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Environmental innovation and R&D collaborations: Firm decisions in the innovation efficiency context

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Abstract
To develop innovation, firms make several decisions on the allocation of resources to specific innovation activities. Important innovation decisions include among others the decision to collaborate with other partners for innovation activities and the decision to engage in complex R&D projects such as projects with environmental benefits. Although there are very few empirical works that examine these two decisions together, while supporting that R&D collaborations are more important for the development of environmental innovations than for conventional innovations, an empirical work that examines the joint impact of these two decisions on corporate innovation efficiency is still lacking. This study aims to fulfill this gap by making one of the first attempts to employ a new dataset based on the Greek Community Innovation Survey (CIS), conducted for the years of 2012–2014 analyzing 2456 companies. Econometric results indicate that firm's decision to eco-innovate exerts a positive influence on firms' innovation efficiency directly. On the contrary, regarding the decision to engage in R&D collaborations, econometric results indicate that there is not a direct or an indirect, via eco-innovation, impact on innovation efficiency.

Keywords R&D collaboration · Eco-innovation · Innovation efficiency · Greek Community Innovation Survey (CIS)

JEL Classification L2 · L5 · O3

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1 Introduction

Firms develop innovations to be competitive, and ultimately gain business success in the long run (Teece, 1996). Innovation is grounded on the generation and acquisition of new knowledge. Firms to acquire new knowledge make decisions to devote their resources to several activities such as R&D, recruitment of highly skilled labor force and reconfiguration of their business operations. These decisions and activities for innovation purposes are related to significant direct and opportunity costs. It is evident, that the examination of the innovation decisions is closely related to the efficiency of these activities or in other words, to the contribution of the resources devoted to innovation activities to the realization of business objectives (Gkypali & Tsekouras, 2015). Tidd and Bessant (2009, p. 29) and Cruz-Cázares et al. (2013) stress that innovation is a complex process and that it should be examined as such, not as a single input or output activity. Therefore, we defend the idea that innovation inputs produce innovation outputs according to an explicit or underlying, innovation production function. In this respect, innovation efficiency may be placed in the broader context of what is called innovation performance.

Extant literature recognises that knowledge, the necessary ingredient for the development of innovation activities, may be generated either internally to the firm or with partner organisations through R&D collaborations. The empirical findings regarding the impact of R&D collaborations on innovation outcomes, although ample, are rather contradictory. The positive impact is mainly attributed to the enlargement and enrichment of the firms' knowledge base (Findik & Beyhan, 2015), while the negative impact is often related to high search, coordination, and transaction costs induced by complex cooperation schemes (Gkypali et al., 2018, 2017, 2018; Kafouros et al., 2015; Statsenko et al., 2020). The structure of incentives in the form of public subsidies, which promote and support R&D collaborations has not been considered as a framework of R&D collaborations decisions, although it may affect significantly the efficiency of innovation activities based on R&D collaborations. The incorporation of public subsidies elevates a parallel regime for the exploration of R&D collaborations which in the current paper is named as "opportunistic R&D collaboration" (ORDC) regime (Guerrero et al., 2021; Tripsas et al., 1995) and is distinguished from the "efficiency based R&D collaboration " (ERDC) regime (Giga et al., 2021; Guan et al., 2016).

Concurrently, firms in the context of sustainable development are heading more and more, towards the reconfiguration of their business operations to facilitate the embodiment of new technologies which minimize the corresponding environmental footprint (Dewick & Foster, 2018). Therefore, an increasing number of eco-innovation projects are included in firms' innovation portfolios. Eco-innovation may be considered as the outcome of a decision taken in the context of innovation efficiency presented above and in that sense, the "efficiency- based eco-innovation" (EECO) (Marzucchi & Montresor, 2017) regime emerges. Moreover, eco-innovation activities are related to R&D synergetic schemes as they are considered as complex projects which require significant knowledge modularity (De Marchi, 2012). On the other hand, eco-innovation may be the outcome of a strict environmental regulation framework (Demirel & Kesidou, 2011), which imposes the positive answer to the question "to eco-innovate or not?". In this vein, eco-innovation is related to the "regulation-driven eco-innovation" (RECO) regime. Even though eco-innovation studies grow in volume, innovation efficiency, eco-innovation projects, and collaboration activities have not been thoroughly elucidated to date.

In the light of the above, we examine the complex interrelationships between firm innovation efficiency and the decisions to engage in R&D collaborations and to undertake eco-innovation. Our theoretical arguments are developed in the context of an innovation system with moderate firms capabilities, and not highly developed business dynamism.

Overall, the employed measure of innovation efficiency is a total factor innovation efficiency, which allows the investigation of the interrelated firm's decisions to undertake eco-innovation and innovation collaboration in terms of their resource's requirements and the corresponding contribution to innovation achievement. Moreover, our methodology incorporates one additional measure of innovation performance that is the ability of the firm to innovate.

The main research contribution of the paper is the fact that it examines the joint impact of two firm decisions (i.e. R&D collaboration and environmental innovation activities) on innovation efficiency. Although previous literature has acknowledged a close interrelation among collaboration and development of green innovations, to the best of our knowledge, empirical studies which examine the simultaneous effect of these two innovation strategies on the overall firm innovation efficiency are still lacking. Thus, this study comes to fulfill this gap. In addition, the majority of the extant studies regarding eco-innovation stream focus on the drivers of the likelihood of a firm to go green utilizing probit and logit models. However, literature calls to examine the eco-innovation phenomenon utilizing more sophisticated models which can concurrently account for econometric issues such as endogeneity and selection problems; "The range of micro econometric methods being used should be expanded beyond logit and probit models" (del Río et al., 2016, p. 2168). This study aims to contribute to this area by utilizing a holistic mixed process regression model tackling the underlined econometric problems.

The information employed in our study is derived from the Greek CIS 2012–2014 for 2456 firms. It is worthy to mention that the specific Greek CIS dataset has not been investigated before. Our econometric strategy is grounded on a system of four-structural equations that capture innovation efficiency, the decision to engage in R&D collaborations, the decision to undertake eco-innovation projects, and the Heckman selection equation, which accounts for the non-innovative firms. The system of equations is estimated using "Conditional Mixed Process" (CMP) modeling (Roodman, 2011), to cope with problems of mixed response left side variables.

Econometric results suggest that a firm's decision to eco-innovate is positively and directly associated with innovation efficiency. Firms are triggered to go green only when they have developed enough their innovation capabilities. Our findings support the EECO regime. However, future regulations embedded in Environmental Management systems within firms are significant drivers for fims' decision to develop an environmental innovation. Thus, the RECO regime is supported too. Regarding the decision to engage in R&D collaborations, econometric results indicate that there is an association neither with the decision to eco innovate nor to the innovation efficiency. More specifically, the decision to cooperate for innovation activities seems to be a detached regime in the Greek Innovation System. It is mainly driven by public subsidies, which means that the ORDC regime prevails. The fact that collaboration does not affect innovation efficiency can be justified by existing literature (Moaniba et al., 2019) which shows that while collaboration can boost innovation sales, at the same time it includes high search, coordination, and transaction costs which offset the positive impact of R&D cooperation (Gkypali et al., 2018, 2017). Further, we add theoretical argumentation on the firms' valuation of eco-innovation as a means of gaining competitive advantage.

Based on our empirical results, it seems that this perception makes firms hesitate to collaborate with other partners to avoid knowledge leaking and imitation of their green innovation activities.

The rest of the paper is structured as follows. The next section addresses the current developments in the literature and builds the research hypotheses, Sect. 3 presents the empirical strategy, Sect. 4 describes the dataset and variables, Sect. 5 presents and discusses the empirical results, while Sect. 6 concludes the paper by highlighting its contribution to literature and policymakers, suggesting also future research paths.

