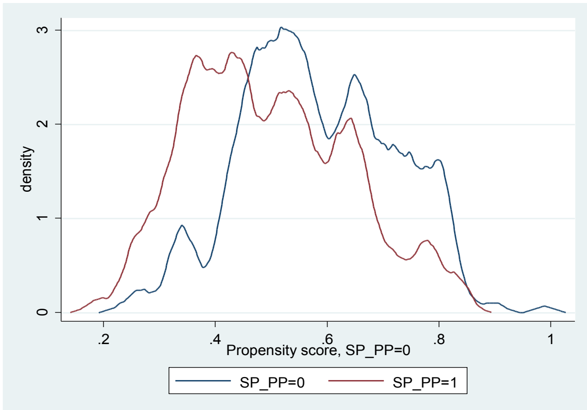
Figures A8 - Distributions of the propensity score (left) and overlap assumption (right) for the treated and the not-treated group before (blue line) and after (red line) the matching for control group (1)



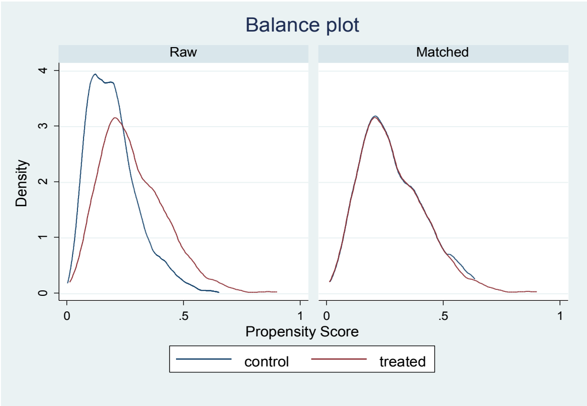


Figures A9 - Distributions of the propensity score (left) and overlap assumption (right) for the treated and the not-treated group before (blue line) and after (red line) the matching for control group (2)





Figures A10 - Distributions of the propensity score (left) and overlap assumption (right) for the treated and the not-treated group before (blue line) and after (red line) the matching for control group (3)



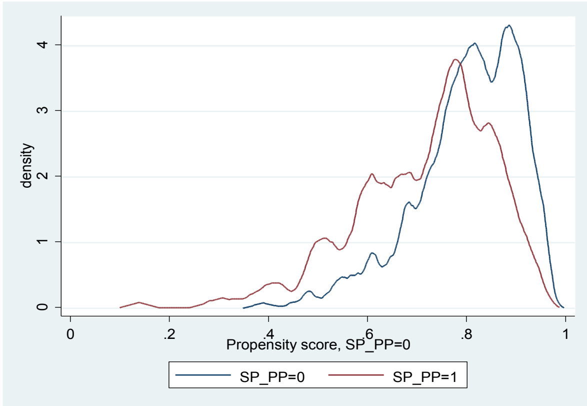


TABLE A11. RESULTS OBTAIN USING THE PSMATCH2COMMAND (SECOND-MATCHING PROCEDURE, TREATMENT= SP&PP)

Control group	Treated	Controls	Difference (ATT)	S.E	T stat
Firms within 1 Treatment (1)	4.22502196	2.72823622	**1.49678574**	.378461528	3.95
Only_SP (2)	4.22502196	3.55680989	**.682645879**	.488824403	1.40
Only_PP (3)	4.22502196	1.52767652	**2.68223985**	.441717828	6.07

TABLE A12. BALANCE OF THE SECOND-MATCHING PROCEDURE

Sample	Ps R2	LR chi2	p>chi2	MeanBias	MedBias
Firms within 1 Treatment (1)	0.048	83.01	0.000	12.9	8.0
	0.004	3.50	0.998	3.5	2.8
Only_SP (2)	0.065	63.14	0.000	13.9	10.3
	0.005	4.58	0.991	4.0	4.0
Only_PP (3)	0.077	119.56	0.000	15.7	12.1
	0.004	3.84	0.996	4.4	4.0

Note: Balancing tests obtained after running the psmatch2 command.

Investigating the policy determinants of eco-innovation modes

Abstract

The present chapter investigates whether and to what extent firms pursuing different approaches to environmental innovation differently "score" on policy measures. The analysis shows that distinct "modes" of eco-innovating are related to distinct institutional drivers, among environmental and innovation policies. Indeed, the study directly keys into the debate in the literature about to effectiveness of distinct public policies in spurring EI by providing an enriched and more nuanced view of environmental innovation processes, with important implications for theorizing about policies aiming at fostering the transition towards increased sustainability.

Keywords: *Environmental Innovation, Environmental Policies, Innovation Policies, Innovation Modes, Cluster analysis*

SECTION 1

Introduction

Market failures might be responsible for the suboptimal supply of both environmental protection and green innovations. This provides rationales for public actions able to sustain pollution reduction while encouraging the development and adoption of environmentally beneficial technology (Jaffe et al., 2005).

Within this framework, a broad research effort has been devoted at understanding whether and to what extent public policies success in providing incentives for the adoption of better abatement technologies. Most of it confirms the primary role of both environmental (Aghion et al., 2016; Brunnermeier and Cohen, 2003; Calel and Dechezlepretre, 2016; Jaffe and Palmer, 1997; Popp, 2006; Triguero et al., 2015) and innovation policies (Horbach 2012; 2016; Ghisetti; 2018) in fostering the pace of introduction and diffusion of environmental technologies.

Basically, these contributions analyze distinct institutional drivers by making use of a broad definition of environmental innovation (here-after EI) or, at best, by identifying EI in row classes (as for example *efficiency-improving vs pollution-reducing, product vs process* or *end-of-pipe technologies vs cleaner production technologies*).

However, a step forwards in the identification of EI's features has been recently made by a fresh stream of literature. This new approach claims that environmental objectives representing the starting point of EI processes (Jakobsen and Clausen, 2016; OECD, 2005, Paulraj, 2009;)

might be achieved by means of several technological trajectories (Castellacci and Lee, 2018) and distinct combinations among forms of knowledge (Marzucchi and Montresor, 2017). Accordingly, as environmental goals are strictly linked to policy drivers and distinct policies may induce to different EI behaviors (Marin et al., 2015), here it is argued that investigating the relations between environmental objectives and policy determinants is of paramount importance for launching accurate policy actions on EI activities.

In order to provide a contribution in this direction, the present chapter bridges together these two research lines and investigates the policy determinants of distinct patters of environmental innovation, here-after "EI modes". In particular, the following research question is asked:

"*Whether and to what extent are policy drivers different within firms with distinct environmental modes?*

To assess this issue, after reviewing both environmental and innovation policy drivers of EI and their potential links with different environmental strategies, a large-scale survey data provided by the Italian Community Innovation Survey is exploited in order to examine to what extent firms pursuing different approaches to environmental innovation differently "score" on policy measures.

This study contributes to the literature in two ways. The first contribution consists of the framework of innovation modes which, in the vein of the evolutionary theory (Nelson and Winter, 2009, Nelson, 1991¸ Tether and Tajar, 2008), provides evidence that firms pursue several approaches to EI. A related contribution is that this research directly keys into the debate in the literature about to effectiveness of distinct public policies in spurring EI, with the added insight of recognizing the role of distinct policy tools in shaping several EI dynamics. Thus, an enriched and more nuanced view of EI processes is here provided, with important implications for theorizing about policies aiming at fostering the transition towards increased sustainability.

The remainder of this chapter is organized as follows. Section 2 provides a synthetic but extensive survey on the institutional determinants of EI while Section 3 discusses the research questions. Section 4 presents the data, the empirical application and illustrates the results. Finally, Section 5 concludes by discussing the main findings.

SECTION 2

The role of public policies

The key role of public policies in managing sustainable transition has been emphasized by a large number of empirical studies devoted at investigating the potential role of public policies in supporting the introduction and diffusion of new environmental technologies (Del Río, 2009; Foxon, 2013; Horbach, 2008; Mowery et al., 2010; Newell, 2010, OECD, 2005, 2010; Triguero et al., 2013). Among the several classifications proposed by scholars (e.g., Crespi and Quatraro, 2013, Crespi et al, 2015; Del Río et al., 2010; Kemp, 1997; Rennings, 2000; Wieczorek and

Hekkert, 2012), policy tools may be grouped into two pillars belonging to environmental and innovation policy domain, respectively (see Crespi 2016 for a detailed list).

The role of environmental policies

The first category refers to environmental policies, that consist of regulation/command instruments (CACs) and market/price-based tools (MBIs).

The CAC's group includes measures imposed by institutions, as for example a performance standard to be met or a technology to be adopted, as well as a certificate or registry over harmful substances to be used. MBI tools encompass environmental taxes and cap and trade systems. The former aim at directly internalizing in the producers the external costs of pollutant activities that are spread over the society in terms of environmental damage by taking different forms, as taxes on energy, SO2 and NOx emissions or taxes on inputs of production processes (water, fuel, use of pesticides) or outputs (air tickets). On the contrary, the latter impose an upper threshold for selected pollutants (cap) after that permits to pollute are allocated and traded (trade) in order to achieve a cost-effective way to reduce emissions.

Both CACs and MIBs present pros and cons. When compared to decentralized incentive systems, such as MIBs, *standards-based* policies are considered less dynamically efficient as the imposition of a standard does not provide enough long-term innovative incentives to develop alternative and better technologies. Otherwise, technology standards may increase the risk of getting stuck into technological "lock-in" since these instruments tend to basically promote the adoption of the less costly technology available when the regulation is established (Kemp, 2000). For all these reasons, CAC instruments may discourage the exploration of radical, and much costly, innovation activities in favor of more incremental and less effective solutions as, for example, *end-of-pipe* technologies. So that, CACs may reduce the potential positive impact of innovation in terms of broader and more ambitious environmental goals (Frondel et al. 2008, 2010; Jaffe et al., 2002;).

On the contrary, the incentives provided by MIBs policies may be more persistent than those associated with CACs, as the former do not vanish when the goal has been met. In this view, MBIs may guarantee a constant demand for innovation (Stewart, 1981). Therefore, in providing a stimulus for going beyond environmental standards, MBIs may create incentive for the exploration of not-incremental innovation (Popp, 2006), thus accelerating the pace of radical innovations and enabling the development of *cost-efficiency* environmental technologies (Crespi et al. 2015, Crespi, 2016).

However, the superiority of MBI's on CACs is not conclusive for, at least, two reasons. First, the effectiveness of economic instruments in stimulating EI strictly relies on firms' responsiveness to price signals which, in turn, may induce firms to lose incentive in introducing green technologies when the cost of polluting is not sufficiently high. Second, if established unliterally in sectors characterized by huge environmental costs and sheltered from international competitiveness, MBI systems risk generating serious competitive disadvantages when compared to countries whit less strict regulations.

Regarding the pros of technology-forcing standard, CACs may overperform MBIs in boosting the diffusion speed of environmental technologies by means of two channels. First, when a technological standard is adopted by a country, exporting countries are consequently forced to adapt their processes and products to the new requirement. Second, adopting countries are also in the condition to penetrate markets where environmental standards have been already established.

In this framework, the relationship between environmental policies and EI is still debated in the discussion on how translate the demand for a greener environment by designing effective policies. For instance, Rennings (1998) claims that environmental regulation is the most cost-efficient way of spurring EI, while Porter and van der Linde (1995) and Kammerer (2009) point the emphasis on the pivotal role played by regulation-inducing EI in providing adopters with competitive advantages as, according to this view, regulation is expected to change both level and nature of competition between companies. Kemp and Andersen (2004) look at regulation as a way to shape EI instead of start or stop it, while Khanna et al. (2009) and Maxwell et al. (2000) argue that only when anticipated, environmental policies provide sufficient stimuli for EI. In emphasizing the role of the policy quality, Costantini and Mazzanti (2012) sustain that only if "properly designed" environmental regulation can promote the development of green technologies instead of harming firms' productivity and competitiveness (Brock and Taylor 2005) through higher production costs (Hicks, 1932).

