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The open eco-innovation mode. An empirical investigation of eleven European countries

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ABSTRACT

This paper deals with the open innovation mode in the environmental realm and investigates the effects that knowledge sourcing has on the environmental innovations (EIs) of firms. Using the Community Innovation Survey (CIS) 2006–2008, we refer to the firm's probability of both introducing an EI and extending the number of EI-typologies adopted. We estimate the impact of the 'depth' and 'breadth' of knowledge sourcing. In addition, we test for the moderating role of the firm's absorptive capacity. Knowledge sourcing has a positive impact on both types of EI-performance. However, a broad sourcing strategy reveals a threshold above which the propensity to introduce an EI diminishes. Cognitive constraints in processing knowledge inputs that are too diverse may explain this result. Absorptive capacity generally helps firms to turn broadly sourced external knowledge into EI. However, internal innovation capabilities and knowledge socialization mechanisms seem to diminish the EI impact of knowledge sourced through deep external interactions. The possibility of mismatches between the management of internal and external knowledge, and of problems in distributing the decision-makers' attention between the two, may explain this result.

1. Introduction

The economic importance of environmental innovations (EIs) is today undisputed in both the business and policy realms (e.g., Wagner, 2006; Ambec et al., 2013). At the intersection of these two realms, EIs have an important 'win–win' effect whereby firms combine competitiveness and environmental sustainability (Porter and van der Linde, 1995; Porter, 2010).

However, this twofold effect comes at the price of a double market-failure – in the generation of new knowledge and in its impact on the environment – which makes environmental regulations a pivotal factor in driving EI. In environmental economics, this EI factor initially received most of the attention, but it did so with a "mechanistic stimulus-response approach" that underscored the role of external market conditions and internal techno-organizational capabilities as innovation drivers (Cleff and Rennings, 1999, p. 200). As a consequence a 'hybrid approach' to the determinants of EI has been developed in which innovation theory is integrated with the analysis of the so-called 'regulatory push/pull effect' of environmental policy (Rennings, 2000). This approach is the theoretical signpost of the present paper. More precisely, we further extend the evolutionary theory underpinning the hybrid approach in order to address a gap with respect to the knowledge base underlying EI. As Horbach et al. (2013, p. 528) have recently recognized, "[the] issue of sources of information and knowledge used in eco-innovative activities is rarely treated in the eco-innovation literature". One of the few stylized facts to have emerged, albeit still in a non-systematic way (e.g., Florida, 1996; Oltra and Saint Jean, 2005a,b; Rennings and Rammer, 2009), is that EIs require knowledge inputs from different and heterogeneous sources, possibly more so than other innovations (Horbach et al., 2013). With the notable exception of the so-called 'eco-industries', firms that strive for EI need to go beyond their core competences (Teece et al., 1997). Accordingly, external knowledge becomes an idiosyncratic EI driver to consider.

For this reason, attention has recently turned to the channels through which eco-innovative firms can access and benefit from external knowledge sources. A large part of the extant literature

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has focused on those kinds of flows that, owing to the public good nature of EI (Corradini et al., 2011, 2014), occur via spillovers, both within and across sectors and regions (e.g., Mazzanti and Zoboli, 2005; Cainelli et al., 2012; Costantini et al., 2013; Ghisetti and Quatraro, 2013). At a more micro-level, interesting insights have also been obtained by the literature on the firm's management of innovation cooperation (e.g., De Marchi, 2012; De Marchi and Grandinetti, 2013).

In spite of important specifications, these channels have been found to increase firms' EI. They thus point to an additional sphere of environmental policy action encompassing, among other things, network/cluster policies and technology/knowledge transfer initiatives. However, to the best of our knowledge, no evidence has yet been obtained on how EI-oriented firms search for external knowledge and then implement it internally. We believe that this is important information from which policies directed to smart and sustainable growth could greatly benefit. The identification of 'EI-friendly' modes of knowledge sourcing and absorption could help policy-makers devise the proper tools with which to extend the benefits of the open innovation mode to the environmental realm. In particular, an extra twofold positive impact could ensue from the eventual emergence of what could be called an 'open eco-innovation mode' (OEIM). On the one hand, openness to external knowledge sources could help firms attenuate the internal constraints (e.g., the lack of capabilities and intangible inputs to the generation/adoption of green-knowledge) that often prevent them from gaining a competitive advantage based on EI. On the other hand, the same kind of openness could also help firms win in terms of sustainability by increasing their connectedness with (and response to) environmentally responsible partners and their social embeddedness in green-oriented innovation systems. Evidence of these benefits would press for extension of the innovation side of the so-called 'environmental policy mix' (Jänicke and Lindemann, 2010; Schmidt et al., 2012; Costantini and Crespi, 2013). Specifically, following a system – rather than a market-failure approach, the aim of such an extension should be to include measures that support the firm's interactions, capabilities and learning (e.g., Metcalfe, 2005; Malerba, 2009), also in line with an increasingly relevant evolutionary framing of environmental policy (Nill and Kemp, 2009).

This paper's analysis of the search by firms for external knowledge is its first element of originality. A second element is its investigation of this phenomenon with respect to a sample of firms in eleven European countries, while previous research has mainly focused on one country at a time, or on a small set of similar countries (e.g., Ziegler and Rennings, 2004; Kesidou and Demirel, 2012). A third original aspect of the paper is its use of an econometric strategy that enables investigation of the impact of external knowledge on two different EI processes: the firm's introduction of an EI, and the enlargement of its EI-portfolio (i.e., the number of EI-typologies).

The rest of this paper is structured as follows. Section 2 reviews the background literature and puts forward our research hypotheses. Section 3 sets out the empirical application through which we test those hypotheses. Section 4 discusses the main results, and Section 5 concludes.

2. Theoretical background

After intense effort (e.g., Rennings, 2000; Kemp and Pearson, 2007; Kemp, 2010), a consensus has emerged on the definition of an EI as: "the production, assimilation or exploitation of a product, production process, service or management or business methods that is novel to the firm [or organization] 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" (Kemp and Pontoglio, 2007, p. 10). This definition is very composite and not confined to the technological sphere: it also encompasses organizational and service-based aspects and covers an array of environmental impacts along the entire environmental pipeline.

In considering the innovation process in Schumpeterian terms, such a pipeline would in principle span from the invention (Johnstone et al., 2010a, 2012) to the diffusion (e.g., Popp, 2010; Verdolini and Galeotti, 2011) phases of techno-organizational outcomes with a green impact. However, in line with much of the literature on the topic, in this paper we focus on the adoption of EIs, for two main reasons. Firstly, the reference to adoption overcomes the problem that not all inventions enter the market and, accordingly, not all the green technologies invented (e.g., patents) can directly influence the firm's environmental performance. Secondly, EI-adoption refers more directly to the firm's 'green capabilities' than to simple exposure to (and benefit from) the diffusion of an environmental technology.

Given the multi-faceted nature of EI (Markard et al., 2012), the ongoing search for its determinants (Del Río González, 2009; Berkhout, 2011) has led to results that pertain to different literature streams. At the crossroads between environmental economics and innovation studies, a relatively new body of literature has emerged and focuses on the most typical drivers of EI, classified as 'market-pull', 'technology-push' and above all 'regulation' effects (Nemet, 2009; Horbach et al., 2012). In regard to the first effect, EIs have been shown to be pulled by turnover expectations and new demand for eco-products (Rehfeld et al., 2007), past economic performance (Horbach, 2008), and customer benefits (Kammerer, 2009). As far as the 'technology-push' effect is concerned, EIs have been related to firms' R&D, knowledge capital endowment (Horbach, 2008), organizational practices and management schemes, such as Environmental Management Schemes (EMS) (Ziegler and Rennings, 2004; Rennings et al., 2006; Wagner, 2007; Rehfeld et al., 2007; Ziegler and Nogareda, 2009). As for the 'regulation' effects, the extant literature has stressed the central role of environmental standards and policies in spurring the adoption of EI and in creating lead markets for eco-innovators (Beise and Rennings, 2005).

Both survey-based studies (Frondel et al., 2008; Del Río González, 2009; Horbach et al., 2012; Rennings and Rammer, 2011; Rennings and Rexhäuser, 2011) and patent-based empirical investigations (Lanjouw and Mody, 1996; Jaffe and Palmer, 1997; Brunnermeier and Cohen, 2003; Johnstone et al., 2010a,b, 2012; Popp, 2010) have emphasized the extremely important effect of regulation on EI. It has been argued that environmental regulations stimulate a mechanism similar to the Hicksian inducement effect (Hicks, 1932) on EI (Porter and van der Linde, 1995). Evidence has been also obtained concerning the economic impact of policy-induced EI (e.g., Costantini and Mazzanti, 2012), the inducement effect of weak regulatory pressures (Ghisetti and Quatraro, 2013), and the net effects exerted by mixed policies[1] (Jänicke and Lindemann, 2010; Schmidt et al., 2012; Costantini and Crespi, 2013) and neighboring countries' policies (Peters et al., 2012) on the direction of environmentally related technological change.[2]

In comparison to the above effects, the extant literature has instead paid little attention to the EI drivers that work through the

[1] The transition toward sustainability depends not only on the presence of a regulatory framework (that may induce innovations) but also on the existence of proper coordination between existing environmental and technological policies (Costantini and Crespi, 2013).