2 Related knowledge & hypothesis development

2.1 Existing knowledge

Efficiency of any economic activity is considered as the evaluation of the mechanisms which transform inputs to outputs, and therefore is measured by the inputs to outputs ratio. In this vein, innovation efficiency can be captured by the relationship between the firms' resources devoted to innovation activities and the level of innovation outcomes achieved, which are in alignment with the overall business objectives (Gkypali & Tsekouras, 2015). Klingebiel and Rammer (2014) provide empirical evidence that the adoption of a resource allocation strategy affects innovation performance, as firms scrutinize a number of strategic decisions to develop their innovation portfolio.

One of the most important innovation portfolio decisions is whether a firm should rely on external sources of knowledge and collaborate with other entities, i.e. competitors, suppliers, customers, and universities. Innovation collaboration allows, among others, to share inputs necessary for the development of successful innovations (Belderbos et al., 2015), share risks and uncertainty (Cassiman & Veugelers, 1998), and gain access to new sources of knowledge, skills and technologies (Cassiman & Veugelers, 1998; Greco et al., 2020; Maietta, 2015). Although the decision of R&D collaboration can be efficiency-driven offering significant gains and enhancing innovation performance, its impact on firms' innovative output is mixed (Belderbos et al., 2015; Moaniba et al., 2019; Un & Asakawa, 2015). In particular, some scholars find a positive impact (Belderbos et al., 2018; Findik & Beyhan, 2015; Huang & Yu, 2011), while others document an insignificant direct effect (Statsenko et al., 2020) or even a negative impact (Kafouros et al., 2015; Kobarg et al., 2019).

The negative impact of innovation collaborations on innovation efficiency, may be attributed to high search, coordination, and transactions costs that the participation in collaborative schemes imply (Cross et al., 2015), or to not-well developed absorptive capacity (Gkypali et al., 2018, 2017). Gulati et al. (2012) stress the role of insufficient sustained mutual understanding and interest between partners, which may imply opportunistic behavior of at least one of the innovation partners. Opportunistic behavior forms a parallel regime for the exploration of R&D collaborations, which in the context introduced here is named as "opportunistic R&D collaboration" (ORDC) regime and is distinguished from the respective "efficiency-based R&D collaboration" (ERDC) regime. Opportunistic behavior may severely hinder the effectiveness of collaborative innovation. Guan et al. (2016) argue that the structure of the incentives of the participants in an innovation network exerts a significant influence on R&D cooperation input–output efficiency. Tripsas et al., (1995) underline the necessity of a government policy intervention, such as the incorporation of public subsidies (Chapman et al., 2018), that facilitates collaborative innovation by decreasing the potential for opportunistic behavior among partners.

The decision to collaborate with other organisations is often related to the necessity of managing complex and technologically advanced R&D projects due to the inadequacy of internal sources and knowledge base (Belderbos et al., 2015). One example of complex R&D projects is an innovation that minimizes the corresponding environmental footprint (Dewick & Foster, 2018). The decision to "go green" can help firms become more efficient by offering either resource and cost advantages or a sales' boost. In this regard, eco-innovation is considered as the outcome of a decision-making process in the context of innovation efficiency presented above. In that sense, the "efficiency-based eco-innovation" (EECO) (Marzucchi & Montresor, 2017) regime emerges. Although the decision to develop environmental innovations is supposed to be beneficial for the firms (Dangelico & Pontrandolfo, 2015), scholars provide empirical controversial evidence with respect to the impact of "going green" on firm's performance (Cai & Li, 2018; Lee & Min, 2015; Madaleno et al., 2020; Tumelero et al., 2019). The overall impact of such a decision is contingent on the type of eco-innovation (Doran & Ryan, 2016) and often related to the motivations and drivers of "going green". A growing body of literature suggests that a firm's decision to introduce eco-innovations is influenced by a spectrum of factors other than value-driven incentives (Horbach, 2016), including policy measures such as regulation (Demirel & Kesidou, 2011). Regulation is considered as one of the most influential drivers of eco-innovation activities (Triguero et al., 2013) creating an important parallel regime, which in this paper is named "regulation-driven eco-innovation" (RECO).

Only very few empirical papers examine the link between the above two mentioned innovation portfolio decisions, documenting that R&D collaboration is more relevant to environmental than conventional innovations (Cainelli et al., 2015; De Marchi, 2012; Tumelero et al., 2019). Environmental innovations imply higher interdependencies with external partners on knowledge, skills, and resources that arise in the development of green R&D projects. This peculiarity of eco-innovation projects is grounded on their systemic, credence, and complex features (De Marchi, 2012). In particular, environmental innovations require more heterogeneous sources of knowledge (Horbach et al., 2013) and they are more closely related to external sources of information (Frigon et al., 2020). According to the literature, the efficiency of R&D cooperation in conventional innovations compared to eco-innovations is one of the main points of differentiation (De Marchi, 2012). However, no systematic attempt has been surfaced to explore the joint effect of these two decisions on innovation efficiency as a system of equations yet. In this paper, we fill this void by exploring these two decisions, i.e. eco-innovation and R&D collaboration, both in the context of a system as well as separately. The main aim is to study whether those interact, and examine for potential cross effects affecting innovation efficiency.

2.2 Hypotheses development

Environmental innovations are demand-driven innovations (Triguero et al., 2013) as they meet market needs enabling firms to differentiate their products and gain competitive advantage (Rennings, 2000), have increased margins or market share and enhance their corporate image and reputation based on green products (Dangelico & Pontrandolfo, 2015; Triguero et al., 2013). Therefore, the development of environmental innovations is expected to have a positive impact on innovation efficiency since it leads to the increase of innovative sales (Dangelico & Pontrandolfo, 2015; Triguero et al., 2013) through the rise of the volume of sold product quantities or/and the increase of their price.

Moreover, based on the Porter Hypothesis (Porter & van der Linde, 1995), the implementation of eco-innovations brings a cost advantage through resource savings, reduction of costs and material utilization in the production or the consumption phase, and pollution prevention creating a win–win situation which can boost the public and the private welfare (Wagner & Llerena, 2011). Cost advantage, as a result of the development of green innovations, is related to the decrease of input costs (Merlin-Brogniart & Nadel, 2021) embedded in innovation efficiency measures. In addition, new routines of radical shift in the innovation pattern are also seen as a way of maximizing past efforts in eco-innovation to dominate the market (Leitner et al., 2010). In this context, we form the following hypothesis:

H1 The decision to develop eco-innovation exerts a positive influence on innovation efficiency.

A growing body of literature (Todeschini et al., 2020; Yang & Lin, 2020) suggests that collaboration is critical to the success of environmentally sustainable innovations. Dangelico et al., (2017) highlight that in green innovations the integration of external partners enables sharing knowledge and skills leading to reduced environmental harms. De Marchi (2012) argues that green innovations require technical and organisational complementarities among several types of organisations to share knowledge upon complex matters. Cainelli et al. (2015) show that cooperating with external partners for innovation is more relevant for eco-innovators than non-eco-innovators. Recent empirical evidence shows that knowledge synergies released through R&D collaboration are advantageous to the introduction of eco-innovations (Tumelero et al., 2019).

In addition, firms participating in R&D collaborative activities are more likely to develop an eco-innovation because through collaboration the high level of costs and risks associated with the development of complex green technologies is alleviated (Cainelli & Mazzanti, 2013; De Marchi, 2012; Souto & Rodriguez, 2015). In addition, since the private return of R&D investment in environmental technology is lower than the corresponding social return, R&D collaboration can help firms to build up their social capital stock, which will allow them to cope with the 'double externality problem' (Rennings, 2000) and ultimately motivate them to 'go green'. In addition, firms develop collaborations to alleviate environmental externalities and cope with regulation push factors which determine especially the decision to go green. Under this light the following hypothesis is formulated:

H2 The decision to develop eco-innovation is positively affected by participation in innovation collaboration projects.

Generation and acquisition of knowledge is a basic ingredient of innovation. Firms acquire knowledge by collaborating with others e.g., firms, universities, etc. Access to external knowledge is one of the most important benefits of collaboration as it may increase firms' knowledge base and ability to organize their own tangible and intangible resources (Greco et al., 2020). Czarnitzki et al., (2007) show that cooperation tactics have a positive effect on a firm's innovation outcome. In addition, R&D collaboration can help firms to share cost, risk, and uncertainties (Cassiman & Veugelers, 1998). As a result of the above, a direct positive impact of R&D collaboration on innovation efficiency is expected and grounded on the reduction of inputs devoted to innovation activities and the relevant risks. Thus, we form the following hypothesis:

H3 Innovation collaboration exerts a direct positive impact on innovation efficiency.