From the empirical point of view, the early studies investigating the link between public policies and innovation have largely made use of the notion of environmental pressures. In specific, pollution abatement and control expenditures (PACE) have been often adopted as environmental policy indicators. For instance, the pioneering econometric study by Jaffe and Palmer (1997) carried out on US manufacturing sectors during the period 1973-1991 shows that environmental regulation stringency, proxied by PACE, positively affects R&D expenditures but not patenting activities. Post-sequential studies using similar analytical frameworks, confirm the potential positive effect of environmental regulation on innovation for US (Brunnermeier and Cohen, 2003), Taiwan (Yang et al., 2012) and Canada (Patry and Lajeunesse, 2008).

With a more narrowed perspective, other analysis focusing on distinct environmental policy instruments argue that superior technological responses to environmental pressures may be induced by both standard and economic incentives. Popp (2006) finds that MBIs are more effective than CACs in stimulating patenting activities in Germany, US and Japan. Similar evidences emerge in Triguero et al., (2015), where EI's determinants are scrutinized for 5,135 SME located in 27 European to scrutinize EI's determinants. The analysis shows that MBIs (measured as environmental taxation) are key factors in explaining the adoption of cleaner technologies, especially when firms are medium in size. In the same vein, Aghion et al. (2016) claim that tax-inclusive fuel prices induce clean technologies innovations, while Calel and Dechezlepretre (2016) find that the involvement in MBI programs (namely the European Union Emission Trading System) increases firms' probability of engaging in low-carbon patent activities by 10%, without crowding-out effects on other technologies.

Different findings have been provided by a bulk of empirical evidences where CACs have been found to overperform MBIs in boosting firms' environmental-friendly behaviors. For instance, exploiting 2003 firm-level data for 7 OECD countries, Frondel et al. (2008) point out that CACs are more important in promoting non-incremental innovation (*end-of-pipe* technologies) than more radical one (cleaner production technologies), while MBIs appear ineffective for both *end-of-pipe* and cleaner technologies. The positive link between CACs and *end-of-pipe* technologies is also found by Demirel and Kesidou (2011), who confirm the ineffectiveness of MBIs (measured as environmental taxation) in sustaining more radical EI activities, such as cleaner production technologies and environmental R&D investments.

The role of innovation policies

The realm of innovation policy embraces both *supply-push* and *demand-pull* instruments. The former concern subsidies in the form of grants, tax reduction and soft or interest-free loans, while the latter essentially refer to green purchasing by governments. According to the classical view of public intervention, the use of these instruments deals with the correction of innovation-related market failures, such as (i) uncomplete appropriability, (ii) financial barriers and (iii) uncertain demand. In this context, innovation policies are expected to provide private agents with incentives to raise the investments' level up to the socially optimal equilibrium (Arrow, 1962).

In general, the first two failures call for *supply-push* policies. On the one hand, technological spillovers stemming from innovative investments do not guarantee the complete appropriability of innovation outcomes, because the imitation might be too easy or the probability that other may benefit from the innovation is too high. On the other hand, the highly risky and uncertain nature of innovation discourages external investors from financing R&D projects. Both these failures generate an under-investment in innovative activities, especially when firms are small and belong to high-tech firms (Canepa and Stoneman, 2003; Hottenrott and Peters, 2012). In this context, *supply-push* measures may provide firms with sufficient funds to implement private innovative investments (Bronzini and Piselli, 2016).

Thanks to data provided by Community Innovation Surveys, *supply-side* innovation policies have been included in the analysis of the role of public intervention in shaping EI dynamics. In so doing, a significant step forwards has been made in the direction of understanding the diversification of the impacts exerted by environmental and innovation policies on EI, especially for *pollution-reducing* and *energy-improving* classes (where the latter are supposed to decrease the use of materials or energy per unit of output, while the former are expected to reduce negative externalities, such as reduction of air, soil, water and noise pollution and dangerous materials without *input-improvement*s). These two typologies have been found to be inherently different, either in the policy drivers. For example, Veugelers (2012) using data from CIS 2006-2008 for a sample of 2.894 Flemish firms, claims that *supply-push* government instruments are less effective in spurring the adoption of *pollution-reducing* and *energy-improving* technologies, while environmental policies (regulation and taxes) turn to be always relevant. Horbach (2016) exploits data from CIS 2006-2008 to analyze the determinants of EI in 19 countries. His main finding is that regulation factors are more important for *pollution-reducing* technologies, while their influence on *energy-improving* technologies appears to be less relevant. This result seems to be stronger for countries located in Eastern Europe, where the concentration of *pollution-reducing* technologies is supposed to be higher because firms face lower levels of environmental standards. Moreover, this category appears positively correlated with *supply-side* measures (mainly subsidies) while, on the contrary, *efficiency-improving* EI turns out to be more related to cost-saving considerations and innovation input, such as R&D expenditures. Analogous findings have emerged in a narrowed analysis focusing on the German case (Horbach et al., 2012). In a similar framework, Doran and Ryan (2016) assess the casual correlation between EI and three groups of drivers: demand-side, supply-side and regulatory variables. The authors draw data from CIS 2008-2010 referring to a sample of 2.127 Ireland firms. They find that the group of regulatory variables, including existing and expected regulation and environmental drivers, is of importance for both typologies.

Moving to *demand-side* measures, rationales for this class of innovation policies are provided by the existence of demand uncertain for green technologies, a market-failure which is partly related to government policy unpredictability (Kemp, 2000). In this case, the main operative tool is Green Public Procurement (GPP). Namely, it consists of the introduction of environmental criteria into tendering procedures in the view of reducing the environmental impact of public purchases, especially for those sectors responsible for high environmental impact, such as transport, buildings and furnishings. In principle, by setting sustainability requirements in public tendering, the use of public demand for greener goods and services may enlarge market opportunities for existing environmental-friendly products, thus providing new stimuli for environmental innovation through the creation of a minimum critical mass for sustainable goods and services that, otherwise, would difficulty get into the market.

Despite of the importance of this policy tool, scarce evidence has been provided about the role of procurement in sustaining the engagement in innovation activities (Aschhoff and Sofka 2009; Guerzoni and Raiteri, 2015; Crespi and Guarascio; 2017), and even less attention has been paid towards Green Public Procurement. In this respect, Cheng et al., (2018) recognize an overall lack of theoretical and empirical analysis devoted at assessing GPP as an environmental policy instrument, as well as to fully understand its innovation properties. Though not focused on GPP, a contribute in this direction has been provided by Ghisetti (2017), where a positive and significative impact of contracts of public furniture with innovative requirements on EI adoption has been found for manufacturing firms belonging to different European countries.

SECTION 3

Research questions

Existing research has shown that both environmental and innovation policies may influence firm's ability in introducing green technologies. As above argued, much literature has pointed the attention on the dichotomy between *pollution-reducing* and *energy-improving* innovations by investigating, among other issues, their links with environmental and innovation policy drivers. In general, the existing empirical evidence shows that, regarding environmental policy tools, CACs are of importance for *pollution-reducing* activities while MBIs appear mainly associated, although less frequently, to *energy-improving* innovations. Moreover, the latter turn out to be positively correlated with innovation tools and, in particular, with *supply-side* tools since as the impact of *demand-side* measures is still scarcely investigated.

In this framework, though an extensive bulk of studies highlights the primary role of public policies in shaping eco-innovation dynamics, there is still space to deep investigate the link between policy and EI by introducing in the analysis the issue of heterogeneity among green innovation strategies.

This hint stems from a recent stream of literature claiming that firms engage in different "modes" of EI instead of following a unique pattern. This aspect is well undelighted by two recent empirical studies.

The first is a study by Marzucchi and Montresor (2017), who look at the "technological" side of EI by exploiting the STI (science-technology innovation) and DUI (doing users innovation) dimensions. In retaining the diverse nature of EI targets, the scholars distinguish efficiency (material and energy reducing process innovations) and non-efficiency related (e.g. *end-of-pipe* technologies) process innovation from green product innovations. The paper draws data from two non-overlapping waves of Spanish Innovation Panel (PITEC) that covers a sample of 4.700 manufacturing firms for the period 2007-2012. Their major finding concerns the so-called hybrid innovation mode, which consists of a combination of STI and DUI that firms are likely to adopt when introducing environmental innovations. In this regard, since as different configurations of STI and DUI correspond to distinct environmental innovations, the scholars conclude that, according to the final objective, each EI strategy requires its specific composition of internal and external knowledge sources. For example, while *R&D-based* knowledge is pivotal for all innovations, *not-R&D based* embodied knowledge (i.e. physical and human capital investments) appears to be relevant only for efficiency related-EI. In contrast, not-R&D based disembodied knowledge (i.e. marketing investments) is mainly associated with non-efficiency EI and green product innovations. Furthermore, by looking at the external sources, cooperation with not scientific partners (i.e. firms in the same groups, suppliers, competitors and customers) turns out to be important for both non-efficiency related EI and green product innovations, while technological cooperation practices (i.e. interaction with universities, private R&D institutes and laboratories, public research organizations) seems to influence only efficiency related EI.

In parallel, the issue of heterogeneity among green innovators clearly emerges in the analysis by Castellacci and Lie (2017), who put the emphasis on the crucial role of active policy efforts in inducing firms to start to invest more actively in green innovations. In a more detail, the authors drawn data for 1.719 manufacturing firms from the 2008 Korean Innovation Survey and build a four-cluster taxonomy of green innovators. The four groups have been found to differ one each other, even in terms of policy drivers. The categories are: *energy-saving* firms associated with high R&D capabilities and strong network with universities, *waste-reducing* and *recycling* firms linked to both market drivers and R&D policies and, finally, *pollution-reducing* firms that are mainly triggered by environmental regulation.

Both studies are particularly worth of noting, as they demonstrate that a better understanding of EI policy determinants strictly relies on the ability to identify EI patterns, thus avoiding establishing too broad or too narrow *ex ante* categories.

Build in the above considerations, the present chapter proposes a similar clustering framework which allows for assessing the heterogeneity of EI strategies for the Italian case. After that, the analysis tries to shed further light on the effectiveness of public policies as EI-enhancing tools, by looking at the whole array of policy measures, such as CACs, MIBs, *supply-side* and *demand-side* measures.

In so doing, the following research questions will be addressed:

1. Do firms' environmental innovation strategies vary according the environmental impact they achieve?
2. Do public policies vary in magnitude and significance according the innovation trajectory followed by innovators?

SECTION 4

Data

The empirical analysis consists of two stages. The first one is dedicated to identifying distinct environmental innovation strategies (EI modes) (research question 1), while the second step investigates the link between the four categories of policy tools and distinct EI strategies (research question 2).

The dataset is based on data collected by the Italian Community Innovation Survey referred to the period 2012-2014. In particular, the 7th Italian CIS survey exploited for this analysis provides data on 17.532 firms belonging to manufacture and service sectors. Firms with at least 10 employees are identified through a stratified random sampling based on size, sector and geographical coordinates, while a census survey includes all firms with more of 249 employees. The web-based questionnaire is about 12 pages long and the response rate for wave 7^{th} has been of 62,8%. The analysis has been restricted to manufacturing firms and the final sample is composed by 4.792 units.

In comparison with previous CIS waves, CIS7 has made up a step forward in the investigation of firms' environmental innovation strategies by collecting information on a wide range of aspects related to EI. Indeed, firms are asked about the type and the goals reached by the environmental innovation carried out over the three-year period as well as the degree of importance attached to its drivers (policy factors, private demand, cost-saving considerations and reputational motivations). In addition, the generic innovation-related module provides a set of quantitative and qualitative data about firm's technology innovation strategy, including information on firm's R&D activities and cooperation practices.

First-stage analysis

The identification of the distinct EI modes follows the approach proposed by Castellacci and Lie (2017) which consists of a clustering procedure preceded by a Principal Component Analysis. The PCA is carried out on ten variables (Table 1): six referring to the achievement of environmental benefits experienced within the enterprises by innovating (namely ECOMAT, ECOENO, ECOPOL, ECOSUB, ECOREP, ECOREC) and four referring to the achievement of environmental benefits experienced during the consumption or use of a good or service by the end user by innovating (i.e. ECOENU, ECOPOS, ECOREA, ECOEXT). The sample is composed by 1.807 manufacturing claiming to introduce at least a process or product environmental innovation over the period 2012-2014.

Standardization process

By looking at Table 2, which reports the total of the environmental goals achieved by EI innovators, a clear trend of complementary between distinct goals emerges. As shown by the high pairwise correlations among the ten variables reported in Table 3, the complementarity could be due to the high degree of complexity and closely which is usually associated with green technologies.

