

Working Paper

Characterizing the policy mix and its impact on eco-innovation in energy-efficient technologies

Valeria Costantini

Roma Tre University

Francesco Crespi

Roma Tre University

Alessandro Palma

University of Rome "Tor Vergata"

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Characterizing the policy mix and its impact on eco-innovation in energy-efficient technologies*

Valeria Costantini, Roma Tre University, Rome, Italy
Francesco Crespi, Roma Tre University, Rome, Italy
Alessandro Palma, University of Rome "Tor Vergata", Rome, Italy

Abstract

This paper provides an empirical investigation of the role played by selected characteristics of the policy mix in inducing innovation in energy efficiency technologies. An original dataset covering 23 OECD countries over the period 1990-2010 combines the full set of policies in the energy efficiency domain for the residential sector with data on patents applied over the same period in this specific technological sector. The econometric results suggest that when the policy mix is characterised by a more balanced use in demand-pull and technology-push instruments, its positive effects on eco-innovation tend to be greater. Moreover, a more comprehensive policy mix is shown to be able to enhance innovation activities for the generation of new energy efficient technologies. However, the simple addition of an indiscriminate number of simultaneous policy instruments may reduce policy mix effectiveness. Finally, our findings confirm previous evidence on the importance of policy spillover effects, and suggests that country-pair policy similarity may represent an important aspect to be accounted for in policy mix design.

Keywords: eco-innovation; policy mix; policy spillovers; energy efficiency; residential sector

J.E.L. 031, 038, Q48, Q55, Q58

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1. Introduction

The analysis of eco-innovation in recent years is attracting growing attention both at academic and policy level. A definition of what eco-innovation is has been widely discussed in recent years and the most complete one is provided by Kemp and Pearson (2007, p.7): “[e]co-innovation is the production, assimilation or exploitation of a product, production process, service or management or business method that is novel to the organization (developing or adopting it) and which results, throughout its life cycle, in a reduction of environmental risk, pollution and other negative impacts of resources use (including energy use) compared to relevant alternatives”.¹ Given this broad definition, the current debate has adopted distinguished analytical perspectives in order to better understand the dynamics, characteristics and determinants of eco-innovation (Arundel and Kemp, 2009; Beise and Rennings, 2005; Berkhout, 2011; Cainelli and Mazzanti, 2013; Kemp and Oltra, 2011; Marin, 2014; Markard *et al.*, 2012; OECD, 2011; van den Bergh *et al.*, 2007; Wagner, 2007). These studies suggest that a variety of factors drive eco-innovation, but also highlight the primary role played by public policies (environmental regulation, energy and technology policies) that are increasingly used to foster the rate of introduction and diffusion of new environmental technologies to meet sustainable development goals (del Río, 2009a; Horbach *et al.*, 2012; Johnstone *et al.*, 2010; Mowery *et al.*, 2010; Newell, 2010).

The bulk of previous literature has focused its attention on the impact of single (though different) policy instruments mainly belonging to the two broad categories of demand-pull and technology-push instruments (Bergek and Berggren, 2014; Horbach *et al.*, 2012; Kemp and Pontoglio, 2011; Peters *et al.*, 2012; Rennings, 2000). Recent empirical contributions demonstrate that these instruments have differentiated impacts on the diverse types of eco-innovation activities such as those related to the introduction of incremental or radical innovations (Nemet, 2009) or those associated with technological exploitation or exploration activities (Costantini *et al.*, 2015; Hoppmann *et al.*, 2013). However, there is growing interest in understanding the role played by the different combinations of the available policy instruments in stimulating and directing technical change. In particular, the literature has recently focused on the role of policy mix, a concept that at its basics considers the combination of policies into a composite set, but that also includes the processes through which different instruments emerge and interact (Flanagan *et al.*, 2011; Rogge and Reichardt, 2015).

Empirical studies that focus on the effects of policy mixes on innovation (Guerzoni and Raiteri, 2015) and in particular on eco-innovation performances (Cantner *et al.*, 2016; Reichardt and Rogge, 2016; Uyarra *et al.*, 2016) represent a limited though rapidly expanding area of research.

¹ Given the wide range of different forms of innovations included in the definition by Kemp and Pearson (2007), in this paper the terms eco-innovation, green technologies, environmental innovation are used interchangeably where not explicitly defined in the text.

Following these contributions, here we propose a quantitative analysis based on a large sample of OECD countries that aims to measure some significant characteristics of the policy mix and quantify their impact on eco-innovation activities through panel data econometrics. In particular, we first focus our attention on the balance in the policy mix between demand-pull and technology-push instruments and, then, we try to evaluate the role played by policy mix comprehensiveness. Finally, considering that policy decisions adopted by other countries are likely to influence domestic innovation performance (Peters et al., 2012; Dechezleprêtre and Glachant, 2014), we aim to address if and to what extent the similarity between domestic and foreign policy mixes fosters countries' eco-innovation performances.

The empirical analysis focuses on the case of Energy Efficiency (EE) technologies, which appears to be appropriate with respect to our research purposes, since a large number of different policies in several countries aims to enhance energy efficiency in the residential sector, especially by fostering the generation and diffusion of new energy-efficient technologies (Sovacool, 2009; IEA, 2015). In particular, in the examined case the full range of demand-pull, technology-push and systemic instruments are usually adopted, allowing us to investigate how and to what extent, beside the role played by distinct instruments, the characteristics of the policy mix have an influence on eco-innovation performance.²

The remainder of the paper is organized as follows. Section 2 provides a literature review on the role of public policies in fostering eco-innovation and on the analysis of policy mix. Section 3 introduces the research case and the research hypotheses to be tested, whereas Section 4 defines the dataset, the operationalization of policy variables and the econometric strategy. Section 5 presents and discuss the econometric results and, finally, Section 6 summarizes the main insights emerging from the study, highlights the policy implications and outlines possible further research lines.

2. Background literature

A large number of economic studies have been devoted to identifying the determinants of eco-innovations (see, for instance, del Rìo, 2009a; Foxon, 2003; Horbach, 2008; OECD, 2011). The analysis of eco-innovation drivers has constituted an empirical issue that has given rise to a flourishing strand of literature in which the role of public policies has been found to be of prominent importance (Bergek and Berggren, 2014; Hašičič *et al.*, 2009; Johnstone *et al.*, 2010, 2012; Schmidt *et al.*, 2012). In more detail, the literature has identified different types of policy instruments that have been classified in several categories which mainly refer to technology-push, demand-pull and systemic instruments (e.g., del Rìo *et al.*, 2010; Kemp, 1997; Rennings, 2000; Wieczorek and Hekkert, 2012).

² A previous work by Costantini et al. (2014a) applied to the EE domain is limited to an analysis of the direct policy-inducement effects on the dynamics of EE technologies without addressing the specific role played by the different policy mix characteristics which is the actual focus and contribution of this paper.

2.1 *The role of distinct policies*

The empirical literature investigating the role of different types of instruments in shaping eco-innovation activities is extensive. Earlier studies, mainly due to limited data availability, use a measure of the environmental regulatory stringency proxied by the expenditures certified by firms for implementing pollution control activities rather than specific information on the policy instrument adopted.³ For instance, the pioneering contribution by Lanjouw and Mody (1996) examines the relationship between patenting activity in broadly defined environmental technologies and environmental regulation stringency measured by pollution abatement and control expenditures (PACE) paid by firms in three industrialized countries, Germany, Japan and the United States, and selected developing countries. Different reactions for patenting activity are highlighted, suggesting that eco-innovation performance positively responds to PACE in advanced economies, whereas the largest part of innovation activities in developing countries is explained by the need to adapt imported technologies to local conditions.

In the same vein, Brunnermeier and Cohen (2003) also investigate the relationship between PACE as a proxy of environmental policy stringency and environmental patents by analysing a dataset of 146 US manufacturing industries from 1983 to 1992. In line with the results by Lanjouw and Mody (1996), they find significant (though not extensive) evidence that pollution abatement expenditures are also positively correlated with successful environmental patent applications in the case of a single country and sector-based analysis.

Subsequent empirical analyses adopt more focused perspectives by selecting specific environmental technology sectors on the one hand, and by using variables specifically linked to different policy instruments on the other. One pioneering empirical exercise in this perspective is provided by Popp (2002). The author observes, over the period 1970-1994 in the US, that higher energy prices determined by higher energy taxation encouraged patenting activities in energy-efficient technologies by firms. In the same vein, Crabb and Johnson (2007) analyse if and to what extent fuel taxes applied in the US in the period 1980-1999 have influenced the pattern of patent applications in automotive energy-efficient technologies sector, confirming the positive effect found by Popp (2002).

Starting from the seminal work by Kemp (1997), more recent contributions analyse the different impacts on eco-innovation performance played by distinguished types of policy instruments, providing new knowledge on the mechanisms that explain how environmental policies determine a positive impulse on innovation activities. An example is given by Popp (2006) that analyses patenting activity in air pollution control equipment in three countries, Germany, Japan and the US, combined with selected environmental protection policies. The main

³ The definition and measurement of environmental regulatory stringency are arguments for an extended debate. As clearly described by Brunel and Levinson (2013), the definition of stringency level is strictly correlated with data availability and can be broadly defined as the ambition level of the adopted policy in terms of environmental targets.

empirical findings are that command-and-control schemes seem to be less effective than market-based instruments in spurring eco-innovation and that inventors respond to environmental regulatory pressure in their own country, but not to foreign environmental regulations.

By considering only process innovation distinguished in end-of-pipe technologies (interpreted as mature innovation) and integrated cleaner production technologies (as less mature innovation), Frondel *et al.* (2007), using a firm-level dataset based on a OECD survey performed in 2003 for seven countries (Canada, France, Germany, Hungary, Japan, Norway and the US), find that only command and control mechanisms play an important role in stimulating end-of-pipeline solutions and a minimal role for integrated cleaner production technologies, whereas market-based options are ineffective in encouraging eco-innovation. In the same way, Demirel and Kesidou (2011) analyse the impact of environmental public policies, measured as binary variables reflecting the existence or not of environmental standards (interpreted as a command and control instrument) or environmental taxes (interpreted as a market-based instrument), on three eco-innovation domains (End-of-Pipeline Pollution Control Technologies, Integrated Cleaner Production Technologies and Environmental R&D) in the UK, finding that the three domains respond differently to different policy tools and that environmental standards mainly affect End-of-Pipeline Pollution Control Technologies, whereas environmental taxes are neutral to eco-innovation actions.

The contribution by Johnstone *et al.* (2010) constitutes a significant step forward in the direction of generalizing these results since the whole range of renewable energy technologies measured by patent applications is combined with the whole range of public policy tools in that domain, in a comprehensive sample of OECD countries for a long time series (1978-2003). The authors conclude that different policy instruments have heterogeneous effects on different renewable energy technologies depending on their degree of technological maturity and that, *ceteris paribus*, feed-in tariffs and public R&D expenditures in renewable energies are the tools that foster the most eco-innovation performances.

The diversification of impacts on eco-innovation activities related to the specific policy instrument adopted is also analysed from the perspective of the classification of environmental regulation tools in the two broad categories of demand-pull and technology-push instruments (Horbach *et al.*, 2012; Peters *et al.*, 2012). Both kinds of instruments have been found to be important in spurring innovation in environmental technologies, with differentiated effects according to the specific technological domain analysed such as, for instance, in the biofuels (Costantini *et al.*, 2015), solar photovoltaic module (Hoppmann *et al.*, 2013) and wind power (Nemet, 2009) sectors. As a general result, demand-pull policies seem to benefit mature technologies to a larger extent than less mature technologies, whereas technology-push policies

turn out to be necessary in stimulating eco-innovation activities in less mature technologies.