Eco innovations are knowledge demanding innovations promoted through better than the easily accessible information and existing skills available to the firm or the industry (De Marchi, 2012). In this vein, firms decide to take advantage of the rich knowledge generated in collaborative schemes. Studies have shown a positive relationship between knowledge acquisition by external partners through intensive external network relationships (Cainelli et al., 2015; De Marchi, 2012; Ghisetti et al., 2015; Li-ying et al., 2018) and the decision of a firm to go 'green'. R&D cooperation has the potential to positively influence the decision of a firm to introduce eco-innovations which have been documented to have a positive impact on economic performance (Tumelero et al., 2019). Moreover, Tumelero et al., (2019) provide empirical evidence that the relation between cooperation in R&D and socioeconomic performance is mediated by the introduction of eco-innovations.

The above rationale signifies that there is a positive indirect effect of innovation partnerships on innovation efficiency through the decision to adopt eco-innovation activities. The additional knowledge required for the development of eco-innovation can be acquired through participation in innovation partnerhips allowing firms to go green. In addition, to overcome high technological barriers that are inherent to eco-innovations, firms cooperate with several entities. Consequently, the development of environmental innovations could increase firm's innovation sales and thus innovation efficiency. Based on the above, we form the following hypothesis:

H4 Innovation collaboration exerts a differential indirect impact on innovation efficiency through eco-innovation. That is, the positive impact of eco-innovation on innovation efficiency is higher for the firms which participate in R&D collaboration schemes.

3 Empirical strategy

The overarching goal of the methodological approach adopted herein is to investigate the impact of a firm's decision to develop an eco-innovation as well as its decision to collaborate for innovation purposes, on innovation efficiency. However, results might be compromised by selection bias due to the focus on innovative firms and endogeneity concerns as firms self-select in the above decisions (Hashi & Stojčić, 2013).

Thus, a system of four interlinked equations arises. The first equation (Eq. 1) refers to innovation efficiency which is a continuous variable, the second and third equations refer to the decisions to eco innovate and collaborate respectively (Eqs. 2 and 3), while the last one Eq. (4) refers to the selection equation regarding whether a firm decides to innovate.

In an attempt to cope with endogeneity and selection bias as well as handle the mixed nature of the dependent variables (one continuous, three dichotomous), the conditional mixed process modeling (CMP) proposed by Roodman, (2011) is adopted. Although there are various methodologies to deal with selection bias and endogeneity, in this case, become unsuitable as we need to cope with the mixed nature of the dependent variables.

The conditional mixed-process (CMP) framework adopted in our study allow us to estimate three equations with linkages among their errors in a broader simultaneous equations setting (Porgo et al., 2018; Roodman, 2011), while considering selection bias through the incorporation of Heckman selection equation (Heckman, 1978, 1979). Moreover, CMP allows (i) To include in the system of equations models of different type with respect to the dependent variable, i.e. censored, tobit regression, probit, ordered probit etc., (ii) The inclusion as explanatory variables in specific equations the dependent variables of other equations and (iii) To cope with recursivity of the system of the equations. It is worthy to note that in the CMP setting, the model can vary by observation facilitating the testing of the above presented hypotheses. Finally, the testing of possible correlation of the errors terms when estimating multiple equations, a prominent characteristic of the econometric setting of our research, is feasible. Thus, conditional mixed-process (CMP) framework is the appropriate econometric process for the estimation of the simultaneous system of the three main equations, i.e. innovation efficiency, eco-innovation adoption and collaboration activity, and the additional selection equation (Roodman, 2011).

3.1 Econometric estimation of a conditional mixed process

In the framework introduced above, innovation efficiency of the *i-th* (i = 1,…n) firm may be modeled as:

$$InnEff_i = \lambda_1 Eco_i^* + \lambda_2 Co_i^* + \boldsymbol{\beta' X_i} + \varepsilon_{1i} \tag{1}$$

where $\boldsymbol{X}_i$ is a matrix including determinants of innovation efficiency as well as additional firm-specific characteristics discussed in Subsection 4.2. The parameters to be estimated are $\boldsymbol{\lambda}_1, \boldsymbol{\lambda}_2\boldsymbol{\beta},$ while ε_{1i} corresponds to the error term. For the measurement and construction of the dependent variable "$InnEff_i$" and the exact measurement of the main variables Eco_i^*andCo_i^* see the following Subsection 4.1.

Equations (2) and (3) below correspond to the decisions to engage in eco-innovation activity and to collaborate with other organisations respectively. The realization of the latent variables for the eco-innovation (Eco_i^*) and collaboration activity (Co_i^*) is observed through the binary variables $Eco_i andCo_i$ according to the following rules:

$$Eco_i^* = \{^{1,\ \ l\ if eco_i > 0}_{0,\ \ l\ otherwise} Co_i^* = \{^{1,\ \ l\ if co_i > 0}_{0,\ \ l\ otherwise}$$

More precisely, we explore the decision to eco-innovate and collaborate via the following probit models:

$$Eco_i^* = \zeta Co_i^* + \boldsymbol{\delta' X_i} + \varepsilon_{2i} \tag{2}$$

$$Co_i^* = \boldsymbol{\gamma' X_i} + \varepsilon_{3i} \tag{3}$$

where $\boldsymbol{X}_i$ is a matrix including variables that can affect the two decisions along with the firm-specific characteristics which will be discussed in Subsection 4.2. Considering a set of factors identified in Subsection 4.2, we use a probit equation to model the probability of a firm i to decide to go green and collaborate. In this setting, Eco_i^*, Co_i^* are the latent variables underlying the dichotomous responses of having introduced an eco-innovation and/or collaboration respectively.

The parameters to be estimated are $\boldsymbol{\gamma}, \boldsymbol{\delta}\, and\ \zeta$ while ε_{2i} and ε_{3i} are the error terms. In Eq. (2) we have included the decision to collaborate to test its impact on the decision to eco innovate. Equation (4) below corresponds to the selection model (Heckman, 1979) determined by barriers undertaking innovation activity. The selection equation is as follows:

$$INNOV_i^* = \boldsymbol{\xi}'\boldsymbol{B_i} + \varepsilon_{4i} \tag{4}$$

where $\boldsymbol{B_i}$ is a matrix of barriers to innovation activity (D'Este et al., 2012), $\boldsymbol{\xi}$ is a vector of parameters to be estimated, while ε_{4i} refers to the error term.

Estimating Eqs. (1–4) individually, yield biased and inconsistent estimates due to selection bias and endogeneity concerns as only innovative firms may have innovative performance and undertake the decisions related to innovation activity as described by Eqs. (2) and (3). Through the exploitation of the conditional mixed process and the construction of a simultaneous system of the above three main equations and the addition of a selection equation (i.e. the decision to innovate or not), we tackle the above econometric issues.

In the system of equations described above, i.e. Eqs. (1–4), the CMP has (n×4) prediction errors (ε_{11}, … ε_{14}, ε_{21}, … ε_{24}, ε_{n1} … ε_{n4}). The four prediction errors for each firm in the CMP are assumed to be correlated. The prediction errors for different firms are assumed to be uncorrelated. The variances and covariances of the prediction errors of the CMP estimator can be represented by a prediction error covariance matrix with the following block structure.

$$Cov(\varepsilon) = \begin{bmatrix} \Sigma & 0 & 0 & 0 \\ 0 & \Sigma & 0 & 0 \\ 0 & 0 & \Sigma & 0 \\ 0 & 0 & 0 & \Sigma \end{bmatrix}$$

which can be expressed more compactly as $\mathrm{Cov}(\boldsymbol{\varepsilon}) = \mathrm{In} \otimes \Sigma$ where Σ is a 4×4 covariance matrix for the 4 prediction errors for a firm, and each 0 is a 4×4 matrix of zeros.