TABLE 2. TEN TYPES OF ENVIRONMENTAL GOALS: DESCRIPTIVE STATISTICS

Variable		Mean	S. Dev	Min	Max	Freq
Environmental benefits obtained within the enterprise						
ECOMAT	Reduced material use per unit of output produced	.5307139	.4991939	0	1	959
ECOENO	Reduced energy use or ENERGY 'foot-print' by firm	.71057	.4536234	0	1	1.002
ECOPOL	Reduced air, water, noise or soil pollution related to the production	.6043165	.4891324	0	1	1.350
ECOSUB	Replaced materials with less polluting or hazardous substitutes	.5002767	.5001383	0	1	1.151
ECOREP	Replaced fossil energy with renewable energy sources	.2047593	.4036373	0	1	955
ECOREC	Recycled waste, water, or materials related to the production	.3768677	.4847355	0	1	982
Environmental benefits obtained by the end user						
ECOENU	Reduced energy use or ENERGY 'foot-print' by the end user	.5168788	.4998534	0	1	827
ECOPOS	Reduced air, water, noise or soil pollution by the end user	.4360819	.4960349	0	1	572
ECOREA	Recycling of product after use by the end user	.2999447	.4583603	0	1	711
ECOEXT	Extended product life through more durable products	.3680133	.4823985	0	1	665

TABLE 3. NUMBER OF ENVIRONMENTAL GOALS REACHED BY CIS7 MANUFACTURING FIRM

# of environmental goals	Freq.	Perc. (%)	Cum. Perc. (%)
1	152	8.41	8.41
2	287	15.88	24.29
3	291	16.10	40.40
4	252	13.95	54.34
5	207	11.46	65.80
6	195	10.79	76.59
7	172	9.52	86.11
8	111	6.14	92.25
9	85	4.70	96.96
10	55	3.04	100
Total	1.807	100	

TABLE 3. CORRELATIONS COEFFICIENTS BETWEEN ENVIRONMENTAL GOALS

	MAT	ENO	POL	SUB	REP	REC	ENU	POS	REA
MAT	1.000								
ENO	0.4731	1.000							
POL	0.3872	0.4818	1.000						
SUB	0.1790	0.1038	0.3281	1.000					
REP	0.1322	0.3872	0.3292	0.2708	1.000				
REC	0.3663	0.1849	0.3316	0.2807	0.2569	1.000			
ENU	0.1755	0.4153	0.2064	0.1334	0.2691	0.1421	1.000		
POS	0.1651	0.1954	0.5696	0.2663	0.2816	0.2419	0.7356	1.000	
REA	0.2260	0.0934	0.2303	0.3706	0.2554	0.4480	0.3683	0.4463	1.000

Note: Sample of green innovators only: n =1807. Tetrachoric correlation

Thus, before performing the Principal Component Analysis, a standardization process is needed to establish if and to what extent a given EI strategy is focused on a specific environmental goal. In detail, the standardization rule is distinctly applied on two groups of variables: IEB (internal environmental benefits) and EEB (external environmental benefits). For both, each of the six (four) variables referred to the benefits experienced within firms (by the end use) is divided by the total number of the environmental goals reached within firms (by the end use) by means of the innovation introduced.

Formally:

$$IEB_y = \frac{IEB_y}{\Sigma_i IEB_y} \qquad EEB_x = \frac{EEB_x}{\Sigma_i EEB_x} \tag{1}$$

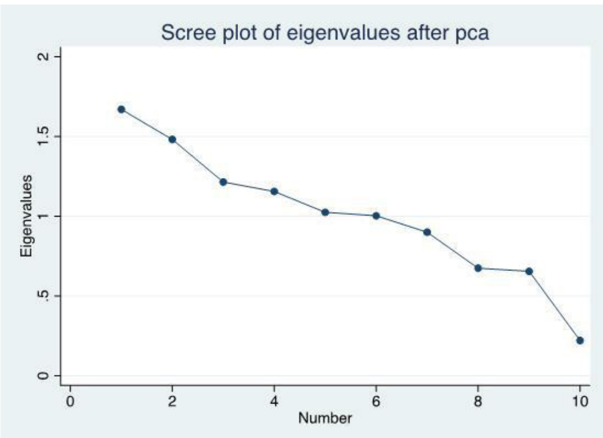
This standardization rule allows to identify distinct EI technological trajectories by assigning higher values to focused innovators, i.e. with narrow EBs, and lower values to those developing broader EI strategies, i.e associated with the achievement of more than one EB. In so doing, environmental innovators are grouped on the basis of the predominance assigned to specific internal and external environmental targets by the innovator.

TABLE 4. RESULTS FROM PCA

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	**1.67052**	**.188764**	**0.1671**	**0.1671**
Comp2	**1.48176**	**.267153**	**0.1482**	**0.3152**
Comp3	**1.2146**	**.0590894**	**0.1215**	**0.4367**
Comp4	**1.15552**	**.130689**	**0.1156**	**0.5522**
Comp5	**1.02483**	**.0216984**	**0.1025**	**0.6547**
Comp6	**1.00313**	**.103102**	**0.1003**	**0.7550**
Comp7	.900026	.225697	0.0900	0.8450
Comp8	.67433	.0196632	0.0674	0.9125
Comp9	.654666	.434042	0.0655	0.9779

Note: Factors with eigenvalue higher than 1 extracted. The final factors together explain 75.50% of total variance.

Figure 5. Scree plot of eigenvalues after PCA



As reported by Table 6, the first factor combines the two variables representing the *pollution-reducing* activities (ECOPOL and ECOPOS). The second factor has very high loading on the two variables measuring recycling innovations (ECOREC and ECOREA), implemented in order to reduce waste streams at both firms and users' level. The third and fourth factors are positively correlated with process and product *energy-saving* innovations (ECOENU and ECOENO), respectively. The fifth principal component has a very high loading on the indicator referring to material-reducing innovations (ECOMAT). Finally, the sixth factor is positively correlated with the variable which measures the replacement of a share of fossil energy with renewable energy sources (ECOREP). Because of the above six indicators are, by construction, independent of each other, it is possible then to reduce the ten highly correlated initial variables to six uncorrelated dimensions.

TABLE 6. RESULTS OF FACTOR ANALYSIS (FACTOR LOADINGS)

	FACTOR 1	FACTOR 2	FACTOR 3	FACTOR 4	FACTOR 5
	Pollution Reducing	*Recycling*	*Process Energy Improving*	*Product Energy Improving*	*Material Reducing*
ECOMAT	-0.0824	-0.0838	0.1310	0.0502	**0.8782**
ECOENO	-0.3574	-0.2065	**0.4015**	0.2073	-0.4194
ECOPOL	**0.6315**	-0.1186	0.1956	-0.2018	-0.1647
ECOSUB	-0.0772	-0.0708	-0.8423	0.0107	-0.1172
ECOREP	-0.0036	-0.0487	0.0664	0.0177	-0.0727
ECOREC	-0.0100	**0.7017**	0.2155	-0.0995	-0.0385
ECOENU	-0.1208	-0.1408	0.0271	**0.6166**	0.0393
ECOPOS	**0.6162**	-0.0359	-0.0544	0.1889	0.0486
ECOREA	-0.0779	**0.6134**	-0.1370	0.0834	-0.0050
ECOEXT	-0.2455	-0.1975	0.0232	-0.6932	0.0355
% of variance	0.1671	0.1482	0.1215	0.1156	0.1025

Note: Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. The numbers in bold indicate the variables that are more strongly correlated to each principal component.

Cluster Analysis

Finally, to properly identify distinct EI modes, a cluster analysis on the above six principal components is performed in two steps. Firstly, different solutions from several hierarchical methodologies are exploited to identify the optimal number of clusters (Hair et al, 2009). After comparing several clustering solutions ranging from two and eight, the optimal number has been chosen on the basis of their statistical significance and economic interpretation. The selected clustering method is the *complete-linkage*, which allows to minimize the within-cluster distance between observations. This strategy identifies a four-cluster solution as the most appropriate for our data. Secondly, a k-means clustering algorithm is applied to assign firms to clusters by imposing a four-cluster solution, as indicated in the previous phase. The results of the cluster analysis are reported in the Table 7.

TABLE 7. RESULTS OF CLUSTER ANALYSIS (K-MEANS CLUSTERING ALGORITHM), MEAN VALUES OF PRINCIPAL COMPONENTS IN EACH CLUSTER

	CLUSTER 1	**CLUSTER 2**	CLUSTER 3	CLUSTER 4
Pollution Reducing	1.320591	**-.1860839**	-1.425.237	-.4230929
Recycling	-.4828052	**1.054614**	-.8884444	-.4446957
Process Energy-saving	.1235243	-.5832346	**.841769**	.2302839
Product Energy-saving	.3246416	-.2266613	**1.540887**	-.7179422
Material Reducing	-.4052693	-.1443267	-.7045328	.8860314
Fossil energy_substituting	.0975199	.1427636	-.0634804	-.2439655
	481	613	219	494
	26.62	33.92	12.12	27.34
	26.62	60.54	72.66	100.00

The first group has a very high mean value for the first principal component analysis and identifies a large group of enterprises (481) introducing *pollution-reducing* innovations. The second cluster scores very high on the second principal component *recycling*, thus identifying 613 firms that carry out innovations to reduce the waste streams during the production process and new recycling technologies experienced by end-users. The third cluster has above-average values on the third and fourth components, classifying a less numerous groups of firms (219) that innovate along the *energy-saving* technological trajectory. Finally, the fourth cluster loads very high for the fifth principal component (material reducing), thereby identifying a group of firms that predominantly introduce *material-reducing* innovations. This latter group encompasses 494 firms.

Econometric analysis & Results

The characteristics of the four groups are detected by the econometric analysis (Table 10). The latter is carried out by running out four logistic regression models which estimate the probability of belonging to a given cluster. A set of CIS drivers grasping different dimensions affecting firms EI behaviors are using as regressors to perform the analysis (Table 8 and 9). The logistic regression could be formally expressed as follow:

$$Prob(Yi = 1) = 1/(1 + \Sigma_k exp(\beta^T_k X_i)) \qquad for\ each\ j = 1 \tag{2}$$

where Y_i represents the set of clusters obtained from cluster's analysis, the vector X_i of explanatory variables and $_j$ reflects the vector of estimated coefficients for each cluster j.

TABLE 8. DRIVERS OF GREEN INNOVATIONS

Variable	Description
Environmental policies	
CACs	High/medium importance of existing regulations on pollution*
MIBs	High/medium importance of existing taxes on pollution*
Innovation policies	
Supply-push	High/medium importance of government grants, subsidies or other financial incentives*
Demand-pull	High/medium importance of requirements for public procurement contracts *
Other drivers	
Reputation	High/medium importance of enterprise's reputation*
Cost-saving	High/medium importance of cost of energy, water or materials*
Private demand	High/medium importance of current or expected market demand*
Voluntary codes	High/medium importance of voluntary codes or agreements*
Sources of innovation	
Internal R&D	Intramural R&D (1 yes; 0 no)
Technological Cooperation	Cooperation arrangements on innovation with scientific partners (1 yes 0 no)
Not Technological Cooperation	Cooperation arrangements on innovation with not scientific partners (1 yes; 0 no)
Firms' characteristics	
Size	Log of turnover (mean value 2012-2014)
Export	Export activities (2012 - 2014), (1 yes; 0 no)
Group	Group belonging (2012 - 2014), (1 yes; 0 no)

*(1 high/medium, 0 no)
Note: Sample of green innovators only: n =1807. The first 7 variables are from the special module on green innovation provided by CIS7. The remaining variables are from the general survey and thus refer to the firm and their general innovation activities, rather than green ones specifically.

