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Does economic growth matter?

Technology-push, demand-pull and endogenous drivers of innovation in the renewable energy industry

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Abstract

This paper aims to contribute to the longstanding technology-push vs. demand-pull debate and to the literature on renewable energy policy assessment. We argue that in addition to the traditional push–pull dichotomy, the drivers of technological change must be differentiated by whether they are exogenous or endogenous to the economic system and must be assessed with respect to their contribution to both the creation and the diffusion of innovation. We apply this perspective to study innovation in the renewable energy (RE) industry in 15 European Union countries from 1990 to 2012. Using different panel data estimators, we find that public R&D investments, policies supporting RE and per capita income all have a positive effect on either innovation creation or diffusion, whereas the variability of policy support has a negative impact on diffusion. However, impacts are heterogeneous and differ depending on the innovation dimension considered. Most importantly, we find that economic growth is a stronger driver of RE diffusion than technology-push or exogenous demand-pull mechanisms, whereas it is relatively ineffective at stimulating innovation creation. The effect of economic growth on RE diffusion exhibits a nonlinear, U-shaped pattern that resonates with the Environmental Kuznets Curve hypothesis. RE penetration remains negligible at low levels of growth whereas it increases sharply only after income per capita has reached a given threshold. This effect has both a direct cause (with increased affluence demand for environmental quality rises) and an indirect cause (with increased affluence expensive RE policies become more affordable and get implemented more extensively). Our findings have implications for policy making. They suggest that for RE diffusion to increase, innovation policies should be carefully balanced. Government action should be directed not only at shielding renewables from competition with fossil fuel technologies, but also at stimulating aggregated demand and economic growth.

Keywords: Deployment policy, Technological innovation, Renewable Energy, Environmental Kuznets Curve, Nonstationary Panel.

JEL classifications: O31, O33, O38, O44, C23

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1. Introduction

The debate about technology-push and demand-pull mechanisms in supporting innovation has dominated the academic arena for at least two decades and continues to attract the interest of economists, management scholars, and industry practitioners alike (Di Stefano et al., 2012). The academic literature has dedicated a considerable amount of attention to studying the relative contribution of these mechanisms to technological progress, alternatively championing one view or the other or arguing that for innovation to occur both push and pull must exist simultaneously (Mowery and Rosenberg, 1979; Johnstone et al., 2010; Zachmann et al., 2014). Besides its relevance for the corporate world, the dichotomy between push and pull has important policy making implications (Rennings, 2000), particularly when government action aims to stimulate technologies that produce environmental benefits, such as renewable energies (Del Rio Gonzàlez, 2009).

However, despite the burgeoning literature on the topic, several important aspects of this debate remain unclear, especially since when it was reignited by the need to support low carbon technologies. Firstly, the literature that examined the impact of innovation support mechanisms addressed different outcomes of the innovation process separately. An important stream of research focused on the impact of support mechanisms on innovation *creation*, typically looking at knowledge exploration activities that result in new patents (e.g. Hoppman et al., 2013; Nemet, 2009). A parallel stream, particularly common in the field of energy policy assessment, focused instead on innovation *diffusion*, examining the impact of various support instruments on the deployment technologies that are already commercially available (i.e. it focused on exploitation activities) (e.g. Jäger-Waldau, 2007; Marques and Fuinhas, 2012). Although distinct, these two facets of the innovation process are also related and should ideally be examined jointly. In the case of renewable energies, for instance, technological innovations produce environmental benefits (i.e. CO_2 emissions reduction) only if they are actually adopted by end users.

Second, research has somehow neglected the question of whether mechanisms to support innovation are more effective when they are exogenously induced (e.g. through the deployment of dedicated public policies) or when they emerge spontaneously as a result of endogenous changes in the economic system (e.g. as a result of economic growth). The distinction is particularly relevant for demand-pull mechanisms. Such mechanisms have often been studied in the context of public policies that exogenously create demand for environmental technologies. Conversely, they have seldom been examined in relation to endogenous drivers of innovation such as economic growth. Thus, several aspects of the relationship between exogenous and endogenous drivers of innovation remain poorly understood. For instance, it is still unclear whether economic growth stimulates innovation directly or only indirectly by creating the necessary conditions for the deployment of exogenous policies.

This dichotomy between technology-push and demand-pull, between exogenous and endogenous drivers of innovation and between innovation creation and innovation diffusion assumes particular relevance for renewable energy (RE) sources. Despite the environmental and social benefits these technologies can generate (IEA, 2011; IPCC 2011), their diffusion remains below the level deemed necessary to curb CO_2 emissions (IEA, 2013). Thus the question of whether and how public policies can foster technological progress and accelerate the market diffusion of renewables assumes particular relevance (Mowery et al., 2010). Advanced economies such as the United States (US) and the European Union (EU) have deployed a range of dedicated policies supporting renewables[5], either by directly funding R&D to foster technological breakthroughs or by implementing demand-pull policies that create niche markets where RE sources are shielded from direct competition with fossil fuel technologies (IEA, 2011). The heterogeneity of these policies somewhat reflects the polarization that the push-pull and the exploration-exploitation debates have assumed in academic circles. Their mixed results also reflect a research gap, which is symptomatic of an incomplete understanding of the effect of the mechanisms supporting innovation creation and diffusion, at least in the renewable energy context.