Normalizing we derive the finally estimated compound- partially symmetric covariance matrix, which is justified in a within-subjects experiment where firms are measured under four treatment conditions.

$$Cov(\varepsilon) = \begin{bmatrix} 1 & P_{12} & P_{13} & P_{14} \\ P_{12} & 1 & & \\ P_{13} & P_{23} & 1 & \\ P_{14} & P_{24} & P_{34} & 1 \end{bmatrix}$$

4 Data and variables

The paper benefits from the 2012–2014 wave of the Greek Community Innovation Survey (CIS), conducted for the period 2012–2014 by the National Documentation Center (EKT)/National Hellenic Research Foundation (NHRF) in cooperation with the Hellenic

Statistical Authority (ELSTAT) and under the supervison of Eurostat. CIS is based on the questionnaire and the respective guidelines derived by Eurostat in order to ensure comparability of the respective indicators across all EU member states (EKT, 2017). CIS, for other than Greece European countries, has been extensively exploited by a number of research works (indicatively see Cainelli et al., 2020; Karlsson & Tavassoli, 2016).

We present here a short description on the CIS questionnaire structure. The first section of the questionnaire consists of general information on firms such as their main economic activity and geographic target markets. Next sections entail questions on product and process innovations and relevant innovation activities including information on firms' innovation expenses, innovative sales and R&D collaboration practices. The next two parts of the questionnaire provide information on the other two types of innovation i.e. organizational and marketing. There are also two separate sections in the questionnaire where the participants are asked about whether they have received any public financial support or have participated in any public sector contract for their innovation activities. Next, the respondents are asked to answer questions on their Intellectual Property Rights (IPR). Another section follows which is dedicated on non-innovators, where the respondents are asked on the barriers and reasons for not innovating. Next, a new module is added in the CIS survey 2012–2014, which concerns environmental innovation. The questionnaire ends with a last section on basic economic and financial information on the enterprises. The data collected in CIS survey are self-reported data by respondents. As a result, information has a subjective basis in contrast to other sources of data such as patents (Mazzanti et al., 2016). Although this can raise issues of response accuracy there are several features of the study (e.g. online survey platform and automatic procedures for monitoring and validation of data collection) which help to alleviate this concern (Aschhoff & Sofka, 2009).

The dataset accounts for 2456 firms with 10 or more employees from 18 different NACE 2 sectors. For our study, we have employed the variables depicted in Table 1. The following paragraphs include the description of the data and variables. All the variables employed in the analysis regarding innovation activities refer to events that took place at any point of time during the three years 2012 to 2014.

4.1 Dependent variables

4.1.1 Innovation efficiency

The main variable of interest is innovation efficiency in logs (InnEff), a continuous variable which is constructed as the ratio of total expenses for innovation activities per firm in 2014 to its total sales in 2014 coming from innovation either from products new to the firm or to the market. This ratio captures how many units of innovative inputs (i.e. expenses) are needed for one unit of innovative outputs (i.e. innovation sales) based on previous literature (Beneito, 2006; Hashi & Stojčić, 2013). Both measures are sourced from the CIS questionnaire and firms' responses which are validated by the National Documentation Center based on Eurostat's practices and guidelines.

The very rich relevant to innovation performance literature has employed a plethora of measures. Among them the most prominent include three main categories. First, a measure which reflect firm's ability to innovate which is applied to the whole population of firms under examination and is captured by a binary variable that takes the value of 1 for firms that have introduced an innovation and 0 for other firms (Cosh et al., 2012). The second

Table 1 Variables and descriptive statistics

Variable	Coding	Basic description	Yes	No
Dependent variables				
R&D collaboration decision	*co*	Decision to collaborate for innovation (0/1)	50.74%	49.26%
Eco-Innovation decision	*eco*	Decision to develop environmental innovation (0/1)	31.31%	68.69%
Innovation efficiency	*InnEff*	Ratio of total innovation expenses to total innovation sales (Cont.)	0.58 (4.24)	
Innovators (Selection Eq.)	*innovat*	Decision to develop innovation (0/1)	57.45%	42.55%
Explanatory variables				
External knowledge acquisition	*rrdex*	Engagement in extramural R&D (0/1)	25.71%	74.29%
	roek	Acquisition of external knowledge (0/1)	32.90%	67.10%
Internal knowledge generation	*rrdin*	Engagement in intramural R&D (0/1)	54.11%	45.89%
	rmac	Acquisition of machinery, software and equipment for innovation activities (0/1)	73.77%	26.23%
	rtr	Training for innovation activities (0/1)	45.02%	54.28%
Absorptive capacity	*empud*	% of employees in the company with university degree (normalized) (Cont.)	27.34 (28.29)	
R&D public subsidy	*funloc*	Public subsidies granted by Local or regional authorities (0/1)	9.70%	90.30%
	fungmt	Public subsidies granted by Central government (0/1)	21.30%	78.70%
	funeu	Public subsidies granted by European Union (0/1)	9.78%	90.22%
Exporting	*expact*	Engagement in exporting (0/1)	56.68%	43.32%
Environmental regulation	*envid*	Adoption of Environmental Management Systems (EMS) (0/1)	33.71%	66.29%
Firm specific characteristics	*size*	< 50 employees (0/1)	72.88%	27.12%
		50–249 employees (0/1)	21.82%	78.18%
		> 250 employees (0/1)	5.29%	94.71%
	gp	Part of an enterprise group (0/1)	20.72%	79.28%

For the variables with a binary outcome, we have included the percentages for each outcome, whereas for continuous variables we have included in the table the mean and standard deviation concerns the commercialization of the innovation outputs and is applied only to innovators. This variable is commonly used in innovation performance analysis since it is derived from questions that are found in the Community Innovation Surveys. It measures the proportion of sales in the past financial year that was from new, or significantly improved, products or services (Laursen & Salter, 2006). Close to this measure of innovation performance is the employment of the variable which is defined as the percentage of the number of firm's products resulted from innovation activities to the total number of firm's products (Gkypali et al., 2018). These two measures are used in the context of the estimation of the innovation production function as a key stage of innovation value chain (Vahter et al., 2014). The third measure of innovation performance lies within the context of innovation efficiency. Essentially the efficiency of any firm or economic activity is defined as the ratio of outputs to inputs (Coelli et al., 2005, pp. 2). In a benchmarking context innovation efficiency is examined using innovation production frontiers and is estimated using either parametric or non-parametric techniques (Carayannis et al., 2016; Cruz-Cázares et al., 2013; Kumbhakar et al., 2012).When benchmarking is not of the primal interest, or the available data are not suitable, innovation efficiency is defined as the outcomes achieved using certain amounts of resources. In this case, the measures employed for inputs and outputs may result in partial measures of innovation efficiency, for instance the ratio of patents to R&D personnel, or to total factor measures of innovation efficiency, e.g. the total innovation outcome to the total firm's resources devoted to innovation activities to firm.

The theoretical framework of the innovation production function implies that firms make decisions with respect to the investment they undertake to fulfill the innovation objectives and the overall business goals. In our theoretical and methodological setting, we investigate two innovation related investment decisions, which absorb firm resources and pose questions on their evaluation. It is apparent that both eco-innovation and innovation cooperation demand the devotion of firm resources and are evaluated with respect to their total innovation outcome which in the case examined here is the turnovers from products which are considered as outcomes of the innovation process. It is worthy to say that the innovation efficiency measure employed is a total factor efficiency measure since it is developed on the grounds of total resources devoted to innovation process and the total outcome of the process. Moreover, in our methodological approach we embrace the abovementioned first category of measures of innovation performance by incorporating a selection equation which disentangles between innovators and non-innovators.