With regard to the specific role played by voluntary instruments, previous contributions mainly address the firm level adoption of an environmental management scheme (EMS) as a potential driver of process and product innovation. Although the empirical investigations are carried out on different datasets for different years and countries, they find that EMS and other managerial activities voluntarily adopted to reduce environmental impacts have a positive influence on both environmental-friendly process and product innovations (Rennings *et al.*, 2006; Wagner, 2008).

In addition to the role of national regulation, there are few empirical contributions that focus their attention on the existence of cross-country policy spillover effects that may positively influence eco-innovation performances. For instance, Lanjouw and Mody (1996) observe that strict regulations on vehicle emissions in the US spurred innovation in foreign countries such as Germany and Japan. On the contrary, Popp (2006) finds that in air pollution control equipment innovations developed in the same three countries, inventors only respond to environmental regulatory pressure in their own country, whereas they are not influenced by foreign environmental regulations.

By considering chlorine-free technology in the pulp and paper industry, Popp *et al.* (2011) find a positive correlation between foreign regulation and domestic innovation by investigating patent applications in seven OECD countries over the period 1985-2003. Dekker *et al.* (2012) also highlight the positive role played by foreign policies and investigate patenting decisions by firms in SO₂ abatement technologies. Based on a panel dataset of 15 countries in the period 1970–1997, the authors show that domestic innovation is affected by both domestic policies and by the international regulatory framework, here measured as the entry into force of international environmental agreements such as the Helsinki and Oslo protocol as part of the Convention on Long-Range Transboundary Air Pollution.

The contribution by Dechezleprêtre and Glachant (2014) adds new insights to the role played by foreign policies promoting wind power for eco-innovation performance, considering a panel of 28 OECD countries over the period 1994-2005. In the analysed case, the authors find that eco-innovation performance, measured by patent applications, increases in response to both domestic and foreign policies. Moreover, they find that domestic innovation activity is influenced by only foreign demand-pull policies, whereas it is neutral with regard to foreign technology-push ones. In parallel, Peters *et al.* (2012) find similar effects for foreign demand-pull policies in the photovoltaic energy sector by looking at the patenting activity of 15 OECD countries over the period 1978-2005.

2.2 *The role of policy mix*

Although there is an extensive literature evidencing the role of distinct public policies in shaping eco-innovation activities, there is still space for investigating how the combination of different policy instruments influences the generation and diffusion of new environmental technologies. The number of contributions that examine the interaction effects between different policies in the context of eco-innovation studies is in fact limited, though this line of research is gaining momentum (see, for instance, Cantner *et al.*, 2016). These studies build on and apply the notion of policy mix which originates from economic policy and political science literatures and has been subsequently adopted in environmental policy and innovation literatures (see Flanagan *et al.*, 2011 for a review of the origins of this notion).

At the basic level, studies regarding policy mix are concerned with a combination of policies into a composite set and with an analysis of how their interactions shape their effectiveness (Cunningham *et al.*, 2013), although more refined conceptualizations of policy mix also include the dynamic processes through which different instruments emerge and interact (Flanagan *et al.*, 2011; Rogge and Reichardt, 2015).

In the context of environmental policy studies, Gunningham and Sinclair (1999) highlight that in order to achieve an environmental goal, a number of different instruments are frequently combined into policy mixes. However, they suggest that nothing guarantees that any combination of instruments is superior to a single instrument approach. On the contrary, different combinations of instruments can have a variety of effects which may range from complementarity to counter-productivity. More specifically, Sorrel and Sijm (2003) note that, though positive combinations between an Emission Trading System (ETS) and other instruments are theoretically possible, in practice the net result of adding instruments to ETS may result in a mix of overlapping and conflicting instruments without any overall coherence. In this respect, del Río (2006, 2009b) provides a thorough analysis of the interactions between ETS and renewable electricity support schemes, suggesting that these may lead to both synergies and conflicts. Moreover, these tend to be context-specific since they depend on the design features of the instruments in specific countries. For instance, in the case of Spain, del Río (2009b) finds that policy interactions may lead to conflicts with regard to some specific criteria (e.g., consumer costs) and synergies with regard to others (e.g., dynamic efficiency). Different cases of combinations of policy instruments for environment protection have been analysed by the OECD (2007) which identifies cases in which the use of instruments in combination helped reach environmental goals, but also a number of cases in which the use of overlapping instruments reduces the economic efficiency of the mix. Where these problems have been identified, they are partly attributed to insufficient (both *ex-ante* and *ex-post*) analyses of the impacts of a given mix of policy instruments. Finally, Lehman (2012), when analysing economic studies on the use of policy mix for pollution control, identifies two main rationales for combining different policies.

First, a policy mix may reduce multiple reinforcing market failures such as pollution externalities and technological spillovers; second, it can be used when high transaction costs are associated with the implementation of single policies. Hence, within the analytical framework developed by Lehman (2012), if both rationales do not hold, the use of a single policy will be sufficient to address pollution control problems.

In parallel, the notion of policy mix has been applied and developed by innovation policy scholars. Early studies attempt to investigate the complementarity mechanisms as well as the substitution effects among coexisting instruments (see, for instance, Branscomb and Florida, 1998; Smith, 1994). Subsequently, the use of the policy mix concept in innovation policy studies has grown considerably although it has been convincingly claimed that the term is under-conceptualised (Flanagan *et al.*, 2011). Many studies still adopt heterogeneous, and sometimes ambiguous, terminology with regard to policy mix characteristics in particular that describe the nature of a policy mix and may be capable of shaping the effectiveness of the policy mix in delivering policy goals (Rogge and Reichardt, 2015). For instance, the OECD (2010) focuses its analysis on the *balance* and *coherence* of the policy mix. With the former characteristic, the OECD (2010) specifically refers to the balance within the mix between demand-pull and technology-push instruments. With the latter, it refers to the extent implemented policies act to support rather than detract from one another.

In the more specific context of analyses of policy mix designed to promote eco-innovation, Rogge and Reichardt (2015) make an effort to clarify the meaning of the main characteristics of policy mix identified in previous literature, both with regard to policy processes and instruments combinations. In particular, regarding the instrument mix, they refer to its *consistency* when positive interactions between different instruments take place and to its *comprehensiveness*, defined as the degree to which the instrument mix addresses all the three policy purposes of technology-push, demand-pull and systemic concerns. These characteristics are expected to impact the performance of policy mix, though in a differentiated, context-specific way, depending on the specific and unique nature of each innovation system (Borras and Edquist, 2013).

Empirical studies that focus on the effects of policy mixes on innovation and in particular on eco-innovation performances represent a limited though rapidly expanding area of research. With regard to the analysis of policy mix in relation to “general” innovation activities, Guerzoni and Raiteri (2015) study the impact of different policy tools and their interactions on business innovation investment in 27 EU member states, and including Norway and Switzerland, using data from the Innobarometer survey (2006-2008). In particular, by applying the propensity score matching method, they study the effects on firm expenditures on all innovative activities of three innovation policies: tax credits, subsidies and public procurement. When analysing the

interactions between these tools, they find that the increase in total innovation expenditure due to the contextual use of both technology-push and demand-pull instruments is higher than the sum of the effects of the three policies considered in isolation. Considering these results, they stress the importance of evaluating innovation policies by looking at the overall policy mix and how its effectiveness is positively affected by the balance between demand-pull and technology-push policies.

With regard to specific contributions that analyse the policy mix and its characteristics in relation to eco-innovation, Reichardt and Rogge (2016) develop a qualitative company case study to analyse the innovation impact of the characteristics of the policy mix in the German off-shore wind sector. They find that in the examined case, the consistency and credibility of the policy mix have been vital sources of innovation incentives. In parallel, Cantner *et al.* (2016) provide an analysis of how the different instruments in the policy mix and its consistency influence inventive activities in renewable energy technologies in Germany. By focusing on the size and structure of co-inventor networks in wind power and photovoltaic sectors, they find a positive influence of both demand-pull and technology-push instruments on inventive activities, though the former effects are technology-dependent. Moreover, their analysis shows that in the examined case, the interaction between technology-push and demand-pull instruments is positive, suggesting complementarity between the two types of instruments. Positive interaction effects are also found between demand-pull and systemic instruments, though only in the case of wind power technologies, suggesting in this specific case the existence of an overall consistency in the policy mix.

Finally, Uyarra *et al.* (2016) adopt a policy mix framework to analyse UK policies for low carbon innovation support. Their study combines document analysis with 35 in-depth interviews, with a specific focus on SMEs operating in the low carbon and environmental sectors. They observe that coherence and consistency concerns are emerging in the UK as a consequence of an increasingly crowded policy landscape and limited coordination between multiple agencies involved at different governance levels. Moreover, their interviews reveal the importance of policy stability, communication and credibility in fostering innovation activities by firms.

Following this empirical literature, our paper aims to provide a contribution in this direction by presenting an econometric analysis based on a large set of country level data. This provides us with new empirical evidence on the impact of selected policy mix characteristics on eco-innovation performance in the case of energy efficiency technologies in the residential sector which has not been analysed by previous innovation literature on policy mix. In so doing, we also try to make a first attempt to include the role played by foreign policies in the analysis, an aspect that has been rarely addressed and which has not yet been considered by the literature

that examines the relationships between policy mix and eco-innovation.

3. Research case and hypotheses

The case of energy-efficient technologies in the residential sector appears to be worth investigating with a view to better understanding how the characteristics of policy mix influence eco-innovation for several reasons. The first one is that a large number of different policies in several countries aims to enhance energy efficiency in the residential sector. In particular, the large discrepancy between those agents making decisions about energy efficiency improvements (mainly firms) and those effectively paying the energy bills (mainly consumers) requires the implementation of multiple policies in order to influence the whole range of agents involved in achieving energy saving targets (Sovacool, 2009). For this purpose, the policy instruments implemented in this sector can be grouped into three main pillars. The first two refer to the broad categories of demand-pull and technology-push instruments with the latter aiming to increase the supply of new scientific and technological knowledge and the former aiming to enlarge the size of the market demand for new technologies (del Rìo *et al.*, 2010). The third pillar considers systemic instruments, i.e. tools that target systemic problems and thus aims to influence the overall functioning of the system (Smits and Kuhlman, 2004; Wieczorek and Hekkert, 2012). In particular, within this broad category, the so-called soft instruments (e.g., information and education or voluntary approaches) aim to enhance the level of consumers' awareness with regard to the potential benefits deriving from the adoption of specific environmental friendly behaviours (Carraro and Leveque, 2013; Jänicke and Weidner, 2012; Kemp, 1997).

The second source of interest rests in the pivotal role that new energy-efficient technologies play in achieving energy efficiency gains in the residential sector (IEA, 2015). The evolution of technologies in this sector has been fast in recent years, especially in OECD countries. If we look at the number of patents, those related to energy efficiency in the residential sector have increased by an annual average rate of about 12% in the period 1990-2010 in OECD countries. Public investments in R&D activities specifically oriented towards energy efficiency in the building sector also faced a substantial increase with an average annual growth rate in the same period of about 15%.⁴ Nonetheless, according to the IEA (2015), further efforts are needed to boost energy efficiency especially in the building sector, recognized as one of the major potential contributors to the transition towards a low-carbon economy. In this respect, public policies and the type of combinations of different instruments forming the policy mix are recognized as critical elements for encouraging innovative investments and the full engagement of the multiple actors involved in the energy efficiency system of innovation.

⁴ For details on data used for these statistics on patents and public R&D investments, see Section 4.