[2] Besides the above effects, EI determinants have also been found, in the form of controls, among specific firms' characteristics such as: size, location, sector and age (e.g., Ziegler and Rennings, 2004; Rennings et al., 2006; Wagner, 2007; Rehfeld et al., 2007; Horbach, 2008; Mazzanti and Zoboli, 2009).

interaction between the firm and its external environment.[3] Among the few recent contributions, it has been found that innovative-oriented industrial linkages and inter-firm networking may trigger EI in a similar way to other innovations (e.g., technological and organizational): for example, by providing firms (SMEs, in particular) with a way to compensate for their lack of economies of scale (Mazzanti and Zoboli, 2009). In contrast, important elements of differentiation have emerged. Information from partners external to the supply chain (e.g., KIBS, research institutions, universities and competitors) has appeared more important for EI than for other innovations (De Marchi and Grandinetti, 2013). Furthermore, innovation cooperation (e.g., in R&D) has been shown to work more effectively for EI than for non-environmental innovations (De Marchi, 2012) but also more selectively. For example, business suppliers and universities have proved to be among the most important partners in terms of EI impact.[4] The need for new environmental solutions which embrace the entire spectrum of elements in the technological system explains the former of these results (Horbach et al., 2012). The complexity of the knowledge that EIs require, and its degree of scientific codification, have been cited to explain the latter (Cainelli et al., 2012).

The systemic nature of EI requires firms to deal with different techno-economic problems which entail different kinds of knowledge and knowledge interactions. Carrillo-Hermosilla et al. (2010), for example, refer to four dimensions of change entailed by an EI, which they call: 'design', 'users' involvement', 'product-service', and 'governance' dimensions. The first dimension pertains to technical choices that the firm grounds on its production and engineering knowledge (e.g., Braungart et al., 2007). The second is a market dimension and relates to the users' involvement in the identification, creation, development and application of an EI. The product-service dimension highlights the importance of a supply chain perspective for EIs. Finally, governance refers to both private (e.g., managerial choices) and public (e.g., policy actions) institutional solutions that the firm needs to use to resolve conflicts over environmental resources: in particular, to overcome lock-in conditions (e.g., due to national security) which act as barriers to EI (Unruh, 2000). The need to cope with all these different dimensions requires environmental innovators to have information and skills that are also distant from the traditional industrial knowledge base in which they operate (De Marchi, 2012). This fact makes knowledge interactions for EI more overarching than they are for technological innovations.

Theory and evidence begin to confirm that, also with respect to EI, firms could benefit from an open innovation mode (Chesbrough, 2003; Chesbrough et al., 2006) in which the knowledge boundaries between the firm and the external environment become permeable. As a further step toward substantiation of this hypothesis, however, it is necessary to investigate whether some specific pillars of the open innovation mode are at work with respect to EI as well, and if so, with which characterizations. Not only is this investigation necessary for firms to devise strategic recommendations in order to benefit from the open innovation mode; it is also crucial for policy-makers to activate proper inducement effects on firm's eco-innovative behaviors concerning the use of external knowledge.

[3] In standard innovation studies, the importance of these kinds of determinants has instead attracted large attention from research on innovation cooperation, knowledge transfer and knowledge sharing (e.g., Hagedoorn and Van Kranenburg, 2003; Arora and Gambardella, 1994; Veugelers, 1997; Tether, 2002; Tödtling et al., 2009).

[4] As for the geographical location of external relationships, agglomeration economies have been found to impact positively on EI, but only in those industrial districts in which the subsidiaries of multinational corporations inject global environmental pressures at the local level (Cainelli et al., 2012).

2.1. Knowledge search patterns and EI

The first pillar of the open innovation mode is represented by the manner in which firms search for external knowledge in order to innovate: that is, their mode of knowledge sourcing. Knowledge sourcing can take different forms (for a recent study see Huggins et al., 2010) which have two characteristics that have attracted a great deal of attention since the work by Laursen and Salter (2006). The first is the breadth of the firm's knowledge search, in terms of the array of sources upon which it draws in order to access external knowledge.

As aforementioned, only sparse evidence has been collected to date on the importance of broad knowledge sourcing for EI. Rennings and Rammer (2009, p. 454), for example, have found that, in introducing energy and resource efficiency innovations, German firms "search for innovation impulses more broadly (i.e., they use more and different information sources) than other innovators". With respect to more general EI, focusing on France and Germany, Horbach et al. (2013, p. 529) have confirmed that "eco-innovative activities require more external sources of knowledge and information compared to other innovations". In our search for more systematic empirical evidence on the EI relevance of broad knowledge sourcing, we rely on two main arguments. The first is the intrinsically systemic nature of EI. As we anticipated in Section 1, EIs are innovations that unfold together with organizational (e.g., adoption of specific management systems) and institutional (e.g., compliance with dedicated regulations) changes, which add further knowledge requirements to those for mastery of new technological knowledge: for instance, the need to obtain scientific knowledge about the materials to be used (from universities and research institutes), the environmental standards to respect (from specific agencies), and the availability of sustainable production inputs (from the suppliers). These broad knowledge requirements are difficult for the firm to satisfy internally, and they are also hard to find in one or a few external knowledge providers.

A second related argument is represented by the multi-purpose nature of EI. The introduction of EI usually requires the firm to combine multiple objectives and to find and manage suitable compromises among them (Florida, 1996; Horbach et al., 2013). Typically, an eco-innovator needs to set multiple targets in terms of, for example, production efficiency, product quality, and environmental standards (Oltra and Saint Jean, 2005a). Once again, this requires additional (to that available internally) knowledge, which is usually dispersed among a number of external knowledge sources.

On the basis of the previous two arguments, we expect to find that the following hypothesis can be supported more extensively than in previous studies:

H1. The breadth of the firm's knowledge sourcing has a positive effect on its EI.

The second characteristic of the firm's open mode of knowledge sourcing that requires special attention in the case of EI is its depth, by which is meant the extent to which firms draw intensively on external knowledge providers (Laursen and Salter, 2006). Unlike breadth, the importance of deep sourcing for eco-innovative activities has not attracted comparable attention in the literature. This is unfortunate, because close and long-lasting relationships are considered to be crucial for successful innovations in general (e.g., Huggins et al., 2010). However, also in this case two arguments render the importance of depth for EI testable on a systematic basis. The first is the lack of cognitive proximity (e.g., Boschma, 2005) with which firms are often required to deal in order to expand their existing knowledge base and successfully achieve an EI outcome (De Marchi, 2012). Except in those sectors with an inherent eco-characterization (e.g., sustainable housing or photovoltaic energy), this distance may be large. Firms may have to access external knowledge on alternative production processes, inputs and/or materials that are distant from those relevant to their core business and could thus result in being quite difficult to grasp and implement (Teece et al., 1997). EIs are generally less path-dependent than other innovations. In pursuing an EI, firms might thus be unable to benefit from their existing knowledge base as a point of departure for a local, and thus more economical, search for new EI solutions (Nelson and Winter, 1982).[5] Unlike as for technological innovations, their knowledge search could start from sources at a certain (cognitive) distance from their initial base and with respect to which a deeper interaction is required to put a viable knowledge-interaction in place.

The second argument that makes deep knowledge sourcing essential for EI is the fact that eco-innovative (especially energy and resource efficiency innovations) firms seem to perceive the lack of suitable co-operation partners as an important innovation barrier (Rennings and Rammer, 2009). As a consequence, a suitable knowledge partner becomes a crucial asset to maintain, possibly with the help of a deep and sustained interaction. In evolutionary terms, the low availability of suitable knowledge sources makes their selection and maintenance crucial for the viability of learning-by-interacting. We can thus advance the following hypothesis:

H2. The depth of the firm's knowledge sourcing has a positive effect on its EI.

Before proceeding with the formulation of our hypotheses, we should point out that we consider sourcing strategies not confined to specific green knowledge. It is certainly true that external knowledge explicitly related to the improvement of environmental performance can have a direct impact on the firm's EI. However, it would be misleading and difficult to isolate green-oriented from non-green-oriented knowledge. As noted above, EI requires the control of not only environment-specific knowledge fields (e.g., those used to classify green patents in the World Intellectual Property Organization (WIPO) International Patent Classification (IPC) Green Inventory) but also multidisciplinary ones. EIs develop through an open innovation mode where external knowledge, not necessarily 'green', enhances the environmental performance of the technologies adopted. In a study at the inter-regional rather than inter-firm/organization level for Italy, Costantini et al. (2013) find that regional environmental performances are affected not only by specific environmental spillovers but also by more general innovation spillovers captured by the patent-intensity of neighboring regions in a wider spectrum of knowledge fields. Although the transfer channel in the study by Costantini et al., is different from ours, and related to the role of Marshallian agglomeration economies, similar insights into the EI role of general external knowledge are found with respect to the innovation cooperation channel (De Marchi, 2012), which is conceptually closer to the one that we will use in our empirical application.