To address this research gap, in this paper we analyze in a comprehensive fashion the relative contribution of three mechanisms supporting both the development and the diffusion of innovations in the renewable energy sector: public R&D investments (i.e. a pure technology-push mechanism), renewable energy support policies (i.e. an exogenous demand-pull mechanism), and economic growth (i.e. an endogenous demand-pull mechanism). Contrary to most of the extant literature that examined the two dimensions separately, we analyze the impact of these mechanisms on both innovation *creation* and innovation *diffusion* (i.e. on both exploration and exploitation activities). Furthermore, we also clarify the complex nexus between economic growth, public policies, and RE deployment, unveiling the cause effect-relationship between endogenous and exogenous drivers of innovation. Using data on the RE industry in 15 European countries from 1990 to 2012, we apply panel data models to estimate the impact of these support mechanisms on RE patents (a measure of innovation creation reflecting exploration) and the share of RE in the total electricity mix (a measure of innovation diffusion reflecting exploitation).

The analysis generates several interesting results and provides further empirical support to the idea that innovation policies should be carefully balanced. First, we note that all of the support mechanisms analyzed (endogenous, exogenous, technology-push, and demand-pull) have a positive effect on either innovation creation or diffusion (or both). This is consistent with previous research arguing that the effectiveness of RE policy support is maximized when different instruments are deployed together (Johnstone et al., 2010; Grubb et al. 2014; Guerzoni and Raiteri, 2014). However, impacts are not

[5] According to REN21 (2010), the number of countries with some kind of RE target and/or deployment policy almost doubled from an estimated 55 in early 2005 to more than 100 in early 2010. Most RE policies are directed to the electricity sector.

homogeneous across different mechanisms and also differ depending on the innovation dimension considered (creation vs. diffusion). Technology-push mechanisms have a stronger and more immediate impact on innovation creation than diffusion (the impact on diffusion becomes visible only a few years after R&D investments are deployed), signalling that public R&D expenditures may be needed to facilitate technological breakthroughs, but they are less effective in supporting short term RE deployment. Exogenous demand-pull policies also have a stronger positive impact on innovation creation than diffusion. However, their contribution becomes less important after controlling for economic growth. We also find that the variability of support mechanisms has a negative impact on innovation diffusion but not on innovation creation (i.e. it hurts exploitation but not exploration).

Second, our results indicate that economic growth is a much stronger driver of innovation diffusion than technology-push or exogenous policy-driven demand-pull mechanisms, whereas it is relatively ineffective at stimulating innovation creation. Most importantly, we note that the contribution of economic growth to renewable energy diffusion becomes important only beyond a minimum level of affluence. We thus argue for the existence of a RE version of the Environmental Kuznets Curve (Grossman and Krueger, 1995), and we predict a convex-increasing relationship between income per capita and RE share: demand for environmentally friendly energy technologies starts emerging only after the population has reached a minimum level of wealth. However, such demand is satisfied through the exploitation of commercially available technologies and it does not produce any significant effect on the exploration of new technologies. The paper further clarifies this complex nexus between economic growth, RE support policies and renewable energy deployment. Although it suggests that economic growth has both a direct and an indirect effect on RE diffusion, through its impact on RE policies, it also indicates that the direct effect is largely predominant over the indirect effect (80% vs 20%).

Finally, we also note that both the direction and the magnitude of the estimated impacts are dependent on the choice of the correct panel data estimator, which must take into account both cross-sectional dependence (CSD) and nonstationarity dimensions of the underlying data generating process.

Besides contributing to the innovation management literature, this paper complements and extends recent studies that examined the impact of renewable energy policies. By focusing on both exploration and exploitation mechanisms, and by explicitly taking into account the role of economic growth our study provides a more comprehensive assessments of the different drivers of innovation in the RE sector and it further clarifies how such drivers may contribute to the development of renewables.

The reminder of this paper is organized as follows. Section 2 reviews the relevant literature. In session 3 we derive testable hypotheses. Section 4 describes the data and the econometric methods used to estimate the empirical models. Section 5 and section 6 present and discuss the main empirical results. Section 7 concludes the paper. Additional methodological details are reported in the Appendix.

2. Literature review

Our work is related to two related streams of literature: the literature on the mechanisms to support innovation and the literature on environmental policy and renewable energy policy assessment.

A taxonomy of innovation support mechanisms

The question of how best to support innovation enjoys a long history in the management literature. For the purposes of this paper, innovation support mechanisms can be classified based on the type of process they activate (technology-push vs. demand-pull), their locus (exogenous vs. endogenous), and they can be examined with respect to the innovation outcome they produce (creation of innovations vs. diffusion of innovations). Although related, the literature has mostly addressed these aspects independently of one another and has not yet reached a consensus over which mechanism is most effective in supporting innovation.

