Resource Efficient Eco-Innovations for a Circular Economy: Evidence from EU Firms

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Abstract. Innovation adoption and diffusion by firms are key pillars for the EU strategy on resource-efficiency and the development of a circular economy. This paper presents new EU evidence regarding the role of environmental policy and green demand drivers to sustain the adoption of resource efficiency-oriented eco-innovations. Using a cross-section of EU firms and accounting for endogeneity, our results suggest that environmental policy and demand-side factors are both significant in driving the adoption of innovations that reduce waste and the use of materials. Internal R&D and relevant market dimensions are not significant, and even play a negative role. The paper provides an important piece of new quantitative-based knowledge, which complements the currently large case study-based evidence on the setting of sound management and policy strategies for the circular economy.

Keywords: circular economy, innovation, firms

Theme: F

[1] SEEDS – www.sustainability-seeds.org.

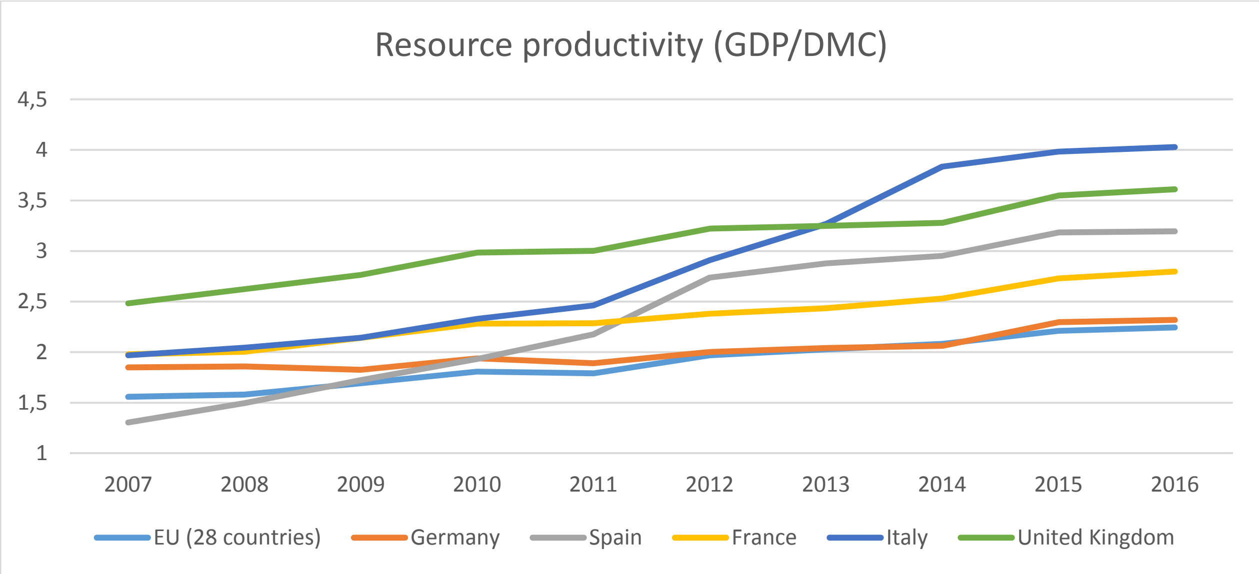
1. Introduction

In December 2015, the European Commission launched its action plan for the circular economy (CE) with the aim of unlocking the growth and jobs potential of the CE and boosting EU competitiveness through new business opportunities and innovative means of production and consumption that overcome resource scarcity and the volatility in material prices (EC, 2015). The decoupling between economic development and environmental impacts, i.e., an increase in economic value while decreasing resource use, depends on innovation and structural change factors (OECD, 2010; UNIDO, 2015). It follows that the transition to a CE is highly influenced by the composition and innovation intensity of the economy, by the evolution of new green markets, and by the environmental and industrial policy settings.

In the EU, the indicator of resource productivity – a key macroeconomic figure for resource efficiency targets and circular economy strategies – has been increasing between 2007 and 2016, as shown in Figure 1, which reports the domestic material consumption (DMC) per unit of GDP on the basis of Eurostat data[2] for selected countries and for EU28. Relevant cross-country heterogeneity is, however, still present (other countries' results available on request). Heterogeneity is high, as is the case in many other environmental realms that are linked to resource efficiency and environmental management (EEA, 2014).

[2] According to Eurostat, DMC "…measures the total amount of materials directly used by an economy and is defined as the annual quantity of raw materials extracted from the domestic territory, plus all physical imports minus all physical exports. Source: http://ec.europa.eu/eurostat/statistics-explained/index.php/Glossary:Domestic_material_consumption_(DMC)

Figure 1 – Resource Productivity in the EU (GDP per unit of material resources used in production (DMC, domestic material consumption) - €/kg)



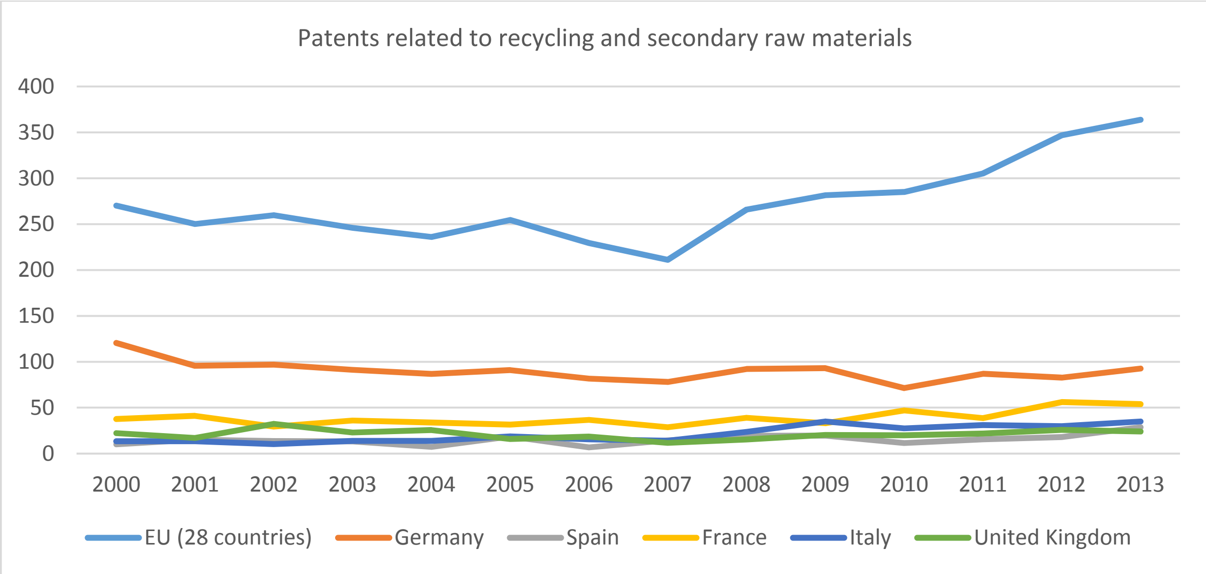
Source: own elaboration on EUROSTAT data (download 8th of February, 2018)

Innovation is among the relevant factors behind resource productivity (EEA, 2014). Green technological development (resource/emission efficiency of production) can compensate for scale economy-driven effects (Marin and Mazzanti, 2013). Given the heterogeneity of technological and environmental performances across sectors, the understanding of the underlying forces requires in-depth meso- and micro-level analyses, which unveils the macroeconomic determinants (UNIDO, 2015).

Although innovation is commonly regarded as the most effective response to sustaining current standards of living while overcoming serious environmental concerns (EEA, 2014), a broad picture of the innovative potential in the field of resource efficiency (RE) and CE-related technologies remains lacking. Though new data on inventions that relate to the CE are now available from Eurostat (Figure 2), the quantitative analysis of diffusion patterns of CE strategies through adoptions of innovations remains a relatively virgin field.