While both breadth and depth may stimulate the firm's EI, their exploitation may become counterproductive at a certain stage. Widening and/or deepening interaction with external knowledge sources may enter a phase of decreasing EI returns because of the explicit and implicit cost of its management. In the case of technological innovations, this has actually been found (Laursen and Salter, 2006) and explained by drawing on the attention-based theories of the firm (Simon, 1947; Koput, 1997; Ocasio, 1997). In short, excessively broad and/or deep knowledge sourcing may entail for the firm a subtraction of organizational/managerial energies and cognitive attention from its ultimate innovative effort. In principle, this may happen also in the case of EI. A clash between engagement in the search for external knowledge and the capacity to implement a successful EI can be actually stronger than in the case of other innovations. The greater complexity and distance of the external knowledge required for eco-innovating, on the one hand, and the relative scarcity of green-specific managerial competences for processing it, on the other hand, may impose greater stress on the attention-resources of the firm. Accordingly, we can put forward the following hypothesis:

H3. Broad and deep knowledge sourcing has an inverted U-shape effect on EI.

On testing the above three hypotheses, an EI-specific aspect warrants special consideration: the different nature of the processes that drive, on the one hand, the firm's propensity to introduce an EI and, on the other hand, the extent of its involvement in the EI realm, through the adoption of different EI-typologies. In a related stream of literature (e.g., Carrillo-Hermosilla et al., 2010; Kesidou and Demirel, 2012), the former has appeared mainly driven by a minimum set of customer and societal requirements. By contrast, the latter is likely to be affected by additional factors, like the search for cost-savings, the availability of suitable organizational capabilities and the imposition of a stricter set of environmental regulations. More in general, the second process, which could in some way represent the extension/intensification of the first, occurs with know-how and along a certain path of EI-learning which could be a source of both experience economies and diseconomies.[6] On the basis of these arguments, we investigate whether these two EI processes are differently affected by the way (breadth and depth) in which knowledge sourcing is conducted. In practical terms, we scrutinize whether the emerging results differ when, instead of looking at the probability of introducing an EI, we consider the number of EI-typologies that an environmental innovator manages.

2.2. External knowledge, absorptive capacity and EI

In extending the open innovation paradigm to the EI analysis, a second pillar that requires consideration is the firm's capacity to scan, acquire, and implement external knowledge: in short, its absorptive capacity (AC).

Since the seminal paper by Cohen and Levinthal (1989), much work has been undertaken in order to understand the factors on which AC depends (in short, its antecedents) and those responsible for its innovation impact (e.g., Lim, 2009; Murovec and Prodan, 2009; Lewin et al., 2011). This debate has led to some interesting results, whose extension to EI appears noteworthy.

The first is the crucial role of R&D in increasing the intelligibility of external knowledge: that is, in reducing the cognitive distance between the firm and the external providers.[7] In the case of EI, whose technological elements are contaminated by other non-technological ones and whose dimensions involve different knowledge spheres, this cognitive distance might be, as aforementioned, larger than for other innovations, and the 'secondary' role

[5] As is well known, the advantages of searching locally can turn into disadvantages when firms become locked-in with respect to their previous knowledge. However, at least initially, they represent an advantage in terms of the capacity to absorb external knowledge.

[6] In the case of standard innovations, this is a result that has already emerged by using Community Innovation Survey (CIS) data, and it has interesting implications in terms of complementarity of policy actions (e.g., Mohnen and Röller, 2005).

[7] Following Cohen and Levinthal (1989), this would be the "second face" of R&D. The first face would be instead related to the generation of new knowledge inputs: an aspect that will have to be considered among the EI determinants in our empirical application.

of R&D thus seems as important as its 'primary' input role.[8] Furthermore, in the environmental realm, the role of R&D in helping the absorption of external knowledge could be reinforced by the fact that the impure public good nature of the internal knowledge that it generates correlates positively with the spillover effects of other investments directed to increase environmental performances (e.g., the emissions abatement of other sectors) (Corradini et al., 2011, 2014). Also with respect to AC, it should be noted that the R&D from which knowledge sourcing could benefit the most may presumably be of a general kind, rather than green R&D. The latter could be less useful in assimilating external knowledge, in the frequent case, as we said, in which this does not have a green-specific content.

The firm's capacity to make use of external knowledge (AC) for the sake of EI can also be favored by mechanisms other than innovation investments which are deliberately devised by the firm to enable the circulation and implementation of external knowledge within its boundaries: mechanisms that the AC literature has called 'social integration mechanisms' (SIM) (Zahra and George, 2002). In brief, these are organizational capabilities, like "connectedness and socialization tactics" (Jansen et al., 2005, p. 999), which substantiate into cross-functional interfaces and formal communication flows across divisions. These mechanisms can be expected to favor the circulation and diffusion of externally acquired knowledge and thus to augment its socialization (Jansen et al., 2009; Hirunyawipada et al., 2010) also for the sake of EI. In particular, we may expect that these SIM enable the firms to accompany the absorption of new external knowledge with unfolding organizational changes that constitute an integral part of their EI.

Given the AC role of R&D and SIM, these are expected to ease and facilitate the exploitation of external knowledge for the sake of EI. Considering the two different types of external knowledge sourcing that we have considered in H1 and H2, we thus put forward the following hypothesis:

H4. The firm's R&D and SIM positively moderate the EI impact of the breadth and depth of the firm's knowledge sourcing.

Possibly more than in the case of sourcing strategies, analysis of the moderating effects of R&D and SIM should be carried out by distinguishing the process of becoming an eco-innovator from that of increasing the EI-portfolio. Unlike the former, the latter refers to firms that have already proved capable of dealing with the knowledge needs and interactions involved in becoming environmental innovators. Somehow, this step into the EI-realm represents an implicit element of firms' capacity to assimilate and exploit external knowledge for EI. In other words, the moderating effect of the firm's AC on its EI-performance can reasonably be attenuated in the presence of already acquired green knowledge. This latter can work as a sort of AC mechanism itself: the presence of previously acquired green capabilities and skills can provide firms with a channel through which to absorb further green knowledge.

3. Empirical application

3.1. Econometric strategy

The theoretical arguments and hypotheses presented in Section 2 will be tested with a set of hierarchical econometric models. First, the impact of the breadth and depth of external sourcing on the firm's EI (H1 and H2) is estimated with the following model, which includes a suitable set of controls for each firm *i*:

$$EI_i = \alpha + \beta_1\, BREADTH_i + \beta_2\, DEPTH_i + \gamma\, CONTROLS_i + \epsilon_i \qquad (1)$$

In order to account for potential non-linearity in the relationship between external knowledge sourcing and EI (H3), the benchmark model (1) is augmented by including squared terms for both breadth and depth variables:

$$EI_i = \alpha + \beta_1\, BREADTH_i + \beta_2\, DEPTH_i + \beta_3\, BREADTH_i^2 + \beta_4\, DEPTH_i^2 + \gamma\, CONTROLS_i + \epsilon_i \qquad (2)$$

Finally, we investigate the moderating effect of factors that affect the absorption of external knowledge and its transformation into actual EI in order to test for H4. For this purpose, in Eq. (3) we consider two dummies for engagement in R&D activities (*RD*) and the presence of social integration mechanisms (*SIM*), respectively, and test for their interaction with breadth and depth:

$$EI_i = \alpha + \beta_1 BREADTH_i + \beta_2\, DEPTH_i + \beta_3\, BREADTH_i^2 + \beta_4\, DEPTH_i^2 + \delta_{1-2}[RD, SIM] + \delta_{3-4}[RD, SIM] * BREADTH_i + \delta_{5-6}[RD, SIM] * DEPTH_i + \gamma CONTROLS_i + \epsilon_i \qquad (3)$$

In order to analyze the two different processes of adopting an EI and extending the kind of EI introduced by the environmental innovators, we define the dependent variable *EI* as the number of EI-typologies adopted by the firm and then estimate Eqs. (1)–(3) with a hurdle negative binomial model (e.g., Cameron and Trivedi, 1998). As is well known, its underlying rationale is that a binomial probability model (in our case, a logit one) governs the binary outcome of whether the count dependent variable has a zero or a positive value. If the hurdle is crossed (i.e., if the dependent variable has positive values), the conditional distribution of the positive values is instead governed by a zero-truncated count model (in our case, a zero-truncated negative binomial).

Given this latter property, the choice of this model is consistent with our research aim. The different generating processes for the zeros and the positive values of our core variable (*EI*) allow us to integrate the analysis of the EI-propensity with a special focus on the EI-portfolio of environmentally innovative firms (that is, firms which have crossed the hurdle of EI). Furthermore, the hurdle model allows us to account for the overdispersion and the excess of zeros that the dependent variable shows, because of the high number of non-environmental innovators (see Table A1).

3.2. Dataset and variables

The empirical application makes use of the Community Innovation Survey (CIS) for the period 2006–2008. Given our research interest we focus on manufacturing sectors for which the types of EI addressed by CIS have attracted the majority of attention in the literature. For reasons of data availability we restrict the analysis to eleven EU countries: Bulgaria, Czech Republic, Germany, Estonia, Hungary, Italy, Lithuania, Latvia, Portugal, Romania and Slovakia.[9]

[8] It should be noted that the latter has been found insignificant by some empirical studies (e.g., Horbach, 2008; Ziegler and Nogareda, 2009; Cainelli et al., 2012; Horbach et al., 2012).