The technology-push demand-pull dichotomy is probably the one most widely studied. Although more recent contributions recognized they are both necessary to support innovation (Johnstone et al., 2010; Zachmann et al., 2014), the two mechanisms were initially conceptualized as mutually exclusive. At the core of the technology-push argument is the idea that the rate and direction of innovation is triggered by the supply side, i.e., by advances in science and technology supported by research and development (R&D) investments (Meyers and Marquis, 1969; Dosi, 1982). By contrast, the demand-pull hypothesis argued that technological change is induced by anticipated changes in market demand, which incentivize research in new directions (Schmookler, 1966).

Both perspectives have been used to justify the implementation of public policies that *exogenously* support innovation. The technology-push view was used to justify the deployment of supply-side policies to foster breakthroughs in certain strategic industries. By the same token, the demand-pull perspective is the theoretical backbone for exogenous policies that enhance the relative competitiveness of emerging technologies vis-à-vis established alternatives in certain niche markets. In such niches, new technologies can be shielded from direct competition (e.g. Kemp et al., 1998) and can therefore more easily attract investments and benefit from economies of scale (Nemet, 2009).

The effectiveness of supply-side technology-push policies has been recently questioned, after noticing that when controlling for the interaction with other policies, supply-side subsidies cease to be as effective as reported in previous studies (Guerzoni and Raiteri, 2014). The use of exogenous mechanisms to stimulate demand was also criticized, and for various reasons, reflecting a contrast between exogenous and endogenous drivers of innovation. First, exogenous policies may not be well suited to fostering breakthrough innovations because they lead firms to prefer exploitation over exploration (Nemet, 2009). This eventually generates lock-in effects and reduces technological diversity in the industry (Malerba, 2009). Since "technological search under a lock-in situation becomes highly localized and incremental in nature, this precludes the development and diffusion of radically different, economically or ecologically superior technological alternatives" (Hoppmann et al., 2013: p. 990). In essence, exogenous policies may favor incremental innovations, but they may not necessarily support the exploration of technological breakthrough. Second, to be effective, deployment policies need to remain stable over many years; as niche markets that rely heavily on direct subsidies do not produce enough incentives to innovate. Once subsidies are removed, new technologies face even greater gaps with their competitors and may be abandoned. Finally, the implementation of deployment policies often requires governments to pick winners in advance (i.e., at a very early development stage). This increases the risk that they "bet on the wrong horse", creating protected market niches for technologies that, although initially promising, may eventually prove inferior in the long run (Sartorius, 2005; van den Heuvel and van den Bergh, 2009).

An alternative view argues that demand-pull mechanisms are most effective when they are *endogenously* driven, i.e., when investments in emerging technologies are triggered by endogenous changes in aggregated demand. When the economy grows, new unsatisfied needs emerge and attract investments independently of support policies, eventually triggering a technology-push cycle. Firms use expected demand to orient their manufacturing efforts. In turn, experience and learning-by-doing, which cannot completely be substituted for by R&D investments, generate improvements and increase the competiveness of new technologies (see Nemet (2009) for a review of the main arguments supporting this perspective). Unsurprisingly, advocates of this perspective challenge the effectiveness of exogenous mechanisms and contend that policies to promote technological change should be directed at stimulating economic growth rather than at shielding innovation from competition. Such strategies also eliminate the problem of picking winners: when innovation is triggered by endogenous growth, markets will naturally select the technologies best suited to respond to expected needs, guiding innovation trajectories to the most appropriate targets (Dosi, 1982).

Innovation support mechanisms for environmental technologies

The debate over these alternative mechanisms to support innovation was reignited by the recent attempts to promote technologies that produce environmental or social benefits, such as renewable energies. The dichotomy between exogenous and endogenous mechanisms has especially been the focus of the broader stream of research that addresses the link between environmental policy and technological change[6]. The crux of this theoretical debate is whether environmentally-friendly innovation is more effectively induced by market-based policies, such as tradable permits or by command-and-control

[6] See Popp et al. (2010) for an excellent survey of the literature and Baumol and Oates (1998) for a rigorous and comprehensive analysis of the economic theory of environmental policy.

policies such as performance- or technology-based standards. The market-based policy argument maintains that, whereas the command-and-control regulations allow relatively little flexibility in the choice of technologies or inputs to the production process, market-based instruments can provide powerful incentives for companies to adopt cheaper and better pollution-control technologies (Hahn and Stavins, 1992; Popp et al., 2010). Conversely, in a seminal contribution, Porter and van der Linde (1995) showed how in practice some of the loss of competitiveness related to command-and-control environmental regulations is compensated by an increase in innovation driven by the policy itself, an argument that found further support in recent empirical work on policy-induced environmental innovations (Mazzanti et al., 2014) and their consequences for export flow dynamics (Costantini and Mazzanti, 2012). The debate is further enriched by the fact that different policies affect different innovation dimensions. In the US, innovation became cheaper and more effective in reducing sulfur dioxide emissions after tradable permits were introduced in 1990. However, the level of innovation, measured by the number of successful patent applications, was actually higher in the command-and-control environment that preceded the introduction of market-based mechanisms (Popp et al., 2003).