The first set of regressors concerns environmental policies tools, grouped in CACs and MBIs. Specifically, CACs instruments are represented by exiting environmental regulation, while MBIs instruments are identified in the exiting environmental taxation. The second set of regressor embraces innovation policy instruments, respectively represented by *supply-push* measures, such as government grants, subsidies or other financial incentives, and *demand-pull* tools referring to specific requirement to meet within public procurement contracts. All the above indicators have been transformed in dichotomous variables that take value equal to 1 if firms assign them medium or high level of importance (value 2 and 3 of the Likert scale), and 0 otherwise. The third set of variables takes into account other drivers as firm's reputation, cost saving motivations, demand from private actors and voluntary code, firm's technological capabilities (represented by internal R&D and technological and not technological cooperation activities with external partners) and finally, firms' individual characteristics, such as size, group and export dummies. Sectoral dummies calculated at a NACE 2-digit are included as regressors.

The main result of the econometric analysis is that policy drivers differently score across the four EI modes, thus confirming that eco-innovating patterns are inherently different. Regarding the role played by environmental policy tools, findings emerging from Table 9 show a strong and positive correlation between CACs and the probability of belonging to cluster 1. In line with empirical evidences by Frondel et al. (2007) and Demirel and Kesiduo (2011), CACs instruments have been found to affect the introduction of less radical innovations, as in the case of *pollution-reducing* technologies that are usually included in the class of *end-of-pipe* technologies.

By looking at innovation policies, the role of *supply-push* measures turns out to be positively associated with *energy-saving* innovations, while *demand-pull* policies are found to positively affect *recycling* innovators. These findings may be explained by two facts.

First, *energy-saving* technologies achieve the double aim to reduce pollution while improving energy-performance, so that, their realization may involve a more complex and radical innovation process which, in turn, implies high degrees of riskiness that may discourage external investors. In this view, firms engaging in *energy-saving* innovations may make use of public financial sustain to a greater extent than those engaging in other, less risky, EI activities. This finding is inconsistent with evidences provided by Veugelers (2012) and Horbach (2008, 2016) who, contrary to the present analysis, use an *ex-ante* classification to unify *energy-saving* and *material-reducing* technologies into a single *efficiency-improving* class.

Second, green public procurement procedures, which essentially follow the LCA approach (Life Cycle Assessment), basically sustain recycling practices for minimizing services and products' environmental impact throughout their whole life cycle, i.e. from the materials production stage to the end-of-life. In this context, the need of meeting environmental criteria, as required by the public tendering, may represent a significant stimulus for the engagement in recycling practices aimed at realizing more eco-friendly goods and services.

Surprisingly, any correlation has been found between policy drivers and cluster 4 encompassing *material-reducing* innovators. This means that firms following this pattern are not triggered by policy factors and other external drivers, as reputation and cost considerations. Rather, the *material-reducing* trajectory is likely to stem from an "unconditioned" pace of technological progress.

To better explain these findings, Table 11 summarizes the main characteristics as follows:

I. *Pollution-reducing EI*. This mode is followed by 481 firms that attach great importance to CACs policies. However, a weak but significant impact on the probability of belonging to this cluster also arises from the *supply-push* indicator. Furthermore*,* compared to other environmental innovators, *pollution-reducing* innovators are found to be smaller and to belong to a group.
II. *Recycling EI.* This group is the most numerous one since it includes 613 environmental innovators aiming at recycling goals at both process and product level. When compared to other eco-innovators, these companies turn out to be triggered by *demand-side* innovation policies and voluntary codes. In contrast, the exploitation of *supply-side* tools appears negatively correlated with the odds of belonging to this group. Finally, recycling innovators are bigger than others and seem to show a own property structure.
III. *Energy-saving EI*. This cluster is the smallest one by consisting of 219 firms. For the group, the crucial policy driver is represented by financial support by governments. On the contrary, *energy-improving* innovations are not fueled by green public purchasing as well as environmental standards impositions. In addition, cost-saving motivations are also relevant for being part of this cluster.
IV. *Material-reducing EI.* This mode is followed by 494 firms. The probability of belonging to this group increases for companies that assign less or null importance to policy drivers, especially to CACs and *supply-push* measures. In addition, firms belonging to cluster 4 are less propense to cooperate with external partners and, as reported by Table 9, show the higher mean value for the internal R&D variable.

TABLE 9. MEAN VALUES OF DRIVER VARIABLES FOR EACH CLUSTER

	CLUSTER 1.	**CLUSTER 2.**	**CLUSTER 3.**	**CLUSTER 4.**
	Pollution Reducing	Recycling	Energy improving	Material Reducing
Environmental policies				
CACs	**.7671518**	.7585644	.543379	.6639676
MIBs	.3243243	**.3784666**	.2283105	.3137652
Innovation policies				
Supply-push	.4345114	.4045677	**.4611872**	.3684211
Demand-pull	.2390852	**.3050571**	.1506849	.2186235
Other drivers				
Reputation	.7733888	**.8384992**	.6712329	.7813765
Cost-saving	.7089397	.7422512	**.7808219**	.7489879
Private demand	.5301455	**.5742251**	.4200913	.4777328
Voluntary codes	.3305613	**.4681892**	.2511416	.3076923
Internal R&D	.6528067	**.7014682**	.652968	**.7145749**
Technological Cooperation	.2453222	**.3050571**	.283105	.2469636
Not Technological Cooperation	.0561331	.0603589	**.0684932**	.0587045
Size	1.689.975	**1.711.339**	1.671.979	1.694.391
Export	.8939709	.9200653	.9178082	**.9271255**
Group	**.7920998**	.7487765	.7260274	.7550607

Numbers in bold indicate the clusters with higher mean value for the specific variables

TABLE 10. RESULTS FROM LOGISTIC REGRESSIONS

	CLUSTER 1.	CLUSTER 2.	CLUSTER 3.	CLUSTER 4.
Environmental policies				
CACs	**0.102*** **	0.036	**-0.062*** **	**-0.058** **
	(0.03)	(0.03)	(0.02)	(0.03)
MBIs	-0.032	0.025	-0.023	0.030
	(0.03)	(0.03)	(0.02)	(0.03)
Innovation policies				
Supply-push	**0.040* **	**-0.060** **	**0.055*** **	**-0.038* **
	(0.02)	(0.02)	(0.02)	(0.02)
Demand-pull	-0.013	**0.057** **	**-0.044** **	-0.011
	(0.03)	(0.03)	(0.02)	(0.03)
Other drivers				
Reputation	-0.022	0.047	**-0.043** **	0.033
	(0.03)	(0.03)	(0.02)	(0.03)
Cost-saving	**-0.040* **	-0.032	**0.042** **	0.027
	(0.02)	(0.03)	(0.02)	(0.02)
Market demand	0.031	0.014	-0.014	-0.027
	(0.02)	(0.02)	(0.02)	(0.02)
Voluntary codes	**-0.043* **	**0.113*** **	-0.028	**-0.053** **
	(0.02)	(0.02)	(0.02)	(0.02)
Internal R&D	-0.034	0.006	-0.011	0.040
	(0.02)	(0.03)	(0.02)	(0.02)
Technological Cooperation	-0.025	0.042	0.023	**-0.043* **
	(0.03)	(0.03)	(0.02)	(0.03)
Not Technological Cooperation	-0.035	0.033	0.015	-0.015
	(0.05)	(0.05)	(0.03)	(0.04)
Size	**-0.013* **	**0.023*** **	-0.009	-0.000
	(0.01)	(0.01)	(0.01)	(0.01)
Export	-0.056	0.001	0.023	0.033
	(0.04)	(0.04)	(0.03)	(0.04)
Group	**0.090*** **	**-0.076** **	0.004	-0.015
	(0.03)	(0.03)	(0.02)	(0.03)

* p<0.10, ** p<0.05, ***p<0.01

TABLE 11. SUMMARY OF THE MOST IMPORTANT CHARACTERISTICS OF EACH CLUSTER OF GREEN INNOVATORS

	CLUSTER 1.	CLUSTER 2.	CLUSTER 3.	CLUSTER 4.
	Pollution Reducing	*Recycling*	*Energy-improving*	*Material Reducing*
Strongest policy drivers	CAC environmental policies	Demand-side innovation policies	Supply-push innovation policies	None
Weakest policy drivers	None	Financial support	CAC environmental policies; Demand-side innovation policies	CAC environmental policies; Supply-push innovation policies
Other drivers	Groups belonging; Small firms	Own propriety; Large firms	Cost-saving	None

SECTION 5

Conclusions

In the European context, the transition towards a "resource efficient and greener economy" has been settled as a key priority (EU, 2011) by the Lisbon Agenda and Europe 2020.

To sustain such a convergence between environmental and economic issues, policy action plays a primary role in providing firms with effective stimuli to develop environmental-friendly technologies. The need for public intervention is justified by the presence of many market-failures hindrances, that are supposed to affect EI to a greater extent than standard innovation. On the one hand, the "double externality problem" makes the typical appropriability problem of innovation exceptionally pronounced when green technologies are implemented as firms bear the costs of less pollution while the society benefits from it (Beise and Rennings, 2005). On the other hand, since as EI activities belong to a less mature field of innovation when compared to traditional technologies (Ghisetti et al., 2015), EI investments are perceived to be highly risky (Kapoor and Oksnes, 2011) and, as a consequence, external investors may be less attracted by them. All these conditions provide strong rationale for adopting policy measures.

The present chapter goes in this direction by exploiting a wide array of policy instruments and their link with EI by accounting for heterogeneity among distinct EI patterns followed by firms. In so doing, a much richer and complex picture of environmental innovation domain is provided through the identification of four eco-innovation modes (namely (1) pollution-reducing, (2) recycling, (3) energy-saving and (4) material reducing) whose implementation turns out to be in most of these cases, positively correlated with environmental and innovation policy tools. The main results of the exploratory exercise can be synthesized as follows:

I. By paying attention on environmental policy drivers, it emerges that those firms grouped in cluster (1) are mainly driven by regulatory instruments (CACs) belonging to the environmental policy class. Consistent with previous analysis, this result confirms that environmental policies success in sustaining less radical EI activities, as in case of *pollution-reducing* technologies. In contrast, any significant relationship emerges for MBIs (environmental taxation), thus signaling that the price of polluting might be not sufficiently high to stimulate innovation activities with beneficial environmental effects. This arises the need to interview under the aspect of the fiscal design.

II. With respect to innovation policy instruments, evidences of positive links with EI have been recognized in two cases. First, *energy-saving* technologies (3) appear to benefit from *supply-push* measures while recycling innovations (2) are positively stimulated by *demand-pull* policies. Both results are in line with theoretical speculations about the corrective role of *supply-side* policies, especially in case of more complex innovation projects as *energy-saving* innovations, and he positive impact of green public demand in successfully stimulating recycling practices through the LCA approach.

III. With respect to other external drivers, it emerges that voluntary codes are relevant for cluster (2), while cluster (3) basically attaches more importance to cost-saving considerations and reputational motivations.

These findings give response to the research questions made in section 3, with some important contributions for the development of EI related literature. Firstly, thanks to the identification of distinct innovation patterns, a more complete representation of EI realm has been provided for the Italian case. Secondly, the key role of public policies in stimulating EI practices has been found to change in sign and magnitude across EI policy tools and modes.

This means that, to increase policy efficiency, distinct policy actions should be set according to specific environmental targets (pollution-reducing, recycling etc..). In other words, this would make environmental and innovation policies effective leverages to increase sustainability.

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The employment impact of eco-innovation modes. Evidence from Italian manufacturing firms

Abstract

This paper explores the employment impact of different green innovation strategies (EI modes) at the firm-level. The analysis is performed within a not-parametric framework that allows to recognize eventual differentiated impact across different quantiles of the growth distribution. The econometric exercise suggests that, regardless to the green technological trajectory followed by firms, the net employment effect of environmental innovation is always positive but only at certain paces of growth statistically significant. This is of particular relevance for *struggling* firms where environmental innovation turns out to be a key candidate for overcoming the economic impasse while, on the contrary, *fast-growing* companies seem to fail in taking advantage from most of the green orientations.

Keywords: *Environmental Innovations, Innovation Modes, Employment Growth, Gibrat's low, Quantile regressions*

SECTION 1

Introduction

The analysis of the impact of innovation with beneficial environmental effects (here-after EI) on employment is gaining increasing momentum at both policy and academic level for, at least, two main reasons. On the one hand, the mounting pressures stemming from institutions, normative groups and consumers, about the transition towards a more sustainable pattern of growth are exponentially increasing the economic costs and the reputational risks of firms' polluting behaviors (Berrone et al., 2013). On the other hand, the dramatic loss of employment experienced by many European countries because of the 2008 crisis has put the unemployment problem, as well as its resolution, on the spotlight. In this context, firms' ability to develop *environmental-friendly* processes and products has gained an undisputed socio-economic relevance as a means for enabling the economic recovery while reducing the negative externalities of pollution and waste (EC, 2010).