In a firm and sector level study, Albrizio *et al.* (2017) focus on green inventions and performances, noting that, "there are various problems of using patents as a proxy for innovation (...) Most "innovations" are not patented (…) most firms in the population do not patent at all (in the sample, just over 1% of firms patent in each year)" (p. 216). The authors also suggest that environmental policy effects through patented (and/or breakthrough) innovation occur only after long time periods (Nicolli and Mazzanti, 2011). The question of what drives technology adoption related to resource efficiency therefore remains open and can provide new considerations for policy makers.

Figure 2 – Patents related to recycling and secondary raw materials



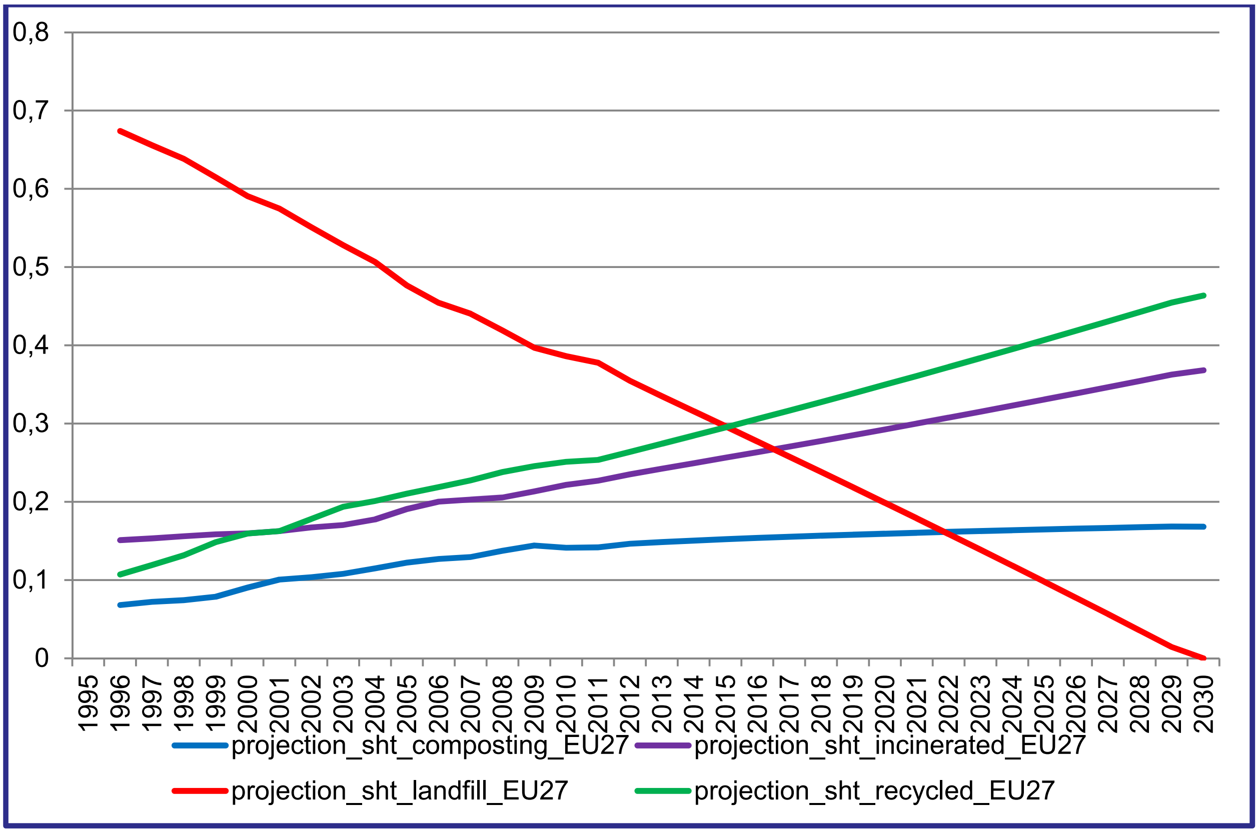
Source: own elaboration on EUROSTAT data (download 8th of February, 2018)

Maintaining pace with the ongoing improvements in recycling dynamics is indeed crucial, but the reduction of waste production is increasingly recognised as central[3]; process, marketing and product innovations are crucial to the fulfilment of the CE strategy (EEA, 2016). The CE path is intrinsically driven by the consolidated waste pattern, which moves away from disposal and towards better waste management and the prevention of waste production. Figure 3 exemplifies the long-run expected policy driven evolution of waste trends, which relate to the opening of new markets and new technologies.

The consumer side is also relevant for this development. For example, recent studies based on large sample surveys suggest that on average US consumers are willing to pay 10% more for products with recycled packaging: 23% are willing to pay more than 10$ while 43% are not willing to pay at all (ISRI, 2014). Heterogeneity is largely driven by gender, age and other socio economic characteristics.

[3] Recent *estimates are that 500 million tons/year of materials in waste waiting to be circulated back to the economic system* are potentially exploitable (http://www.emininn.eu/). This finding is a somewhat radical change that leads to winners and losers. The net benefit that arises from the reorganisation of the international value chain is now unclear and is scoped for further research. The analysis of innovation adoptions is a piece of the set of analyses around the role of innovation and structural change in the circular economy transition. 'Waste based value chains' evolution plays a pivotal role, as well as the involved sectors, among others that use waste as inputs, such as the following: paper and paperboard, wood-based panels, renewable energy sources, and metals. Global plastic packaging value chains are another example; without product redesign and innovations, 30-50% of plastics will never be used (EMF, 2015).

Figure 3 – Waste management and disposal trends in the EU27 (expected patterns, % of total waste generation)



Own Elaborations conducted within the activities of the WMGE EEA Topic centre activities (http://www.eionet.europa.eu/etc-wmge)

The aim of this paper is to bridge the resource efficiency realm of a CE approach to eco-innovation and its main drivers. We present new EU evidence on the role of environmental policy and green demand drivers to sustain the adoption of resource efficiency oriented eco-innovations (Mazzanti and Zoboli, 2006; Kemp and Pontoglio, 2011 for surveys on eco-innovations). We exploit a large European dataset on manufacturing and services firms, namely, EU data from the Community Innovation Survey CIS5, the first wave that hosted a proper section on environmental innovation adoptions and adoption motivations (Mairesse and Mohnen, 2010)[4]. Specifically, we focus on three types of environmental innovations closely related to a CE-oriented approach and to resource efficiency: (i) reduced material use per unit of output; (ii) recycled waste, water, or materials and (iii) improved recycling of product after use.

Focusing on these three EI variables, the aim is to provide new insights within the literature on innovation adoptions, with a focus on the CE. This literature intrinsically relies upon survey data (Cassiman and Veugelers, 2002; Mairesse and Mohnen, 2010). We also take advantage of recent works on environmental innovations, with the aim of extending the scope and finding more robust estimates addressing endogeneity. Among others, Veugelers (2012) and Borghesi *et al.* (2015), while not specifically focusing on resource efficiency-oriented innovations, show evidence from single countries and do not cope with endogeneity. Managi *et al.* (2014) attempt to address endogeneity and focus on resource-efficiency but again offer only single country-based evidence. Other contributions focus on the EU (Ghisetti *et al.*, 2015), again with the general aim of analysing all environmental innovations, but without addressing the endogeneity issue. Using EU data and taking into account the endogeneity of binary-framed policy and demand covariates, this paper focuses on the relationships between policy and demand factors as levers of resource-efficiency innovations. We account for the endogeneity problem by using instruments taken from external statistical sources. Our results confirm the central role of policies and demand-pull factors in driving the transition towards a full CE implementation. We also find puzzling (but reasonable) outcomes when the role of internal R&D and the relevant market dimensions are analysed.

The paper is structured as follows. Section 2 presents the theoretical background and the relevant literature. Section 3 presents the dataset, discusses the econometric strategy and reports our main econometric findings. Section 4 concludes the paper.

2. Circular economy and resource efficiency at the firm level: definition and anecdotal evidence.

A rigorous definition of the circular economy is outside the scope of the paper. Indeed, several good contributions have already surveyed the issues in defining the CE (Kirchherr *et al.*, 2017) and in linking it to other crucial concepts, such as sustainability (Geissdoerfer *et al.*, 2017).