Following the reviewed literature, in the empirical investigation we have chosen a selection of issues to be analysed considering the specific features of the technological domain under scrutiny and data availability. This adaptive strategy implies several caveats that will be explicitly discussed in the description of the operationalization of policy mix characteristics into indicators and in the interpretation of results.

According to previous contributions and considering available information on the set of policy instruments related to energy efficiency objectives, we identify two characteristics of the policy mix that can be measured and whose specific impact on eco-innovation performance can be evaluated.

First, as suggested by the OECD (2010), we focus our attention on the *balance* in the policy mix between demand-pull and technology-push instruments. This issue appears to be of particular relevance in the context of eco-innovation studies where it has been claimed that the public financing of demand-pull measures aimed at stimulating the deployment of green technologies in the energy sector (mainly renewables) has been disproportionate compared with investments in R&D policies (Frondel *et al.*, 2008; Laleman and Albrecht, 2014; Nemet, 2009). On the one hand, an unbalanced policy mix in favour of demand-pull instruments could lead to a reduced variety of alternative technologies and possible lock-in effects in inferior technologies (Costantini and Crespi, 2013; Hoppmann *et al.*, 2013). On the other hand, a disproportionate use of technology-push instruments could slow down expectations on demand expansion, partly reducing private investments in new technologies. Moreover, the implementation of a balanced policy mix in terms of demand-pull and technology-push instruments may help to establish a reliable policy framework that can foster innovation efforts towards both exploitation and exploration activities (Costantini *et al.*, 2015). To give an example for the specific domain under scrutiny, if a national government decides to impose a high energy tax on electricity consumption without increasing R&D expenditure on energy efficiency, the final result of such an unbalanced policy mix will be an increase in energy prices without a parallel enhancement of domestic technological capacities in energy efficiency. This may lead to increasing technology imports from abroad without a positive effect on the domestic capacity of generating the new technologies needed by consumers. On the contrary, an unbalanced policy mix mostly favouring technology-push policies without a proper set of demand-pull instruments influencing consumers' behaviour may convince innovative investors that there is an inadequate internal demand for new technologies, reducing profit expectation and thus lowering the propensity to innovate. Based on these considerations, we hypothesize that:

HP1. *A more balanced policy mix in terms of demand-pull and technology-push instruments, ceteris paribus, has a positive influence on innovation performance in EE technologies.*

Second, we try to evaluate the role played by the *comprehensiveness* of the policy mix that can be defined, as already recalled in the literature review, as the contextual use of different types of instruments encompassing the three pillars of technology-push, demand-pull and systemic policies (Rogge and Reichart, 2015). The inherent complexity of a policy framework aimed at enhancing energy efficiency suggests that a large range of instruments has to be implemented at the same time, acting both on the demand and the supply side, activating different response mechanisms within the system ranging from purely economic decisions taken by market operators to changes in consumption behaviours by individuals (Sovacool, 2009). As previously recalled, in the case of energy consumption in the residential sector where the final users do not always correspond to agents paying the energy bill, the adoption of a market-based mechanism that aims to increase the price of energy may not necessary lead to a reduction in energy consumption. More responsible energy saving behaviour is likely to occur if additional complementary information programmes are settled, leading to increased demand for energy-efficient technologies. Hence, in this context, the use of soft instruments such as voluntary and non-coercive measures in addition to standard market-based and command and control tools can help to control for side effects or reinforce the efficacy of the main instruments employed (del Río and Howlett, 2013). Finally, other systemic instruments that aim to target institutional, infrastructural, policy strategy and agent interaction issues are expected to play a role in fostering eco-innovation in the analysed sector (Smits and Kuhlman, 2004; Wieczorek and Hekkert, 2012) such as, for instance, the creation of a national energy efficiency agency or the construction of a specific technological platform on energy saving technologies. Building on this discussion, we therefore formulate the following research hypothesis:

HP2a. *A more comprehensive policy mix positively influences innovation performance in EE technologies.*

However, the positive impact of *comprehensiveness* may be somewhat reduced if an excessive number of different policies is settled. Considering the different types of interactions between different instruments evidenced by the literature (Bressers and O'Toole, 2005; Gunningham and Sinclair, 1999), Flaganan *et al.* (2011) conclude that the simple accumulation of theoretically complementary instruments at some point may lead to negative or contradictory interactions. Detrimental uncertainties can emerge when a disproportionate variety of policy tools is jointly implemented. An example in the field of energy efficiency may be the adoption of several norms directed toward the same goal that contain contradictory elements, as occurred in selected countries such as Italy and Spain when implementing the EU Directive on building labelling codes and standards. Another example is related to those cases in which the adoption of

incremental norms over time led economic operators to consider labelling codes as not compulsory, thus reducing the strength of the dissuasive power of administrative controls and limiting the demand increase of energy-efficient goods for building and construction activities. More generally, the existence of increasing costs in order to be compliant with different regulatory frameworks and the dispersion of economic resources across a myriad of public interventions may increase agents' perceptions of conflicts in the final objectives of different tools, resulting in reduced credibility in the overall policy strategy. Hence, as stressed by Arundel and Kemp (2009), when the portfolio of policy tools is too diversified, it may also act as a barrier to innovation. This prompts us to formulate the following research hypothesis:

HP2b. *There is a limit beyond which an excessive variety of policy tools shaping policy mix comprehensiveness display a negative effect on innovation performance in EE technologies.*

Finally, decisions and policy strategies adopted by other countries are likely to influence internal innovation performance. The pure policy spillover effects analysed by recent contributions on green technologies consist in the influence played by foreign policies on domestic innovation performance. On the one hand, foreign demand-pull policies may increase the potential market for such technologies, thus positively influencing domestic investments in eco-innovation activities (Peters *et al.*, 2012). On the other, technology-push foreign policies are expected to generate international knowledge spillovers that can benefit domestic technological capabilities (Dechezleprêtre and Glachant, 2014).

Together with the direct influence exerted by foreign policies on domestic innovative activities, the cross-country coordination of policies may provide a positive impulse for innovation performance. This argument may be grounded in more general contributions on the potential benefits of environmental policy international coordination (Jacobs, 2012). For instance, Bovenberg and Clossen (2012) show that the international coordination of environmental policies aimed not only at setting common targets, but also at adopting similar policy schemes across countries, substantially increases the cost-effective achievement of the targets. More specifically, by analysing the functioning of a market-based instrument such as emission taxation, Carraro and Topa (1994) show that firms decide to innovate earlier if there is international coordination across countries compared with a situation where governments freely set the domestic tax rate. Along the same lines, Beise and Rennings (2005) show that the creation of lead markets that pull eco-innovation is more effective for selected clean energy technologies (wind energy and fuel-efficient passenger cars) when a country adopts environmental regulations also adopted by other countries. Finally, the issue of international environmental policy similarity has been the object of a recent contribution by Dechezleprêtre *et*

al. (2015) on the cross-border diffusion of new environmental technologies which shows that the smaller the country pair regulatory distance, the higher the cross-border flows of compliance technologies. Though the focus of this last contribution is on cross-border diffusion of eco-innovation and not on its generation, it provides the basis for developing a workable definition of policy similarity in terms of country pair policy distance.

In this paper, we propose that the issue of cross-national policy coordination may also be interpreted under the lens of policy mix analysis. In particular, we want to address if and to what extent the similarity between domestic and foreign policy mixes fosters countries' eco-innovation performances. Hence, we formulate the following hypothesis:

HP3. *The similarity between domestic and foreign policy mixes positively affects innovation performance in EE technologies.*

4. Empirical strategy

Building on the reviewed literature on the drivers of eco-innovation, the proposed empirical analysis aims to evaluate the impact of policy mix characteristics on the generation of new technologies in the energy efficiency sector by controlling for the different forces that can shape innovation dynamics in the considered sector.

The linear econometric model to be estimated is as follows:

$$Y_{i,t} = \alpha_i + \gamma_t + \beta_o + \beta_1(DomPol_{i,t-p}) + \beta_2(DomPolMix_{i,t-p}) + \beta_3(ExtPol_{i,t-p}) + \beta_4(ExtPolSim_{i,t-p}) + \beta_5(InnSys_{i,t-p}) + \varepsilon_{i,t} \quad (1)$$

where $Y_{i,t}$ indicates the innovation performance measure in the EE residential sector, $i=1,\dots,N$ indexes countries (23 OECD), $t=1990,\dots,2010$ indexes time, α_i are country-specific unobserved time invariant effects, γ_t are year-specific unobserved country invariant effects, p stands for eventual lag structure and $\varepsilon_{i,t}$ are stochastic errors.

In order to test our hypotheses and account for different factors influencing innovation activities in the sector under scrutiny, five specific groups of variables have been considered representing respectively: the EE domestic policy setting (*DomPol*), the range of different characteristics of the EE domestic policy mix (*DomPolMix*), the EE policies adopted by foreign countries (*ExtPol*), the similarity degree between the domestic and foreign policy mix (*ExtPolSim*), and the national innovation system (*InnSys*) as an additional control on country fixed effects.

4.1 Dependent variables

Measuring eco-innovation is not an easy task and the empirical literature identified different types of indicators (Kemp and Pearson, 2007). Surveys based on questionnaires are able to capture a wide range of firms' strategies (del Río González, 2005; Frondel *et al.*, 2008; Horbach *et al.*, 2013; Kesidou and Demirel, 2012; Lanoie *et al.*, 2011; Oltra *et al.*, 2010; Wagner, 2007), but they mostly provide qualitative information and may be subject to misleading interpretations by respondents. Specific information on R&D expenditures can be considered a good proxy of innovation activities, but this is rarely available for the private sector when specific technological sectors are under scrutiny.

Information contained in patent documents represents a viable alternative for analysing eco-innovations since it is publicly available for a reasonably long time series and provides detailed information that allows researchers to conduct rich quantitative analyses. Consequently, the use of patent data is widespread in the economics of innovation literature (Archibugi and Pianta, 1996; Cohen *et al.*, 2000; Griliches, 1990; Guellec and van Pottelsberghe de la Potterie, 2002; Lanjouw *et al.*, 1998; Lanjouw and Schankerman 2004; Malerba and Orsenigo, 1996; Pavitt, 1984; van Zeebroeck *et al.*, 2006) and also in the contributions that specifically analyse eco-innovation (Dechezleprêtre *et al.*, 2011, 2015; Hašič *et al.*, 2009; Jaffe and Palmer, 1997; Johnstone *et al.*, 2010; Oltra *et al.*, 2010; Wagner, 2007).

However, the use of patent data presents several drawbacks: among others, the distribution of patents across firms and sectors is highly skewed, there is a large variance in patent quality and, most importantly, only a fraction of innovations is patented (Griliches, 1990; Jaffe and Trajtenberg, 2004). With regard to our study, by adopting patents as a measure of eco-innovation, we are able to capture only some of the technological eco-innovation activities, thus excluding all the other forms of eco-innovation that are part of the broad definition provided by Kemp and Pearson (2007). Accordingly, the interpretation of the empirical results should account for such a limited information content of the adopted innovation measure.

In this work, following the contribution by Costantini *et al.* (2014a), innovation in the EE domain is measured by the count of patent applications filed at the EPO by 23 OECD countries over the period 1990-2010.⁵ Despite the extensive work on defining relevant patent classes related to eco-innovation, some specific domains still remain poorly investigated. In the case of EE technologies, standard international patent classification tools only partially represent the whole range of sub-domains characterizing this field. The patent database developed by Costantini *et al.* (2014a) and here adopted allows the Y02 Cooperative Patent Classification

⁵ Austria, Australia, Belgium, Canada, Switzerland, Germany, Denmark, Spain, Finland, France, the United Kingdom, Greece, Ireland, Italy, Japan, Korea, Luxembourg, Netherland, Norway, New Zealand, Portugal, Sweden, the United States.