An issue which has to be considered when calculating the ratio of innovation efficiency is that innovative sales in CIS are reported for firms which have developed product innovation. It is widely acknowledged that when a firm innovates, it creates not only new products but also complementary new processes (Eggers, 2011; Toh & Ahuja, 2021). Complementarities between product and process innovation have been investigated on the premises of Milgrom and Roberts (1990) seminal paper. The process–product interaction is developed around the argument that the two components complement each other, with the first reducing production cost and the latter improving product functionalities. The cost reduction due to process innovation bolsters the yields of product innovation, since new or improved products are coming out in the market with a significant price advantage (Berchicci et al., 2014). Hullova et al., (2019) have categorized the interdependence of product and process innovation in (i) Complementarities-in-use (Damanpour, 2010), (ii) Integration mechanisms which facilitate synchronous consideration of product and process innovation (Rosell et al., 2014) and (iii) Complementarities-in-performance (Cassiman & Veugelers, 2006; Turkulainen & Ketokivi, 2012). In all categories the examination of only one type of innovation does not shed light on the relationship between innovation and efficiency. In the same vein, complementarities between product and process innovation may induce high coordination costs if a certain level of integration between the two types of innovation is not achieved (Hullova et al., 2019). In both cases the non-inclusion of the interdependence between product and process innovation in the analysis of innovation efficiency is expected to bias the empirical results.

Based on the above theoretical considerations, we have calculated innovation efficiency for firms that have introduced (i) Product innovation, which count for 142 cases and (ii) Both product and process innovation which count for 601 cases. Therefore, the total number of firms under examination is 743, which finally is slightly reduced to 730 because of missing values issues. As a result, there are no observations in our econometric estimates where innovation efficiency is calculated for firms which have introduced only process innovations. It is noticeable that firms which introduce both product and process innovation is above of four times more compared to the firms which introduce only product innovation. This is quite strong evidence which validates the above theoretical considerations.

Another issue which has to be considered for the calculation of innovation efficiency is the time lag between R&D expenditure and sales of the resulting innovative products. However, empirical results of the relevant literature indicate that the use of time lags exhibit only a weak or no effect on innovation efficiency (Hollanders & Esser, 2007) revealing time persistence of innovation related activities. Coad and Rao (2010) employing a panel vector autoregression model to a firm-level longitudinal dataset, provide strong empirical evidence that firms behavior with respect to innovation expenditures, and the corresponding performance, exhibit high time persistence. In the same vein, according to the dominant 'technological trajectory' concept, innovation are processes that show high degrees of cumulativeness and irreversibility and, as a result, are characterized by a high level of time persistence (García-Quevedo et al., 2014). We should also mention that the dataset employed in our research is the outcome of a combined effort of two European authorities covering a three-year period (2012–2014) which results into a cross-section dataset.

4.1.2 Decisions to eco-innovate and collaborate

The additional two dependent variables are the firms' decisions to eco-innovate (*Eco*) and co-operate for innovation (*Co*). Regarding the variable (*Eco*), we have constructed it based on the firms' responses on the following question: *"During the three years 2012 to 2014, did your enterprise introduce a product (good or service), process, organisational or marketing innovation with any of the following environmental benefits?"*. CIS survey lists ten (10) categories of possible environmental benefits either obtained within the enterprise (e.g. reduced pollution or 'CO2' footprint etc.) or obtained during the consumption or use of a good or service by the end user (e.g. facilitated recycling or extended product life). The generated dummy variable takes the value 1 if a firm has introduced an environmental innovation by picking "yes" at least in one of these types of environmental benefits, and 0 otherwise. Although each environmental innovation type of benefits would permit for a separate investigation, the focus of our study is on the decision to eco innovate and not on the types of environmental innovation and respective benefits (Ghisetti et al., 2015). In addition, firms might choose to implement all or just a fraction of those activities without compromising the content of the endeavor promoting a business strategy facilitating eco-innovation (Triguero et al., 2013) or green growth and circular economy (Chatzistamoulou & Tyllianakis, 2022).

Regarding the variable (*Co*), we have exploited the already reported dummy variable in the microdata set we have received by the Statistical Authority. The survey participants are asked whether they have co-operated on any of their innovation activities with other enterprises or organisations during the years 2012 to 2014. This variable equals to 1 when the firm's response to that question is positive, and to 0 otherwise. We have also included in the model a fourth dependent variable (*innovat*) to account for the non-innovators and alleviate the selection bias issue. This variable captures the binary decision of a firm to innovate or not. We have constructed this variable based on the firms' responses on whether they have introduced or not any type of innovation or followed any ongoing/abandoned innovation activity during 2012–2014. This variable takes the value 1 if the respondent has picked at least one 'Yes' to any type of innovation activity that is undertaken by the firm during the time reference and it equals to 0 otherwise. The basic descriptive statistics of the dependent variables are presented in the upper part of Table 1.

4.2 Explanatory Variables

Based on the relevant literature, we have included in our system of equations explanatory variables grouping them in the following categories: variables which refer to the internal and external knowledge sources which a firm exploits for its innovation activities, absorptive capacity, public subsidies, and firm-specific characteristics. All explanatory variables refer to events that took place at any point of the period covered by the survey (i.e. 2012–2014). Regarding the first set of variables capturing external knowledge, we consider the engagement in extramural R&D activities (*rrdex*) and acquisition of external knowledge (*roek*), both of which are binary outcome variables. These variables are documented in previous empirical studies as determinants of the decision to develop green innovations (Cainelli et al., 2015; De Marchi, 2012; Jové-Llopis & Segarra-Blasco, 2018) or the decision to collaborate with other partners for innovation purposes (Belderbos et al., 2018; Maietta, 2015).

Internal knowledge is captured by the variable (*rrdin*) which measures the engagement of a firm in intramural R&D activities, the variable (*rmac*) corresponding to whether a company has acquired advanced machinery, software or other equipment for its innovation activities, and the variable (*rtr*). The last variable refers to whether a company has undertaken in-house or contracted out training for its personnel specifically for the development and/or introduction of new or significantly improved products and processes. These variables have been documented in previous works either as drivers of the decision of a firm to develop an environmental innovation (Borghesi et al., 2015) or its decision to R&D collaborate with other organizations (Maietta, 2015; Piga & Vivarelli, 2004). Responses (yes/no) to these activities by the respondents concerning the above two first blocks are encoded as binary variables for the econometric analysis.

To measure absorptive capacity, we have included the continuous variable (*empud*) which is defined as the ratio of the number of employees with a university degree to the number of firms' total employees. We have included this variable in the three equations as there is empirical evidence that it affects firms' decisions to go green (Ghisetti et al., 2015), to participate in collaborative R&D schemes (Tsai, 2009), and innovation performance (Gkypali et al., 2018, 2017). Survey participants were asked to report approximately the percent of their enterprise's employees which had a tertiary degree. Based on the responses, we normalized this variable and have constructed a new one which takes values from 0 to 87.5%. In addition, we have included the variables (*funloc*), (*fungmt*) and (*funeu*) to capture the effect of public subsidies measuring whether or not a firm has received public subsidies granted by local or regional authorities, central government or the European Union respectively for the financial support of its innovation activities. We have encoded the "yes/no" responses to this question resulting to three dummy variables with binary outcomes. We have included these variables as determinants either of the decision to eco innovate (Costantini et al., 2015), the decision to R&D collaborate (Leckel et al., 2020; Piga & Vivarelli, 2004) and ultimately innovation outcome (Greco et al., 2017).

Apart from the above variables, we have included an additional one only for the equation which refers to the decision of firms to go green. This variable (*envid*) refers to future environmental regulations embedded in Environmental Management Systems (EMS) within firms as a driver of their decision to develop environmental innovations based on previous studies (Crespi et al., 2015; Papagiannakis et al., 2019). The survey participants were asked to answer whether their enterprise have procedures in place to regularly identify and reduce their enterprise's environmental impacts. The derived variable is already encoded in the microdata set we have received (by the statistical authority) and it has a binary outcome based on the firms' "yes/no" responses.

We also control for firm-specific characteristics such as group membership (*gp*), the number of employees (size)[1] and industry effects which are related to eco innovation decision (Cainelli et al., 2020), the propensity of firms to R&D collaborate (Miotti & Sachwald, 2003) or innovation efficiency (Hashi & Stojčić, 2013). Furthermore, we control for the effect of exporting activity with the variable (*expact*) as a source of learning for innovation activities (Gkypali et al., 2021) and a driver of a firm to follow collaboration practices (Cassiman & Veugelers, 1998).