For social science applied purposes, a very informative, although quite broad, definition of the CE is the one provided by the EC (2015): a more circular economy is one "…where the value of products, materials and resources is maintained in the economy for as long as possible, and the generation of waste is minimised." (p. 2). Along this definition, the implicit role of resource efficiency is, in our view, recognisable. This approach can also be found in several international case studies that are the anecdotal point of departure of the analysis, as they testify how enhanced waste-based value chains are frameworks where CE related innovation may arise. We provide here those that are the most compelling ones in our view.

Case studies and examples originate from many different sectors. There may be examples from 'old economy' industries that innovate, such as sustainable fashion industries that reutilise materials and old clothes and key materials such as glass that may be reused to build cement.[5] Key old economy sectors such as automobiles may play a role by integrating organisational and technological innovations. A famous case study is the French Choisy le roi automotive plant (Renault) working on remanufactured parts. The new reorganised and fully reshaped plant consumes 80% less energy, 88% less water and 92% less chemical products and produces 70% less waste. Waste is barely landfilled; 43% of the carcasses are re-usable, and 48% are recycled in the company's foundries to produce new parts. The remaining 9% is valorised in treatment centres.

Another interesting case study is Biofuels Ltd, a Finnish firm that focuses on the decentralised production of fuel bioethanol in Finland using side streams from the food industry and from domestic waste. Specifically, through new processes (called Etanolix for food waste and Bionolix for domestic waste), the waste is converted into an ethanol (85%)-water (15%) mixture at food industry sites. Then, the ethanol is concentrated/dried to a purity of 99.8% in a dehydration facility.

Radical innovations can derive from emerging start-ups. REEP Tech Ltd, an Israeli start up, invented a scanner system that processes printed paper; the scan tool deletes existing text or figures from printed paper, which can thus be reused in printers again, and saves the written information as a file in a cloud archive. Dry phase patterning is another potentially path-breaking technology for electronic circuits; the new process is based on mechanical machining of the material, rather than on the traditional use of chemical etching[6]. Finally, acre display is a thin, creatable, biodegradable electrochromic display that is produced with conventional printing processes; packaging and display printing can be performed simultaneously[7].

3. Theoretical background

The concept of eco-innovation (EI) is wide and widely investigated from different perspectives. Definitions of EI (Kemp, 2000, 2010) highlight the ecological attributes of specific new processes, products and methods. A discussion of the definitions and relevant dimensions of EI is presented by Carrillo-Hermosilla *et al.* (2010) and more recently in a critical survey paper, which covers many dimensions of EI, by Barbieri *et al.* (2016).

For the sake of the analysis, we borrow the definition chosen by De Jesus and Mendonça (2018), namely, "new or improved socio-technical solutions that preserve resources, mitigate environmental degradation and/or allow recovery of value from substances already in use in the

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[5] Several market examples, pilot projects and case studies are available at https://www.ellenmacarthurfoundation.org/circular-economy.

[6] See http://www.dppatterning.com for details.

[7] Applications of this technology potentially include screen printed labels, low-end displays with short usage time, medical diagnostics, labels for perishable foods, labels for logistics tracking and smart cards. See https://www.acreo.se/expertise/acreo-display.

economy." (p. 77). The authors outline the relevance of EI as a transformative process towards a more circular economy, i.e., in their words, towards a "…new usage-production closed-loop system." (p. 76).

A better understanding of the EI-CE linkages requires, as a pre-condition, a deeper investigation of the potential drivers of those dimensions of EI that are more relevant for a CE transition. We focus, specifically, on those dimensions that are strictly linked to material resource efficiency, as it will be clarified in describing the variables under scrutiny in the empirical analysis.

Although the relevance of innovative activities is acknowledged, the empirical literature in this respect is scant. This is surprising, given the rich array of drivers and barriers potentially involved. De Jesus and Mendonça (2018) identify "soft" (i.e., regulatory or institutional) as well as "hard" (technical, economic) drivers and barriers. In this paper, we focus on both kinds of factors; more specifically, our attention is devoted to soft barriers related to the regulatory framework, on one hand, and to the market and demand pull factors, on the other. Overall, we adopt a micro-CE perspective, where the attention is to circular models implemented by individual actors (in this case, firms) (De Jesus *et al.*, 2018).

To derive testable predictions, we link different strands of research related to the drivers of EI. First, the work is connected to contributions from the literature on the incentives by firms to invest in EI adoption to reduce compliance costs and/or emissions (Milliman and Prince 1989, Downing and White, 1986)[8]. The associated contributions suggest that the chosen environmental policy instruments and their design can be crucial in determining adoption and innovation incentives in general. However, there seems to be consensus on the conclusion that stricter environmental regulation is expected to increase adoption incentives, although recent work appears to cast doubts with respect to specific technologies or environmental policy tools (Perino and Requate, 2012).

The second field of analysis is related to the so-called Porter hypothesis, which stresses the potential virtuous link between well-designed environmental regulation and competitiveness (Ambec *et al.* 2012; Costantini and Mazzanti, 2012). In the original formulation (Porter, 1991 and Porter and van der Linde, 1995), such theoretical conjecture suggests that more stringent environmental policies do not (necessarily) cause a loss of competitiveness. In contrast, an improvement in productivity or profits may result in regulated agents. The underlying mechanics are based on the positive potential impact environmental regulation may have in boosting productivity, efficiency and improvements in organisational or product/process innovations. An underlying hypothesis is that there are factors preventing firms from fully exploiting their efficiency or technological potential; under this

[8] For an excellent survey, see Requate (2005).

assumption, regulation triggers improvements by making inefficient behaviours costlier, creating a potential *win-win* situation[9].

Although the theoretical bases of these two strands of literature differ, there appears to be agreement on the potentially positive impact of environmental regulatory stringency on the incentives of regulated firms to adopt cleaner technologies. We expect this finding to also apply when the innovation adoption under scrutiny is linked to resource efficiency and to the CE realm. Although the CE strategy does not set specific binding targets, as done for climate change, the overall objective is to reduce the use of materials and resources in the production and consumption phases. Consequently, if regulated firms perceive a stronger commitment towards environmental objectives, the conceptual framework suggests that more EI adoption will occur:

Testable Hypothesis H_1. *Environmental regulations boost the adoption of resource efficient, CE related technologies.*

The second research question addresses the role played by market conditions, the most prominent being market demand, on the incentives to adopt cleaner technologies. Horbach *et al.* (2012) identify "market pull factors" as potential drivers of eco-innovation incentives. Among these factors, an important role is played by customer benefits (Kammerer, 2009), such that market demand for green goods can indeed, in principle, drive eco-innovation (e.g., van den Bergh, 2008). Although certain doubts are cast on the robustness of this conclusion (see, again, Horbach *et al.*, 2012), it appears to be confirmed by more recent contributions (see, among others, Dangelico, 2016). These considerations lead us to the second testable prediction.

Testable Hypothesis H_2. *Market demand for "green" products is expected to encourage the adoption of resource efficient, CE related technologies.*

We will not only test for the relevance of demand pull factors; we will also focus on the relevant market geographical dimension to identify possible impacts related either to the stronger competition in wider markets or to the public good nature of the benefits related to innovation.

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[9] Jaffe and Palmer (1997) and Kozluk and Zipperer (2015), among others, suggest different possible definitions for the Porter hypothesis (PH). According to the so-called weak PH, environmental regulation stimulates innovation by placing constraints on regulated firms. A strong PH suggests that regulation is not only able to spur innovation, but also that this gain in efficiency completely offsets any loss in competitiveness. Finally, a narrow PH highlights the relevance of policy design in stimulating innovation.

3. Dataset and econometric modelling

3.1. Dataset

The empirical analysis uses statistical information at the firm level taken from the European community innovation survey (CIS).[10] Using this statistical source, we construct a sample of 48,059 service and manufacturing firms for the 2006-2008 period. These firms are located in nine different European countries, depending on data availability: Portugal, Estonia, Hungary, Sweden, Lithuania, Germany, Italy, the Czech Republic, and Romania.[11] The mostly heterogeneous coverage reflects the focus of the analysis on CIS data by Ghisetti *et al.* (2015). It is useful to remember that the data collected in this survey are self-reported information by respondents and thus not of an objective nature, as in case of information drawn from other variables such as patents (Mazzanti et al. 2016). Relying on patent data may have limitations, as already said. For this reason, we focus on CIS-based EI adoption.