A subset of the above research focused explicitly on mechanisms to support renewable energy technologies. When applied to the RE sector, the push-pull exogenous-endogenous conceptualization produces the taxonomy shown in Figure 1.[7] Even within the more limited domain of energy technologies, there is no consensus (yet) on which of the two mechanisms (push vs. pull) and which of the two loci (endogenous vs exogenous) are the most effective to support innovation.

Figure 1 about here

In the RE context, technology-push and demand-pull mechanisms have been primarily studied in relation to *exogenous* policies that support low-carbon innovations[8]. Following the large number of different RE policies deployed in several countries over the past decade, an emerging body of empirical literature has started examining the effectiveness of these policies and the support mechanisms underlying them (Jäger-Waldau, 2007; Fouquet and Johansson, 2008; Masini and Menichetti, 2012; Marques and Fuinhas, 2012) as well as the determinants of RE policy choices (Schaffer and Bernauer, 2014). This literature is too vast to be summarized here (see Table 1 for a succinct taxonomy)[9]. Suffice here to note that it produced mixed findings, suggesting that the relationship between RE support policies and RE

[7] In this paper, we are especially interested in analyzing the impact of innovation mechanisms that can be activated, either directly or indirectly, through policy instruments. Thus we will not discuss endogenous technology-push mechanisms (i.e. corporate R&D investments), as they are clearly outside the scope of our study.

[8] Interestingly, the push and pull mechanisms discussed in the innovation management literature resonate well with two of the environmental policy pillars proposed by Grubb et al. (2014): pricing and markets (a demand-pull mechanism) and strategic investments in technological innovation (a clear push mechanism aimed at supporting R&D).

[9] See Basher et al. (2015) for a more comprehensive review of this literature.

diffusion remains, at best, elusive and heavily context-dependent. For instance, Johnstone et al. (2010) find that quantity-based policies (e.g. TGCs) favored the development of wind energy, whereas direct investment incentives such as FITs are deemed effective in supporting innovation in solar and waste-to-energy technologies. Conversely, Borghesi et al. (2015) provided less clear-cut evidence on the effects of environmental policies to promote the development of cleaner energy technologies. While confirming the importance of well-designed, long-term and time-consistent policies, they also noted that the impact of certain schemes such as the EU-ETS is dependent on several sector-specific factors.

The impact of innovation support mechanisms has also been examined with respect to cross-border and cross-sector spillovers, i.e. whether policy implemented in a given jurisdiction or aimed at promoting the growth of a specific industry produce second-order effects in other jurisdictions or sectors. Peters et al. (2012) note that while both domestic and foreign demand-pull policies trigger innovation in a given country, there is no evidence that domestic technology-push policies foster innovative output outside of national borders (an argument often used by the opponents of such policies). They also detect no indication that market growth induced by domestic demand-pull policies leads to more national innovative output than market growth induced by foreign demand-pull policies. Consequently, they suggest that demand-pull policies create significant country-level innovation spillovers, which could eliminate incentives to national policymakers for stimulating domestic market creation. The related problem of cross-sector spillovers was addressed by Corradini et al. (2014), which found that policies that oblige companies to abate emissions in a given sector may trigger R&D investments in other sectors, thereby creating joint private and public benefits.

Though distinguished, most of these studies addressed only certain support mechanisms and examined their impact on one specific outcome of the innovation process (either creation or diffusion). For instance, recent studies that focused on RE capacity deployment (e.g. Polzin et al., 2015) neglected the dichotomy between exploration and exploitation and disregarded the role of other important elements such as economic growth and the impact of policy variability. By the same token, other studies such as Nesta et al. (2014) that examined the impact of regulation and market structure on innovation creation (i.e. the generation of RE patents) did not consider the consequences of these factors for RE capacity deployment. Similarly, other recent contributions that examined both innovation creation and diffusion, limited their analysis to some specific RE technologies only. For instance, focusing on exogenous support mechanisms in the biofuels sector, Constantini et al. (2015) show that both demand-pull and technology-push factors are important drivers of innovation. They also note that technology exploitation activities in first generation technologies are mainly driven by demand pull policies (both quantity and price-based), whereas technology exploration efforts in advanced generation biofuels react positively to both price-based demand-pull incentives and technology-push policies.

Our study also complements a related subset of this literature that has explicitly looked at the problem of policy variability. Although the idea that discontinuities in policy support may discourage RE deployment has already attracted the attention of energy policy scholars, the question has so far been addressed using case-based approaches, for specific technologies such as biomass and mostly from the point of view of RE investors (White et al., 2013). We complement this work by examining the impact of policy variability on both innovation creation and diffusion, and for the whole range of RE technologies.