Descriptive statistics of the above explanatory variables are presented in the downside of Table 1. Table 2 includes the pairwise correlation matrix of the employed dependent and explanatory variables.

5 Results and discussion

The CMP estimation results of the system of Eqs. (1–4) are presented in Table 3. The first column refers to the innovation efficiency equation incorporating the decisions to engage in eco-innovation and R&D collaborations. The next two columns correspond to Eqs. (2) and (3), that is the decisions to eco-innovate and to participate in collaborative innovation schemes respectively. Finally, in the last column, the estimation results of the selection equation are presented. Table 4 includes marginal effects regarding the three Eqs. (2–4).

[1] Size has been considered as a crucial factor of innovation decisions and output. Following the structure of the Greek Business Sector, which is close to many other European countries, the Greek wave of the CIS accounts mainly for small enterprises. The 86% of the survey population belongs to the group of 10–49 employees, the 13% to the class size of 50–249 and the 1% to the size class > 250 (EKT, 2017). The relevant literature provides mixed empirical results with respect to the impact of firm's size on the propensity to innovate. Although large firms are considered in general more innovative, small companies can be more innovative, compared to their larger counterparts, due to other characteristics such as ability to adapt and make quicker decisions or the opportunity to have less bureaucracy (Damanpour, 2010).

Table 2 Correlation matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. R&D Collaboration decision (co)	1																
2. Eco-Innovation decision (eco)	0.16	1															
3. Innovation Efficiency (InnEff)	0.16	0.04	1														
4. Engagement in extramural R&D (rrdex)	0.37	0.17	0.14	1													
5. Acquisition of external knowledge (roek)	0.31	0.15	0.08	0.27	1												
6. Engagement in intramural R&D (rrdin)	0.27	0.15	0.31	0.34	0.21	1											
7. Acquisition of advanced machinery, equipment, software and buildings for innovation activities (rmac)	0.21	0.17	0.30	0.18	0.18	0.23	1										
8. Training for innovation activities (rtr)	0.30	0.16	0.20	0.29	0.39	0.38	0.29	1									
9. % of Employees in the company with university degree (empud)	0.17	– 0.03	0.17	0.15	0.10	0.21	-0.04	0.20	1								
10. Public subsidies granted by Local or regional authorities (funloc)	0.03	0.09	0.13	0.04	0.05	0.03	0.09	0.05	0.02	1							
11. Public subsidies granted by Central government (fungmt)	0.14	0.05	0.23	0.16	0.06	0.14	0.16	0.16	0.15	0.12	1						
12. Public subsidies granted by European Union (funeu)	0.16	0.01	0.19	0.14	0.12	0.13	0.06	0.10	0.14	0.08	0.20	1					
13. Part of an enterprise group (gp)	0.21	0.07	0.02	0.20	0.10	0.09	0.00	0.11	0.22	– 0.07	– 0.01	0.04	1				

Table 2 (continued)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
14. Small-sized firms (< 50) (size < 50)	0.10	0.11	0.02	0.06	0.04	0.07	0.06	0.07	0.06	0.01	0.12	0.06	0.26	1			
15. Small-medium sized firms (50–249) (size50-249)	−0.18	−0.15	−0.04	−0.17	−0.08	−0.16	−0.13	−0.12	−0.04	−0.01	−0.10	−0.09	−0.46	−0.79	1		
16. Environmental Regulation (EMS) (envid)	0.06	0.28	0.02	0.17	0.03	0.07	0.14	0.10	−0.10	0.08	0.09	0.07	0.14	0.20	−0.33	1	
17. Exporting activity (expact)	0.04	0.07	0.05	0.09	0.04	0.19	0.01	0.06	0.09	0.02	0.11	0.10	0.06	0.09	−0.12	0.16	1

Table 3 Estimation results of the mixed process regression

		Innovation efficiency	Eco-Innovation	Collaboration	Innovators (Selection Eq.)
Eco-Innovation decision		2.612*** (0.342)	–	–	–
R&D Collaboration decision		−0.121 (0.499)	0.168 (0.299)	–	–
External knowledge acquisition	Engagement in extramural R&D	–	0.211* (0.111)	0.765*** (0.110)	–
	Acquisition of external knowledge	–	0.167* (0.095)	0.549*** (0.105)	–
Internal knowledge generation	Engagement in intramural R&D	–	0.237*** (0.081)	0.126 (0.109)	–
	Acquisition of machinery and equipment for R&D activities	–	0.524*** (0.089)	0.242** (0.112)	–
	Training for innovative activities	–	0.123 (0.085)	0.196** (0.096)	–
Absorptive capacity		0.004 (0.003)	0.003 (0.002)	−0.000 (0.002)	-
R&D Public Subsidy	Local or regional authorities	0.360 (0.257)	0.233* (0.132)	−0.053 (0.144)	–
	Central government	0.689*** (0.206)	−0.102 (0.101)	0.328*** (0.108)	–
	European Union	0.720*** (0.254)	−0.113 (0.138)	0.382*** (0.144)	–
Exporting		−0.117 (0.168)	–	0.043 (0.098)	–
Environmental Regulation (EMS)		–	0.379*** (0.088)	–	–
Firm specific characteristics	Part of an enterprise group	–	0.134 (0.097)	0.340*** (0.113)	0.003 (0.078)
	Small-sized firms (<50)	−0.502 (0.382)	0.140 (0.187)	−0.11* (0.058)	−0.746*** (0.150)
	Small-medium sized firms (50–249)	−0.553 (0.349)	0.155 (0.172)	−0.210 (0.187)	−0.525*** (0.152)
	Industry dummies	Yes	Yes	Yes	Yes
		Model information			
	Observations		2,201		
	Log-Pseudolikelihood		−4131.222		
	Model p-value		0.000		

Table 3 (continued)

	Innovation efficiency	Eco-Innovation	Collaboration	Innovators (Selection Eq.)
Equation correlations				
Equations				H_0: No disturbance correlation
Collaboration & Eco-Innovation Equations				−0.073 (0.189)
Collaboration & Innovation Efficiency				0.094 (0.152)
Collaboration & Selection Equation (Innovators)				0.127 (0.175)
Eco-Innovation & Innovation Efficiency				−1.009*** (0.170)
Eco-Innovation & Selection Equation (Innovators)				−0.340 (0.287)
Innovation Efficiency & Selection Equation (Innovators)				0.781** (0.370)

(i) All models include constants, (ii) Robust standard errors in parentheses, (iii) Stars indicate statistical significance at 1% ***, 5% ** and 10% *, (iv) The symbol "+" stands for a very small number

Table 4 Average marginal effects

		Average marginal effects		
		Eco-Innovation	Collaboration	Innovators (Selection Eq.)
Eco-Innovation decision		–	–	–
Collaboration decision		0.055 (0.098)	–	–
External knowledge acquisition	Engagement in extramural R&D	0.069* (0.037)	0.234*** (0.032)	–
	Acquisition of external knowledge	0.055* (0.031)	0.168*** (0.031)	–
Internal knowledge generation	Engagement in intramural R&D	0.078*** (0.027)	0.039 (0.033)	–
	Acquisition of machinery and equipment for R&D activities	0.172*** (0.030)	0.074** (0.034)	–
	Training for innovative activities	0.040 (0.028)	0.060** (0.029)	–
Absorptive capacity		0.001 (0.001)	-0.000^{+} (0.001)	–
R&D Public Subsidy	Local or regional authorities	0.076* (0.043)	−0.016 (0.044)	–
	Central government	−0.033 (0.033)	0.100*** (0.033)	–
	European Union	−0.037 (0.045)	0.117*** (0.044)	–
Exporting		–	0.013 (0.030)	–
Environmental Regulation (EMS)		0.124*** (0.029)	–	–
Firm specific characteristics	Part of an enterprise group	0.044 (0.032)	0.104*** (0.034)	0.001 (0.026)
	Small-sized firms (< 50)	0.046 (0.061)	−0.110* (0.058)	−0.253*** (0.050)
	Small-medium sized firms (50–249)	0.051 (0.056)	−0.064 (0.057)	−0.178*** (0.051)
	Industry dummies	Yes	Yes	Yes
		Model Information		
	Observations		2201	
	Log-Pseudolikelihood		−4131.222	
	Model p-value		0.000	