3.2. Econometric modelling

In the econometric specifications, we estimate the following equation (Horbach, 2008; Veugelers, 2012; Cainelli *et al.*, 2015):

$$Y_i = f(\mathrm{ENREG_i}, \mathrm{ENDEM_i}, \mathbf{X}_i)$$

where Y_i is a dummy variable that takes value 1 if firm *i* introduces an EI and 0 otherwise. The value 0 includes two types of firms: (i) firms introducing other types of innovations, but not eco-innovations and (ii) firms that do not introduce any kind of innovation. It is worth noting that this choice is (quite) common in the eco-innovation literature (Cainelli *et al.*, 2015). $\mathbf{X}_i$ is a vector of control variables including the following: (i) RRDIX, a dummy taking value 1 if the firm undertakes in-house R&D;

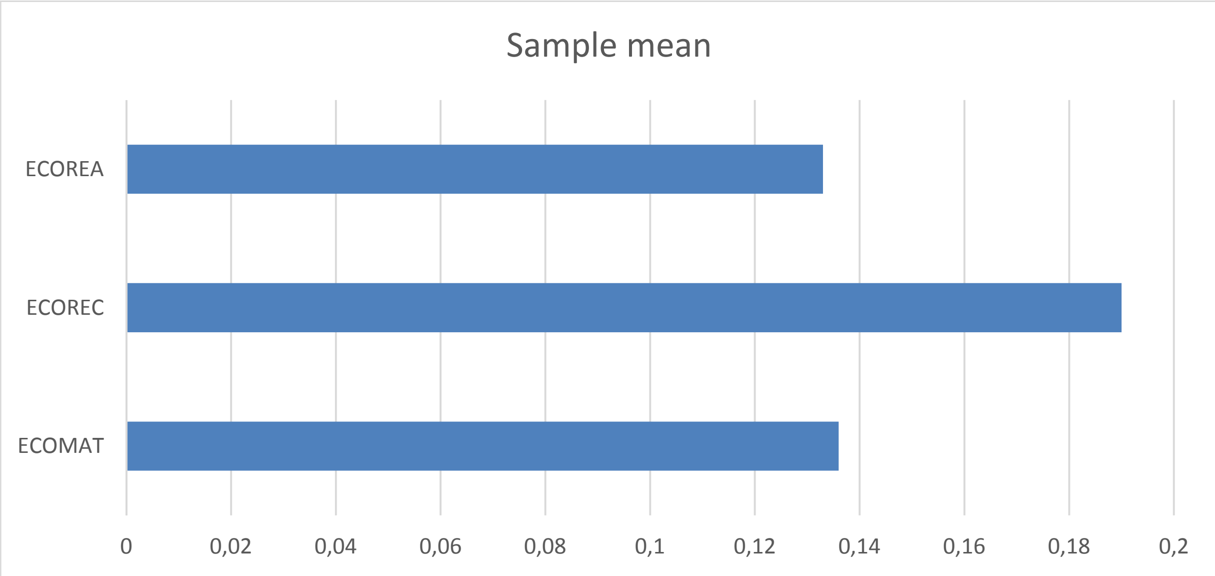
[10] Specifically, data are gathered from the Cd-Rom - Eurostat source (scientific use files) through a formal agreement between Eurostat and our University for research purposes. It is worth noting, quoting Eurostat document "How to apply for microdata?" by the EC and Eurostat (January 2017), that 'most microdata sets released by Eurostat are partially anonymised'. In addition to removing direct identifiers from the records, some variables are further anonymised, i.e. grouped together, aggregated etc. This may limit the possibility of using microdata for empirical analysis, e.g. if continuous variables, such as employment, are needed. On the other hand, the paper analyses innovation functions through exploiting binary variables. Studies on production functions should instead rely on estimations based on the alternative safe data centre in Luxembourg (non-anonymized data).

[11] These countries are selected according to data availability. Conversely, these countries can be considered representative of all environmental innovative activities under scrutiny in this paper. Indeed, these countries represent between 73.1% (ECOREC) and 77.2% (ECOREA) of all eco-innovation in the manufacturing sector, according to Eurostat data (extracted 2/5/2017).

(ii) BGROUP, a dummy taking value 1 if the firm belongs to a business group; (iii) C_HO, a dummy taking value 1 if the headquarters of the business group is located in the same country of the firm (iv) MARLOC, MARNAT, MAREUR and MAROTH, dummy variables taking value 1 if the geographical market of the firm is respectively local, national, European or global (MARLOC is the reference dummy); (v) EURO, a dummy variable that takes value 1 if the country where the firm is located is within the Euro area; and (vi) ETS, a dummy variable that takes value 1 if a firm belongs to an industry under the European emissions trading system (ETS). We control for firm size and industry characteristics through the natural logarithm of a firm's sale in 2006 and a set of industry dummies at the two-digit level. Finally, in order to better control for country heterogeneity we include in our econometric specifications the natural logarithm of the country population and of per-capita real GDP. Both of these two variables, taken from the Penn World Table (version 9.0), refer to 2006 and account for country size and productive efficiency.

The dependent variables, which capture EI relevant for resource efficiency, are ECOMAT (environmental benefits from the production of goods or services within an enterprise, which is measured as reduced material use per unit of output), ECOREC (environmental benefits from the production of goods or services within the enterprise, utilising recycled waste, water, or materials) and ECOREA (environmental benefits from the after sales use of a good or service by the end user, measuring improved recycling of product after use). These three variables are adopted since they are closely linked to technological EI aimed at improving the performance of products and processes in a manner that is compatible with a CE transition. See Figure 4 for a sketch of the dependent variables at the EU level.

Figure 4 – Resource efficiency innovation adoption in the EU (CIS5 data) – share of firms[12]



The two main explanatory variables are related to "existing environmental regulations or taxes on pollution" (ENREG), to test hypothesis H_1, and "current or expected market demand from your customers for environmental innovations" (ENDEM), to test H_2. The descriptive statistics are reported in Table 1.

Table 1: Descriptive statistics

	Mean	Std. Dev.	Min	Max
ECOMAT	0.136	0.342	0	1
ECOREC	0.190	0.392	0	1
ECOREA	0.133	0.339	0	1
ENREG	0.168	0.374	0	1
ENDEM	0.096	0.295	0	1
RRDIN	0.160	0.367	0	1
BGROUP	0.246	0.431	0	1
MARNAT	0.655	0.475	0	1
MAREUR	0.381	0.485	0	1
MAROTH	0.197	0.397	0	1
C_HO	1.078	1.230	0	1
ETS	0.193	0.395	0	1
ln(SALE)	12.839	4.279	0	31.297

Two econometric problems may arise in estimating this model. First, there may be correlation at the firm level between each of the three EI variables and the propensity to introduce technological

[12] The three dependent variables appear to describe somewhat different innovations, although they are correlated. Correlations among the three are between 0.38-0.61. These correlations are statistically significant at the 1% level. All correlations for the set of independent variables are available on request. The correlations do not present very high values.

innovations (INNOVA). Second, there may be endogeneity for the two main explanatory variables (ENREG and ENDEM).

The first econometric problem is related to the decisions made by firms to introduce EI or/and a technological innovation (INNOVA): the latter is defined as the following: (i) new or significantly improved goods; (ii) new or significantly improved services; and (iii) new or significantly improved methods of manufacturing or producing goods and services. The two decisions about eco and technological innovations may be jointly determined. A way to test the potential correlation between INNOVA and the EI variables consists of estimating a bivariate probit model, and then computing a Wald test. In other words, the (potential) relatedness between these two decisions can be tested by analysing the correlation of the error terms of these two equations: one referring to the technological innovations and the other to the eco-innovations. Tables A.1, A.2 and A.3 report the (baseline) econometric estimates using a bivariate probit model, which allows us to account for this correlation for each of the three chosen EI variables. This test shows that the hypothesis of no correlation between these two innovation adoption variables cannot be rejected. This means that the phenomenon of eco-innovation adoption is correlated with the general propensity to innovate. In our case, adoption of eco-innovations seems to be a phenomenon that cannot be treated in isolation from INNOVA. This would imply the estimation of a two equations system: one for the technological innovation and the other for the eco-innovation. However, there is a quite important result in econometrics that shows that in Seemingly Unrelated Regressions (SUR) models, when all the equations have the same regressors (this is our case), the efficient estimator of this model is a simple OLS estimated equation by equation (Greene, 2011). In other words, we can estimate our (baseline) specification using a LPM without taking into account the correlation between the error terms of these two equations since they have the same regressors.