[9] The data are taken from the CIS 2006–2008 anonymized micro-data dataset provided by Eurostat. This CIS wave is the first one that systematically collects harmonized information on EI with a wide European coverage. We have restricted the working sample to countries which included the section on EI in the questionnaire; we have excluded Cyprus and Ireland because of missing values in variables of interest. The number of potential observations for which we have information on the adoption of EI in these eleven countries is 27,690. However, given the structure of the CIS questionnaire, information on our key explanatory variables is available only for innovative firms: that is, firms with product or process innovations, or innovation

Table 1
Variables description.

Variable	Description
EI	Number of EI typologies introduced by firms
BREADTH	Number of external information sources the firms rely upon
DEPTH	Number of external information sources to which firms attribute a high degree of importance
COOP	R&D cooperation with cooperation partners (DUMMY)
EXPORT	Engagement into international markets (DUMMY)
INNOPOL	Existence of public support to firm's innovation activities (DUMMY)
lnTURNOVER	Natural logarithm of firm's turnover in 2006
MNC	Affiliation to a multi-national corporation (DUMMY)
POLSTR	Logarithm of country/sector CO_2 emission intensity in terms of Value Added in 2006
RD	Engagement in R&D activities (DUMMY)
SIM	Importance of the internal information flows for firm's innovation activities (DUMMY)

The main reason for using this data source is that it is possible to draw information on both the adoption of EI, and firms' deliberate open innovation strategies concerning the sourcing and exploitation of external knowledge.[10] Furthermore, the CIS has the advantage of a European coverage with fully comparable country data, which suits the purpose of our work.

Of course, the CIS is not free from limitations. First, the data collected are self-reported by the respondents and thus less objective than other data, for instance those on patents. Second, the CIS dataset does not allow evaluation of the diffusion of EI, which is crucial for firms to improve their environmental performance. In spite of these and other limitations (for which see Mairesse and Mohnen, 2010), the dataset which can be built on the basis of the CIS 2006–2008 is particularly suitable for implementing our econometric strategy.

Firstly, the dependent variable, *EI*, is defined as a count variable by referring to the nine different types of EI that the CIS encompasses.[11] In principle, each EI-category would warrant separate investigation (Carrillo-Hermosilla et al., 2010). However, our focus in this paper is different. We are interested in identifying the existence of regularities across the different typologies of EI in recourse to and exploitation of knowledge sourcing. These regularities represent important benchmarks against which to evaluate the variations entailed by specific couplings of EI-types and knowledge providers.[12] The cross-country distribution of *EI* is depicted in Table A2.

With respect to our independent variables, those related to knowledge sourcing are built following Laursen and Salter (2006). *BREADTH* is defined as the number of external information sources on which the firm relies for its innovation activities out of the list of 9 potential knowledge providers (that is, suppliers; customers; competitors; consultants and private R&D institutes; universities;

Table 2
Variables descriptive statistics.

Variable	*N*	Mean	Min	sd	Max
EI	14,366	2.79	0	2.97	9
BREADTH	14,366	5.19	0	2.75	9
DEPTH	14,366	0.92	0	1.28	9
COOP	14,366	0.24	0	0.43	1
EXPORT	14,366	0.69	0	0.46	1
INNOPOL	14,366	0.21	0	0.41	1
lnTURNOVER	14,366	13.44	−6.91	4.01	24.39
MNC	14,366	0.15	0	0.36	1
POLSTR	14,366	−0.85	−4.99	1.50	2.16
RD	14,366	0.42	0	0.49	1
SIM	14,366	0.74	0	0.44	1

government or public research institutes; conferences, trade fairs, exhibitions; scientific journals and trade/technical publications; professional and industry associations). *DEPTH* instead counts the number of these external information sources to which the firm attributes a high degree of importance among the four listed options (i.e., not used, low, medium, high importance). Cross-country distributions or *BREADTH* and *DEPTH* are reported in Table A2.

The second set of explanatory variables is represented by the AC antecedents. These are included as individual regressors and in Eq. (3) as interacting terms. First, we employ a dummy, *RD*, to capture the firm's internal R&D investments.[13] Social integration mechanisms of external knowledge are also captured by a dummy (*SIM*) considering the importance that firms attribute to those internal information channels/flows through which external ones will possibly circulate to be absorbed. In particular, following Fosfuri and Tribó (2008), *SIM* takes value 1 if the information originating from within the boundaries of the company (or from the industrial group to which it belongs) has a medium or high importance for the firm's innovation activities, and 0 otherwise.

As for the controls, we first account for the firm's size by including the logarithm of its turnover (*lnTURNOVER*) in the first year of the reference period, i.e., 2006. *COUNTRY*- and *SECTOR*-specificities in terms of market and technological opportunities, as well as institutional settings, are controlled for with the inclusion of a series of dummies.[14] We then add two characteristics related to the internationalization of the firm which the extant literature

activity during the period 2006–2008. Because of this filter, observable firms reduce to 15,324 and to a final working sample of 14,366 firms, because of additional, non-systematic missing values in the considered variables. This issue, which restricts the generalizability of our results to innovative firms, should be taken into account when drawing implications from our study.

[10] In contrast, while also important, the use of patent data (in green technologies) (e.g., Johnstone et al., 2010a; Popp, 2010; Marin, 2014) would result in two drawbacks: difficulties in grasping information on the adoption of open innovation modes; attention to inventions, rather than to adopted innovations (Griliches, 1998).

[11] The CIS defines EI consistently with the definition that we provided in Section 2. Six types of EI refer to environmental benefits deriving from the production of goods or services: reduced material use per unit of output; reduced energy use per unit of output; reduced CO_2 footprint (total CO_2 production); replaced materials with less polluting or hazardous substitutes; reduced soil, water, noise, or air pollution and recycled waste, water, or materials. The other three EI are related to the benefits deriving from the after-sales use of a good or service: reduced energy use; reduced air, water, soil or noise pollution; improved recycling of product after use. The Cronbach's Alpha of our dependent variable is 0.8832.

[12] The analysis of the large number of potential combinations between EI and knowledge provider typologies would require a cumbersome discussion and empirical test which would fall outside the scope of this paper.

[13] Although available, we do not use the continuous variable for R&D investment. Because this refers to the last year of the period (i.e., 2008), some endogeneity problems may emerge with the dependent variable (*EI*), which instead refers to the entire period (i.e., 2006–2008).

[14] Eleven dummies are used to capture location in the EU counties that we consider. Seven sector dummies for manufacturing sectors have been included. These have been built according to the finest sectoral classification available in our CIS data, which is based on the NACE Rev. 2: C10-C12; C13-C15; C16-C18; C19-C23; C24-C25; C26-C30 and C31-C33. In unreported regressions, sector dummies have also been interacted with country ones; results do not change.

Table 3
Variables correlation matrix.

Id	Variables	1	2	3	4	5	6	7	8	9	10	11
1	EI	1										
2	BREADTH	0.28	1									
3	DEPTH	0.16	0.38	1								
4	RD	0.26	0.34	0.17	1							
5	COOP	0.16	0.24	0.17	0.27	1						
6	SIM	0.17	0.38	0.21	0.29	0.16	1					
7	lnTURNOVER	0.19	0.14	0.10	0.12	0.14	0.05	1				
8	MNC	0.11	0.09	0.00	0.10	0.20	0.15	0.22	1			
9	EXPORT	0.15	0.17	0.09	0.29	0.20	0.15	0.22	0.22	1		
10	INNOPOL	0.11	0.20	0.12	0.28	0.21	0.14	−0.04	−0.01	0.14	1	
11	POLSTR	−0.09	−0.04	−0.03	−0.14	−0.03	−0.01	−0.07	−0.02	−0.13	−0.06	1

considers to be important determinants of EI performance (e.g., Cainelli et al., 2011, 2012): *EXPORT*, a dummy which reflects whether the company is engaged in international markets, and *MNC*, which denotes whether the firm is affiliated to a multinational corporation. Although technology-push factors are already considered through the inclusion of *RD* (and *SIM*) as individual regressors, we add a further control in the same respect: *COOP*, a dummy which captures the firm's engagement in formal innovation cooperation agreements. Last, but not least – given their centrality in the hybrid approach we are adopting – we control for the likely effect of policy and regulation in pulling/pushing EI (e.g., Del Río González, 2009). At the outset, we account for them in general terms by looking at whether the firm has received public support for its innovation activities (*INNOPOL*). Unfortunately, CIS data do not allow us directly to retain more specific environmental policies at the firm level.[15] In order to overcome this problem, we have thus considered other data sources. In particular, by exploiting EUROSTAT data on "Air emissions accounts by industry and households", we follow some recent studies on the issue (e.g., Costantini and Crespi, 2008) and adopt as a proxy for environmental policy stringency (*POLSTR*) the logarithm of the CO_2 Emission/Value Added ratio in each country-sector combination for the year 2006.[16]

Tables 1 and 2 provide syntheses of the variables descriptions and their main statistics, respectively. Table 3 presents the matrix of their correlation coefficients. The main regressors of our econometric exercise show signs consistent with our hypotheses

4. Results

4.1. External knowledge and the adoption of EI

Following the econometric strategy that we have proposed, we first test our four hypotheses with respect to the firm's adoption of EI (Table 4). When the role of the other EI predictors is controlled for (in the baseline Model I), the modes of knowledge sourcing that we have addressed have a significant effect on EI adoption.[17] The wider the array of knowledge sources on which the firm draws (*BREADTH*), the more probable is the introduction of an EI. H1 is thus confirmed, suggesting that *BREADTH* may increase the firm's coverage of the multiple knowledge needs entailed by the multi-dimensionality of EI.