In the renewable energy context, *endogenous* mechanisms to support innovation have mostly been studied indirectly, by the literature that examined the relationship between economic growth and emissions per capita (the so-called Environmental Kuznets Curve hypothesis). Advocates of the endogenous demand-pull perspective challenge the effectiveness of exogenous RE support policies and question their economic justification, mostly on the ground that RE subsidies lead to an inefficient allocation of resources and, in the long run, reduce the competitiveness of the renewables industry rather than accelerating it (Sandén, 2005). Conversely, the endogenous view argues that RE diffusion is best induced by economic growth, because during the early stages of growth, investments are inevitably attracted by the technologies that cost the least (and are possibly the least environmentally friendly). It is only after income per capita has reached a given threshold that investments are redirected to less polluting but more expensive technologies. This perspective resonates well with the Environmental Kuznets Curve (EKC) hypothesis, positing an inverted U-shaped relationship between economic growth and emissions per capita (Grossman and Krueger, 1995). The EKC hypothesis implies that government support should be directed at stimulating aggregated demand rather than at establishing niche markets. Although an appealing hypothesis, the effectiveness of growth in stabilizing emissions has recently been questioned. For instance, Musolesi and Mazzanti, (2014) found that an EKC for CO_2 emissions is only visible for northern European countries that anticipated the Kyoto protocol and have better institutional frameworks. Likewise, Mazzanti and Musolesi (2013) noticed that EKC seems to be less evident than initially hypothesized after serial correlation and (heterogeneous) time effects have been accounted for.

In sum, the literature is increasingly recognizing the importance of studying different innovation support mechanisms both in general and in the RE industry. However, most studies that examined the impact of these mechanisms in the RE sector generated mixed findings, suggesting that the results are context-dependent and are heavily influenced by model specification choices. Furthermore, the majority of the studies that examined the impact of different instruments supporting RE deployment have studied them independently of one another. More critically, although some authors have explicitly recognized complementarities between exogenous push and pull mechanisms, they have typically neglected the role of endogenous mechanisms. The few papers have started investigating the contribution of the endogenous drivers of RE diffusion and the impact of policy variability have mostly adopted a case-based approach

(Hoppmann et al., 2013; 2014). By the same token, scholars have not simultaneously examined the effect of these different support mechanisms on both innovation creation and diffusion. Thus, a rigorous and systematic empirical analysis of these effects is still lacking.

To address this gap, in the remainder of this paper, we examine the joint effect of three interrelated drivers of technological change in the energy sector, looking at their impact on both innovation creation and innovation diffusion. Our work contributes to the above literature by providing a more comprehensive and holistic analysis of the various drivers of innovation in the RE sector, which considers multiple technologies in several countries and for different innovation outcomes.

Table 1 about here
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3. Hypotheses

Exogenous technology-push mechanisms

There are a host of welfare-centric arguments emphasizing the merit of exogenous technology-push policies, such as public R&D spending as a driver of technological change in the clean energy sector. In short, government funding plays a pivotal role in the innovation process because of the importance of diffuse externalities. Since knowledge spillovers are pervasive, it is hard for any single firm to appropriate all the returns to innovations (Stiglitz, 2014). Innovation management researchers have also argued that technology-push instruments have a positive effect on innovation because they help firms broaden their search strategies and pursue unconventional technological trajectories (Dosi, 1988). Within the RE innovation literature, a few studies have documented a positive influence of domestic technology-push policies in advancing RE technologies. Watanabe et al. (2000) found that public R&D funding helped to achieve significant innovation in the Japanese photovoltaic (PV) industry, resulting in a dramatic decrease in solar cell prices between 1974 and 1994 (from \$350/W to \$5.4/W, in 2005 prices). Klaassen et al. (2005) and Söderholm and Klaassen (2007) also detected the positive effect of public R&D funding on wind energy technology innovation in four European countries (Denmark, Germany, Spain, and the United Kingdom (UK)). Johnstone et al. (2010) found that technology-specific R&D subsidies had a significant and sizable effect on innovation (measured by patent data) in wind, solar, and geothermal RE. Braun et al. (2010) also found that public R&D funding stimulates innovation in RE technologies, particularly for solar technologies. Veugelers (2012) presented firm-level evidence confirming that firms introducing clean innovations are responsive to eco-policy interventions. In line with the extant literature, we maintain that technology-push policies exert a positive impact on both innovation creation and innovation diffusion. Therefore, we use the following propositions as our default hypotheses:

H1a: In the RE sector, exogenous technology-push policies have a direct and positive impact on the rate of innovation creation.

H1b: In the RE sector, exogenous technology-push policies have a direct and positive impact on the rate of innovation diffusion.

Exogenous demand-pull mechanisms

In contrast to technology-push policies, which offer incentives for firms to innovate, demand-pull (or market-pull) policies aim to increase the adoption and diffusion of renewables by creating demand for RE technologies. Most of the studies that have examined demand-pull mechanisms focused on exogenous instruments, i.e. on government support measures aimed at creating niche markets where RE sources are shielded from direct competition with fossil fuel technologies. Examples of such measures include quantity-driven policies like quotas and price-driven policies like feed-in tariffs (FITs), fiscal incentives, such as tax credits and rebates, and public finance policies such as low-interest loans. Numerous empirical studies have shown that RE support policies have been effective and efficient[10] in promoting renewable generation (Meyer, 2003; Jäger-Waldau, 2007; Fouquet and Johansson, 2008; IEA, 2008; REN21, 2009; Marques and Fuinhas, 2012). In addition to their contribution to increasing the diffusion rate of RE, market-pull policies have also been a catalyst for innovation in RE technologies (Hoppmann et al., 2013). Although empirical studies in support of this hypothesis is scarce for RE, it has been argued that both price-based measures (e.g. FITs) and quantity-based measures (e.g. TGCs) are effective in inducing innovation for RE sources (Johnstone et al., 2010), though at different stages of technology development (IEA 2004, 2011). We expect exogenous demand-pull policies such as feed-in-tariffs to have an effect on both innovation diffusion and innovation creation. In the short run, the market niches created by these policies favor the diffusion of technological innovations that are already commercially available. In the long run, providing policies are stable enough, they should also induce firms to undertake new R&D investments and eventually stimulate the creation of innovation. Thus, we propose to formally examine the following hypotheses:

H2a: In the RE sector, exogenous demand-pull policies have a direct and positive impact on the rate of innovation creation.

H2b: In the RE sector, exogenous demand-pull policies have a direct and positive impact on the rate of innovation diffusion.

[10] Policy effectiveness refers to a policy's ability to achieve its stated objectives (e.g. attaining a certain RE target). Efficiency refers to a policy's ability to do so at minimum cost.

Demand-oriented deployment policies have not been exempted from criticism, however. First, a number of theoretical and empirical papers have come to a strong consensus that to be effective in enhancing demand for new RE technologies demand-pull measures must be complemented by technology-push instruments and public R&D investments (e.g. Grubb, 2004; Fischer, 2008; Bürer and Wüstenhagen, 2009; Johnstone et al., 2010; Acemoglu et al., 2012; Zachmann et al., 2014). The logic is simple. By using the public R&D during the early phase of the innovation chain and then deploying demand-pull policies in later stages (when the technology is closer to market commercialization), the adoption and diffusion of new RE technologies is easier to accelerate. Together, R&D and deployment policies create a positive feedback cycle (Watanabe et al., 2000), where the resulting benefits in turn create positive feedback to the policy cycle (IPCC 2011). Another rationale for overlapping policies is to prevent lock-in of dominant technologies by helping the renewable sector on a lower-cost pathway (Fischer and Preonas, 2010).

The effectiveness of demand-oriented policies can also be challenged on the ground that these instruments may discourage exploration, inducing the RE industry to pursue incremental innovation trajectories (Menanteau, 2000; Sartorius, 2005; Nemet, 2009; van den Heuvel and van den Bergh, 2009). Other studies also emphasized that for deployment policies to be effective, they must be applied consistently and over a sufficiently long time horizon (Masini and Menichetti, 2012). Therefore, as exogenous policies are subject to political discretion (Hoffmann et al., 2008) and typically erratic, their long-term effectiveness can indeed be questioned. Lack of consistency in policies becomes a noneconomic barrier, which enhances the perceived risk of developing and financing RE installations (de Jager and Rathmann, 2008). We aim to contribute to this debate by testing the following hypotheses:

H3a: In the RE sector, the variability of exogenous demand-pull policies has a direct and negative impact on the rate of innovation creation.

H3b: In the RE sector, the variability of exogenous demand-pull policies has a direct and negative impact on the rate of innovation diffusion.

Endogenous demand-pull mechanisms

Although the literature has extensively studied exogenous instruments for supporting the RE industry, it has somewhat neglected endogenous drivers such as economic growth. We posit that in the RE industry economic growth can accelerate both innovation creation and diffusion either directly or indirectly.

First, economic growth can exert an indirect effect on innovation[11]. The level of economic affluence of a country induces the population to demand greater environmental quality because of its effects on quality of life and wellbeing (Bayer and Urpelainen 2013).[12] Such demand may create "institutional pressure" and induce policy makers to implement legislation that makes renewables more competitive vis-a-vis fossil fuel technologies, thereby creating new market opportunities. However, since environmental policies are typically costly, they are more likely to be implemented on a large scale in rich countries. In turn, as maintained by the hypotheses 1 and 2, exogenous policies should have a positive effect on both innovation creation and diffusion. Therefore, we propose:

H4a: In the RE sector, economic growth affects the rate of innovation creation indirectly, by favoring the deployment of RE support policies.

H4b: In the RE sector, economic growth affects the rate of innovation diffusion indirectly, by favoring the deployment of RE support policies.

Second, economic growth can also have a direct effect on innovation creation. Irrespective of any policy support firms may respond to the anticipated demand for higher environmental quality by undertaking long-term investments in RE. As firms usually prefer equity over debt for funding R&D activities with uncertain outcomes (Hall and Lerner, 2009; Rosenberg, 1990), income is a strong driver of exploration activities (Hall, 1988). The effect is particularly important for firms exploiting relatively mature RE technologies, such as crystalline silicon photovoltaics, for which "[t]he resources available for R&D are strongly linked to existing cash flows" (Hoppmann et al., 2013, p. 995). One may object, though, that exogenous demand-oriented policies would produce a similar income effect. However, as exogenous policies are subject to political discretion (Hoffmann et al., 2008), they may generate additional uncertainty about future profits and thus discourage exploration and innovation (Nemet, 2009).