The second econometric problem is related with the potential endogeneity of the two main explanatory variables. The sources of endogeneity may be three: (i) omitted variables; (ii) measurement errors; and (iii) simultaneity (causalities go both ways). In our case, all these three sources of endogeneity may be at work. In particular, it is not obvious that causality directions go from environmental regulations and current or expected market demand to eco-innovations. If these two explanatory variables are endogenous, they can be correlated with the error term. Since estimated coefficients of endogenous variables are inconsistent and biased, we need to implement an Instrumental Variable (IV) approach.

To address the endogeneity of the explanatory variables we therefore estimate a Linear Probability Model with Instrumental Variables (IV-LPM, see Miguel et al. 2004). We instrument the two main explanatory variables (ENREG and ENDEM) with two different instruments: (i) the election participation (ELECTION) in each of the nine countries during the 1995-2000 period and (ii) the blood donations at the country level for the year 2009 (BLOOD). With regard to the second instrument, we use information at country level taken from the Eurobarometer survey commissioned by the European Commission on the following question: "Have you given blood before?" We use these two instruments since some papers show that political participation and blood donation are good proxies for social capital (Guiso *et al.*, 2004). Therefore, the idea behind this choice is that in countries where the social capital, measured by political participation and blood donation, is higher, the sensibility towards environmental policies and the demand for environmental innovations should be greater.

We recognise that other instruments may be used. In fact, we tested other instruments such as environmental, energy, and resource taxes and environmental protection expenditures. The main problems with these instruments is that they are correlated not only with the endogenous variables but also with the outcome variable. This is not surprising since there is a clear-cut relationship between these different types of environmental taxes and eco-innovations. The endogeneity of the main two explicatory variables is confirmed by some statistical tests. In fact, we tested the endogeneity of ENREG and ENDEM using the Wu-Hausman and the Durbin-Wu-Hausman tests. Both these tests confirm that ENREG and ENDEM are endogenous.[13] This means that we need to instrument these endogenous explanatory variables. In addition, for all the three estimates the first-stage F statistic on excluded instruments is larger than 10. As is known, this test allows us to reject the null hypotheses of weak instrumentation.

4. Empirical results

Tables 2-4 report the econometric evidence for the three dependent variables of the model. For each of these tables, column [1.] reports the probit estimates, column [2.] reports the dprobit estimates with the marginal effects, column [3.] reports the IV-LPM estimates excluding some explanatory variables and finally, column [4.] reports the IV-LPM estimates of our most complete econometric specification. Table 2 shows our findings for ECOMAT: environmental benefits from the production of goods or services within the enterprise and reduced material use per unit of output. It clearly emerges that the existing environmental regulations and/or fiscal duties on pollution (ENREG) significantly and positively explains the adoption of innovation by firms. H_1 is not rejected.

[13] The recent econometric literature suggests another estimator that can be used when the outcome variable is a dummy and the endogenous regressors are not continuous; this is the special regression method (SRM), first proposed by Lewbel (2000) and then implemented by Dong and Lewbel (2015). This approach assumes that the model includes a particular regressor, the special regressor V, with three properties: (a) it is exogenous and appears as an additive term in the model; (b) it is continuously distributed; and (c) it has a thick-tailed distribution, although this hypothesis is not strictly necessary. Unfortunately, in the dataset, we cannot find variables with these characteristics.

In addition, ENDEM is significant in explaining increases in EI related to reduced material use per unit of output; consequently, the testable hypothesis H_2 is not rejected. The other key factors behind innovation are in-house R&D (RRDIN) and countries belonging to the Euro area (EURO). Interestingly, other market-related factors do not appear to play a crucial role in driving eco-innovations; for example, belonging to a business group has a negative role. These results are robust also using the IV-LPM. The sign and statistical significance of coefficients associated with ENREG and ENDEM are confirmed. Therefore, the testable hypotheses cannot be rejected when focusing on resource and material saving EIs. In contrast, the control variables that refer to reference markets (as described by dummies MARNAT, MAREUR and MAROTH) are no longer significant when adopting an IV approach. It is worth noting that when an IV approach is adopted, the presence of R&D is no longer significant. Finally, firms that are part of the EU ETS seem to feature a larger likelihood of adopting eco-innovation related to material use. Climate regulation seems in this case to enhance more generally the environmental attitude of firms, suggesting complementarity between material savings and climate related EI.

Table 3 (first column) shows similar results for ECOREC (environmental benefits from the production of goods or services within the enterprise, recycled waste, water, or materials). This innovation refers to recycling strategies, the core of the first wave of waste policies in the EU. ENREG and ENDEM maintain their statistical significance and sign. The same holds with respect to R&D and belonging to a group. In contrast to the ECOMAT case, when addressing EIs related to recycling, the reference market can indeed make a difference; in the probit estimate (column 1 in Table 3), firms exporting in the European market are also characterised by a lower EI likelihood. Things change when we adopt an IV-LPM approach (second column in Table 3); ECOREC appears less relevantly related to the necessity of absorbing innovation by means of internal research and knowledge pools, and such an internal R&D effort becomes negative in explaining the presence of EI adoption. All dummies related to reference markets (national, European, other global-like markets) imply a decrease in EI oriented to recycling, which signals the relevance of localised markets. This implication highlights that at least in the first phase of the waste/material-related innovation adoption wave, local markets are dominant with respect to firm strategies (Cainelli *et al.*, 2015). This statement is coherent with the local public good flavour of waste externalities and the decentralised management of such environmental issues.

However, ENREG and ENDEM, the variables of interest, retain their sign and significantly explain adoption. In sum, external (policies and demand) phenomena are at play, while other internal (R&D) and market-related factors do not have a straightforward impact.

It is worth noting that while the negative (or not significant) sign related to in-house R&D is explainable by general R&D investments targeted to general innovations (firms with R&D, which are, on average, larger in size, tend to focus on general - i.e., not ecological - innovations), the literature on EI has seldom shown very robust and constant (across datasets and sectors) significant roles for R&D among the drivers or show correlated factors[14]. Among others, the seminal paper on eco-innovation drivers by Horbach (2008) places R&D in the supply side factors that enhance technological capabilities. For Germany, he finds significant R&D effects behind environmental product innovation adoption (German establishment survey), while in other empirical works (Mannheim Innovation Panel), R&D does not significantly explain the adoption of 'general' environmental innovations with medium/high effects on the health and environment. For Germany, Frondel *et al.* (2008) find that (environmentally oriented) R&D is not one of the 'facility characteristics' that explains the adoption of abatement technology. The presence of dedicated staff who manage environmental issues and the necessity of reducing environmental impacts are more relevant and significant factors. Cainelli *et al.* (2012) focus on a regional system; they also find certain negative and insignificant effects regarding the presence of R&D. The researchers note that 'R&D is far too a generic and weak innovation commitment to enhance the adoption of EIs. While it may be found significant in increasing the firm knowledge base and its absorptive capacity, other techno-organisational internal features are possibly required to complement better the adoption of EI' (p. 718). Finally, a more recent paper by Borghesi *et al.* (2015), in a study that analyses the effects of the EU emissions trading on energy and climate change innovations, finds very mixed evidence about the R&D significance. In certain cases, negative, although not significant, coefficients also arise. Overall, the researchers note that general R&D is relevant for enhancing the capacity to absorb and adopt innovation from the market. More radical innovations may need specific forms of R&D and/or specific cooperation with other firms or research institutions (Cassiman and Veugelers, 2002).