Table 4
Hurdle negative binomial estimation results (Logit part).

Variables	(I)	(II)	(III)	(IV)
BREADTH	0.0984***	0.271***	0.263***	0.255***
	(0.00835)	(0.0288)	(0.0290)	(0.0293)
DEPTH	0.0664***	0.0976***	0.137***	0.182***
	(0.0186)	(0.0358)	(0.0379)	(0.0509)
BREADTH^2		−0.0177***	−0.0181***	−0.0196***
		(0.00281)	(0.00290)	(0.00303)
DEPTH^2		−0.00744	−0.00551	−0.00443
		(0.00767)	(0.00715)	(0.00774)
BREADTH*RD			0.0337*	
			(0.0181)	
DEPTH*RD			−0.109***	
			(0.0350)	
BREADTH*SIM				0.0486**
				(0.0191)
DEPTH*SIM				−0.119**
				(0.0486)
POLSTR	0.00638	0.00718	0.00700	0.00689
	(0.0236)	(0.0236)	(0.0236)	(0.0237)
COOP	0.439***	0.442***	0.441***	0.441***
	(0.0549)	(0.0551)	(0.0552)	(0.0551)
SIM	0.256***	0.210***	0.207***	0.0730
	(0.0479)	(0.0489)	(0.0491)	(0.0939)
RD	0.345***	0.324***	0.242**	0.323***
	(0.0471)	(0.0475)	(0.105)	(0.0475)
lnTURNOVER	0.0192***	0.0203***	0.0201***	0.0201***
	(0.00689)	(0.00692)	(0.00692)	(0.00693)
MNC	0.171***	0.185***	0.181***	0.184***
	(0.0627)	(0.0628)	(0.0629)	(0.0629)
EXPORT	0.252***	0.250***	0.248***	0.248***
	(0.0471)	(0.0472)	(0.0473)	(0.0473)
INNOPOL	0.126**	0.130**	0.129**	0.129**
	(0.0536)	(0.0537)	(0.0538)	(0.0538)
Country Dummies	YES	YES	YES	YES
Sector Dummies	YES	YES	YES	YES
Constant	−0.631***	−0.922***	−0.902***	−0.865***
	(0.138)	(0.147)	(0.148)	(0.150)
Observations	14,366	14,366	14,366	14,366
Prob > Chi^2	0.00	0.00	0.00	0.00
McFadden adj. R^2	0.167	0.169	0.170	0.170
Log PseudoL	−7945.0505	−7922.8386	−7917.458	−7917.7947

Robust standard errors in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

The probability of being an environmental innovator also increases with the competences that the firm acquires through deep interaction with its external knowledge providers (*DEPTH*). H2 is confirmed as well, supporting the idea that intensive interactions transform a spot-like knowledge exchange into learning-by-interacting for the sake of EI.

Again, with respect to the probability of eco-innovating, Model II (Table 4) plugs into the baseline model the squared terms of our focal regressors in order to investigate the presence of non-linear

[15] In the Section on "Innovations with Environmental Benefits", the CIS questionnaire includes a question on the role of environmental regulations (either existing or expected). However, its formulation impedes inclusion of the relative variable in the econometric specification. Given that it is addressed only to those firms which have introduced an EI, endogeneity problems could emerge.

[16] In Section 4.3 we describe some robustness checks that we have carried out on alternative specifications for this policy stringency variable.

[17] For the sake of parsimony, we do not comment on the coefficients of the controls.

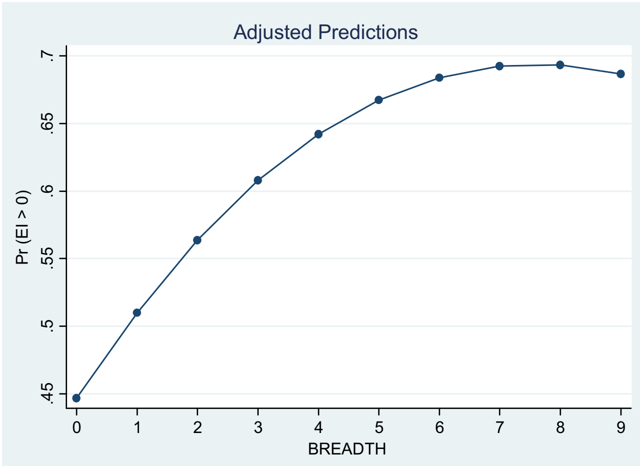

Fig. 1. Curvilinear effect of BREADTH on the predicted EI-probability (Logit part).

effects. In doing so, H3 appears only partially supported. On the one hand, the impact of *DEPTH* does not seem to be bounded (*DEPTH*^{2} is actually not significant). Increasing the intensity of learning-by-interacting always gives the firm more refined knowledge and enhances the probability of introducing an EI. On the other hand, the benefits of a broad sourcing strategy stop increasing above a certain level (*BREADTH*^{2} is significantly negative). In this regard, it seems that, although some knowledge variety is required in order to step into the EI realm, broadening the external search above a certain level may expose the firm to redundant and/or inconsistent information signals. These problems may make the firm less prompt, if not even more reluctant, to introduce an EI.

In the latter respect, a closer look at the inverted U-shaped effect of *BREADTH* on the EI-adoption (Fig. 1) can help refine our analysis. The marginal return of an increasingly broad sourcing strategy tends to decrease and becomes not significantly different from zero when *BREADTH* reaches a medium-high number of knowledge sources for the firm (i.e., 7 and 8 out of 9). When *BREADTH* reaches its maximum value, its marginal effect becomes even negative.[18]

Finally, we may conclude that both the variety and the intensity of the firm's search for external knowledge can assist the decision to introduce an EI. Policy support for knowledge transfer/sourcing can thus be considered beneficial in sustaining the environmental performance of firms' innovation. However, when designing support schemes, policy-makers should bear in mind that the benefits of the firm's knowledge sourcing are constrained in terms of breadth.

Turning to the role of AC with respect to the adoption of EI (Table 4, Models III and IV), the validation of our H4 appears partial. R&D, as expected, increases per se the probability of becoming an environmental innovator. R&D also positively moderates the EI impact of *BREADTH*, consistently with H4. According to the AC logic, R&D can help the firm scan and master external knowledge, and reduce the cognitive distance from the external sources. Given the general nature of our R&D variable (that is, not limited to green-R&D), and the general type of knowledge sourcing captured by *BREADTH*, this result appears consistent. Because it is not confined to the environmental innovation sphere alone, R&D provides the firm with adaptable and flexible knowledge/capabilities that can be helpful in making more efficient use of the wide set of external knowledge sources that EIs require.

In contrast with H4, *DEPTH* is negatively moderated by R&D, suggesting that their combination is an obstacle to the introduction of EI. Different, though tentative, explanations for this may be provided. Firstly, the deeper the interaction with the external knowledge source, the more it will be oriented toward precise aims, and the higher will be the chance of it creating mismatches with internally developed R&D (Carlile, 2004).[19] Unlike for *BREADTH*, the knowledge that the firm obtains through deep and structured interactions with external sources may become irreversible and thus hard to re-adapt if it conflicts with the one obtained through internal R&D investments. Secondly, even irrespectively of the occurrence of these mismatches, firms' decision-makers may more easily incur organizational burdens and problems related to allocating their attention between internal and external knowledge sources, when the latter are intense rather than non-structured (Ocasio, 1997).

Mixed results in testing for H4 also emerge with respect to the role of *SIM*. At the outset, when its interaction with *BREADTH* and *DEPTH* is also considered, *SIM* loses its significance as an additive direct regressor. As expected, the investigated integration mechanisms seem to work on EI only indirectly, through the socialization of external knowledge. However, such socialization only occurs with respect to the organizational diffusion of the diverse knowledge inputs that the firm obtains from a broad mode of knowledge sourcing (i.e., with respect to *BREADTH*). This confirms H4 and is once again a consistent result. Indeed, by construction *SIM* refers to a general capacity to circulate information within the firm, and is not related to the transmission of specific types of knowledge. This general and flexible nature suits the aim of transmitting internally knowledge that is acquired through a non-structured kind of sourcing with multiple knowledge sources. By contrast, H4 is not confirmed when the interaction between *SIM* and intense external knowledge is considered: *DEPTH***SIM* is significant and negative. The interpretation of this result is similar to the one that we provided above with respect to the moderation effect of R&D, and it reinforces the mechanisms that we pointed out there: knowledge mismatches, attention problems, and the organizational burden imposed by the absorption of deeply sourced external knowledge. In this specific case, we may add that the general *SIM* in question may not be suitable for disseminating within the firm a kind of knowledge that a deep interaction presumably makes specific and in need of tailored dissemination mechanisms.