(CPC)⁶ based on patent classes for green technologies to be integrated with the specific work carried out by Noailly and Batrakova (2010), mapping EE technologies in the building sub-sector and the detailed analysis on the sub-sector of electrical appliances developed by Costantini *et al.* (2014b). A complete list of keywords and patent classes used for mapping this technological domain is provided in the Appendix, Tables A1a-A1b.

The selected patents applied to the EPO are classified by application date and assigned to the applicant's country. When multiple assignee countries are present for a single patent, we have assigned a proportion of the considered patent to each country on the basis of the number of assignees for each country. We are aware that several studies have tried to analyse innovation dynamics by also controlling for patent quality (Hall *et al.*, 2005; Jaffe and Trajtenberg, 2004; Popp, 2002). In this respect, two general issues are considered here. First, given that EPO applications are more expensive than applications to national patent offices, inventors typically apply to the EPO if they have strong expectations in terms of economic exploitation of the invention. Hence, for the purpose of this paper, we have chosen EPO data instead of single national patent offices because the difference in costs provides a quality hurdle that reduces applications for low-value inventions (de Rassenfosse and van Pottelsberghe de la Potterie, 2013; EPO, 1994). Although the European market is significant, some bias towards applications from European inventors is still expected. In the empirical analysis undertaken in this study, this bias is addressed through the inclusion of country fixed effects.⁷

4.2 *Independent variables*

In this work, we propose a specific effort to map public policies in the field of energy efficiency. In order to empirically test our research hypotheses on the characteristics of the policy mix, we need to retrieve information on the three policy pillars identified as relevant in the previous sections.

4.2.1 *Policy pillars*

With regard to the demand-pull pillar, we consider the impact of energy taxation on the market

⁶ The Cooperative Patent Classification, as developed by the United States Patent and Trademark Office (USPTO), classifies patents into nine sections, A-H and Y, which in turn are sub-divided into classes, sub-classes, groups and sub-groups.

⁷ According to Popp (2005), there are different ways to measure knowledge production in the green technologies field using patent data. In order to provide robustness checks for these different measures, in the Appendix we have reported results obtained for Table 2 estimated on two alternative dependent variables, a citation-based patent measure, as reported in Table A6, and a patent stock measure, as reported in Table A7. With regard to the citation-weighted patent measure, following Squicciarini *et al.* (2013), we have built a count indicator based on forward citations in the five years after their publication using the information contained in the OECD EPO Indicators Database. In the patent stock measure, we have followed the methodology proposed by Popp (2005). In both cases, empirical results reported in the main text, obtained using a pure patent count measure, are mainly confirmed. Accordingly, in the following sections, we report econometric results based on this latter innovation measure. All results for Tables 3-6 are confirmed when the two alternative dependent variables are considered and they are fully available upon request from the authors.

price in energy demand for the residential sector as a price-based instrument.⁸ In so doing, we follow previous contributions which generally found that prices played a significant and positive role in fostering innovation dynamics in more efficient energy technologies (Jaffe and Stavins, 1995; Newell *et al.*, 1999; Noailly, 2012; Popp, 2002; Verdolini and Galeotti, 2011). Since we are interested in capturing the role of this policy in affecting residential energy consumption and consequently favouring EE innovation, we calculate the average tax rate applied to energy consumption in the residential sector for each country and year (here expressed as USD at constant 2010 prices per unit of energy consumed, expressed in tonnes of oil equivalent (toe)). In order to consider the different mix of energy commodities used in the residential sector at the country level, we weight energy tax rates by consumptions related to each specific source as follows:

$$DomPol_{Demand-pull_{i,t}} = Energy Tax_{i,t} = \frac{\sum_{n=1}^3 (Energy\ tax_{i,t}^n \cdot Ener_cons_{i,t}^n)}{\sum_{n=1}^3 (Ener_cons_{i,t}^n)} \quad (2)$$

where n indexes the energy commodity (diesel, electricity and natural gas), whereas i and t refer to countries and time, respectively. Tax rates are taken from IEA Energy Prices and Taxes Statistics (IEA, 2012a), whereas data on energy consumption are taken from IEA Energy Balance Statistics (IEA, 2012b). All data strictly refer to the residential sector. In this way, the stringency level of the policy adopted and its relative impact on the specific residential energy input mix used in each country can be considered simultaneously, thus controlling also for the peculiarity of the residential sector within the country-specific national energy system.

The technology-push policy pillar is quantified by taking the stock of public R&D efforts in EE (expressed in million USD at 2010 constant prices) taken from IEA Technology Statistics (IEA, 2013a, online database) as:

$$DomPol_{Technology-push_{i,t}} = RD\ in\ EE_{i,t} = \sum_{s=0}^t \{RD\ in\ EE_{i,s} \cdot e^{[-\delta(t-s)]}\} \quad (3)$$

In so doing, we are supposing that technological knowledge has a cumulative character and, hence, can be summed over time, but that knowledge capital is also subject to an obsolescence rate (Evenson, 2002). We have applied an average decay rate of 15 per cent to the Perpetual

⁸ Due to data constraints, different forms of demand-pull policies such as command and control instruments can be analysed only in qualitative terms and they are included in the analysis of the characteristics of the policy mix.

Inventory Method suggested by OECD (2009), so that in eq. (3) δ indicates the discount rate, i indexes countries and s, t indicate time.⁹

The third policy pillar refers to systemic instruments that specifically address issues related to the promotion of energy efficiency in the residential sector. Measurement problems in this case are relevant since we only have qualitative information on the set of instruments identified by the IEA and available from the Energy Efficiency Policy and Measures Database (IEA, 2013b). We collect information from the IEA database on EE policy instruments in three sectors (buildings, lighting, residential appliances) for OECD countries, still in force or ended in the 1990-2010 period, classified in six types (Table1).

Table 1- Policy types and instruments

Type #	Policy Type	Instrument
1	<i>Economic Instruments</i>	Direct investment Fiscal/financial incentives Market-based instruments
2	<i>Information and Education</i>	Advice/aid in implementation Information provision Performance label Professional training and qualification
3	<i>Policy Support</i>	Institutional creation Strategic planning
4	<i>Regulatory Instruments</i>	Auditing Codes and standards Monitoring schemes Obligation schemes Other mandatory requirements
5	<i>Research, Development and Deployment (RD&D)</i>	Demonstration projects Research programmes
6	<i>Voluntary Approaches</i>	Negotiated agreements Public voluntary schemes Unilateral commitments

Source: IEA (2013b)

For the construction of our indicator representing systemic instruments, we only consider policies classified in types 2, 3, 6, namely Information and Education, Policy Support and Voluntary Approaches. With regard to the first type, it includes all forms of support to the cognitive-informational context as guidelines and recommendations to improve the adoption of energy saving behaviours at the household level (e.g., the Germany's Blue Angel eco-labelling scheme for highly insulated, hot water tanks, adopted in 2006) or to diffuse the notion of energy

⁹ The literature suggests a depreciation rate varying between 5 and 30 per cent (Benkard, 2000; Gallagher et al., 2012; Hall, 2007, Nemet, 2009). As a robustness check, we also tested different decay rates, namely 10 and 20 per cent. Results in Tables 2-4 are based on a 15 per cent decay rate and results obtained by applying different rates are quite similar to those reported in the text. Full details on robustness checks are available upon request.

efficiency at different education degrees in order to prepare executives to be ready to adopt an energy-efficient managerial culture (e.g., the Energy Smart Schools programme adopted in 1998 in the U.S.).

The second type includes policies that aim to reinforce the support provided by the institutional context in achieving energy efficiency targets such as, for instance, through the creation of ad hoc government agencies (e.g., the creation of the National Agency for Energy Efficiency in Italy in 2008).

The third type refers to all voluntary approaches that may help the introduction and adoption of energy-efficient behaviours, as described by Kemp (1997), consisting in agreements between private agents and governments to assist consumers and building industries in achieving better energy performances (e.g., the Voluntary Building Initiatives Programme adopted in Australia in 2006).

Considering the qualitative information of the IEA database, we have assigned value 1 if there is a policy in one of the three types for each country and year. The final measure of systemic instruments is given by the sum of counts as the cumulative number of policy instruments in force at time t in country i :

$$DomPol_{systemic\ instruments_{i,t}} = \sum_{q=2,3,6} \left(\sum_{s=0}^t (POL_{i,s}^q) \right) \quad (4)$$

where $q \in [2,3,6]$ represents the three policy types selected as specified in Table 1.

According to Johnstone *et al.* (2010), this modelling choice allows the whole range of policies still in force at time t in country i to be considered for each year and changes occurring to policies over time can also be accounted for.

4.2.2 The characteristics of the domestic policy mix

In order to test the first hypothesis related to the *balance* between demand-pull and technology-push instruments in the domestic policy mix (HP1), we compute a similarity index between these two pillars. Considering that these are expressed in different units, USD per toe for energy tax and millions USD for R&D in EE, we have scaled this second indicator by total residential energy consumption, thus obtaining two homogenous measures expressed in USD per toe. The empirical formulation of this measure is adapted from the contributions by Frenken *et al.* (2007) and Los and Timmer (2005) for the cognitive proximity matrix used to assess the technological relatedness. Accordingly, our measure of policy mix balance is as follows:

$$DomPolMix_{Balance_{i,t}} = \left[\frac{\left| \frac{Ener\ tax_{i,t} - \frac{RD\ in\ EE_{i,t}}{\sum_{n=1}^3 (Ener_cons_{i,t}^n)}}{\sqrt{Ener\ tax_{i,t} + \frac{RD\ in\ EE_{i,t}}{\sum_{n=1}^3 (Ener_cons_{i,t}^n)}}} \right|^{-1}}{2} \right] \quad (5)$$

The closer the similarity in the intensity of the two policy instruments, the greater the balance between them and the higher the expected positive influence on EE innovation.

The second characteristic of the policy mix under scrutiny refers to its *comprehensiveness* and thus includes all types of instruments: demand-pull, technology-push and systemic. This variable has been built using all the qualitative information provided by the IEA database (Table 1), where demand-pull and technology-push instruments are also homogeneously mapped and quantified in a binary (0-1) system as are the systemic instruments. Although the EE policies for the 23 OECD countries derived from the IEA database vary in distribution across types and instruments depending on the country under investigation, they can be classified as the three pillars previously mentioned. For demand-pull policies, examples include the adoption of compulsory energy labelling for buildings (Canada, the Netherlands, the United Kingdom, Italy), or the codification of minimum energy performance requirements for electrical appliances (Australia and Japan) as regulatory instruments, in addition to the already described energy taxation channel (that in this case is qualitatively measured with value 1 if the country adopts an energy tax policy). Within technology-push policies, there are examples of direct public investments in R&D activities (such as support for solid-state lighting, SSL, R&D activities to accelerate market introduction of high-efficiency, high-performance SSL products in the U.S., adopted in 2000), or the implementation of demonstration projects (such as, for instance, the Solar Decathlon initiative adopted in the U.S. in 2002 or the large-scale PV demonstration project in the UK adopted in 2002).

In order to test our hypotheses (HP2a), we calculate a proxy for policy mix *comprehensiveness* as an aggregate stock of total policies for EE given by the sum of the stocks of policy instruments (as in eq. 5) belonging to the whole range of policy types described in Table 1:

$$DomPolMix_{Comprehensiveness_{i,t}} = \sum_{q=1}^6 \left(\sum_{s=0}^t (POL_{i,s}^q) \right) \quad (6)$$

where $q \in [1,2, \dots,6]$ represents all the six policy types.