A number of *green-specific* channels may occur when EI is turned into employment growth. Firstly, the irreversibility nature of being compliance with the environmental policy framework may make EI activities (Mazzanti and Rizzo, 2017; Oltra and Saint Jean, 2009), as well as EI outcomes (see Chassagnon and Haned; 2015; Diaz-Garcia Gonzalez-Moreno and Saez-Martinez; 2015) more persistent than those related to standard innovations (here-after SI) and, thus, better linked with employment growth opportunities. Secondly, the so-called *win-win* strategies, theorized in the Porter hypothesis and the discussion on "whether it pays to be green", depict EI as a way to increase the occupational level through the competitive advantages addressed by new green process (energy and material reducing, recycling technologies) and new green products (differentiation, access to new market, absorption of green demand from downstream stages of the value chain).

Within this theoretical framework, EI has been so far intended as a "whole" or, more often, it has been categorized by using dichotomic terms as, for example, process *vs* product innovation or *end-of-pipe vs cleaner production* technologies. However, EI seems however to be featured by a highly heterogenous nature that makes this phenomenon more complex than that described by a single or double classification. In this regard, recent empirical evidences detect more than one "mode" of dealing with it, thus providing a new and multifaceted sketch of EI. Green innovators may in fact differ across EI engagement (Marin at al., 2015), technological trajectories (Montresor and Marzucchi, 2017) and environmental goals achieved (Castellacci and Lee, 2017).

These considerations draw attention to the need for exploring the relationship between EI and growth by developing a broad analytical framework for EI. The aim of this paper is then to highlight such complexity and the importance of adopting new lens for the analysis of EI to better identify its linkages with firms' growth and possibly identify its differences from others, less sustainable, ways of innovation.

To address this issue, I draw on the idea developed by evolutionary theories and industrial organization studies that innovation growth drivers might be differentiated according to the pace at which a firm grows. In particular, many analyses show that the growth premium arising from innovative activities is greater when the pace of growth is faster (see Coad et al., 2014, for a recent review). This means that the characteristics of rapidly growing firms (young, small, etc..) play a key role for a better exploitation of growth opportunities from innovation. However, with specific regard to EI, the narrowed literature scrutinizing this link by looking beyond the "average effect" do not account for EI heterogeneity. Then, the novelty of this paper is to close this gap by jointly addressing the following research questions:

I. Whether the growth outcome of EI depends on the "mode of innovation" along different quantiles of the growth distribution?
II. Whether the growth outcome of eco-innovation depends on the firms' pace of growth?

In so doing, I exploit the EI modes classification proposed in Chapter 2 to investigate the relationship between EI and growth by means of a quantile regression approach. This allows to overcome the "average effect for the average firm" by focusing on the differences of the impact across the (conditional) growth distribution. A growth version model of Gibrat low of Proportional Effect (Gibrat, 1931) is adopted to partially cope with endogeneity problems. Accordingly, the dependent variable is represented by the employment growth observed during the period 2014-2016, while all the covariates - including innovation modes- are referred to the period 2012-2014.

The exercise is carried out by exploiting a unique dataset of 3.424 manufacturing firms with 10 or more employees. Data on innovation strategies are obtained from the 2012-2014 Community Innovation Survey (CIS), while data on 2014-2016 employment dynamics are drawn from Aida-Bureau van Dijk database. The remainder of the paper is organized as follows. Section 2 provides a literature survey aiming at embedding the analysis within the framework of EI in order to identify the relations with average employment growth. Section 3 stresses the need to go beyond the "average" effect as well as to control for endogeneity, thus motivating the choice of adopting such a methodological framework. Section 4 presents the data, the empirical application and illustrates the results. Finally, Section 5 concludes by discussing the main findings emerging from the study and highlighting the policy implications.

SECTION 2

Linkages between innovation and employment dynamics

From a microeconomic perspective, the explanation of the occupational effects of environmental innovation is shaped on the theoretical background beyond the relation between standard innovation and employment dynamics. In this regard, the question about "*how innovation affects employment*" is not trivial. In theoretical terms, the net occupational impact of the technical progress is seen as the final outcome of a number of compensation and displacement effects that stem from different innovation activities and affect employment in several ways (Table 1).

The compensation mechanisms responsible for turning competitive advantages into *employment-creating* effects involve both price and the demand effects. While the former are linked to the productivity changes realized by new process innovations, the latter are associated with additional demand for product innovations as well as their complementary products.

Regarding price mechanisms, it could be argued that the efficiency gains realized by new process innovations lead to lower unit costs (i.e. same amount of output with less labor input) that may be passed into lower prices. Such a decrease in prices may stimulate the demand and, consequentially, the production of a greater amount of final output, thus boosting the labor demand (Harrison et al., 2014; Simonetti et al., 1995; Vivarelli and Pianta, 2003). However, the magnitude of this positive effect on employment relies on several factors ranging from the amount of the price decrease, the price elasticity of demand, the degree of competition, to, more in general, the behavior of economic agents (Garcia et al., 2004).

From the other hand, demand-effects may sustain growth by means of new products, whose introduction in the market may lead firms to increase because of an overall market expansion or at the expense of their competitors. As in the previous case, the magnitude of the demand effects on employment may be influenced by several factors including demand elasticity, the existence of substitutes products and competitors' reactions (Garcia et al., 2004).

Yet, such compensation mechanisms may be counteracted by the so-called displacement mechanisms arising at both process and product innovation level. For example, *input-saving* technologies and/or the realization of new product may require less labor input for the same amount of output, thus destroying labor force[1]. Furthermore, new product innovations may lead to a decrease in demand for existing substitutes, with negative occupational effects due to a reduction of the final output (Harrison et al., 2014).

In a nutshell, the net effect of innovation on employment, which is hardly predictable for both process and product innovation, is even more uncertain in presence of complementarities in use between process and product innovations (Kafts, 1990, Martinez-Ros, 2009), that are usually associated with major levels of novelty (Reichstein and Salter, 2006) and stronger firm's capabilities (Ballot et al. 2011). Moreover, this synergy seems to lead to better economic results (Evangelista and Vezzani, 2011) although its link with employment dynamics is still scarcely investigated.

TABLE 1. PRICE AND DEMAND EFFECTS OF INNOVATION ON EMPLOYMENT AT THE FIRM LEVEL

	Compensation effects *(creating effects)*	**Displacement effects** *(destroying effects)*
Price effects	*Process innovation*: Cost reduction passed on to price expands demand (+) *Product innovation*: New products require more labor (+)	*Process innovation*: Less labor input for a given output (-) *Product innovation*: New products require less labor (-)
Demand effects	*Product innovation*: Increase in demand of existing complementary products (+)	*Product innovation*: Decrease in demand of existing substitutes (-)

Focusing on environmental innovation

The picture sketched above is made more complex when the distinction between EI and SI is

1 However, by considering the distinction between low and high skilled positions, a "skill bias effect" (Caroli & Van Reenen, 2001; Autor et al., 2003) may be in place if low-skilled positions are destroyed while high-skilled position are created.

accounted for. In this regard, whether and to what extent price and demand channels linking together technical progress and employment, might differ for innovations with and without beneficial environmental effects is still a key open question as, as a matter of fact, it is a priori unclear if the impact on employment due to productivity gains and/or additional demand differ between EI and SI. This may rely on a number of policy and market factors.

On the one side, EI is the privileged objective for policy actions because of its potential role of mediation between sustainability and economic goals (Crespi, 2016). This aspect, as largely argued by the schools of thought of the "irreversibility hypothesis", the "Porter hypothesis" and the discussion on "whether it pays to be green", is crucial in making EI growth opportunities greater than those attached to SI (Ambec et al., 2013; Lanoie et. al 2011; Porter & Van der Linde, 1995) as, when in presence of a policy framework, firms are supposed to be more prone to introduce "green", instead of "dirty", innovation (Mazzanti and Rizzo, 2017; Oltra and Saint Jean, 2009, Chassagnon and Haned, 2015; Diaz-Garciaz et al., 2015). On the other side, differences in employment impacts between EI and SI may also be driven by many market factors that are responsible for the amount of final output at the firm-level, namely: (i) the degree of competition in the market for environmental products, (ii) the demand elasticity, (iii) the degree of complementarity or substitutability with old products made by firms, (iii) the amount of labor required to realize the new product and (vi) the degree of complementarity between forms of innovation.

Up to now, the scarce and mixed empirical evidence on the occupational effects of EI at the firm-level is mainly based on the process/product and *end-of-pipe*/cleaner production dichotomies. For instance, with regard to environmental process innovations, Horbach and Rennings (2013) show that *cleaner* process innovations lead to labor creation to a greater extent than *end-of-pipe* process innovations that, in contrast, have been found to be associated with a decrease in employment by Rennings and Zwick (2002) and Pfeiiffer and Rennings (2001). Licht and Peters (2014) show that both environmental and not environmental process innovation play a little role for employment growth. Concerning product innovation, they find that the employment contribution of non-green product innovations is larger than that stemming from green product innovations while, on the contrary, Horbach and Rennings (2013) point out that environmental product innovators growth faster than not green process and green product innovators.

With an eye to better identify the link between new green technologies and employment, the present study makes a step forwards compared to previous analysis. In so doing, I provide a more fine-grained picture of EI by taking into account the issue of heterogeneity, as detected by the most recent empirical analysis in this field (Marin et al., 2015; Marzucchi and Montresor, 2017; Castellacci and Lee, 2018). These contributions show that, in the realm of green technologies, distinct environmental goals are the starting point of each innovation strategy. Such an evidence, consistent with the new perspective occurring in the standard innovation field (Evangelista and Vezzani 2010, Filippetti 2011; Bianchini et al., 2018), calls for going beyond the sharp distinctions among single innovation activities and shifting the focus on the concept of "modes" of innovation, that are generally intended as a manner to pursuit a certain outcome by combining innovation activities together (Karlsson and Tavassoli, 2016). So that, the present study makes use of distinct EI "modes" identified on the basis of their related environmental outcome[2].

SECTION 3

Beyond the endogeneity problem and the "average" effect

The second element of novelty of this analysis deals with the choice of the methodological framework. In a more detail, the relation between employment growth and EI modes is explored by accounting for two factors: (i) the endogeneity problem and (ii) the pace of growth of the firm.

The endogeneity problem is based on the idea that an innovation may require additional employees to be developed and then realized (Horbach and Rennings, 2013). In such a case, the causality relation between EI and employment growth does not longer rely on prices and demand effects, as argued in section 2. To partially alleviate the problem of endogeneity, this empirical investigation makes use of a Gibrat-like growth model. By including "lagged" innovation variables, this specification allows to evaluate the occupational impact of distinct EI modes by looking at what happens to employment dynamics after, and not during, the introduction of a given EI mode.

Yet, given the much emphasis that the growth-related literature put on the pace at which a firm grows as a way to better identify growth drivers, the Gibrat-like growth model has been framed within a not-parametric framework. The main rational beyond this choice is provided by the crucial shift in emphasis occurring in the industrial studies field on "why and how firms grow" to "which firms actually increase their size" (Arrighetti and Ninni, 2009). Even if the Gibrat's law still represents a key reference in the academic debate, the modern view of firms' growth argues that the growth process might be far from the random walk predicted by the contributions à la Gibrat. As pointed out by Geroski (1999), the unpredictability of the event "growth"- that in the Gibrat's framework relies on the idea that the trend of size expansion followed by a given firm is independent from its starting size- is likely to be dependent on certain unobservable advantages instead of pure randomness. In this regard, a bulk of econometric investigations show that the Gibrat's law is confirmed only when episodes of selectivity are recognized (Becchetti and Trovato, 2002; Lotti et. al., 2003; 2009). In these cases, the chances of growth have been found to be higher for specific groups of firms (i.e. small firms, innovative, etc..) and lower in others, thus suggesting that the degree of homogeneity within the sample is

2 The identification is the same proposed in chapter 2.

extremely worthy of attention when growth is under scrutiny. Such interpretation suggests that different patterns of growth, as well as opportunities of growth, rely on a number of endogenous and exogenous factors. While the former are usually referred to the quantitative and qualitative composition of firms' internalized resources, that represent their ability to react to external conditions and exploit opportunities to enter in a successful development path, the latter embrace a wide range of elements, including market size, demand trends and market competition and innovation dynamics. By focusing on the latter, here I adopt a quantile regressions analysis, that represents a suitable attempt to deal with the existence of heterogeneous impact of growth drivers. These methodologies have been largely used in the standard innovation field (see for example Coad and Rao, 2006) with the key finding that rapidly growing firms tend to maximize opportunities from innovation to a greater extent than slowly growing ones. The main explanation is that, given their small size and young age, rapidly growing firms are more prone in commercializing their innovations and undertaking riskier innovation activities when compared to their bigger peers, since the former are less embedded than the latter by organizational inertia and learning impediments (Criscuolo et. al., 2012; Majumdar, 1999).