(i) All models include constants, (ii) Robust standard errors in parentheses, (iii) Stars indicate statistical significance at 1% ***, 5% ** and 10% *, (iv) the symbol "+" stands for a very small number

5.1 The decision to develop environmental innovations in the innovation efficiency context

According to the empirical results, the decision of a firm to engage in eco-innovation activities exerts positive and statistically significant impact on its innovation efficiency (*Hypothesis 1* is not rejected). Firms, that go green, develop innovation capabilities which increase the innovation output per unit of innovation input. Thus, the "Efficiency-based Eco-innovation (EECO)" regime is supported. Firms with well-developed innovation competencies, allowing them to support the introduction of innovations with intricate and sophisticated characteristics, such as green innovations, exploit technological and market opportunities, and exhibit superior innovation efficiency. This result is in accordance with the body of literature arguing that eco-innovations are demand driven innovations that can enable firms to use their green innovation in their marketing strategies, differentiate their products to gain competitive advantages, attain a better position in the market, enhance their corporate image and reputation and ultimately boost their sales.

The fact that eco-innovation decision is associated with innovation efficiency is also supported through the correlation of the error terms (ρ) of the two respective equations which is presented in the lower part of Table 3 and is statistically different from zero). One example of non observable determinants relationship, reflected on significant value of the corresponding ρs, could be the experience of R&D managers to deal with R&D projects which can affect both the decision of a firm to eco-innovate and its innovation efficiency. This means that if the two equations were estimated separately we would have problems of endogeneity due to confounding factors, which here are tackled through the joint estimation of these equations.

Although a major part of the relevant literature indicates that environmentally innovative firms cooperate with external partners to gain access to new skills and information as well as to reduce risks and costs embedded in the development of complex green technologies, our empirical results do not reveal such a relationship between R&D collaboration and eco-innovation decisions (*Hypothesis 2 is not accepted*). More specifically, R&D collaboration does not affect the probability of a firm's decision to eco-innovate nor the correlation coefficient of the unobserved heterogeneity of the two equations is significant (see the lower part of Table 3). This result is in line with recent evidence documenting that organisations tend to be conservative in collaborating with external partners to protect their technologies and avoid imitation (de Paulo et al., 2020).

In some respect, we could argue that firms consider eco-innovation as a valuable asset that should be internalized, to become rare and non-immitable to competitors, distinguishing the firm in the marketplace and grounding its competitiveness. Therefore, R&D collaboration is not the proper approach to get access to the necessary knowledge and skills in the case of eco-innovation projects. On the contrary, according to the empirical results presented in Table 3 and Table 4, firms acquire the set of required technological competencies for the development of eco-innovation mainly through the engagement in the intramural knowledge generation process. This becomes evident since two out of the three of the group "Intramural knowledge generation" variables, are positive and statistically significant. The internal generation process allows the minimization of knowledge leaking to competitors and ensures the non-imitability of green technologies developed strengthening the firm's competitiveness.

Apart from internal knowledge generation, firms to eco innovate and be able to tackle issues of complexity linked to the development of green technologies, tend to acquire knowledge by their external environment. Although it seems that R&D collaboration is not the proper approach to acquire external knowledge, firms use other ways of gaining it and develop environmentally friendly products or business processes. In this direction one could mention the outsourcing of R&D activities, the acquisition of existing know-how, copyrighted works, patented or non patented inventions from other organizations. This is supported by our results where the variables for the engagement in extramural R&D and the acquisition of external knowledge are significant drivers of the decision of a firm to eco-innovate, supporting previous empirical studies. However, the group of variables which refers to the internal knowledge generation is a more prominent block compared to the one that refers to the external knowledge generation (see average marginal effects in Table 4). It is shown that the successful internalisation of knowledge by firms is the most important driver for their decision to go green comparing internal to external knowledge sources.

While the decision of a firm to go green is supported that it is an “efficiency-driven decision (EECO)”, empirical findings of this study show that it is a “Regulation Eco innovation driven” (RECO) decision too, as the incorporation of Environmental Management Systems (EMS) has a highly significant effect on the eco innovation decision. EMS implementation help firms to build and establish corporate environmental strategies and management systems such as auditing to abide by future regulations on the environment. These environmental management systems ultimately increase the propensity of a firm to be willing to develop green innovations. Finally, firm size and industrial distribution do not reveal any significant contextual differences regarding their relationship with the decision of a firm to go green.

Overall, results document that the decision to engage in business strategies fostering eco-innovation, of any form, boost innovation efficiency. From a policy perspective, firms engaging in eco innovation activities generate employment, and particularly green jobs (Moreno-Mondéjar et al., 2021), while eco-innovation activity links to the adoption of circular economy business strategies and thus promotes the green transition (Chatzistamoulou & Tyllianakis, 2022). The beneficial effects for environmental quality and facilitation of sustainability have been envisaged in a series of European policies such as the Eco Innovation Action Plan (European Commission, 2011b) and the Resource Efficiency Flagship Initiative (European Commission, 2011a).

5.2 The decision to participate in R&D collaborations in the innovation efficiency context

As presented in the theoretical framework section, innovation collaborations[2] are expected to exert a positive impact on innovation efficiency, through the opportunity which is given to firms, to access abundant knowledge sources and advanced technologies. However, empirical results indicate that participation in R&D collaboration schemes exerts no direct systematic impact on innovation efficiency *(Hypothesis 3 is not accepted).* Thus, the

[2] Augmenting the estimation strategy to include the collaboration breadth as the ratio of the collaboration types available a firm could potentially engage with in the main equation, results remain unchanged. This is in in line with recent literature where collaboration breadth does not foster innovative behavior (Kobarg et al., 2019; Lin, 2017), or innovative performance (Statsenko et al., 2020) while an inverse U-shaped relationship (Kobarg et al., 2019; Lin, 2017) is also among the evidence in the literature. We owe this to an anonymous reviewer’s comment.

"efficiency-based R&D collaboration" (ERDC) regime is not supported. This empirical finding is in line with the stream of research documenting that R&D collaboration includes high search, coordination, and transaction costs which in combination with not well-developed firm's absorptive capacity (Gkypali et al., 2017a, 2017b, 2018), lack of sustained mutual understandings and interests between partners such as free-riding, opportunistic behavior, and misappropriation, ultimately offset the positive impact of R&D cooperation. Although, previous works (Apa et al., 2021; Guisado-González et al., 2018) have shown that absorptive capacity plays an important role regarding the ability of firms to gain from collaboration mechanisms in terms of their innovation output, this is not confirmed in the case examined in the current research.

The fact that the decision of a firm to collaborate with other partners is not associated with its innovation efficiency can be explained by the modest level of innovation performance of Greek firms. In particular, Spanos (2021) argues that the typical participant in collaborative R&D research activities comes from countries with comparatively strong national innovation performance. The financial crisis heavily affected Greece and thus its innovation system showing medium to low levels of innovation performance which could have influenced firms' decision to cooperate for innovation eventually.It is noteworthy that R&D collaborations do not influence innovation efficiency even indirectly, through the eco-innovation. Eco innovators who participate in R&D partnerships do not exhibit superior innovation efficiency compared to their counterparts who have decided not to join R&D cooperation schemes (*Hypothesis H4 is not accepted)*. The empirical results regarding the R&D cooperation equation imply that cooperation decision is not related at all with the eco-innovation decision and even more with innovation efficiency. The decision to participate in R&D partnerships is a separate and detached, from innovation efficiency and the decision to eco-innovate, regime. This finding is not in line with empirical evidence which supports the positive role of innovation collaboration on the decision to eco-innovate.