Moreover, the inclusion of this variable in squared terms in the model allows us to eventually capture non-linear effects. In particular, we can test the existence of a threshold level beyond

which the variety of policy instruments contemporaneously implemented becomes excessive, with an increasing risk of conflicting interactions leading to negative effects in terms of innovation performance (HP2b).

The adoption of this approach allows us to make a first step forward with regard to the analysis by Sovacool (2009) based on case studies towards quantifying the overall effect of different combinations of policy instruments in terms of eco-innovation performance in EE technologies, in relation to the selected policy mix characteristics. However, given data constraints, our analysis is not able to identify specific policy interaction effects and the eventual sources of complementarities or conflicts within the policy mix.¹⁰

4.2.3 *The role of foreign policies*

In order to provide results that are comparable with existing empirical evidence, we first have to compute indicators to assess the direct influence played by foreign policies interpreted as policy spillovers. These are measured for each f -th policy pillar ($DomPol_{r,t}^f$) representing demand-pull, technology-push and systemic instruments as defined in sub-section 4.2.1 according to the following expression:

$$ExtPol_{spillover}_{i,t}^f = \sum_{r=1}^C X_{ir,t_0} \cdot DomPol_{r,t}^f \quad \forall r \neq i \quad C = 22 \quad (7)$$

where the overall effect is represented by the sum of the foreign policies implemented in each r -th country weighted by the bilateral initial trade flows.¹¹

Here a clarification on the weighting system used to aggregate different policies is needed. In our analysis, given the focus on the domestic innovation performance, the weighting system must reflect the relative dimension of foreign market potential for new domestically generated technologies. For this purpose, we build the weighting matrix by taking the bilateral export flows only in energy intensive manufacturing sectors $X_{ir,t}$ from country i to country r taken from the UN-COMTRADE database (see Table A2 for a list of classes and codes). This is a well-established procedure, especially in the international knowledge spillover literature (Keller, 2004) which suggests that a sector-based analysis has to be preferred to an aggregate trade measure since the latter might reduce the capacity of the empirical model to account for the real

¹⁰ We are aware that this issue represents a limitation of our work that needs to be addressed by future research when more detailed quantitative and comparable information become available.

¹¹ In the sparse contributions addressing the role of policy spillovers in eco-innovation, different measures have been adopted (Dechezleprêtre and Glachant, 2014; Peters et al., 2012). In this paper, we follow the suggestion by Dechezleprêtre et al. (2015) to adopt the same type of indicators for assessing the role of domestic and foreign policies as an effective empirical strategy.

effects associated with international channels (Acharya and Keller, 2009).¹²

However, the adoption of this bilateral export flows as a weighting system for measuring the strength of the international relationship between each couple of countries may be somewhat endogenous with regard to innovation performance in EE technologies. In other words, the ability to develop new EE technologies could ensure larger comparative advantages in exporting goods characterised by high energy efficiency in the selected energy intensive manufacturing sectors (see Table A2). In order to overcome this potential issue, the weighting system is taken as fixed over time, by considering the initial value of the export bilateral matrix.¹³ This also allows us to deparure the analysis of the influence exerted by changes over time in international market conditions. For the same reason, we have calculated the average value of exports in the first two years (1990-1991) considered in the dataset.

Turning to our third research hypotheses, following the approach proposed by Dechezleprêtre *et al.* (2015) of measuring the regulatory distance between country pairs, we measure the similarity between domestic and foreign policies with reference to the three policy pillars and the two characteristics of the policy mix considered in our analysis.

The first similarity indicator is hence calculated considering the policy distance between each *i*-th country and the other *r* countries for each *f*-th policy pillar as:

$$ExtPolSim_{i,t}^f = \sum_{r=1}^C X_{ir,t_0} \cdot \left(\frac{|DomPol_{i,t}^f - DomPol_{r,t}^f|}{\sqrt{DomPol_{i,t}^f + DomPol_{r,t}^f}} \right)^{-1} \quad (8)$$

The original formulation proposed by Dechezleprêtre *et al.* (2015) directly adopts the absolute value of the distance between the regulatory standards across each country-pair (the numerator in eq. 8), whereas here we adopt the same methodology as described in eq. (5), thus accounting for the magnitude of domestic and foreign policy efforts in each pillar.

The second set of indicators measures the degree of similarity between the two characteristics of the policy mix here analysed: the *balance* between demand-pull and technology-push policies and the *comprehensiveness* of the policy mix.

With regard to the former, we construct the inverse of the absolute distance in the balance level of the domestic policy mix for country *i* compared with all other countries (r) ($\forall r \neq i \in C =$

¹²The classes selected for the export flows variable refer to the maximum available disaggregation for OECD countries with a direct link to energy consumption. Although it would be more appropriate to consider only the flows directly related to the residential sector, it is not possible to obtain trade flows associated with end use of the residential sector from trade data since the classification combines industries, services and households. This computational choice due to lack of data availability should be considered when commenting on empirical results.

¹³ We would like to thank an anonymous referee for highlighting this issue and suggesting the adopted solution.

22), aggregated by the same weighting matrix as for policy spillovers:¹⁴

$$ExtPolSim_{Balance_{i,t}} = \sum_{r=1}^c X_{ir,t_0} \cdot \left(|DomPolMix_{Balance_{i,t}} - DomPolMix_{Balance_{r,t}}| \right)^{-1} \quad (9)$$

Finally, the similarity in policy mix *comprehensiveness* is expressed as follows:¹⁵

$$ExtPolSim_{Compreh_{i,t}} = \sum_{r=1}^c X_{ir,t_0} \cdot \left(\frac{|DomPolMix_{Compr_{i,t}} - DomPolMix_{Compr_{r,t}}|}{\sqrt{2} \sqrt{DomPolMix_{Compr_{i,t}} + DomPolMix_{Compr_{r,t}}}} \right)^{-1} \quad (10)$$

4.2.4 Control variables

In the econometric analysis we control for the role of national innovation systems as a major driving force in the knowledge production process which may not be completely absorbed by the introduction of country fixed effects in the estimation.

We measure national innovation capacity by computing two alternative measures that capture technological capabilities. First, we calculate a knowledge stock based on national gross expenditure in R&D (GERD) taken from OECD Main Science and Technology Indicators (OECD, 2013), net of public R&D in EE. For the technology-push EE specific measure, we adopt a perpetual inventory method with a decay rate equal to 15 per cent. Second, we consider the total number of patents applied by different countries to the EPO (with the exclusion of specific EE patents), given by the PATSTAT online database as an alternative measure.¹⁶

4.3 Econometric issues

The use of patent data as proxies of the innovation activity implies that we have to deal with count variables with non-negative values. Appropriate econometric models for this kind of variable are the Poisson Regression Model (PRM) and the Negative Binomial Regression Model (NBRM). According to Allison and Waterman (2002) and Greene (2007), the conditional negative binomial model for panel data developed by Hausman *et al.* (1984) is not a true fixed-effects method since it does not control for all time-invariant covariates. Considering the country-based panel dataset here adopted, a fixed-effects estimator is highly recommended in

¹⁴ In this case we follow the same formulation proposed by Dechezleprêtre *et al.* (2015) since the balance indicator (eq. 5) already accounts for the overall effects of technology-push and demand-pull instruments.

¹⁵ The indices computed in eqs. (9)-(10) have also been measured using alternative formulations. In particular, the similarity in the balance of the policy mix in eq. (9) has been also calculated by applying the full similarity formula as eq. (10) and vice versa. Results reported in Section 5 are not influenced at all by the specific formulation of the external similarity measure adopted. All results are fully available upon request from the authors.

¹⁶ For an overview of all variables and data sources, see the Appendix, Tables A2-A3-A4a,b-A5a,b.

order to control for unobservable country-specific heterogeneity. The Poisson fixed-effects estimator, with count data equivalent to the within groups estimator, allows unobserved heterogeneity to be dealt with, but it can be biased by an excess in zeros and an overdispersion problem (Cameron and Trivedi, 1986, 1998). To this end, Santos Silva and Tenreyro (2006) show that a Poisson fixed-effects estimator performed by a pseudo-maximum likelihood technique controls for both unobservable country-specific heterogeneity and zero values and overdispersion problems. Finally, Cameron and Trivedi (2013) describe how the default standard errors in Poisson panel models are likely to be biased and that they have to be replaced with cluster-robust standard errors, by clustering on the individual i . Accordingly, we have estimated eq. (1) by performing a Poisson fixed-effects method with robust standard errors clustered in country i .

When looking at temporal structure, it is worth mentioning that all explanatory variables are treated with a potential number of lags equal to p . This is quite a common choice in the literature where the dependent variable is represented by an innovation output measure. This modelling choice also reduces potential endogeneity issues related to regressors such as, for instance, innovation input or policy variables which may be endogenously linked to the dependent variable.

In order to test the validity of alternative lag structures, we have performed a Bayesian information criterion (BIC) applied to the model in eq. (1) testing for p assuming value 1, 2, 3. Since the penalty term for the number of parameters in the model is larger in BIC than in AIC, the first one is to be preferred as a more stringent overfitting model test.¹⁷ The resulting temporal structure from BIC values is characterized by a one-year lag. This empirical result is consistent with existing contributions (see Johnstone *et al.*, 2010, among others). Moreover, from a conceptual point of view, energy efficiency policy variables over this medium term are fairly stable or growing slightly because they respond to a long run commitment in policy design and it is therefore difficult to estimate complicated lag structures.¹⁸

The inclusion of policy variables in the regressors may present econometric problems related to potential bias in estimations due to endogeneity. At the theoretical level, this arises if mutual causality between policy and innovation exists since successful innovative activities may ensure increased competitiveness in specific sectors, resulting in policy decisions that may lead to the adoption of stringent environmental policies in those fields in which technologies are already available. Since the use of lagged policy variables may not be enough to mitigate potential endogeneity, we also control for this potential bias by implementing an instrumental variable Poisson estimator with endogenous regressors performed by GMM (Cameron and Trivedi, 2013;

¹⁷ Results on BIC for alternative lag structures are available upon request from the authors.

¹⁸ This is also valid for the other explanatory variables, especially those related to innovation capabilities (Hall *et al.*, 1986).

Wooldridge, 2010) applied to eq. (1).¹⁹

5. Empirical results

The first part of the empirical analysis follows the contributions discussed in Section 2 and refers to the estimation of a baseline model in which the role played by domestic policies in shaping innovation performance in EE technologies is tested. Such a test is designed to provide us with solid empirical ground on which to validate our specific hypotheses on policy mix characteristics.

Results reported in Table 2 show that for both variables related to the national innovation capacity, the associated coefficients result positive and statistically robust, revealing that technological capabilities play a significant role in shaping innovation activities in the specific technological domain under scrutiny. Though the BIC test seems to prefer the total patents per capita in terms of model fitting, this latter variable may suffer from potential endogeneity with regard to the dependent variable. Given that all results are fully consistent if the two alternative innovation variables are adopted, in the following specifications we use the stock of GERD as a control variable for national technological capabilities.²⁰

Moving to the analysis of results related to individually tested EE policies, results reported in Table 2 suggest that demand-pull and technology-push instruments are able to stimulate innovative performance in EE technologies. According to previous findings on different eco-innovation domains (Costantini *et al.*, 2015), the most effective policy instrument is the demand-pull option represented here by the energy tax variable, with a higher estimated coefficient compared with that for the technology-push policy variable, namely the stock of R&D in EE. Systemic instruments also provide a positive impulse to innovation performance in EE technologies, though the statistical robustness of the estimated coefficient is limited. When the three policy pillars are simultaneously included in the regression model (Column 6), the associated coefficients are partly reduced, but the model fitting tests (both AIC and BIC) indicate that the contemporaneous inclusion of all policy variables improves the model quality.