With specific regard to the literature on differentials in green-led growth, which is currently scarcely developed, the assumption that "*extracting value from green technology and transforming it into higher growth*" is not a "*one size fits all*" strategy has been proved by Colombelli et al. (2015) and Leoncini et al. (2017). The first study argues that the derived demand for green patents sourcing from environmental regulation spurs green new-born firms, the so-called "green gazelles", that are grow faster than the average. In contrast and inconsistent with literature on generic innovation, Leoncini et al. (2017) sustain that, when compared to non-green patents, the impact of green patents is higher only for medium-growing firms. They suggest that, because of the complex and costly nature of EI, only relatively established firms are able to benefit from the introduction of green technologies.

To date, at the best of the author's knowledge, any attempt to investigate the relationship between EI and employment growth by both considering EI multifaced nature and firms' pace of growth has been provided. Filling this gap is then the objective of the following empirical investigation.

SECTION 4

Data & Growth model

The present analysis is based on a longitudinal dataset obtained by matching data from two different sources: (1) the 7th wave of Italian CIS; and (2) the AIDA BureauVan Dijk dataset. The resulting sample is composed by 3.424 manufacturing firms with 10 or more employees for which a wide range of data on environmental strategies and a growth indicator, as employment, are available.

A growth version of the original logarithmic representation of the Gibrat's Law, expressed as a quantile regression, is formulated as follows:

$$Growth(Y)_{i,t} = lnY_{i,2016} = lnY_{i,2014} = \alpha_o + ln\,(Y_{i,2014}) + \beta_\theta X'_{i,2012\,-2014} + \varepsilon_{it\theta} \tag{1}$$

where $Y_{i,2016}$ and $Y_{i,2014}$ are employment indicators for firm *i* in 2016 and 2014, α_o is the usual constant term, X_i denotes control variables and $\varepsilon_{it\theta}$ is the error term with the usual statistical properties. The quantile regression coefficient estimates β_θ solve the following minimization problem for ρ:

$$min(\beta)[\Sigma^n_{i=1}\rho_\theta(\Delta ln(Y)_{i,t} - \beta_\theta X_{i,2012\text{-}2014})] \tag{2}$$

where $\rho_\theta(\mu) = \theta_\mu$ if μ= 0, otherwise $\rho_\theta(\mu) = (0\text{-}1)_\mu$ if μ< 0.

As previously declared, the growth indicator representing the dependent variable is calculated as the logarithmic difference between $firm_i$'s employees in 2016 and employees in year 2014 (Coad and Rao 2006; Coad 2010; Leoncini 2017). Beyond the above-mentioned theoretical considerations about the links between EI and employment growth[3] (see section 3), among the list of possible growth indicators (assets, employment, market share, physical output, profits, sales), the use of employment dynamic allows to satisfy some relevant methodological issues (Delmar et. al., 2003). For example, employment does not require comparisons within industries for firms with the same product range, which are needed when market share and physical output indicators are adopted. In addition, when compared with other indicators, such as asset value and profits, employment is relatively insensitive to the capital intensity as well as the degree of integration of the industry. Finally, in contrast to sales dynamics, employment is insensitive to inflation and currency exchange rates.

Moving to innovation dynamics, that represent the focus regressors of the analysis, I apply

3 Other indicators of growth have been used by scholars to investigate the economic impact of EI. By looking at the link between regulation, innovation and firms' turnover, Ambec, Cohen, Elgie, & Lanoie, (2013) find that a 1-unit increase in environmental regulation stringency leads an increase in environmental R&D by 0.49 which, in turn, allows turnover to increase by 0.37. However, the direct effect of a 1-unit increase of environmental stringency on turnover is found to be negative (-0.78). Doran & Ryan (2016) adopt the ratio between turnover and employees. Their results show that both generic innovation and generic EI exert a significant, but opposite, impact on growth. In particular, the impact of generic innovation on turnover is found negative, while generic EI appears to positively affect firms' performances. Marin (2014) points the attention on the ratio between value added and employees by providing evidence that green patenting activities lead to a substantially lower return when compared to not-green patents.
Finally, Ghisetti and Rennings (2014) investigate the effects of efficiency improving (EREI) and externality reducing (EI) innovations on firms ROA, by finding that EREI innovations are positively and significantly associated with the ROA, while EI innovations exert a negative but weakly impact.

three specifications of the model in the attempt to provide a complete view of the relationship between environmental innovation strategies and growth. In each model, the baseline is formed by the group of firms which have not introduced any type of innovation during the reference period (Vezzani and Evangelista; 2010; Filippetti, 2011)[4].

In model (1) named "Generic Innovation", the innovation dynamics have been shaped according two dichotomic variables have been included: (i) the one referring to standard innovation (SI) and (ii) the one relating to environmental innovation (EI)(Table 2). Both variables take value one if the firm claims to introduce technological innovations (process and/or product), without and with environmental effects respectively.

TABLE 2. FIRMS BY INNOVATION STRATEGY

Innovation domain	Freq.	Percent	Cum.
non_innovators	1,429	41.73	41.73
SI	620	18.11	59.84
EI	1,375	40.16	100.00
Total	*3,424*	*100.00*	

The second specification (2), called "Innovation type" focuses on the type of innovation introduced. It includes two set of variables, each one made of three dummy variables (only process, only product and Process&product) referred to both not-environmental and environmental innovation (Table 3).

TABLE 3. FIRMS BY INNOVATION TYPE

	non_innovators	only_process SI	only_product SI	process& product SI	Total
non_innovators	1,429	330	41	249	2,049
only_process EI	503	0	0	0	503
only_product EI	411	0	0	0	411
process&product EI	461	0	0	0	461
Total	2,804	330	41	249	3,424

4 Such a choice might arise the issue of the selection bias, according to which not innovative firms are supposed to be structurally different from those who innovate. In order to mitigate this problem, I propose two argumentations. Firstly, by conditioning the analysis on "surviving", it might be argued that the dissimilarities between firms that survive and firms that exit from the market reflect those characteristics which partially drive the selection between innovative and not-innovative. Secondly, the adoption of a quantile regression framework implies that the estimates along different quantiles of the distribution of the growth rates are referred to firms with similar pace of growth, thus more similar to one each other (see Table 6). Both these two elements may increase the homogeneity in the sample and alleviate selection bias issues.

Finally, the third specification of the model (3) "Innovation mode" accounts for the heterogeneity across innovation patterns (Table 4) while considering the not environmental and environmental content of the innovation strategy[5]. Indeed, the following categorical variable representing distinct "modes" has been included:

I. SI mode
II. EI_pollution-reducing
III. EI_recycling
IV. EI_energy-saving
V. EI_material-reducing

TABLE 4. FIRMS BY INNOVATION MODE

Innovation outcome	Freq.	Percent	Cum.
None	1,429	41.73	41.73
SI mode	620	18.11	59.84
EI_pollution-reducing	355	10.37	70.21
EI_recycling	473	13.81	84.02
EI_energy-saving	168	4.91	88.93
EI_material-reducing	379	11.07	100.00
Total	3,424	100.00	

A set of control variables that are often included in growth rate regression models has been added (Table 5). Namely, the model controls for: the 2014 log level of the dependent variable (Emp_{t-1}), the growth rate of turnover from 20012 to 2014 ($\Delta Demand_{t-1}$) as a proxy for product demand (Horbach and Rennings, 2013), a continuous variable representing firm's age (Age_{t-1}) log transformed, an ordinal variable capturing firms human capital endowment and referring to the share of workers with tertiary degree ($Empud_{t-1}$), a dummy variable denoting the belonging to a group ($Group_{t-1}$), an ordinal variable ($Market\_share_{t-1}$), denoting the growing dimension of the market in which the firm operates and competes (national, European and inter-national). Finally, a set of industry and geographical dummies have been also included.

5 The identification of EI modes is reported in Chapter 2.

TABLE 5. DESCRIPTIVE STATISTICS OF THE SAMPLE (N = 3,424).

Variable name	Description	Mean	Std.Dev	Source
$\Delta Growth_t$	Difference of employees in 2016 and 2014 (%)	8.1299	164.0541	AIDA BvD
Generic Innovation				
Standard Innovation (SI) $_{t-1}$	Introduced a product or process standard innovation – 1 yes, 0 no	.1810748	.3851364	CIS 2012-2014
Environmental Innovation (EI) $_{t-1}$	Introduced a product or process environmental innovation – 1 yes, 0 no	.4015771	.4902888	CIS 2012-2014
Innovation type				
only_process SI $_{-1}$	Introduced only a process standard innovation during 2012-2014 – 1 yes, 0 no	.0963743	.2951527	CIS 2012-2014
only_product_SI $_{t-1}$	Introduced only a product standard innovation during 2012-2014 – 1 yes, 0 no	.0119743	.1087859	CIS 2012-2014
process&product_SI $_{t-1}$	Introduced both process and product standard innovation during 2012-2014 – 1 yes, 0 no	.0490654	.2597175	CIS 2012-2014
only_process_EI $_{t-1}$	Introduced only a process environmental innovation during 2012-2014 – 1 yes, 0 no	.1469042	.3540621	CIS 2012-2014
only_product_EI $_{t-1}$	Introduced only a product environmental innovation during 2012-2014 – 1 yes, 0 no	.120035	.32505	CIS 2012-2014
process&product_EI	Introduced both process and product environmental innovation during 2012-2014 – 1 yes, 0 no	.1346379	.3413862	CIS 2012-2014
Innovation mode				
SI mode $_{t-1}$	Introduced a product or process innovation without environmental effect during 2012-2014 – 1 yes, 0 no	.1810748	.3851364	CIS 2012-2014
EI_pollution-reducing $_{t-1}$	Introduced a product or process innovation for pollution-reducing during 2012-2014 – 1 yes, 0 no	.1036799	.3048894	CIS 2012-2014
EI_recycling $_{t-1}$	Introduced a product or process innovation for recycling during 2012-2014 – 1 yes, 0 no	.1381425	.3450999	CIS 2012-2014
EI_enegy_improving $_{t-1}$	Introduced a product or process innovation for energy_improving during 2012-2014 – 1 yes, 0 no	.0490654	.2160362	CIS 2012-2014
EI_material reducing $_{t-1}$	Introduced a product or process innovation for material_reducing during 2012-2014 – 1 yes, 0 no	.1106893	.3137928	CIS 2012-2014
Emp_{t-1}	Employment level in 2014	213.1574	758.0261	AIDA BvD
$\Delta Demand_{t-1}$	Difference of turnover in 2014 and 2012 (%)	8.09506	40.55187	AIDA BvD
Age_{t-1}	Age in 2014	2.787.617	1.698.536	AIDA BvD
$Empud_{t-1}$	Percentage of tertiary educated employees on total employment (categorical variable 0 -6)	1.716.706	147.322	CIS 2012-2014

Group $_{t-1}$	Group belonging during 2012-2014 – 1 yes, 0 no	.6179907	.4859498	CIS 2012-2014
Market share $_{t-1}$	Market share during 2012-2014 (categorical variable 1 -3)	2.214.661	1.133.665	CIS 2012-2014

Note: All values are reported before log transformation

TABLE 6. EMPLOYMENT GROWTH BY INNOVATION MODES.