On the contrary, empirical results suggest that R&D collaboration is mainly driven by public subsidies. Firms deciding to be engaged in R&D collaborations are not motivated mainly by their needs to increase and deepen their innovative capabilities, but by gaining access to collaborative national or European R&D funded projects. Thus, the "Opportunistic R&D collaboration (ORDC)" regime prevails. In particular, public funding offsets the search, coordination, and transaction costs that suffer firms which decide to participate in innovation partnerships. Moreover, public subsidies assist firms to learn about their candidate partners, their capabilities, expand their network and be able to select the appropriate ones (Fontana et al., 2008). It is noticeable that regional public funds devoted to the promotion of R&D collaboration provide little support, in contrast to national and European funds, which are of great importance.

Furthermore, we have examined the effect of public subsidies not only on R&D collaboration decision but also on innovation efficiency. Results showcase that public subsidies achieve outstanding results in terms of innovation efficiency as they may relax financial constraints, mitigate technological risks, and lead to partnerships with social and economic positive externalities (Greco et al., 2017). This becomes even more crucial in the times of the deep financial crisis which Greece has suffered when the CIS 2012–2014 took place. Link et al., (2021) argue that in the case of US SMEs, public funding targeting the reinforcement of business innovation activities, generates an unanticipated but equally significant effect; the increase of the probability of firms receiving innovation grants, to enter the stock market on the ground of their developed technology.

Findings also indicate that the acquisition of external knowledge drives the decision of firms to collaborate with other partners supporting previous studies which refer to the "open innovation" concept (Chesbrough, 2003). Except for external knowledge, results show that Greek firms are motivated to collaborate when they have invested in their internal knowledge development and assimilation through the acquisition of machinery and their engagement in training for innovation activities following previous findings.

Apart from the impact of absorptive capacity on the R&D collaboration decision, we have examined its impact on innovation efficiency. In particular, the impact of absorptive capacity, defined as the percentage of firm's highly skilled employees, on innovation efficiency is not significant, and highlights the distinction between potential and realized absorptive capacity. Zahra and George (2002) linked absorptive capacity to a set of organisational routines and strategic processes through which firms acquire, assimilate, transform and apply knowledge with the aim of value creation. In particular, they divide absorptive capacity into potential (acquire, assimilate) and realized (transform and apply) absorptive capacity and argue that it is highly likely that some firms may have potential capacity but do not realize the benefits. For example, a firm may be able to identify, understand and assimilate external knowledge, but the firm may not be able to integrate such knowledge with its prior existing stock of knowledge. In the same vein, Camisón and Forés (2010) link potential and realized absorptive capacity with external learning capacity and internal learning capacity, respectively, with each "based on differentiated processes, routines and strategies". In order the potential absorptive capacity to be transformed in significant business outcomes and to improve efficiency, i.e. to realized absorptive capacity, additional resources and innovation capabilities, are needed (Harris & Yan, 2019).

In addition, regarding other examined drivers of the R&D collaboration decision in the innovation efficiency context, results show that export activity does not exert a significant influence either on R&D collaboration decision or innovation efficiency, contradicting previous research indicating that exports help firms to gain experience and knowledge from abroad, increase their propensity to engage in R&D collaborative activities (Spanos, 2021) and ultimately support their innovation outcomes. This finding is in accordance with the endogenous self selection of Greek firms in the exporting status taking into account R&D efficiency (Gkypali & Tsekouras, 2015). Regarding firm-specific characteristics, results show that group membership and firm size are positively related to the likelihood to collaborate with other organisations following the relevant empirical literature.

6 Concluding remarks

We investigate the interrelationship between innovation efficiency and two strategic firm's decisions, and in particular to eco-innovate and to participate in R&D collaborations. We develop the theoretical framework which on the one hand introduces the role of eco-innovation and R&D cooperation on innovation efficiency, while on the other highlights the possible links between the two decisions. On this ground, we provide alternative, but not mutually exclusive, decisions regimes concerning innovation efficiency. Our conceptual framework is transformed to a system of four structural equations, which is estimated employing Greek CIS data for the 2012–2014 wave, and the Conditional Mixed Process estimator accounting for the mixed nature of the left side variables of the equations. Based on the econometric results, we deduce that eco innovation improves firms' innovation efficiency, by allowing them to position their products in the market where the environmental preferences are becoming constantly of increasing importance, differentiate themselves from their counterparts and boost their competitiveness. Therefore, eco-innovation decision fits the EECO regime while the regulation-driven eco-innovation (RECO) regime is proven also to be an appropriate context. A win–win situation surrounds the eco-innovation projects, in the sense that allow firms to comply with environmental regulation, and at the same time arm them with a significant competitive advantage as it is reflected on their innovation efficiency.

Based on the fact that we have concluded that eco-innovation is a demand-pull and a regulation-driven decision we consider the following policy recommendations. First, policymakers should enhance consumer awareness for green products (e.g. eco-labeling, environmental footprint etc.) which can increase the demand of "eco" products and ultimately act as a motivation for firms to develop environmental innovations. Second, we recommend that policymakers increase the stringency of regulation on the environment which can as a result affect positively firms' decision to go green. From a policy perspective, eco-innovation generates employment through the creation of green jobs in line with the recent European directives such as the European Green Deal, fostering green growth.

Further, we document that the firms' decision to participate in R&D collaborations is not innovation efficiency-driven, but fits to the opportunistic R&D collaborations (ORDC) regime, where the public subsidies determine decisively the decision-making process. The "hidden costs" of collaboration such as search, coordination, transaction, and monitoring costs prevail and offset the benefits of cooperation activities, which, given the low level of absorptive capacity of the Greek firms, is difficult to be realized at their higher potential. Policy-wise, the weak effect of collaboration projects on innovation activity could be strengthened by schemes incentivizing public–private partnerships and the implementation of policy measures which strenghten the firms' realized absorptive capacity.

Moreover, businesses meet their needs for technology and technological capabilities required for environmental innovation, resorting mainly to internal knowledge generation processes and not to R&D collaborations. Issues related to IPR in the context of R&D collaborations, combined with firms' perception of the value of environmental innovations in terms of building their competitive advantage, hinder the adoption of R&D partnerships as a source of enrichment of their eco-innovation related knowledge base. As a result, eco-innovators participating in R&D collaborations do not exhibit innovation efficiency positive differentials compared to their counterparts which decide not to collaborate.

Policy measures that would propel the increase and deepen of firms' absorptive capacity accompanied by a significant reduction of the cooperation costs, could change the incentives structure for the engagement in R&D cooperation and integrate firms' strategic innovation decisions. For example, subsidies could be directed not towards the formation of new R&D partnerships between Higher Education Institutes and firms, but towards hiring of new highly skilled personnel, R&D equipment, and business process reengineering. The selection of partners could be facilitated by agents who would focus their efforts to create protocols and other ways of preventing knowledge dissipation among the different partners developing trust among them to tackle issues of this prevailing opportunistic behavior.

Nevertheless, this study is not free of limitations. That being said, among the limitations one finds the cross-section structure of the data. However, empirical results of the relevant literature indicate that the use of time lags exhibit only a weak or no effect on innovation efficiency (Hollanders & Esser, 2007) revealing time persistence of innovation related activities. A future study with panel data can examine the effect of the decision to collaborate or eco innovate on innovation efficiency of future years since the impact of these decisions can appear in a later time basis for enterprises. According to standard practice of Eurostat, CIS panel data are not available due to confidentiality and anonymity policy. However, in some cases, indicatively Germany, France, UK, Italy and Spain, special permissions exclusively for research purposes, have allowed the employment of CIS panel data. As far as Greece concerns, only one wave of the CIS is available and hence the investigation of the dynamics of the relationships we introduce in this paper is not possible for now.

Last but not least, this research work examines inter alia the relation between the decision to eco innovate and innovation efficiency, without taking into account the different types of environmental innovation a firm can develop (e.g. facilitated recycling or extended product life). Future research can accommodate this concern.

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Declarations

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