As in the case of H3, H4 also suggests an important differentiation between *BREADTH* and *DEPTH* in the probability of eco-innovating. The former strategy seems to rely on the firm's AC to become exploitable. The latter seems to provide the firm with more immediately usable knowledge, but it may create clashes with the firm's internal innovation capabilities and socialization routines. From a policy point of view, support for stable interactions with external knowledge sources (e.g., with dedicated research labs, suppliers and/or customers) should take these problems into account.

[18] We have obtained this result by implementing the following test. We have calculated the turning point algebraically by setting to zero the first derivative of the marginal effects function (estimated on the logit part of our hurdle model). The punctual estimation of the *BREADTH* value at which the function has a maximum (i.e., the first derivative equals zero) is 7.63. However, the first derivative is not significantly different from zero (at the 95% level) for values of *BREADTH* between 6.66 and 8.59. Hence, for values of *BREADTH* which are higher than 8.59, the function has a negative slope. Given the way in which *BREADTH* is created in our application (i.e., an integer number), null marginal effects are in place when *BREADTH* equals 7 or 8. The presence of negative marginal effect is limited to the cases in which *BREADTH* is at its maximum value (i.e., 9).

[19] This occurs even if our R&D variable refers to the search for general knowledge. Certainly, one may expect that, given the specificity of the knowledge acquired through deep sourcing, a more specific R&D capability such as that captured by environmental R&D may create stronger clashes. In the absence of information on green R&D we leave this test for further research.

Table 5
Hurdle negative binomial estimation results (zero-truncated negative binomial part).

Variables	(I)	(II)	(III)	(IV)
BREADTH	0.0324***	0.0133	0.00946	0.0133
	(0.00308)	(0.0112)	(0.0113)	(0.0114)
DEPTH	0.0125***	−0.0217**	−0.00699	−0.0232
	(0.00481)	(0.00970)	(0.0113)	(0.0172)
BREADTH^2		0.00188*	0.00225**	0.000963
		(0.001000)	(0.00105)	(0.00112)
DEPTH^2		0.00704***	0.00702***	0.00712***
		(0.00169)	(0.00165)	(0.00169)
BREADTH*RD			−0.000839	
			(0.00612)	
DEPTH*RD			−0.0242***	
			(0.00935)	
BREADTH*SIM				0.0135*
				(0.00791)
DEPTH*SIM				0.000923
				(0.0161)
POLSTR	0.0142*	0.0141*	0.0140*	0.0141*
	(0.00824)	(0.00823)	(0.00823)	(0.00822)
COOP	0.0172	0.0164	0.0185	0.0158
	(0.0152)	(0.0152)	(0.0153)	(0.0152)
SIM	0.0391**	0.0488**	0.0453**	−0.0176
	(0.0189)	(0.0191)	(0.0192)	(0.0424)
RD	0.0943***	0.0989***	0.130***	0.0993***
	(0.0147)	(0.0147)	(0.0387)	(0.0148)
lnTURNOVER	0.0106***	0.0104***	0.0103***	0.0102***
	(0.00306)	(0.00304)	(0.00305)	(0.00304)
MNC	0.0885***	0.0878***	0.0874***	0.0880***
	(0.0173)	(0.0173)	(0.0173)	(0.0173)
EXPORT	−0.0430**	−0.0430**	−0.0431**	−0.0421**
	(0.0171)	(0.0171)	(0.0170)	(0.0170)
INNOPOL	0.0168	0.0148	0.0150	0.0149
	(0.0151)	(0.0151)	(0.0151)	(0.0151)
Country Dummies	YES	YES	YES	YES
Sector Dummies	YES	YES	YES	YES
Constant	1.153***	1.200***	1.195***	1.226***
	(0.0547)	(0.0594)	(0.0601)	(0.0610)
Obs count >0	8,841	8,841	8,841	8,841
McFadden adj. R^2	0.3362	0.3365	0.3365	0.3364
Prob > Chi^2	0.00	0.00	0.00	0.00
Log PseudoL	−19738.875	−19729.305	−19725.928	−19727.495

Robust standard errors in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

4.2. External knowledge and EI-portfolio

We now move to the second part of our econometric analysis, related to the decision of environmental innovators to enlarge their portfolio of EI-typologies (see Table 5). As stated, this second step in the analysis amounts to investigation of a sub-sample of our firms, which are already environmental innovators.

BREADTH and *DEPTH* are still important in the benchmark model (Model I) and increase the support for H1 and H2. This provides us with an important basis for generalizing the importance of an open mode of innovation with respect to EI. Knowledge sourcing also helps environmental innovators to deal with the different environmental realms (e.g., energy, materials, CO_2) that different EIs entail.

However, as soon as we move to the augmented specifications for the test of the remaining hypotheses, important differences emerge with respect to the logit part of our econometric model. In general, these differences are consistent with those theoretical and empirical works which have shown that introducing an EI and intensifying EI-performance are different processes (Kesidou and Demirel, 2012) and entail different policy actions (as Mohnen and Röller (2005) found with respect to technological innovations). More precisely, the fact that environmental innovators have

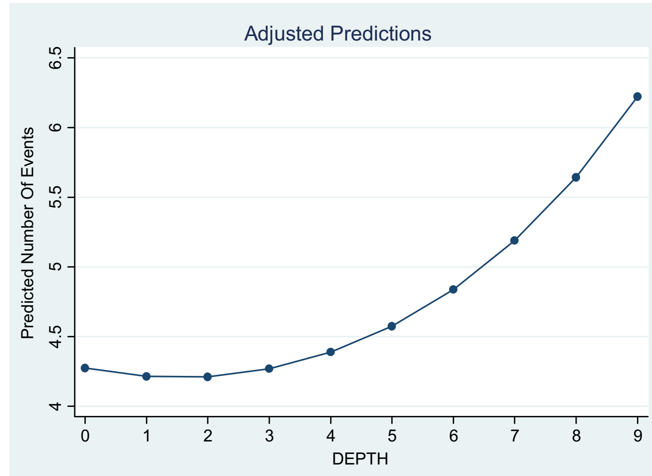

Fig. 2. Curvilinear effect of DEPTH on the predicted number of EI-typologies (zero-truncated negative binomial part).

already entered the EI realm, and have thus presumably already used green knowledge and knowledge sources, makes them (more) EI-competent firms. Accordingly, with respect to these firms, the opportunities and the constraints of accessing and managing external knowledge yield different results.

Unlike the logit part, the search for non-linear effects (Model II) this time leads to full rejection of H3. On the one hand, the constraints on the impact of *BREADTH* now disappear. The returns from a broad knowledge sourcing strategy are still non-linear, but they are now increasingly higher, the greater is *BREADTH* (*BREADTH*^{2} is significant and positive, except for the last model). When an attempt is made to enlarge the EI-portfolio with other types of innovations – which are different but can still benefit from the firm's EI knowledge baseline – the risk of redundant and/or conflicting insights can possibly be more easily accommodated. Furthermore, if the target is an increasing number of EI-typologies, accessing a high number of providers is increasingly more important in terms of knowledge variety.

H3 is rejected also with respect to *DEPTH*. In Model II, *DEPTH* and *DEPTH*^{2} are both significant but negative and positive, respectively, thus indicating a U-shaped effect. Closer analysis of this curvilinearity (Fig. 2) reveals that the presence of negative marginal returns is limited to firms with no deep interactions, while marginal effects not significantly different from zero are in place only for firms with few profound interactions (i.e., 1 or 2).[20] Overall, as much as with *BREADTH*, the presence of an EI knowledge-baseline provides the firm with the opportunity to take (possibly increasing) stock also of an increasing intensity of interactions. This is a quite interesting result, especially if one considers the risks of lock-in that sustained and repeated external interaction could potentially entail.

Important elements of differentiation with respect to the probability of eco-innovating also emerge when the role of AC is considered, although they still lead to only partial confirmation of H4. Firstly, the second face of R&D now appears to be of much less help (Model III). While it still has a direct impact on the firm's capacity to extend its EI-portfolio, investing in R&D no longer

[20] Following the same methodology described for the curvilinearity of *BREADTH* in the logit part of our model, we have analyzed the turning point of the *DEPTH* marginal effects function. The punctual estimation of the *DEPTH* value at which the function has a minimum is 1.54. For *DEPTH* values between 0.74 and 2.33 marginal returns are not different from zero, while for values between 0 and 0.74 the marginal effects are significantly negative. Hence, given the integer nature of *DEPTH*, we can conclude that only when *DEPTH* equals 0 is there a negative return, while when *DEPTH* is 1 or 2 the marginal effects are zero.

Table 6
Bivariate probit on EIPROF and EINOPROF.