Variable	n	Mean	S.D.	Min	.25	.75	Max
non-innovators	1429	-0.01	0.33	-3.81	-0.08	0.10	2.74
SI mode	620	0.02	0.40	-4.51	-0.05	0.12	4.52
EI_pollution-reducing	355	0.03	0.20	-1.61	-0.04	0.10	1.13
EI_recycling	473	0.02	0.21	-2.22	-0.04	0.09	0.89
EI_energy-saving	168	0.05	0.24	-0.47	-0.04	0.10	2.22
EI_material-reducing	379	0.03	0.37	-3.10	-0.05	0.11	2.85

SECTION 5

Results from OLS

Table 7 shows the results of the standard regressions for models (1), (2) and (3). Starting from the first model, the positive and statistically significant correlation between innovation variables and employment dynamics suggests that, with or without "green" purposes, being an innovator always leads to an employment growth premium. However, the positive impact increases in magnitude and significance when the technologies adopted are related to environmental issues. By distinguishing among innovation types, as proposed in model (2), the main finding is that following the not-environmental mode exerts a positive impact on employment only if process and product innovation activities are jointly performed. As previous studies find out that complementarities between process and product innovations are usually associated with strong capabilities and higher degree of novelty (Reichstein and Salter, 2006; Ballot et al. 2011), there is reason to believe that only in such a case not-environmental innovation positively affect employment by activating those creating mechanisms above argued.

On the contrary, adopting new green technologies always induces a positive occupational effect, even if product and process innovation activities are separately pursued. Yet, not relevant differences in terms of magnitude among the three options (only_process, only_product, process&product) have been recognized. This finding seems to suggest that, at the firm level, price and demand channels responsible for job creating effects are highly responsive to green innovations, thus proving evidence that engaging in process and product EI turns to be always a successful strategy.

Finally, by accounting for the heterogeneity within innovation modes, the third specification (3) shows that the lowest, but still positive, impact on occupation stems from the SI mode while, with regard to new green innovations, the highest positive impact is associated to *energy-saving* technologies, a finding in line with Horbach and Rennings (2013).

As regards the control variables, the initial size (Emp_{t-1}) turns out to negatively influence firms' pace of growth. This finding, inconsistent with the Gibrat's law, suggests that compared to big firms, small enterprises increase, on average, faster. Similarly, increases in product demand ($\Delta Demand_{t-1}$) and market share ($Market\_share_{t-1}$) appear to positively affect the employment dynamics, while any impact is found to stem for the variables Age_{t-1}, $Group_{t-}$ and $Empud_{t-1}$.

Overall, the first stage of the analysis provides empirical evidence that, in general, innovation sustains employment growth. Moreover, while this impact seems to be always positive both for process and product environmental innovations (no matter if jointly and separately introduced), not-environmental innovation appears to be turned into growth only when the two categories are jointly introduced. In other words, I found evidence that the growth opportunities associated with EI activities, actually, greater. Such a result, supported by the theoretical foundations build around the *green-specific* channels, provides evidence about the higher responsiveness of the market to environmental-friendly issues.

TABLE 7. THE IMPACT OF INNOVATION ON EMPLOYMENT GROWTH, OLS ESTIMATES.

	(1) Generic Innovation	(2) Innovation Type	(3) Innovation mode
SI_{t-1}	0.0364* (0.0188)		
EI_{t-1}	0.0531*** (0.0123)		
only_process SI_{t-1}		0.00994 (0.0176)	
only_product SI_{t-1}		-0.0508 (0.112)	
process&product SI_{t-1}		0.0842*** (0.0307)	
only_process EI_{t-1}		0.0520*** (0.0133)	
only_product EI_{t-1}		0.0517*** (0.0171)	
process&product EI_{t-1}		0.0526*** (0.0175)	

SI mode $_{t-1}$			0.0358*
			(0.0188)
EI_pollution-reducing $_{t-1}$			0.0547***
			(0.0147)
EI_recycling $_{t-1}$			0.0464***
			(0.0139)
EI_energy-saving $_{t-1}$			0.0724***
			(0.0197)
EI_material-reducing $_{t-1}$			0.0461**
			(0.0213)
Emp $_{t-1}$	-0.0163***	-0.0168***	-0.0159***
	(0.00578)	(0.00582)	(0.00578)
ΔDemand $_{t-1}$	0.456***	0.454***	0.455***
	(0.0671)	(0.0672)	(0.0671)
Age $_{t-1}$	-0.0164	-0.0165	-0.0165
	(0.0103)	(0.0104)	(0.0103)
Empud $_{t-1}$	0.00292	0.00338	0.00294
	(0.00410)	(0.00405)	(0.00409)
Group $_{t-1}$	-0.00507	-0.00534	-0.00514
	(0.0117)	(0.0117)	(0.0117)
Market_share $_{t-1}$	0.00940*	0.00956*	0.00949*
	(0.00548)	(0.00549)	(0.00548)
Constant	-0.226***	-0.222***	-0.226***
	(0.0662)	(0.0663)	(0.0663)
Observations	3,424	3,424	3,424
R-squared	0.055	0.058	0.055

Robust standard errors in parentheses. ***, **, * denote 1%, 5% and 10% levels of significance, respectively. All regressions include controls industry affiliation and macro-area of establishment of the national headquarters.

Results from quantile regressions

Moving now to the non-parametric analysis (Tables 8, 9, 10), firms' innovation dynamics seem to differently score across the growth distribution, thus supporting the idea that growth is a process which involves different drivers according to its pace. This confirms that the choice of the non-parametric approach is the most suitable to properly scrutinize the relationship between innovation and growth.

Very surprisingly, the quantile regressions show that the slower is the pace of growth the greater is the positive contribution of both SI and EI in terms of employment opportunities.

Inconsistent with previous literature on generic innovation, this result may be striking at first. However, explanations for this may be provided by the fact that firms - for the exception of the role of product demand (Demand $_{t-1}$) that positively stimulate growth at every pace of growth - are qualitatively different across quantiles (Navaretti et. al., 2014) as proved by the changing sign and magnitude of the controls. For instance, by deviating from the Gibrat' s law (Sutton, 1997), firms with better growth dynamics (from 50th to 90th quantile) are found to be younger and smaller. Coherently with recent empirical literature (Coad et. al., 2013), this confirms the existence of growth advantages for newly created and smaller companies. The theoretical rationale beyond such a result is twofold. Firstly, the minimum-efficient size (MES) argumentation asserts that firms must reach and cross a certain size threshold to keep existing and maintaining a market preserve (Almus, 2002). Secondly, according to the passive and active learning theories (Ericson and Pakes, 1995; Jovanovic, 1982), small and young firms are likely to grow faster than their peers as they possess more information about their effectiveness in the market which, in turn, allows them to better adjust their size if the level is suboptimal. In parallel, the amount and availability of human capital endowment (Empud $_{t-1}$) representing, among others, a good indicator for firms' intangible assets, supports only in certain circumstances the grasping of opportunities of growth (Garnsey et al., 2006). In this regard, as shown by the empirical estimations, Empud$_{t-1}$ has been found to contribute to the explanation of growth only for firms between the 10th and 75th quantile. Conversely, the lack of significance detected growing firms may suggest that in these cases the human capital endowment is more oriented to strengthen and balance the internal organizational structure instead of pursuing growth-related objectives (Arrighetti et al., 2009). Finally, the size of the market (Market_share $_{t-1}$) is found to be negative and not significant for companies with better growth dynamics (50th, 75th and 90th). This result may be explained by the features associated to firms with stable and rapid paces of growth. Differently from the former, the latter that are smaller in size and younger in age might not be enough equipped in terms of searching, absorbing and transforming capabilities to exploit external knowledge for accessing in new and foreign markets (Autio et al., 2000).

By focusing on innovation dynamics, model (1) reported in Table 8 shows that compared to SI, the impact stemming from EI is particularly higher in the left side of the distribution (10th quantile). In the second specification (2) (Table 9), the main finding is that the positive influence of SI mainly arises from the process&product category along all the quantiles. On the contrary, when environmental goals are addressed, engaging only in process innovation is a sufficient strategy to positively stimulate employment growth (mitigate employment losses), especially in the lowest quantile. The highest impact of EI on *struggling* firms is confirmed by the third specification (3) (Table 10), where the EI modes growth premium turns to be about 2 p.p. higher than that sourcing from the SI mode, with a maximum of 7.6 p.p. recorded for the *recycling* mode. This strong result may be explained by the weakness of the peers included in the same quantile. In fact, there is reason to suppose that struggling firms may lack of financial and economic soundness to engage in EI, since as their economic efforts are mainly finalized at "surviving" instead of "being competitive".

As the growth performance improves, the magnitude of both SI and EI decreases. In the same vein, such a result may be explained by arguing that the odd of introducing generic and green technologies increase for firms that are more stable in size (Table 11).

Finally, the evidences emerging for fast-growing firms deserve a comment on their own. As shown by Table 10, firms belonging to this cluster take advantage only from three modes of innovations: SI mode*, pollution-reducing* and *energy-improving* innovation. This may be due to the fact that, because of their small and young nature, fast-growing firms may lack of those requirements needed to properly deal with other EI strategies, typically characterized by a high technical risk/uncertainty (Aghion et al., 2009; Cuerva et al., 2014). In this view, these companies may possess a lower ability to evaluate the major complexity (Consoli et al., 2016) and marketability of EI innovations (Leoncini et al., 2017). Yet, gazelles may not benefit from better opportunities of financing (Schneider & Veugelers, 2010) linked to the major accountability on financial market, as in case of older and bigger firms. So that, they may be not able to successfully cope with the higher cost of EI (Gagliardi et al., 2016) and avoid crowding out (Hall et al., 2016). Conversely, the introduction of *pollution-reducing* and *energy-improving* technologies could be both driven by the compliance with policy framework (Horbach, 2008; Veugeler, 2012;) instead of strategic "green-related" purposes.

By summing up, using quantile regression allows for major qualifications of the standard OLS analysis. First, as concerns the Gibrat's law shaping the present model, a key finding is that the indicator representing the path dependence (Emp_{t-1}) affect the average growth but its impact is particularly marked for high-growth firms. Second, as regard the focus regressors, we find that innovation drivers positively score across all quantiles. However, the magnitude of the coefficients decreases when growth performances improve and their statistically significance often vanishes when environmental objectives are addressed by firms in the top quantiles.

TABLE 8. THE IMPACT OF INNOVATION ON EMPLOYMENT GROWTH, QUANTILE ESTIMATES (MODEL 1)

	10 th	25 th	50 th	75th	90 th
SI $_{t-1}$	0.0391*	0.0208**	0.0231***	0.0291***	0.0394*
	(0.0213)	(0.00847)	(0.00792)	(0.0104)	(0.0230)
EI $_{t-1}$	0.0664***	0.0233***	0.0216***	0.0252***	0.0328*
	(0.0179)	(0.00773)	(0.00622)	(0.00607)	(0.0187)
Emp $_{t-1}$	-0.00776	-0.00366	-0.0101***	-0.0220***	-0.0348***
	(0.00648)	(0.00322)	(0.00201)	(0.00295)	(0.00454)
ΔDemand $_{t-1}$	0.338***	0.304***	0.320***	0.351***	0.396***
	(0.0545)	(0.0327)	(0.0343)	(0.0304)	(0.0650)
Age $_{t-1}$	0.00160	0.00201	-0.00358	-0.0274***	-0.0354***
	(0.00791)	(0.00450)	(0.00370)	(0.00553)	(0.00962)
Empud $_{t-1}$	0.0118**	0.00584*	0.00560***	0.00315*	0.000507
	(0.00463)	(0.00305)	(0.00176)	(0.00188)	(0.00503)
Group $_{t-1}$	0.0124	0.00558	-5.80e-05	0.0128	0.0199
	(0.0156)	(0.00802)	(0.00548)	(0.00790)	(0.0145)
Market_share $_{t-1}$	0.0314***	0.00919***	0.00358	-0.00159	-0.00829
	(0.00908)	(0.00350)	(0.00219)	(0.00261)	(0.00649)
Constant	-0.494***	-0.308***	-0.170***	0.0311	0.209***
	(0.0609)	(0.0329)	(0.0313)	(0.0301)	(0.0611)
Observations	3,424	3,424	3,424	3,424	3,424

*p>0.10, **p>0.05, ***p>0.010. Bootstrapped standard errors are reported in parentheses. They are based on 50 replications of the data. All regressions include industry affiliation and macro-area of establishment of the national headquarter.