Economic growth can also stimulate innovation diffusion directly. Even if renewables remain a more expensive option, they may still be preferred over fossil fuel technologies because consumers with greater budget surpluses are willing to pay higher prices for products and services with greater environmental quality. This argument finds ample evidence in the literature on EKC, which describes the relationship between prosperity and the environmental degradation (e.g. per capita pollution) as an inverted U-shape. Simply put, the EKC hypothesis states that at the early stages of growth the environment tends to suffer but beyond some level of income per capita, pollution reduces. Grossman and

[11] We thank an anonymous reviewer for bringing this issue to our attention.
[12] The argument that the demand for environmental quality rises with income is typically advanced under the "prosperity/affluence hypothesis" in environmental economics (e.g. Baumol and Oates 1979; Field 1994).

Krueger (1995) first provided statistical evidence for the existence of an EKC relationship for two indicators of environmental quality: sulfur dioxide and dark matter (smoke). Stern (2014), among others, provides a typical survey of recent empirical work on the EKC relationship. Although recent contributions (Mazzanti and Musolesi, 2013; Musolesi and Mazzanti, 2014) challenge the validity of the EKC hypothesis, we argue this concept can be applied to the case of RE. In the same vein, (per capita) pollution falls once an income threshold is reached: higher income induces the population to demand a higher RE share (as a percentage of overall energy consumption) as an indicator of environmental quality.[13] Therefore, we propose the following hypotheses:

H5a: In the RE sector, the rate of innovation creation increases more than proportionally with an increase of gross domestic product (GDP) per capita (i.e. there is a U-shaped relationship between GDP per capita and innovation creation).

H5b: In the RE sector, the rate of innovation diffusion increases more than proportionally with an increase of gross domestic product (GDP) per capita (i.e. there is a U-shaped relationship between GDP per capita and innovation diffusion).

4. Data and model specification

4.1. Data

The impact of the different drivers of innovation creation and diffusion in the RE industry was tested using data from 15 EU countries over the period 1990–2012. The 15 countries include Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, the Netherlands, Portugal, Spain, Sweden, and the UK, henceforth referred to as the EU-15 countries. The main reason for focusing on these EU-15 countries owes to their higher renewable progress compared to new member states. Besides, this particular group of EU-15 countries is often considered in the various policy assessments of renewable development in the EU (e.g. Ragwitz et al., 2007). The start date was chosen to reflect the rapid deployment of RE sources after 1990 as a result of the energy policies adopted by the EU; the endpoint was chosen based on the availability of data when we started this research.

Our first dependent variable must reflect innovation creation in the renewable energy sector. We use patent data, a popular measure of innovation creation. Following Johnstone et al. (2010), we use patents applied to the European Patent Office (EPO). This is consistent with our sample, which represents predominantly European countries. In line with Costantini et al. (2015), we do not rely on patents applied to USPTO because US firms have a higher propensity to apply to USPTO than to other international

[13] This hypothesis has already been supported by some evidence in Menegaki and Tsagarakis (2015).

offices. Our dependent variable is thus defined as a pure patent count data based on the number of patents applied to EPO in the field of renewable energy. The data were extracted from the OECD's Directorate for Science, Technology and Industry patent database.

Our second dependent variable, which accounts for the diffusion of RES, is the ratio of renewable to total electricity. This metric is commonly used to monitor the progress of RE development in the EU. Furthermore, it is particularly appropriate for our study because, unlike other indicators such as added capacity, RE share depends on the stock of renewable generation capacity at time *t*, not on the new capacity installed (i.e. RE flow). Given the long operating life of power generation units (25 years or higher), this stock is influenced by all the policies implemented up to time *t* regardless of whether any policies have been discontinued or not. RE share data were collected from the *World Energy Balance* dataset, published by the International Energy Agency (IEA). The RE sources include geothermal, solar photovoltaics, solar thermal, tidal/ocean/wave energy, wind power, municipal waste, primary solid biofuels, biogases, biogasoline, biodiesels, other liquid biofuels, nonspecified primary biofuels and waste, and charcoal. Following the tradition of previous empirical work, we have excluded hydropower from the definition of RE. This choice is also consistent with our goal of testing the impact of different policy instruments on technological change, because large hydropower plants are mature technologies and cannot be used as a proxy for innovation in the energy industry.

Exogenous technology-push instruments were measured by calculating the public R&D spending in the RE industry (excluding hydropower) relative to total public R&D spending in the electricity generation industry. The RE research, development and deployment (RD&D) spending data were obtained from IEA's *Detailed Country RD&D Budgets.* To calculate the relative contribution of RD&D, we used the product "total RD&D in million US dollars" (2012 prices) and the flow "renewable energy sources (excluding hydro)" as the numerator and "renewable plus fossil budgets" as the denominator.

Exogenous demand-pull instruments were operationalized through a Renewable Energy Policy (REP) index variable. The REP index, adapted from Aguirre and Ibikunle (2014), was originally based on the information available in the IEA/IRENA Joint Policies and Measures Database.[14] The REP index includes five policies expressed as dummies: economic instruments, policy support, regulatory instruments, RD&D and voluntary approaches. Note that the RD&D dummy does not reflect public spending in R&D for renewables, (which is accounted for by the dedicated variable discussed above). Instead, it accounts for demonstration projects to increase awareness (i.e. a demand-pull mechanism) and for special funding for collaborative research. To create a single policy index that varied over years and across countries, we created a series of dummy variables reflecting the adoption of each policy. Following Nesta et al. (2014), we constructed the REP index as the sum of all implemented policies.