The results discussed so far allow us to conclude that the role of public policies in driving innovation activities in EE technologies is confirmed and that both the database and the specified baseline model can represent reliable empirical ground for testing the validity of our

¹⁹ The results for estimation of Table 2 in the text by IV Poisson are reported in the Appendix, Table A8, revealing that the Poisson fixed-effects estimates are robust and not affected by endogeneity issues. All the other estimates reported in Tables 3-6 have been also checked for robustness by performing the same regression with a IV Poisson estimator. All results remain robust but, for the sake of brevity, results are available upon request from the authors.

²⁰ Results reported in Tables 2-6 are obtained by applying a one-year lag to covariates in order to control for potential endogeneity. The temporal structure has been selected according to robustness checks carried out with the help of a Bayesian Information Criterion (BIC) for three alternative lag structures, namely one, two or three-year lag. According to the BIC test, we select the specification with the lower BIC value, corresponding to the one-year lag temporal structure.

specific research hypotheses.

Table 2 - Direct effect of domestic demand-pull, technology-push and systemic policies

	(1)	(2)	(3)	(4)	(5)	(6)
Stock of GERD	1.381*** (0.33)		1.218*** (0.32)	1.281*** (0.30)	1.098** (0.39)	1.041** (0.37)
Total patents per cap.		0.973*** (0.07)				
Dom. pol. (demand-pull)			0.877*** (0.21)			0.677*** (0.14)
Dom. pol.(technology-push)				0.136*** (0.04)		0.075*** 0.02
Dom. pol.(systemic instr.)					0.165* (0.07)	0.091* (0.05)
No. Obs.	460	460	460	460	460	460
Log-Likelihood	-3400	-2700	-3000	-3200	-3200	-2900
Chi-sq	169	1147	207	666	867	1549
AIC	6739	5363	6085	6369	6486	5894
BIC	6763	5388	6114	6398	6515	5932

Robust clustered standard errors in parentheses

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

According to HP1, we consider the role played by policy mix *balance* between demand-pull and technology-push instruments. As shown by results in Columns (1)-(5) in Table 3, the adopted indicator measuring policy mix balance significantly enters the econometric model with a positive sign, confirming our hypothesis on the enhancing role of this policy mix characteristic for innovation performance in EE technologies. Though we are not able to distinguish between different generation technologies within the EE domain, a possible interpretation of this result is that when the distribution of economic resources and policy efforts between demand-pull and technology-push instruments is more balanced, both exploration and exploitation innovation activities are fostered leading to an overall increase in innovation performance.

This influence is statistically robust whether accounting for the three distinguished policy pillars or not since the coefficient for the balance of the domestic policy mix remains positive and statistically robust in all models, without significant changes in the coefficient value. It is clear that the influence of the balance characteristic is relatively lower than that played by the two policy pillars taken alone since the coefficient value is smaller than those for demand-pull and technology-push instruments. At the same time, by looking at the AIC and BIC tests, it is worth noticing that the model fitting improves when, together with systemic instruments, the two policy pillars are complemented by considering their balance in the econometric estimation.

Table 3 - Effects of domestic policy mix characteristics-balance (HP1)

	(1)	(2)	(3)	(4)	(5)
Stock of GERD	1.421*** (0.33)	1.256*** (0.32)	1.317*** (0.31)	1.147** (0.39)	1.069** (0.38)
Dom. pol. (demand-pull)		0.811*** (0.18)			0.656*** (0.14)
Dom. pol.(technology-push)			0.116** (0.04)		0.059** (0.02)
Dom. pol.(systemic instr.)				0.157* (0.06)	0.094* (0.04)
Dom. pol. mix (balance)	0.005*** (0.00)	0.003*** (0.00)	0.003*** (0.00)	0.005*** (0.00)	0.002*** (0.00)
No. Obs.	460	460	460	460	460
Log-Likelihood	-3300	-3000	-3100	-3100	-2900
Chi-sq	3097	34000	3542	4614	5200
AIC	6540	6004	6313	6314	5857
BIC	6569	6037	6346	6347	5898

Robust clustered standard errors in parentheses

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

Turning to the second research hypothesis, in Table 4, we test the influence played by the *comprehensiveness* of the policy mix. We first show that policy mix comprehensiveness positively affects innovation performance in EE technologies. Moreover, this effect is additional to those independently exerted by the three policy pillars here considered. However, as hypothesised (HP2b), policy mix comprehensiveness cannot increase indefinitely since when too many instruments are simultaneously adopted, policy mix effectiveness tends to be reduced. The quadratic term of the comprehensiveness variable presents a statistically robust negative coefficient, meaning that a threshold level in this characteristics exists beyond which some negative interaction effects may occur as a result of policy fragmentation. The analysis of these potential negative interactions is not the focus of our analysis since our data and the empirical strategy are designed to test only for the overall effect played by policy mix characteristics. Nevertheless, we believe our results provide a good starting point for future research on the sources of possible negative effects within comprehensive policy mixes.

Turning back to econometric results, model fitting increases when the quadratic term is included in the analysis, with a higher coefficient value for the comprehensiveness variable than the case in which only the linear effect is considered (Column 1).

Interestingly, the robustness of these results is not reduced when we include the three variables for demand-pull, technology-push and systemic instruments and when the balance variable is also considered. Moreover, results reported in Column 7 seem to confirm the validity of adopting a research approach that tries to investigate the effect on the eco-innovation performance of the overall policy-mix as distinct from the role played by single instruments. Indeed, policy instruments in the three pillars play important positive effects in fostering

innovation in EE technologies (especially demand-pull and technology-push tools), but in order to understand the overall effect exerted by public intervention, it is also necessary to consider how different instruments are combined into mixes. From a statistical point of view, this is confirmed by the lower values of the AIC and BIC in the specification reported in Column 7, suggesting that the full model presents the best fitting in terms of model specification.

Table 4 - Effects of domestic policy mix characteristics - comprehensiveness (HP2a,b)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Stock of GERD	1.226** (0.41)	1.113** (0.35)	1.049** (0.33)	1.075*** (0.27)	1.073** (0.35)	1.011*** (0.29)	1.043*** (0.29)
Dom. pol. (demand-pull)			0.579*** (0.17)			0.404* (0.16)	0.347* (0.16)
Dom. pol.(technology-push)				0.135*** (0.02)		0.104*** (0.03)	0.091** (0.03)
Dom. pol.(systemic instr.)					0.034* (0.06)	0.023* (0.05)	0.047* (0.05)
Dom. pol. mix (balance)							0.003*** (0.00)
Dom. pol. mix (compreh.)	0.128* (0.06)	0.495*** (0.08)	0.420*** (0.08)	0.451*** (0.08)	0.474*** (0.10)	0.395*** (0.09)	0.385*** (0.10)
Dom. pol. mix (compreh.) sq.		-0.143*** (0.03)	-0.123*** (0.03)	-0.150*** (0.03)	-0.141*** (0.03)	-0.133*** (0.03)	-0.139*** (0.03)
No. Obs.	460	460	460	460	460	460	460
Log-Likelihood	-3200	-2800	-2700	-2600	-2800	-2600	-2500
Chi-sq	1106	455	1130	4738	737	3654	3700
AIC	6468	5579	5338	5312	5575	5202	5123
BIC	6497	5612	5375	5349	5612	5247	5173

Robust clustered standard errors in parentheses

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

Finally, together with the role played by national policies, according to HP3, we empirically test if, and to what extent, those adopted by foreign countries may also influence domestic innovation performance. The three mechanisms here investigated refer to: i) the direct influence played by foreign policies on domestic innovation activities in the form of demand-pull, technology-push and systemic instruments policy spillovers; ii) the role played by the similarity in terms of policy distance between countries in single policy instruments; iii) the influence exerted by the similarity between countries in terms of policy mix characteristics. The empirical results that test the first channel are reported in Table 5.

As shown in Columns 1-2, there is clear and robust evidence that the adoption by other countries of demand-pull policies oriented toward the deployment of EE in the residential sector boosts domestic innovation performance. This policy spillover effect remains statistically robust whether the characteristics of the domestic policy mix are included or not in the regressors. In addition, the model fitting improves when the characteristics of domestic policy mix and policy spillovers are jointly considered, revealing that both internal and external policy dimensions

have to be accounted for. Demand-pull policies implemented by foreign countries complement domestic policies by creating the conditions for an enlarged demand for energy-efficient technologies that may be partly satisfied by the production of new technologies in the domestic context.

Table 5- Effect on domestic innovation of external policies (direct spillover effect)

	(1)	(2)	(3)	(4)	(5)	(6)
Stock of GERD	1.197** (0.42)	1.136*** (0.33)	0.817** (0.37)	0.863** (0.36)	1.019** (0.39)	1.019** (0.39)
Dom. pol. (demand-pull)	0.376*** (0.11)	0.221* (0.12)	0.439*** (0.13)	0.216* (0.09)	0.601*** (0.13)	0.601*** (0.13)
Dom. pol.(technology-push)	0.064** (0.02)	0.084** (0.03)	0.073** (0.03)	0.095*** (0.02)	0.085*** (0.02)	0.085*** (0.02)
Dom. pol.(systemic instr.)	0.064 (0.05)	0.054 (0.05)	0.007 (0.07)	0.026 (0.06)	0.076 (0.05)	0.076 (0.05)
Dom. pol. mix (balance)		0.003*** (0.00)		0.003*** (0.00)		
Dom. pol. mix (compreh.)		0.294*** (0.08)		0.275*** (0.07)		
Dom. pol. mix (compreh.) sq.		-0.113*** (0.03)		-0.112*** (0.03)		
Ext pol. (demand-pull spill.)	1.970*** (0.59)	1.121** (0.40)				
Ext pol. (technology-push spill.)			0.608*** (0.15)	0.450*** (0.12)		
Ext pol. (systemic instr. spill.)					0.026 (0.02)	0.026 (0.02)
No. Obs.	460	460	460	460	460	460
Log-Likelihood	-2700	-2500	-2600	-2400	-2900	-2900
Chi-sq	2274	6400	2052	1100	1706	1706
AIC	5405	4998	5288	4837	5819	5819
BIC	5446	5052	5330	4890	5861	5861

Robust clustered standard errors in parentheses

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

In Columns 3-4 of Table 5, the same mechanism is investigated on the technology-push side and the results are similar to those that emerged for demand-pull policy spillovers. The efforts made by foreign countries in stimulating innovation in EE by investing public resources in specific R&D activities create a knowledge stock that can spill its positive effects over the national borders, fuelling the generation of new EE technologies in other countries. Also in the case of technology-push foreign policies, the spillover effect is confirmed singularly as well as when combined with the characteristics of the domestic policy mix, with a model fitting test (both in AIC and BIC) that again reveals the importance of considering both internal and

external policy effects.²¹ The adoption by foreign countries of systemic instruments, contrary to demand-pull and technology-push instruments, does not appear to have any significant effect on domestic innovation performance. This result is probably due to the measurement method adopted for the construction of this policy variable that provides only limited information on the actual weight of these policies in different innovation systems. Further work is certainly needed to better qualify the role of these instruments in shaping eco-innovation activities.