TABLE 9. THE IMPACT OF INNOVATION ON EMPLOYMENT GROWTH, QUANTILE ESTIMATES (MODEL 2)

	10 th	25 th	50 th	75th	90 th
only_process SI $_{t-1}$	-0.0103 (0.0344)	0.00920 (0.0128)	0.00903 (0.0101)	0.0235** (0.0119)	0.0178 (0.0216)
only_product SI $_{t-1}$	0.0756 (0.0593)	0.0356* (0.0190)	0.00517 (0.0161)	-0.00861 (0.0380)	-0.0109 (0.0589)
process&product SI $_{t-1}$	0.0661*** (0.0250)	0.0390*** (0.0117)	0.0485*** (0.0103)	0.0469*** (0.0163)	0.0624** (0.0243)
only_process EI $_{t-1}$	0.0791*** (0.0193)	0.0219** (0.00941)	0.0200** (0.00813)	0.0240*** (0.00857)	0.0343** (0.0170)
only_product EI $_{t-1}$	0.0351 (0.0237)	0.0176 (0.0130)	0.0156 (0.0104)	0.0217** (0.00986)	0.00271 (0.0169)
process&product $E_{I\ t-}1$	0.0800*** (0.0229)	0.0344*** (0.0108)	0.0308*** (0.00703)	0.0281** (0.0112)	0.0475** (0.0201)
Emp $_{t-1}$	-0.00908 (0.00645)	-0.00388 (0.00358)	-0.0112*** (0.00210)	-0.0235*** (0.00213)	-0.0381*** (0.00512)
ΔDemand $_{t-1}$	0.319*** (0.0608)	0.300*** (0.0443)	0.318*** (0.0312)	0.341*** (0.0420)	0.401*** (0.0568)
Age $_{t-1}$	0.000825 (0.0117)	0.00242 (0.00440)	-0.00407 (0.00283)	-0.0265*** (0.00571)	-0.0346*** (0.0102)
Empud $_{t-1}$	0.0129** (0.00569)	0.00549* (0.00294)	0.00612*** (0.00156)	0.00393* (0.00205)	0.00152 (0.00507)
Group $_{t-1}$	0.0144 (0.0147)	0.00390 (0.00902)	-6.32e-05 (0.00602)	0.0140* (0.00844)	0.0234 (0.0150)
Market_share $_{t-1}$	0.0269*** (0.00855)	0.00976*** (0.00311)	0.00355 (0.00256)	-0.00102 (0.00252)	-0.00676 (0.00569)
Constant	-0.476*** (0.0714)	-0.295*** (0.0449)	-0.164*** (0.0266)	0.0401 (0.0343)	0.207*** (0.0620)
Observations	3,424	3,424	3,424	3,424	3,424

*p>0.10, **p>0.05, ***p>0.010. Bootstrapped standard errors are reported in parentheses. They are based on 50 replications of the data. All regressions include industry affiliation and macro-area of establishment of the national headquarter.

TABLE 10. THE IMPACT OF INNOVATION ON EMPLOYMENT GROWTH, QUANTILE ESTIMATES (MODEL 3)

	10 th	25 th	50 th	75th	90 th
SI mode $_{t-1}$	0.0410* (0.0223)	0.0205** (0.00969)	0.0233*** (0.00757)	0.0292*** (0.00788)	0.0383* (0.0213)
EI_pollution-reducing$_{t-1}$	0.0652*** (0.0235)	0.0235* (0.0128)	0.0239*** (0.00732)	0.0253** (0.0115)	0.0357* (0.0189)
EI_recycling $_{t-1}$	0.0767*** (0.0228)	0.0233** (0.0109)	0.0218*** (0.00814)	0.0181* (0.00955)	0.0207 (0.0206)
EI_energy-saving $_{t-1}$	0.0620** (0.0296)	0.0324*** (0.0111)	0.0246*** (0.00867)	0.0276* (0.0146)	0.0521** (0.0255)
EI_material-reducing $_{t-1}$	0.0658*** (0.0194)	0.0157 (0.0125)	0.0177** (0.00830)	0.0270*** (0.00974)	0.0207 (0.0218)
Emp $_{t-1}$	-0.00890 (0.00622)	-0.00362 (0.00341)	-0.0102*** (0.00219)	-0.0213*** (0.00326)	-0.0333*** (0.00565)
ΔDemand $_{t-1}$	0.347*** (0.0524)	0.300*** (0.0365)	0.321*** (0.0259)	0.341*** (0.0394)	0.387*** (0.0683)
Age $_{t-1}$	0.00180 (0.0105)	0.00192 (0.00380)	-0.00361 (0.00440)	-0.0279*** (0.00574)	-0.0366*** (0.0110)
Empud $_{t-1}$	0.0116*** (0.00427)	0.00593** (0.00271)	0.00559*** (0.00154)	0.00327 (0.00259)	0.00245 (0.00580)
Group $_{t-1}$	0.0146 (0.0200)	0.00519 (0.00908)	-3.20e-05 (0.00541)	0.0135 (0.00912)	0.0180 (0.0134)
Market_share $_{t-1}$	0.0318*** (0.00773)	0.00882** (0.00396)	0.00359 (0.00271)	-0.00143 (0.00271)	-0.00741 (0.00599)
Constant	-0.501*** (0.0637)	-0.304*** (0.0361)	-0.170*** (0.0273)	0.0380 (0.0393)	0.205*** (0.0624)
Observations	3,424	3,424	3,424	3,424	3,424

*p>0.10, **p>0.05, ***p>0.010. Bootstrapped standard errors are reported in parentheses. They are based on 50 replications of the data. All regressions include industry affiliation and macro-area of establishment of the national headquarter.

TABLE 11. MEAN VALUES OF EI MODES ACROSS QUANTILES.

Quantile	**EI MODES**				**GROWTH**
	Pollution-reducing	*Recycling*	*Energy-saving*	*Material-reducing*	
10th	.0701754	.0877193	.0350877	.0935673	-.2239177
25th	.09375	.1875	.03125	.1125	-.0685601
50th	.1756757	.2162162	.1081081	.1486486	.0069396
75th	.1390728	.1523179	.0662252	.1258278	.0900346
90th	.1098266	.0924855	.0578035	.0751445	.2670014

SECTION 6

Conclusion & Policy implications

The intertwin between economic and environmental goals is gaining growing momentum in the current policy and academic debate as it represents the central pillar of sustainable development. If theoretical predictions are not univocal as regards to the occupational impact of EI, the empirical literature provides even more mixed results about the relation between green technologies and employment growth. Generally, scholars depict EI as a "whole" or distinguish into broad categories (process vs product or *end-of-pipe* vs *input-saving* classes) thus neglecting EI multifaced and complex nature (Ghisetti et al., 2015). To fill this research gap, this paper provides an attempt to investigate the relations between firms' growth and innovation while considering distinct environmental innovation behaviors adopted by Italian manufacturing firms.

In parallel, since as a typical path of growth does not exist, the analysis pays attention to the heterogeneous nature of the growth process. Indeed, growth patterns can vary significantly one each other on the basis of a number of factors, including innovation behaviors (Coad and Holzl, 2012; Coad and Rao, 2006; Colombelli et al., 2015; Leoncini et al., 2017). Hence, focusing on the "average effect for the average firm" will neglect such heterogeneity which, conversely, may be better captured by considering different quantiles of the distribution of the growth rates, where growth is modelled as a function of firm's innovation.

The overall picture emerging from the analysis suggests a good deal of the heterogeneity in the capacity of EI innovation activities to support expansion of size in term on number of employees. First, from standard OLS regression, I find that all innovation activities are related with employment growth, but the beneficial impact of innovation is greater when environmental goals are achieved. From a policy perspective, this preliminary finding provides support for a simultaneous use and better integration of technology policies innovation and environmental policies.

Second, I recover a differentiated effect for the most of the EI variables included in the model when distinct growth rates are taken into account. This highlights how the effect of environmental innovation activities on average growth may be hardly detected. In particular, a related key finding is that the statistically significant relation between growth and EI modes mainly originates from *struggling* firms while, with exception of a positive influence stemming for *pollution-reduc*ing and *energy-improving* modes, "gazelles" are found to run not on a "green" track. This is striking at first, but there are explanations for these findings. As shown by Table 8, firms belonging to both clusters 10th and 90th report the lowest mean values for the dummies associated with EI modes. The former may in fact be too financially weak to cover with EI activities, while the latter may be too young and small for providing themselves with a sufficient level knowledge to successfully perform EI strategies. This arises many issues linked with deterring barriers to EI (Marin et al., 2014, Ghisetti et al., 2015).

In conclusion, the analysis suggests that, regardless to the specificity of the technological trajectory followed by firms, the net employment effect due to the adoption of new green innovations is always positive but only, in certain cases, statistically significant. This is of particular relevance for *struggling* firms where EI turns out to be a key candidate for overcoming the economic impasse while, on the contrary, fast-growing companies seem to fail in taking advantage from certain green orientations.

These findings must be to take in consideration in the design stage of innovation policies. If from the one hand, environmental targets are not so decisive for the differentiation of the growth premium, as a positive impact is detected for all the four identified modes, on the other hand, the distinction between innovation with and without environmental effects is a key issue from a policy perspective. Given the findings for quantiles 10^{th} and 90^{th}, I claim that public measures in favor of EI should be launched with an eye toward a better integration between environmental and innovation policies as well as a more "tailored" idea of policy intervention. In particular, much more attention should be paid at overcoming the deterring barriers that prevent *struggling* and *fast-growing* firms from successfully engaging in EI.

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General conclusions

Main findings

The present research project has been framed within the modern approach to innovation policy-making, which has been broadly narrated in the general introduction. The key pillar linking the three chapters of the dissertation refers to innovation activities realized by Italian manufacturing firms during the recent years. Manufacturing firms have in fact been traditionally considered as technological forward, by playing a primary role in fostering the pace of technical progress. Each chapter has been basically thought to contribute to the policy and academic debate by providing empirical evidence on new and still unexplored research questions ranging from innovation-related policy drivers to innovation-related employment effects.
Important contributions have emerged from the empirical exercises, whose key features can be summarized as follows:

1. Chapters 1 has pointed the attention on the linkage between supply-side and demand-side public policies and innovation tout-court. The study shows that the adoption of a "policy mix" scheme for boosting firms' innovation investment needs to be revisited and improved by institutions as not all policy measures properly work as innovation-enhancing instruments. In particular, public procurement, especially when adopted in the Italian context, seems to suffer from a considerable number of barriers at administrative level and, more in general, it is likely to be narrowed by a short-term and static-efficiency vision.

2. Given the undisputed socio-economic relevance that the convergence between environmental and economic goals has gained during the last decades, chapters 2 has been focused on environmental innovation. In particular, the study has exploited a wide array of EI policy drivers by contextually accounting for heterogeneity in performing EI strategies. By identifying four EI modes, the econometric exercise has undelighted the relevance played by most of policy tools in sustaining this peculiar type of innovation. In particular, the empirical analysis has shown the presence of positive links between (i) regulatory policies and pollution-reducing innovations, (ii) green public procurement and recycling technologies and (iii) supply-side policies and energy-improving innovations.

3. The main contribution provided by chapter 3 has consisted of the investigation of the relationships between innovation modes and employment growth at the firm's level. The analysis has shown that all environmental innovation activities are related with employment growth, but the beneficial impact of innovation is greater when environmental goals are

achieved. Moreover, such a positive relation between growth and EI modes has been found to mainly originate from struggling firms, while "gazelles" have turned out to run on "non-green" track.

In a nutshell, each contribution of the present thesis supports the view that public policies, effectively or potentially, matter for sustaining firms' R&D investment, promoting the engagement in green technologies and contrasting innovation-related barriers for enabling occupational growth.

The dissertation finds its collocation within the new and modern approach of innovation policy-making, which basically calls for a more active, proactive and systemic use of policy measures for jointly supporting the recovery and the sustainable development of economic systems. As this represents the main challenge of the modern society, I claim that policy action must do its part.