Given that resource use, material use and waste are largely environmental public goods with local effects and decentralised territorial management and policy governance, the unexpected relevance of international effects is not surprising (the questions refer to 'within your enterprise' innovation benefits). In relation to resource and waste management, firms generally fail to internalise impacts that are far from their boundaries. ECOREC and ECOMAT present expected and similar results; both recycling and material use refer to consolidated resource efficiency firms' strategies that were previously pushed ahead in the mid-1990s.

[14] The overall evidence could be driven by the specific set of countries defined based on CIS data availability for EI. Further investigations can be performed on a sub-sample of countries (e.g., main countries in terms of GDP per capita and R&D, laggard countries) to verify the eventual heterogeneity in the R&D-EI adoption link.

Table 4 reports our findings for ECOREA: environmental benefits from the after-sales use of a good or service by the end user, *improved the recycling of the product after use*. It is worth noting that H_1 and H_2 are again not rejected using this EI proxy. This finding holds both in the standard probit (column 1) as well as in the IV-LPM model (columns 3 and 4) estimates. Consequently, the role of regulation and of market demand is robust to endogeneity issues. The result that demand matters is not surprising, given that ECOREA is the type of EI we scrutinise that is closer to the consumers' level. The puzzling evidence stemming from empirical analysis in the ECOREC case is confirmed here both with respect to R&D and to the reference market. Lastly, both when dealing with ECOREC and ECOREA, the impact of being part of the EU ETS maintains its sign only if endogeneity issues are not approached properly. In a IV-LPM model, firms that are subject to the EU ETS are less likely to adopt EI related to recycling inside the firm or to improved recycling after use. This confirms the puzzling impacts of the EU ETS on eco-innovation. A possible explanation for this conclusion can be linked to substitutability between climate and recycling related eco-innovation.

A concluding comment is necessary for the relative impact of the main explanatory variables on the three selected EI dimensions under scrutiny. From Tables 2 to 4 it is clear that recycling-related innovation (ECOREC and ECOREA) is more strongly affected by regulation than resource efficiency. Reduction of material use is therefore more difficult to target with policy. A possible explanation can be related to the focus of policies, that only recently are turning (for example) to waste minimisation.

Table 2: Determinants of EI

Dependent variable	ECOMAT			
Estimation method	PROBIT	DPROBIT	IV-LPM	IV-LPM
	Coeff.	Marginal Effects		
	[1.]	[2.]	[3.]	[4.]
ENREG	0.806***	0.223***	0.529***	0.403***
	[0.018]	[0.005]	[0.057]	[0.054]
ENDEM	0.676***	0.192***	0.816***	0.967***
	[0.021]	[0.007]	[0.101]	[0.149]
RRDIX	0.560***	0.148***	0.008	0.004
	[0.018]	[0.005]	[0.019]	[0.028]
BGROUP	-0.080***	-0.018***	-0.051***	-0.055***
	[0.017]	[0.003]	[0.006]	[0.008]
MARNAT	0.075***	0.016***	-0.004	-0.007
	[0.018]	[0.004]	[0.004]	[0.005]
MAREUR	0.051***	0.011***	-0.005	-0.001
	[0.018]	[0.004]	[0.005]	[0.005]
MAROTH	0.084***	0.019***	-0.019***	-0.019*
	[0.020]	[0.004]	[0.008]	[0.01]
C_HO	0.041***	0.009***	0.019***	0.016***
	[0.007]	[0.001]	[0.001]	[0.002]
EURO	0.182***	0.041***	0.057***	0.034***
	[0.018]	[0.004]	[0.006]	[0.006]
ln(SALE)	0.028***	0.006***	0.002***	0.002*
	[0.002]	[0.0004]	[0.0008]	[0.001]
ETS	0.182***	0.043***	…	0.018**
	[0.018]	[0.004]		[0.007]
ln(POP)	0.071***	0.016***	…	0.007***
	[0.008]	[0.001]		[0.002]
ln(GDPP)	-0.131***	-0.029***	…	0.028***
	[0.024]	[0.005]		[0.010]
Industry dummy	Yes	Yes	Yes	Yes
N. Obs.	46,429	46,429	46,429	46,429
Pseudo R2	0.226	0.226	…	…
First-stage F statistics on excluded instruments	…	…		
ENREG			190.4	217.8
ENDEM			89.1	41.3
Wu-Hausman F test (p-value)	…	…	0.000	0.000
Durbin-Wu-Hausman test (p-value)	…	…	0.000	0.000

*** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are clustered at the firm level. Instruments= BLOOD, ELECTION.

Table 3: Determinants of EI

Dependent variable	ECOREC			
Estimation method	PROBIT	DPROBIT	IV-LPM	IV-LPM
	Coeff.	Marginal Effects		
	[1.]	[2.]	[3.]	[4.]
ENREG	1.147***	0.386***	2.324***	1.971***
	[0.017]	[0.006]	[0.132]	[0.154]
ENDEM	0.629***	0.208***	1.168***	2.788***
	[0.022]	[0.008]	[0.232]	[0.420]
RRDIX	0.352***	0.107***	-0.400***	-0.610***
	[0.018]	[0.006]	[0.042]	[0.076]
BGROUP	-0.025	-0.007	-0.128***	-0.197***
	[0.016]	[0.004]	[0.013]	[0.022]
MARNAT	0.043***	0.012***	-0.045***	-0.076***
	[0.017]	[0.004]	[0.012]	[0.017]
MAREUR	-0.021	-0.006	-0.062***	-0.062***
	[0.018]	[0.005]	[0.012]	[0.015]
MAROTH	0.116***	0.033***	-0.130***	-0.181***
	[0.019]	[0.005]	[0.018]	[0.027]
C_HO	-0.046***	-0.013***	0.018***	0.027***
	[0.007]	[0.002]	[0.004]	[0.006]
EURO	0.289***	0.082***	0.244***	0.137***
	[0.017]	[0.004]	[0.015]	[0.019]
ln(SALE)	0.023***	0.006***	-0.009***	-0.015***
	[0.002]	[0.0003]	[0.001]	[0.002]
ETS	0.227***	0.067***	…	-0.108***
	[0.018]	[0.005]		[0.021]
ln(POP)	0.124***	0.035***	…	-0.002
	[0.007]	[0.002]		[0.007]
ln(GDPP)	0.011	0.003	…	0.233***
	[0.023]	[0.006]		[0.031]
Industry dummy	Yes	Yes	Yes	Yes
N. Obs.	46,429	46,429	46,429	46,429
Pseudo R2	0.245	0.245	…	…
First-stage F statistics on excluded instruments	…	…		
ENREG			190.4	217.8
ENDEM			89.1	41.3
Wu-Hausman F test (p-value)	…	…	0.000	0.000
Durbin-Wu-Hausman test (p-value)	…	…	0.000	0.000

*** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are clustered at the firm level. Instruments=BLOOD, ELECTION.

Table 4: Determinants of EI

Dependent variable	ECOREA			
Estimation method	Probit	dProbit	IV-LPM	IV-LPM
	COEF.	MARGINAL EFFECTS		
	[1.]	[2.]	[3.]	[4.]
ENREG	0.935***	0.242***	1.801***	1.491***
	[0.018]	[0.005]	[0.098]	[0.104]
ENDEM	0.772***	0.205***	0.601***	1.702***
	[0.021]	[0.007]	[0.172]	[0.285]
RRDIX	0.288***	0.063***	-0.269***	-0.401***
	[0.019]	[0.004]	[0.031]	[0.052]
BGROUP	-0.039***	-0.007***	-0.091***	-0.137***
	[0.018]	[0.003]	[0.010]	[0.015]
MARNAT	0.060***	0.018***	-0.027***	-0.046***
	[0.019]	[0.003]	[0.008]	[0.011]
MAREUR	-0.032	-0.006	-0.051***	-0.045***
	[0.020]	[0.003]	[0.008]	[0.010]
MAROTH	0.004	0.0009	-0.110***	-0.140***
	[0.021]	[0.004]	[0.013]	[0.018]
C_HO	-0.067***	-0.013***	0.012***	0.014***
	[0.007]	[0.001]	[0.003]	[0.004]
EURO	0.265***	0.059***	0.195***	0.114***
	[0.019]	[0.003]	[0.011]	[0.013]
ln(SALE)	0.0009	0.0001	-0.011***	-0.014***
	[0.002]	[0.0004]	[0.001]	[0.001]
ETS	0.093***	0.019***	…	-0.101***
	[0.020]	[0.004]		[0.014]
ln(POP)	0.149***	0.029***	…	0.006
	[0.008]	[0.001]		[0.005]
ln(GDPP)	0.057***	0.011***	…	0.159***
	[0.027]	[0.005]		[0.021]
Industry dummy	Yes	Yes	Yes	Yes
N. Obs.	46,429	46,429	46,429	46,429
Pseudo R2	0.219	0.219	…	…
First-stage F statistics on excluded instruments	…	…		
ENREG			190.4	217.8
ENDEM			89.1	41.3
Wu-Hausman F test (p-value)	…	…	0.000	0.000
Durbin-Wu-Hausman test (p-value)	…	…	0.000	0.000

*** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are clustered at the firm level. Instruments= BLOOD, ELECTION.

5. Concluding remarks

The dynamics of CE-related innovation imply a slow techno-economic transformative process; it is possibly more a 'reform' than a 'revolution', passing through the adoption of both incremental and radical innovations. The main aim of this paper was to assess the role played by two key drivers of clean technology adoption in relation to the CE, policies/regulations and market demand. We conducted this analysis by adopting econometric techniques that allowed us to account for endogeneity that plagues survey cross-section data, usually leading to biased estimates. Our main results confirm the relevance of environmental policies and current and expected demand in driving EI in the form of adoption. This result is robust across the different EI indicators we adopted, although they show different strengths; product-related innovation related to recycling and organisational innovations related to the after-use are suggested to be more strongly affected by policy. A somewhat surprising result, which appears to depart from several existing contributions, relates to the insignificant to negative role played by R&D and market-related factors that are detached from direct 'demand influences', for instance, the wideness of reference markets (i.e., local, national, European or global). Indeed, when endogeneity is properly approached, market factors and R&D turn insignificant when focusing on resource efficiency innovation adoption inside the firm, while their impact is even negative when focusing on organisational innovation related to ease of recycling after product use and to recycling inside the firm. Overall, the failure of firms to internalize benefits from technology adoption may help in explaining the impacts of market related factors, while the effects of internal R&D contribute to a puzzling body of evidence in the literature.

The CE business windows that pass through the adoption of various environmental innovations are dependent on the policy platform. This policy platform's construction has evolved through the history of waste policies, from the first EU Packaging Directive in 1994 to the End of Life Vehicles Directive in the late nineties and the WEEE Directive. Important stimulus was also provided by the Landfill Directive in 1999. Finally, the 2008 Waste Framework Directive constituted the last item before the definition of the CE strategy; this extends the scope of the reasoning, adding a strong orientation towards innovations and business opportunities, departing from the core waste prevention objective, which implicitly stimulates better designs, resource efficiency, recycling, re-use, and new forms of organising production and consumption.

The relevance of policies shows that, on the one hand, the environmental benefits (mixed public goods such as resource efficiency *in primis* and energy savings) are clear and possibly broad; on the other hand, the (net) economic benefits for firms and sectors depend on how the CE transition occurs. In other words, public policies remain crucial in driving the EU towards a full CE implementation.

Future research should attempt to improve the current quality of data collection around EI with more specific information on types of EI. More disaggregated geographical datasets and mergers with balance sheets and other *meso* indicators are original pathways to understand the drivers and effects of EI in the resource efficiency / waste realm. The efforts will give more robust empirical results to the analysis of the CE transition.

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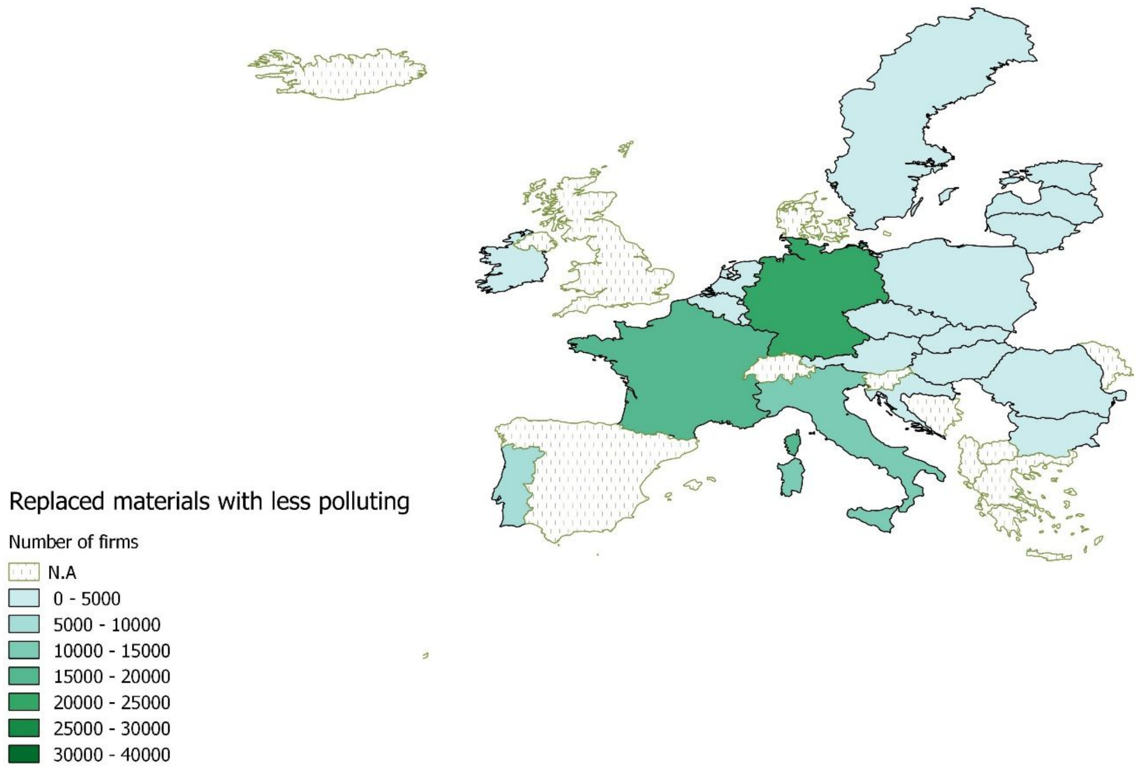
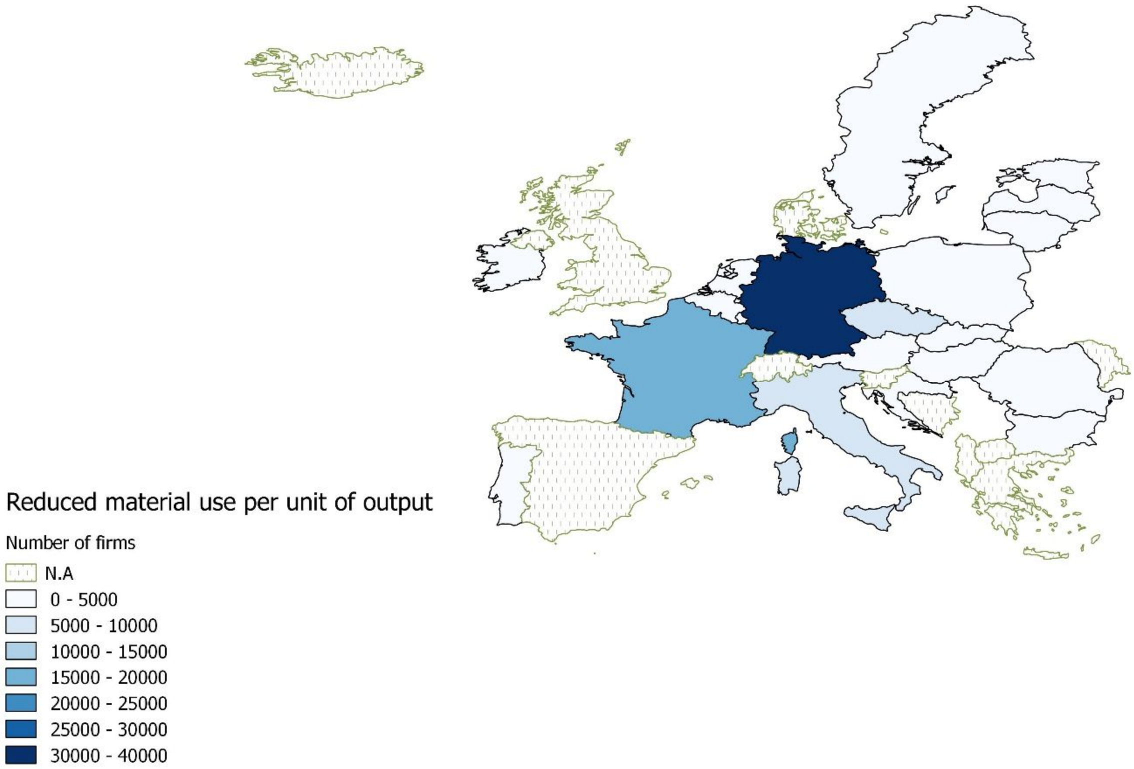
Appendix