The second channel we include in the analysis refers to the role played by the country-pair policy similarity in each specific policy pillar forming the mix. For this purpose, we include in the econometric model the indicator described in eq. (8) that is able to account for the magnitude of foreign policies, but also for the country-pair distance in policy efforts. According to results reported in Columns (1)-(3) of Table 6, we find first evidence that policy similarity between country pairs can play a positive role in driving innovation activities in EE technologies, though the statistical significance of the estimated coefficient is weak for demand-pull and technology-push instruments and absent in the case of systemic instruments. However, when we address the impact of our indicators accounting for the similarity between the characteristics of domestic and foreign policy mixes (Column 4-6 in Table 6), the coefficient associated with the balance between demand-pull and technology-push instruments (measured as in eq. 9) turns out to be positive and significant. This result suggests that when one country adopts a policy mix balance in terms of demand-pull and technology push instruments which is not distant from that adopted by those foreign countries importing a high share of energy intensive goods from it, an additional positive effect on innovation activities in EE technologies is generated. On the contrary, such an effect is not identified when investigating the similarity between countries in terms of policy mix comprehensiveness.

The analysis of the importance of foreign policies in shaping eco-innovation activities here provided should be considered explorative and the issue certainly deserves further investigation. However, our results give some indication that domestic innovation performance in EE technologies is influenced by public policies adopted by foreign countries and that, when designing a country policy mix, it could be worth taking into account the choices made in particular by foreign countries which are potentially significant markets for domestically generated technologies. In so doing, the proposed analysis enriches previous findings by Dechezleprêtre *et al.* (2015) on the cross-border diffusion of new technologies, confirming the usefulness of adopting country-pair policy distance measures for addressing the influence of

²¹ The bilateral correlation between the three policy domain spillover variables is very high (see Table A5a in the Appendix). This explains why we do not include in Table 5 a model in which policy spillovers variables are jointly included. The model results provide coefficient values that are similar to Columns 1-6, but the coefficient for demand-pull policy spillover is no longer statistically robust. Since the effects of multicollinearity bias are that the estimated coefficient values are unstable and difficult to interpret, we have preferred not to include this model in Table 5. However, econometric results are available upon request from the authors.

policy similarity between countries on the generation of eco-innovations.

Table 6 - Effect on domestic innovation due to regulatory distance and external similarity of the policy mix (HP3)

	(1)	(2)	(3)	(4)	(5)
Stock of GERD	1.043***	1.062***	1.015***	1.108***	1.055***
	(0.29)	(0.29)	(0.30)	(0.29)	(0.29)
Dom. pol. (demand-pull)	0.326	0.383*	0.350*	0.262	0.344*
	(0.17)	(0.15)	(0.17)	(0.13)	(0.17)
Dom. pol.(technology-push)	0.092**	0.078**	0.083**	0.065**	0.091**
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)
Dom. pol.(systemic instr.)	0.044	0.038	0.015	0.038	0.046
	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)
Dom. pol. mix (balance)	0.003***	0.004***	0.003***	0.002***	0.004***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Dom. pol. mix (compreh.)	0.383***	0.374***	0.334***	0.366***	0.358***
	(0.10)	(0.09)	(0.06)	(0.09)	(0.08)
Dom. pol. mix (compreh.) sq.	-0.138***	-0.136***	-0.126***	-0.138***	-0.134***
	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)
Ext. pol. sim. (demand-pull)	0.027*				
	(0.01)				
Ext. pol. sim. (technology-push)		0.032*			
		(0.02)			
Ext. pol. sim (systemic instr.)			0.063		
			(0.06)		
Ext. pol. sim (balance)				0.059***	
				(0.01)	
Ext. pol. sim (comprehensiveness)					0.020
					(0.04)
No. Obs.	460	460	460	460	460
Log-Likelihood	-2500	-2500	-2500	-2500	-2500
Chi-sq	53000	49000	51000	41000	24000
AIC	5114	5100	5093	5014	5117
BIC	5168	5154	5147	5067	5170

Robust clustered standard errors in parentheses

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

5. Conclusions

This study provides an empirical analysis of the influence of the characteristics of the policy mix on innovation performance in energy efficiency technologies for the residential sector in 23 OECD countries for the period 1990-2010. With regard to the existing literature, we contribute by analysing the specific role played by the design of the policy mix and its characteristics in influencing the dynamics of innovation in EE technologies.

According to a well-established empirical literature that analyses other clean technology

domains, the presented evidence shows that innovation performance in energy efficiency technologies is driven by both demand-pull and technology-push policy instruments. In addition, building on the information provided by the IEA on different policies implemented in EE across countries, our analysis investigates the role played by systemic instruments (including soft instruments) which turn out to be positive though statistically weakly significant. In this respect, our analysis provides a first econometric assessment of this issue in the case of EE which certainly needs to be complemented when more refined, quantitative information becomes available.

Building on this preliminary set of results, our analysis focuses on the effects associated with two selected characteristics of the policy mix on innovation performance in EE technologies, namely policy mix *balance* and *comprehensiveness*. In order to do so, a specific effort has been devoted to the operationalization of these two characteristics into measurable indicators, given data constraints. The provided empirical evidence suggests that when the policy mix is characterised by a more balanced use in demand-pull and technology-push instruments, its positive effects on eco-innovation tend to be greater. Hence, the balance between these two policy pillars emerges as a key characteristic to be addressed when designing policy mix, reinforcing market incentives and innovation capabilities for the development of new products and technologies.

Our analysis also suggests that a more comprehensive policy mix is able to enhance innovation activities for the generation of new EE technologies. The simultaneous implementation of policy instruments acting on the demand and technology sides and on the system as a whole appears to foster eco-innovation performance. However, the presented evidence highlights that the simple addition of an indiscriminate number of simultaneous policy instruments may reduce policy mix effectiveness. Though our analysis could not unveil the sources of potential conflicting effects among the examined policy instruments, an implication arising from our analysis is that policy coordination issues have to be addressed when designing a comprehensive policy mix since they may severely harm the efficacy of implemented policies.

In this paper we also propose an investigation into the effects of foreign policies on domestic innovation performance in EE technologies, including an explorative analysis of the role played by the relations between domestic and foreign policy mixes. Our findings confirm previous evidence on different technological domains suggesting that policy spillover effects are important in shaping domestic eco-innovation activities. In particular, in line with previous findings on the renewables sector, we confirm the major innovation impulse provided by demand-pull foreign policies for the energy efficiency sector as well. Furthermore, in contrast with existing literature on different sectors, in the examined case we find positive and robust statistical evidence that technology-push policies adopted in foreign countries also help foster

domestic innovation activities.

In addition, building on the idea that coordinated policies across countries may reinforce the ability of public policies to foster eco-innovation, we analyse the role of similarity between domestic and foreign policy mixes. In particular, by elaborating on the empirical measure of country-pair policy distance developed by Dechezleprêtre *et al.* (2015), we show that cross-country similarity in demand-pull and technology-push policies positively influences domestic innovation performance in EE technologies. Moreover, when looking at the characteristics of the policy mix, cross-country similarity in the policy balance indicator is seen to be important for shaping eco-innovation activities in the considered sector, whereas there is no evidence of potential effects related to comprehensiveness when domestic and foreign policy mixes are compared. These results suggest that when deciding on the design of domestic policy mix, the decisions adopted on the same matter by other countries should be taken into account.

The outlined empirical findings represent a step further with regard to existing studies since they provide new insights for the design of a policy mix that aims to foster innovation performance in EE technologies. Moreover, the proposed methodology could be applied to an analysis of other technological domains, thus leading to a possible generalization of our results which points to the existence of an independent effect played by the composition of the policy mix compared with the direct effect exerted by distinct policy instruments.

Considering the analytical difficulties in examining the issue at stake, our investigation is not able to deal with some relevant elements related to policy mix analysis. In particular, the examined characteristics, though grounded on previous theoretical contributions, have also been chosen considering the availability of statistical information suitable for a quantitative analysis on a representative sample. Hence, further policy mix characteristics could be explored when other information sources become available. Moreover, in our analysis, we focus on the overall eco-innovation effect of policy mix composition in terms of key characteristics which is, however, the result of complex interactions between different instruments that could be addressed by future research.

Finally, in this paper we do not study policy processes that may explain not only the evolution but also the impact of policy mixes, and we do not explicitly address the long-term strategic component of policy mix. In this respect, a proper understanding of the mechanisms linking policy mix design and eco-innovation performances undoubtedly requires the continuous integration of complementary quantitative and qualitative research efforts.

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Appendix

Table A1a - Patent classes by technological domains and keywords

Main domain	Sub-domain	CPC Class	Sub-classes	Keywords
Insulation	Heat Saving	E06B	3/24, 3/64, 3/66, 3/67	
		E06B	3	high perform+ OR insulat+ OR low energy
		C03C	17/00, 17/36	low e
		E06B	3/67F	vacuum
		E06B		aerogel
		E06B	3/20	
		E06B	1/32, 3/26	thermal break
		E04B	1/74, 1/76	
		E04B		Polyurethane OR PUR OR polystyrene OR EPS OR XPS OR heavy gas+ OR pentane OR insulat+
		E04B		Flax OR straw OR (sheep+ AND wool)
		E04F	15/18	
		E04F		Sea shell
		E04D	11	Insulat+
	E04D	11	Green roof	
	E04D	11, 9	thatch+	
	F16L	59/14		
	Water saving	F24H		Water AND (sav+ OR recover+)
		F16K	1	Water AND (sav+ OR recover+)
		E03C	1	Water AND (sav+ OR recover+)
Cooling reduction	E04F	10		
	C03		Glass AND (reflect+ OR sunproof OR heat resist+)	
	E06B	3	Glass AND (reflect+ OR sunproof OR heat resist+)	
	B32B	17	Glass AND (reflect+ OR sunproof OR heat resist+)	
High-efficiency boilers	HE-boilers	F23D	14	Low
		F24D	1	
		F24D	3, 17	
		F24H, excluding F24H7		
Heat and cold distribution and CHP	Heating system	F24D	5, 7, 9, 10, 11, 13, 15, 19	
	Storage heaters	F24H	7	
	Heat exchange	F28F	21	
	Cooling	F25B	1, 3, 5, 6, 7, 9, 11, 13, 15, 17	
	Combined heating and refrigeration systems	F25B29		
	Heat pumps	F25B30		
	CHP	X11-C04 R24H240/04 (ICO)		
Ventilation	Ventilation	F24F	7+	
Solar energy and other RES	Solar energy	F24J	2	
		H01L	31/042, 31/058	
		H02N	6	
	Biomass	F24B		Wood+
Geothermal	F24J	3		
Building materials	Construction structures	E04B	1	Building+ or house+
	Materials	C09K	5	Building+ or house+
Climate control systems	Temperature control	G05D	23/02	
	Electric heating devices	H05B	1	
Lighting	Lighting	F21S		Not vehicle, not aircraft
		F21K	2	Not vehicle, not aircraft
		H01J	61	Not vehicle, not aircraft
		F21V	7	House or home or building
	LED	H01L	33	Light and LED
		H05B	33	Light and LED

Source: Costantini et al. (2014a)

Table A1b – Patent classes by technological domains and keywords

CPC general Class related to each appliance		Technologies aimed at improving efficiency of home appliances	Description
Refrigerators and freezers	F25D See http://www.cooperativepatentclassification.org/cpc/scheme/F/scheme-F25D.pdf	Y02B 40/32	Motor speed control of compressors or fans
		Y02B 40/32	Thermal insulation
Dish-washers	A47L 15/00 See http://www.cooperativepatentclassification.org/cpc/scheme/A/scheme-A47L.pdf	Y02B 40/42	Motor speed control of pumps
		Y02B 40/44	Heat recovery e.g. of washing water
Washing-machines	D06F (excluding D06F31/00, D06F43/00, D06F47/00, D06F58/12, D06F67/04, D06F71/00, D06F89/00, D06F93/00, D06F95/00 as well as their subgroups). See http://www.cooperativepatentclassification.org/cpc/definition/D/definition-D06F.pdf	Y02B 40/52	Motor speed control of drum or pumps
		Y02B 40/54	Heat recovery, e.g. of washing water
		Y02B 40/56	Optimization of water quantity
		Y02B 40/58	Solar heating