Variables	(I)	(I)	(II)	(II)	(III)	(III)	(IV)	(IV)
	EIPROF	EINOPROF	EIPROF	EINOPROF	EIPROF	EINOPROF	EIPROF	EINOPROF
BREADTH	0.0606***	0.0645***	0.1333***	0.1465***	0.1282***	0.1418***	0.1233***	0.1398***
	(0.0048)	(0.0050)	(0.0170)	(0.0170)	(0.0172)	(0.0172)	(0.0175)	(0.0174)
DEPTH	0.0362***	0.0252**	0.0484**	0.0185	0.0703***	0.0436**	0.1019***	0.0590**
	(0.0096)	(0.0102)	(0.0193)	(0.0205)	(0.0209)	(0.0219)	(0.0283)	(0.0295)
BREADTH^2			−0.0073***	−0.0083***	−0.0071***	−0.0085***	−0.0094***	−0.0088***
			(0.0016)	(0.0016)	(0.0017)	(0.0017)	(0.0018)	(0.0018)
DEPTH^2			−0.0025	0.0018	−0.0014	0.0033	−0.0008	0.0030
			(0.0039)	(0.0043)	(0.0038)	(0.0041)	(0.0039)	(0.0043)
BREADTH*RD					0.0078	0.0201*		
					(0.0103)	(0.0107)		
DEPTH*RD					−0.0520***	−0.0648***		
					(0.0187)	(0.0201)		
BREADTH*SIM							0.0443***	0.0167
							(0.0115)	(0.0115)
DEPTH*SIM							−0.0735***	−0.0545*
							(0.0271)	(0.0281)
POLSTR	0.0045	0.0284**	0.0050	0.0292**	0.0048	0.0291**	0.0044	0.0290**
	(0.0134)	(0.0137)	(0.0134)	(0.0137)	(0.0134)	(0.0137)	(0.0134)	(0.0137)
COOP	0.1842***	0.2474***	0.1858***	0.2494***	0.1874***	0.2490***	0.1849***	0.2493***
	(0.0288)	(0.0307)	(0.0288)	(0.0307)	(0.0289)	(0.0307)	(0.0288)	(0.0307)
SIM	0.0983***	0.1551***	0.0777***	0.1347***	0.0747***	0.1334***	−0.0727	0.0945*
	(0.0284)	(0.0285)	(0.0288)	(0.0288)	(0.0289)	(0.0290)	(0.0578)	(0.0566)
RD	0.2399***	0.1876***	0.2312***	0.1781***	0.2387***	0.1301**	0.2303***	0.1776***
	(0.0264)	(0.02723)	(0.0265)	(0.0274)	(0.0610)	(0.0627)	(0.0265)	(0.0274)
lnTURNOVER	0.0128***	0.0152***	0.0133***	0.0157***	0.0133***	0.0155***	0.0130***	0.0156***
	(0.0038)	(0.0042)	(0.0038)	(0.0042)	(0.0038)	(0.0042)	(0.0038)	(0.0042)
MNC	0.1456***	0.1116***	0.1508***	0.1165***	0.1489***	0.1143***	0.1505***	0.1160***
	(0.0338)	(0.0360)	(0.0338)	(0.0360)	(0.0338)	(0.0361)	(0.0339)	(0.0360)
EXPORT	0.1249***	0.1239***	0.1235***	0.1223***	0.1226***	0.1212***	0.1226***	0.1216***
	(0.0277)	(0.0282)	(0.0278)	(0.0282)	(0.0278)	(0.0282)	(0.0278)	(0.0282)
INNOPOL	0.0753**	0.0703**	0.0779***	0.0725**	0.0778***	0.0716**	0.0776***	0.0719**
	(0.0295)	(0.0310)	(0.0295)	(0.0310)	(0.0295)	(0.0310)	(0.0295)	(0.0310)
Country and Sector Dummies	Yes	Yes	Yes	Yes				
Constant	−0.7776***	−0.5280***	−0.9049***	−0.6642***	−0.9029***	−0.6526***	−0.8466***	−0.6473***
	(0.0823)	(0.0820)	(0.0879)	(0.0869)	(0.0884)	(0.0873)	(0.0895)	(0.0886)
Rho	0.8002		0.7997		0.7995		0.7997	
	(0.0073)		(0.0073)		(0.0073)		(0.0073)	
Wald test of rho = 0	2947.83***		2944.92***		2941.84***		2938.12***	
Prob > Chi^2	0.00		0.00		0.00		0.00	
Observations	14,366		14,366		14,366		14,366	
McFadden adj. R^2	0.1199		0.1209		0.1213		0.1215	
Log likelihood	−14719.353		−14703.208		−14696.504		−14693.576	

Robust standard errors in parentheses.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.

facilitates the absorption of external knowledge for the same purpose, in terms of either *BREADTH*, or *DEPTH*: in terms of R&D, H4 would be fully rejected. As in the case of the probability of EI-adoption, sustained patterns of interaction make (some) external knowledge sources more structural and potentially more conflicting with the ones exploited internally, possibly facing managers with problems of choice and attention allocation (*RD*DEPTH* is significantly negative). This time, however, R&D also loses its previous significance in moderating the impact of *BREADTH*. For environmental innovators already endowed with EI-related competencies, a general kind of technological knowledge like that enhanced by the R&D engagement may not be that crucial in augmenting the contribution of a wide set of external knowledge to an enlargement of their EI-portfolio.[21]

This time, some (limited) confirmation of H4 is only provided by consideration of the AC role of *SIM*. On the one hand, also with respect to the extension of the EI-portfolio, *SIM* switches from an additive to a solely moderating impact, confirming their indirect role in the open innovation mode for EI. On the other hand, this moderating role becomes even necessary for *BREADTH* to have any relevance (*BREADTH*SIM* is the only significant *BREADTH*-related variable). Rather than simply reinforcing the impact of diverse external knowledge inputs, organizational mechanisms for knowledge socialization thus appear necessary for a broad sourcing strategy to make the firm adopt EI more extensively. Furthermore, unlike the findings of the first part of our analysis, these mechanisms do not clash with the intensity of external knowledge relationships, although they do not help them either (*DEPTH*SIM* is not significant). In the case of environmental innovators, SIM may have already worked to transmit EI-related knowledge in the case of previous EI adoptions, and this may explain the lack of mismatch with an intense kind of external sourcing.

4.3. Robustness checks

Although, as aforementioned, the aim of the paper is to identify regularities in the open innovation mode which hold true across different kinds of EI, it is interesting to see how far our hypotheses are

[21] In this last respect, a green kind of R&D would presumably be more functional: a hypothesis that, for the lack of data, we postpone to our future research agenda.

sensitive to a more disaggregated analysis. As a robustness check, we have therefore tested whether our hypotheses hold for different groups of EI. In particular, in light of the relation between EI and firm's competitiveness (Ambec and Lanoie, 2008), we consider whether the viability of an open eco-innovation mode is related to the direct profitability of EIs, or whether it is a general result driven by the EI knowledge requirements, as we outlined in Section 2. Drawing on Ghisetti and Rennings (2014), we consider the expected profitability gains from EI and distinguish between *EIPROF* and *EINOPROF*. More precisely, *EIPROF* equals 1 when the firm introduces EIs that directly affect its profits, i.e., innovations that reduce the use of energy or materials per unit of output. *EINOPROF* instead captures whether the firm introduces EIs that do not directly affect its profits.[22] Because firms may jointly adopt these two kinds of EI, we run a set of bivariate probit regressions on Eqs. (1)–(3), whose results are reported in Table 6.

The (Wald) test on *rho* confirms the validity of bivariate estimates. The results for *EIPROF* and *EINOPROF* largely confirm the evidence previously reported on the effect of *BREADTH* and *DEPTH* and on the AC leverages (*RD* and *SIM*). The main exceptions concern the coefficients of *BREADTH***SIM*, which is only significant for *EIPROF*, and for *BREADTH***RD*, which is only significant for *EINOPROF*.

The test of our research hypothesis also appears robust with respect to the choice of alternative proxies for policy stringency. Firstly, the results (available on request) do not change when a different timing is considered for emissions and value added, namely: 2006–2008 for emissions and 2006 for value added; 2003–2005 for emissions and 2003–2005 for value added. Secondly, the results are robust when pollutant emissions other than CO_2 are considered (these results are available on request). More precisely, the test of our four hypotheses remains largely unaltered when we build and consider as proxies for policy stringency aggregate indicators of greenhouse gases (GHG), acidifying gases (AC), and ozone precursor gases (OZ).[23]

5. Conclusions

In spite of several shared features, EIs are substantially different from standard technological and non-technological innovations. The 'win–win' effect that they entail makes their support crucial for combining firm's competitiveness with environmental sustainability and for achieving smart and sustainable patterns of growth. On the other hand, the manifold market failure that EIs entail makes the role of public policy and regulations crucial. The so-called 'regulatory push-pull effect' is thus essential for EI. However, policies to stimulate this effect should take careful account of the particular set of incentives, mechanisms and behavioral patterns with which agents become involved in EI activities. Our work sheds some new light on these aspects and responds to the need for deeper understanding of how EI is generated, which is a crucial step toward improvement of the current and prospective policy mix (e.g., Jänicke and Lindemann, 2010; Costantini and Crespi, 2013). This is particularly important in the EU, where, through an increasing financial and institutional effort, EIs have been set at the core of environmental, competitiveness and innovation policies (Borghesi et al., 2013).