Figure A1 – Number of firms adopting CE-oriented eco-innovations in the EU




Reduced material use per unit of output
Number of firms
N.A
0 - 5000
5000 - 10000
10000 - 15000
15000 - 20000
20000 - 25000
25000 - 30000
30000 - 40000

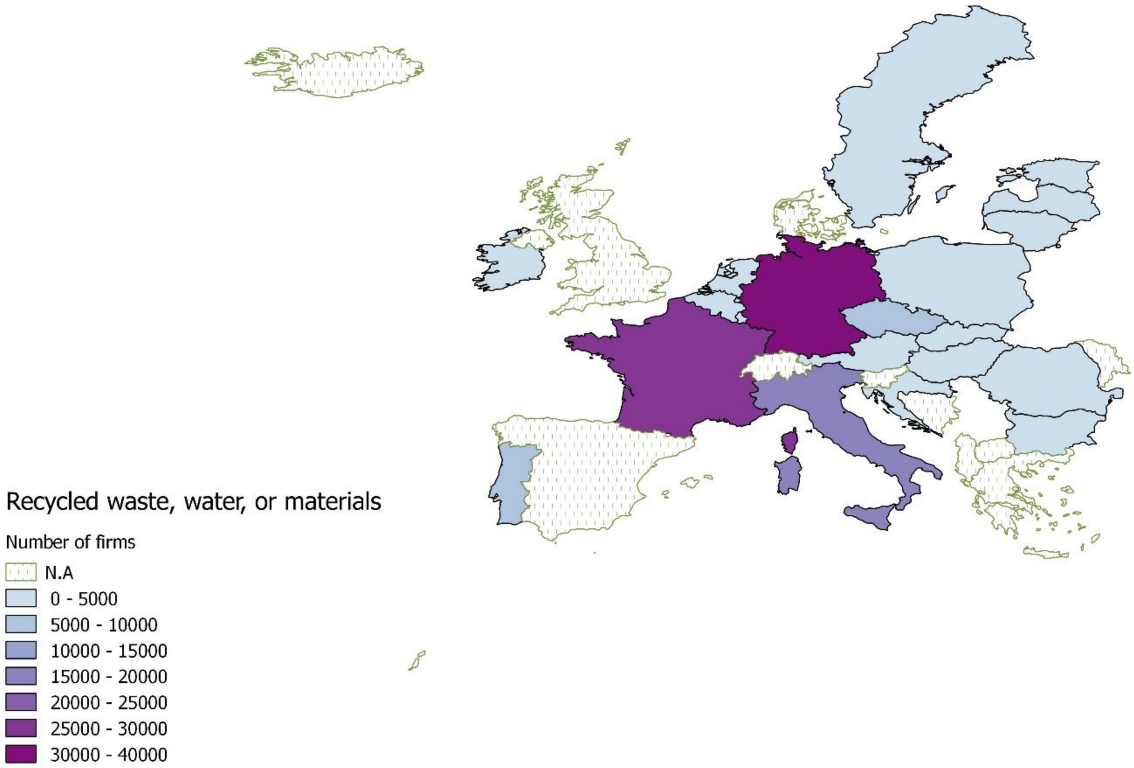

Recycled waste, water, or materials
Number of firms
N.A
0 - 5000
5000 - 10000
10000 - 15000
15000 - 20000
20000 - 25000
25000 - 30000
30000 - 40000

Table A.1: Bivariate probit estimates

Dependent variables	ECOMAT	INNOVA
	[1.]	[2.]
ENREG	0.813***	0.598***
	[0.017]	[0.018]
ENDEM	0.676***	0.429***
	[0.021]	[0.024]
RRDIX	0.574***	1.627***
	[0.018]	[0.019]
BGROUP	-0.078***	0.095***
	[0.017]	[0.016]
MARNAT	0.075***	0.196***
	[0.018]	[0.017]
MAREUR	0.053***	0.081***
	[0.018]	[0.017]
MAROTH	0.075***	0.190***
	[0.020]	[0.019]
C_HO	0.041***	0.074***
	[0.007]	[0.007]
EURO	0.184***	0.356***
	[0.018]	[0.017]
ln(SALE)	0.028***	-0.008***
	[0.002]	[0.002]
ETS	0.183***	0.048***
	[0.018]	[0.018]
ln(POP)	0.075***	-0.112***
	[0.008]	[0.007]
ln(GDPP)	-0.128***	-0.066***
	[0.024]	[0.023]
Industry dummy	Yes	Yes
N. Obs.	46,429	
Wald test (p-value)	0.000	

*** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are clustered at the firm level.

Table A.2: Bivariate probit estimates

Dependent variables	ECOREC	INNOVA
	[1.]	[2.]
ENREG	1.148***	0.603***
	[0.017]	[0.018]
ENDEM	0.628***	0.431***
	[0.021]	[0.024]
RRDIX	0.362***	1.631***
	[0.182]	[0.019]
BGROUP	-0.022	0.096***
	[0.016]	[0.016]
MARNAT	0.043**	0.195***
	[0.017]	[0.017]
MAREUR	-0.019	0.080***
	[0.018]	[0.017]
MAROTH	0.110***	0.191***
	[0.019]	[0.019]
C_HO	-0.047***	0.075***
	[0.007]	[0.007]
EURO	0.287***	0.358***
	[0.017]	[0.017]
ln(SALE)	0.023***	-0.009***
	[0.002]	[0.002]
ETS	0.227***	0.052***
	[0.018]	[0.052]
ln(POP)	0.126***	-0.113***
	[0.007]	[0.007]
ln(GDPP)	0.011	-0.067***
	[0.023]	[0.023]
Industry dummy	Yes	Yes
N. Obs.	46,429	
Wald test (p-value)	0.000	

*** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are clustered at the firm level.

Table A.3: Bivariate probit estimates

Dependent variables	ECOREA	INNOVA
	[1.]	[2.]
ENREG	0.942***	0.603***
	[0.018]	[0.019]
ENDEM	0.773***	0.432***
	[0.021]	[0.024]
RRDIX	0.297***	1.633***
	[0.019]	[0.019]
BGROUP	-0.038***	0.095***
	[0.018]	[0.016]
MARNAT	0.061***	0.196***
	[0.019]	[0.017]
MAREUR	-0.029	0.081***
	[0.020]	[0.017]
MAROTH	0.001	0.193***
	[0.021]	[0.019]
C_HO	-0.067***	0.075***
	[0.007]	[0.007]
EURO	0.264***	0.356***
	[0.019]	[0.017]
ln(SALE)	0.0006	-0.009***
	[0.002]	[0.002]
ETS	0.092***	0.356***
	[0.024]	[0.017]
ln(POP)	0.151***	-0.113***
	[0.008]	[0.007]
ln(GDPP)	0.058***	-0.067***
	[0.026]	[0.023]
Industry dummy	Yes	Yes
N. Obs.	46,429	
Wald test (p-value)	0.000	

*** significant at the 1% level; ** significant at the 5% level; * significant at the 10% level. Standard errors are clustered at the firm level.