Source: Costantini et al. (2014b)

Table A2 – SITC Rev 3 CODE in COMTRADE taken for the aggregate “energy consuming manufacturing sectors plus building sector”

Code	Description	Code	Description
201	Milling, planing and impregnation	287	Other fabricated metal products
202	Panels and boards of wood	291	Machinery for production, use of metal products
203	Builders' carpentry and joinery	292	Other general purpose machinery
204	Wooden containers	295	Other special purpose machinery
205	Other products of wood; articles of	297	Domestic appliances n. e. c.
243	Paints, coatings, printing ink	300	Office machinery and computers
251	Rubber products	311	Electric motors, generators and transport
252	Plastic products	312	Electricity distribution and control
261	Glass and glass products	313	Isolated wire and cable
262	Ceramic goods	314	Accumulators, primary cells
263	Ceramic tiles and flags	315	Lighting equipment
264	Bricks, tiles and construction prod	316	Electrical equipment n. e. c.
265	Cement, lime and plaster	321	Electronic valves and tubes, other
266	Articles of concrete, plaster and cement	322	TV, and radio transmitters, apparatus
267	Cutting, shaping, finishing of stone	323	TV, radio and recording apparatus
268	Other non metallic mineral products	401	Production and distribution of electricity
282	Tanks, reservoirs, central heating	742	Architectural and engineering activity
283	Steam generators		

Table A3 – Variable description and data sources

Variable name	Description	Source
Stock of GERD	Stock of gross RD expenditures as in eq. (3) net of RD in EE	OECD MSTI Indicators and IEA RD Statistics
Total patents per cap.	Number of total patents filed to the EPO per capita	OECD PATSTAT, OECD STATS
Dom. pol. (demand-pull) Energy Tax	Ratio between the energy taxation levy on the total cost of energy consumption as in eq. (2)	IEA Energy Prices and Taxes Statistics, IEA OECD Energy Balance Statistics
Dom. pol. (technology-push) RD in EE	Stock of public gross RD expenditures in energy efficiency eq. (3)	IEA RD Statistics
Dom. pol. (systemic instr.)	Stock of those qualitative policies classified as EE systemic instruments as in eq. (4) (Table 1)	IEA Energy Efficiency Policy online Database
Dom. pol. mix (balance)	Balance between DP and TP policies as in eq. (5)	IEA Energy Prices and Taxes Statistics, IEA OECD Energy Balance Statistics, IEA RD Statistics
Dom. pol. mix (compreh.)	Stock of number of policies (Table 1) as in eq. (6)	IEA Energy Efficiency Policy online Database
Dom. pol. mix (compreh.) sq.	Square of sum of all policies as in eq. (6)	
Ext. pol. (demand-pull spill.)	DP policy as in eq. (2) adopted by foreign countries weighted by export flows in energy intensive goods as Table A1a –A1b as eq. (7)	IEA Energy Prices and Taxes Statistics, IEA OECD Energy Balance Statistics, IEA RD Statistics, IEA Energy Efficiency Policy online Database UN-COMTRADE
Ext. pol. (technology-push spill.)	TP policy as eq. (3) adopted by foreign countries weighted by export flows in energy intensive goods as Table A1a –A1b as eq. (7)	
Ext. pol. (systemic instr. spill.)	EE compl. policy as eq. (4) adopted by foreign countries weighted by export flows in energy intensive goods as Table A1a –A1b as eq. (7)	
Ext. pol. sim. (demand-pull)	Similarity between the domestic and foreign DP policy adopted by the other OECD countries, weighted by bilateral trade flows as in eq. (8)	
Ext. pol. sim. (technology-push)	Similarity between the domestic and foreign TP policy adopted by the other OECD countries, weighted by bilateral trade flows as in eq. (8)	
Ext. pol. sim (systemic instr.)	Similarity between the domestic and foreign EE complementary policies adopted by the other OECD countries, weighted by bilateral trade flows as in eq. (8)	
Ext. pol. sim (Balance)	Coherence between the balance of the domestic policy mix and the balance of foreign policy by OECD trade partners as in eq. (9)	
Ext. pol. sim (Comprehensiveness)	Coherence between the comprehensiveness of the domestic policy mix and that of foreign policy mixes adopted by OECD trade partners as in eq. (10)	
Energy consumption in residential sector	Energy consumption for the three aggregated sources, diesel, electricity and natural gas	IEA OECD Energy Balance Statistics

Table A4a – Dependent variable statistics

Variable name	Obs	Mean	Std. Dev.	Min	Max	Var.
Total Patents in EE	483	114.41	196.25	0	894	38,512
<i>No. of zeros</i>	20					
Total Patents in EE weighted by forward citations	483	25,672.63	77284.29	0	510090	5,979,000
<i>No. of zeros</i>	20					
Stock of Total Patents in EE	483	530.21	1026.11	0	4876.71	1,052,890
<i>No. of zeros</i>	12					

Table A4b – Independent variables statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Stock of GERD	483	15.03	1.72	11.57	19.06
Total patents per cap.	483	-2.71	2.38	-8.74	2.22
Dom. pol. (demand-pull)	483	-1.77	0.69	-3.07	-0.50
Dom. pol. (technology-push)	483	3.95	1.94	-2.32	8.45
Dom. pol. (systemic instr.)	483	0.91	0.95	0.00	4.34
Dom. pol. mix (balance)	483	4.00	7.64	1.32	112.68
Dom. pol. mix (compreh.)	483	1.16	1.06	0.00	3.91
Dom. pol. mix (compreh.) sq.	483	2.47	3.15	0.00	15.30
Ext pol. (demand-pull spill.)	483	14.86	1.59	11.12	17.49
Ext pol. (technology-push spill.)	483	22.41	1.85	17.97	26.58
Ext pol. (systemic instr. spill.)	483	18.06	2.56	0.00	22.45
Ext. pol. sim. (reg. space demand-pull)	483	-19.14	1.73	-23.56	-14.70
Ext. pol. sim. (reg. space technology-push)	483	-15.00	1.78	-21.40	-10.69
Ext. pol. sim (reg. space systemic instr.)	483	15.64	1.92	9.93	19.52
Ext. pol. sim (Balance)	483	17.61	2.03	12.07	23.11
Ext. pol. sim (Comprehensiveness)	483	15.71	1.90	10.24	20.20

Table A5a – Correlation matrix (values)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(2)	0.68														
(3)	-0.09	0.02													
(4)	0.79	0.63	0.04												
(5)	0.46	0.25	-0.19	0.47											
(6)	0.20	0.15	-0.33	0.27	0.12										
(7)	0.45	0.26	-0.08	0.41	0.65	0.22									
(8)	0.51	0.24	-0.18	0.46	0.68	0.30	0.94								
(9)	0.83	0.68	0.03	0.64	0.28	0.12	0.18	0.24							
(10)	0.89	0.68	-0.16	0.67	0.40	0.22	0.40	0.45	0.83						
(11)	0.58	0.53	-0.05	0.44	0.42	0.16	0.54	0.52	0.54	0.77					
(12)	-0.77	-0.58	0.17	-0.51	-0.30	-0.12	-0.15	-0.23	-0.80	-0.79	-0.49				
(13)	-0.65	-0.63	-0.09	-0.45	-0.05	-0.04	-0.06	-0.11	-0.85	-0.63	-0.41	0.65			
(14)	0.75	0.70	-0.03	0.59	0.47	0.16	0.39	0.38	0.85	0.82	0.71	-0.71	-0.68		
(15)	0.74	0.50	-0.06	0.68	0.40	0.08	0.23	0.30	0.76	0.79	0.56	-0.67	-0.55	0.69	
(16)	0.81	0.68	0.00	0.63	0.42	0.12	0.47	0.45	0.82	0.85	0.70	-0.71	-0.67	0.89	0.70

Table A5b – Correlation matrix (labels)

Code	Full label
(1)	Stock of GERD
(2)	Total patents per cap.
(3)	Dom. pol. (demand-pull)
(4)	Dom. pol. (technology-push)
(5)	Dom. pol. (systemic instr.)
(6)	Dom. pol. mix (balance)
(7)	Dom. pol. mix (compreh.)
(8)	Dom. pol. mix (compreh.) sq.
(9)	Ext pol. (demand-pull spill.)
(10)	Ext pol. (technology-push spill.)
(11)	Ext pol. (systemic instr. spill.)
(12)	Ext. pol. sim. (reg. space demand-pull)
(13)	Ext. pol. sim. (reg. space technology-push)
(14)	Ext. pol. sim. (reg. space systemic instr.)
(15)	Ext. pol. sim. (Balance)
(16)	Ext. pol. sim. (Comprehensiveness)

Table A6 – Poisson panel fixed-effect estimator applied to Table 2 with forward citation-weighted patent count dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)
Stock of GERD	0.033 (1.35)		-0.879 (1.10)	0.517 (0.61)	-0.899 (1.61)	-0.652 (1.29)
Total patents per cap.		2.113*** (0.34)				
Dom. pol. (demand-pull)			3.311*** (0.75)			2.594*** (0.67)
Dom. pol.(technology-push)				0.469*** (0.05)		0.174* (0.08)
Dom. pol.(systemic instr.)					0.392*** (0.10)	0.059 (0.15)
No. Obs.	460	460	460	460	460	460
Log-Likelihood	-1900000	-1300000	-1200000	-1500000	-1700000	-1200000
Chi-sq	4315	1608	7188	2631	4129	14000
AIC	3800000	2600000	2500000	2900000	3500000	2400000
BIC	3800000	2600000	2500000	2900000	3500000	2400000

Robust clustered standard errors in parentheses

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

Table A7 – Poisson panel fixed-effect estimator applied to Table 2 with total patent stock dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)
Stock of GERD	1.817*** (0.34)		1.578*** (0.27)	1.641*** (0.28)	-0.899 (1.61)	1.011*** (0.29)
Total patents per cap.		1.392*** (0.17)				
Dom. pol. (demand-pull)			1.114*** (0.25)			0.721*** (0.14)
Dom. pol.(technology-push)				0.199*** (0.06)		0.103*** (0.02)
Dom. pol.(systemic instr.)					0.392*** (0.10)	0.270*** (0.07)
No. Obs.	460	460	460	460	460	460
Log-Likelihood	-11000	-6000	-8800	-9700	-1700000	-7000
Chi-sq	291	506	826	1043	4129	18000
AIC	22000	12000	18000	19000	3500000	14000
BIC	22000	12000	18000	19000	3500000	14000

Robust clustered standard errors in parentheses

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

Table A8 – IV POISSON GMM estimator applied to models reported in Table 2

	(1)	(2)	(3)	(4)	(5)	(6)
Stock of GERD	1.366*** (0.15)		1.222*** (0.14)	1.260*** (0.14)	1.170*** (0.17)	1.127*** (0.17)
Total patents per cap.		0.861*** (0.08)				
Dom. pol. (demand-pull)			0.864*** (0.15)			0.723*** (0.14)
Dom. pol.(technology-push)				0.135*** (0.03)		0.064* (0.03)
Dom. pol.(systemic instr.)					0.116 (0.07)	0.039 (0.07)
No. Obs.	437	437	437	437	437	437

Robust clustered standard errors in parentheses

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