The recent findings in the literature suggest that, also in the environmental realm, firms increasingly follow an open mode of innovation in which knowledge-sharing and knowledge-transfer are crucial EI drivers. However, little is known yet about the specific characteristics of what could be called an "open eco-innovation mode" (OEIM), and about its actual impact on environmental performances on a systematic basis (that is, on a multi-country, multi-sector level). In this paper we have tried to fill this gap by putting forward some hypotheses which we deem characteristic of an OEIM in terms of knowledge sourcing and absorptive capacity.

The empirical analysis that we have carried out with respect to eleven European countries has shown that some of the building blocks of open innovation are at work also in the case of EI. However, this holds true under a number of specifications and differences with respect to the findings of studies focused on technological innovation (e.g., Laursen and Salter, 2006). These peculiarities should inform both business strategies and, above all, policy actions aimed to support the adoption and impact of an OEIM.

Firstly, knowledge sourcing has, per se, a different impact on the firm's propensity to introduce an EI and on the extension of its EI-portfolio. In the former case, for example, while intensive interactions appear beneficial to whatever extent they are used, broadly acquired external knowledge can become difficult to manage and, after a certain point, even discourage firms from adopting an EI. In extending the portfolio of EI-typologies, instead, the search for external knowledge sources benefits from an EI knowledge baseline which provides the environmental innovators with an important safeguard against the potential redundancy of information inputs coming from the outer environment.

This first set of results has important implications for the design of a smart policy mix supporting EI. This policy mix should support not only the firm's internal eco-innovative efforts (e.g., R&D) but also its interactions with external actors and knowledge sources. Accordingly, network/cluster policies and technology/knowledge transfer initiatives can have an important social impact, given that they could increase innovation activities, which make firms more environmentally sustainable. This policy recipe is conditional on the specific system of environmental innovators in which the open innovation mode is stimulated. Win–win effects can be expected only when eco-innovators do not face congestion problems from an excessive array of external knowledge sources, or when eco-innovators can use their pre-existing knowledge-base to turn even wide knowledge sourcing into the extension of their EI-portfolio. In brief, knowledge sourcing is not a one-fits-all strategy in the environmental realm.

Important conclusions can also be drawn with respect to the firms' leverages that increase the absorption of external knowledge for the purpose of EI. While engagement in R&D is an important EI driver, its AC-leverage role appears to be less clear-cut. Given the systemic nature of EI, 'generalist' R&D investments are arguably as important as green-specific R&D investments. However, the contribution of R&D is limited to the understanding of broadly sourced knowledge for the purpose of introducing an EI. By contrast, internal R&D investments generally hamper the exploitation of deep external interactions. In other words, it seems that, when structured learning processes are in place on both sides, internal and external knowledge are not as complementary as they are in other innovative contexts (Cassiman and Veugelers, 2006). When a smart policy mix is designed, this result recommends careful consideration of the specific circumstances in which support for R&D is beneficial for EI and thus able to improve the environmental

[22] *EINOPROF* captures innovations relative to: reduced CO_2 'footprint' (total CO_2 production); replaced materials with less polluting or hazardous substitutes; reduced soil, water, noise, or air pollution; recycled waste, water, or materials; reduced energy use after-sale; reduced air, water, soil or noise pollution after-sale and improved recycling of product after use. See Ghisetti and Rennings (2014) for the rationale of the distinction between EI with and without direct profitability gains.

[23] Data for these indicators have been obtained by extracting emissions data for selected pollutants for each country-sector combination from the World Input-Output Database (WIOD). In building these indicators, we have followed the methodology proposed by the Eurostat Manual for Air Emissions Accounts (Eurostat, 2009) in weighting each pollutant reported in WIOD. Some missing values for the emissions of NH_3 and CH_4 in Slovakia and of N_2O and NO_x in Romania were found in WIOD. These missing values have been substituted with the sector means of the other countries.

impact of firms' economic activities. The same concern should drive the planning and implementation of profit-oriented environmental strategies (e.g., Ambec and Lanoie, 2008). Certainly, the role of R&D warrants deeper investigation. In particular, further research should consider the amount of investment in R&D: an aspect that, owing to data constraints, we have not been able to address in this paper.

Interesting results have also emerged from our analysis of the firm's social integration mechanisms (*SIM*). Organizational capabilities that could increase the socialization of external knowledge are important in the EI realm as well. Their support, for example through policy-aided organizational changes (e.g., environmental management systems), should thus be a further aspect in the design of a smart policy mix for the purpose of EI, but still with caveats. In spite of the clashes that we have identified in recourse to deep knowledge search strategies for the potential environmental innovator, their enabling role has also appeared crucial for the absorption of broadly sourced knowledge, confirming the complex techno-organizational nature of EI. This is particularly the case of environmental innovators, for which these *SIM* are indispensable for turning a variety of knowledge sources into a variety of EI solutions. Organizational capabilities able to increase the socialization of external knowledge are thus pivotal in the EI realm as well. Consequently, their support should be considered a further aspect in the design of a smart policy mix sustaining the adoption of environmental innovations.

Finally, the two EI processes that we have analyzed – i.e., adopting an EI and extending the EI-portfolio – differ substantially, not only in terms of standard determinants but also with respect to the benefits of the open innovation mode. As we have already noted, this recommends extreme caution to policy-makers wanting to extend the socio-economic benefits of EI by exploiting the mechanisms of the open innovation mode. The basic pillars of this OEIM should be built by policy-makers in different ways depending on the knowledge bases of the targeted firms.

The previous results make continuation of the analysis conducted by this paper extremely important. In particular, two aspects warrant especial attention in its future extension. Firstly, panel data would be required to go beyond the interpretation of simple correlation coefficients for the results of our cross-sectional estimates: a requirement, however, that is still difficult to address on a cross-country base. A further step that would increase the accuracy of the policy and management implications is investigation of the effects that interactions with different types of knowledge providers may have on the introduction of the different types of EI.

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Appendix A.

See Tables A1 and A2.

Table A1
Distribution of EI.

EI	Freq.	Percent	Cum.
0	5,525	38.46	38.46
1	1,074	7.48	45.93
2	1,314	9.15	55.08
3	1,240	8.63	63.71
4	1,118	7.78	71.50
5	958	6.67	78.16
6	902	6.28	84.44
7	737	5.13	89.57
8	596	4.15	93.72
9	902	6.28	100
Total	14,366	100	

Table A2
Distribution of the EI, BREADTH and DEPTH by COUNTRY.

COUNTRY	0	1	2	3	4	5	6	7	8	9	Total	Perc. values >0 (%)	Mean
EI													
BG	1,916	163	158	86	66	48	48	42	31	43	2,601	26	0.94
CZ	266	126	152	174	129	115	111	98	78	84	1,333	80	3.58
DE	632	154	204	199	187	160	145	122	112	238	2,153	71	3.47
EE	496	146	178	140	102	74	54	40	28	22	1,280	61	2.13
HU	144	53	73	74	61	54	52	24	21	25	581	75	3.11
IT	1,184	149	216	207	218	189	193	151	118	107	2,732	57	2.61
LT	94	32	26	21	30	24	21	15	12	17	292	68	2.97
LV	63	23	10	7	7	9	13	5	1	3	141	55	2.02
PT	336	146	173	169	192	179	188	150	131	265	1,929	83	4.29
RO	339	73	102	138	108	90	71	81	58	92	1,152	71	3.35
SK	55	9	22	25	18	16	6	9	6	6	172	68	2.79
BREADTH													
BG	121	290	301	458	329	219	218	169	71	425	2,601	95	4.44
CZ	34	33	43	69	107	166	203	219	154	305	1,333	97	6.24
DE	604	16	32	62	120	188	226	202	213	490	2,153	72	4.91
EE	20	56	130	144	198	238	210	154	54	76	1,280	98	4.83

Table A2 (*Continued*)

COUNTRY	0	1	2	3	4	5	6	7	8	9	Total	Perc. values >0 (%)	Mean
HU	25	19	25	44	63	71	75	88	76	95	581	96	5.74
IT	26	197	231	275	378	350	330	361	187	397	2,732	99	5.24
LT	12	32	24	33	40	36	36	22	21	36	292	96	4.73
LV	13	3	10	11	16	24	24	18	10	12	141	91	4.95
PT	26	133	107	136	201	242	280	254	146	404	1,929	99	5.72
RO	38	45	80	81	151	196	170	114	56	221	1,152	97	5.46
SK	2	11	15	22	28	23	23	22	11	15	172	99	4.94
DEPTH													
BG	1,648	402	309	129	55	27	17	6	3	5	2,601	37	0.76
CZ	566	355	229	108	43	16	9	5	2	0	1,333	58	1.12
DE	1,086	552	295	119	62	24	11	3	0	1	2,153	50	0.91
EE	658	412	124	54	20	10	2	0	0	0	1,280	49	0.75
HU	223	149	105	62	24	9	6	2	1	0	581	62	1.28
IT	1,467	772	308	105	49	16	6	5	1	3	2,732	46	0.76
LT	176	63	30	12	6	5	0	0	0	0	292	40	0.71
LV	70	27	23	13	4	3	1	0	0	0	141	50	1.06
PT	937	455	270	142	68	27	17	7	1	5	1,929	51	1.06
RO	533	272	159	96	53	21	6	3	1	8	1,152	54	1.15
SK	80	53	23	11	4	1	0	0	0	0	172	53	0.89

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