[14] Available at: http://www.iea.org/policiesandmeasures/renewableenergy/ (accessed 1 Dec. 2014)

Note that the use of RE share as a dependent variable also rationalizes the measure we use to construct the REP index, reflecting the existence of different policy types across countries. To see how the REP index is consistent with the choice of our dependent variable (i.e. RE share) consider, for example, in 2007, Spain implemented FIT for PV and discontinued it in 2009. Such a policy would cause an increase in installed PV capacity in 2007 and 2008, but not from 2009 onwards. However, the photovoltaic systems installed in 2007 and 2008 will continue to generate electricity in 2009 and beyond, thereby contributing to the RE share even after the policy has been discontinued. In other words, a RE policy implemented at time t^* will have an impact on renewable stock from $t=t^*$ until $t=t^*+T$, where T is the operating life of a power unit. Given that our data cover an interval less than T, we can assume that all policies implemented have continued to exert their effect throughout the whole observation period.

To operationalize the variable assessing the variability in the level of policy support, we constructed a REP variance indicator as the first difference of the REP index (i.e. $\sigma_{REP} = REP\ index_{i,t} - REP\ index_{i,t-1}$). Finally, endogenous demand mechanisms were accounted for by considering economic growth, measured as GDP per capita (in 2005 US dollars). Data for this indicator were obtained from the World Bank's *World Development Indicator*.

4.2 Model specification and econometric issues

The research hypotheses were tested by estimating the following panel data models:

$$ln\ Y_{sit} = \alpha_i + \varphi_i t + \beta_{it}\ X_{it} + u_{it}, \tag{1}$$

where $i=1,2,\dots,N$ and $t=1,2,\dots,T$ index the cross-sectional units and time series, respectively; the subscript s denotes whether the dependent variable is patent counts (for RE innovation) or the share of RES in electricity generation (for RE diffusion). The vector $X_{it} = (REP\ index_{it}, \sigma_{REP_{it}}, ln\ R\&D_{it}, lnGDP_{it}, lnGDP^2_{it})$ contains the independent variables, where $REP\ index$ accounts for exogenous demand-pull policies supporting renewables and σ_{REP} accounts for policy variability. The term $\ln R\&D$ is the logarithm of the contribution of RE R&D spending to the total RD&D budget in the fossil and renewable sectors when the dependent variable is RES's share in electricity production. For the RE innovation model with patent counts as the dependent variable, we use R&D spending in levels (in 2012 constant prices). The terms $lnGDP$ and $lnGDP^2$ are the log of per capita income and income squared, respectively. The coefficients α_i denote country-specific effects, including unobserved heterogeneity. The variable t is the common linear time trend, whereas u_{it} represents random disturbances dependent across countries. Notice that, in line with Hypothesis 5, we expect the coefficients of $lnGDP$ and $lnGDP^2$ to obey $\beta_{GDP} < 0$ and $\beta_{GDP^2} > 0$ for all i so that the results lend support to the U-shape relationship between RE sources and per capita income as discussed above.

Given the different properties of the dependent variables (patent counts vs. RE share), we use different estimators for the innovation creation and the innovation diffusion model. For the RE innovation model with patent counts as the dependent variable, the empirical model is estimated using both Poisson and negative binomial estimators. However, since patent data typically are over-dispersed (i.e. the variance exceeds the mean), the negative binomial estimator is generally preferred over the Poisson estimator. In both models, we allow country fixed effects to partly address the differences in patent quality across countries (Costantini et al., 2015). Conversely, for the RE diffusion model, where the dependent variable contains a unit root (see Appendix A for further discussion), the choice of panel data estimators is guided by the need to incorporate the time series properties of the data (i.e. unit root, cointegration and cross-sectional dependence). To that end, we apply both a traditional fixed effects estimator (which is used widely in the applied RE literature) and a state-of-the-art methodology (i.e., the common correlated effect mean group estimator of Pesaran (2006)) to address nonstationarity and cross-sectional dependence (CSD) in the data. CSD is caused by, among other factors, by cross-border spillovers (Corradini et al., 2014), a common phenomenon in the RE industry. See the discussion in Appendix A and B for further details.

Finally, to test hypothesis 4 we conducted a mediation analysis to understand if and to what extent the effect of economic growth (a treatment variable) on RE diffusion (the outcome variable) is mediated by RE policies (a potential mediator). Following Baron and Kenny (1986), the model for RE diffusion (including mediator) is given as:

$$E[Y|a,m] = \alpha_1 + \beta_1 a + \theta m, \tag{2}$$

the model for the mediator is:

$$E[M|a] = \alpha_2 + \gamma a, \tag{3}$$

where Y (outcome) is RE diffusion, *a* (treatment) is economic growth, and *m* is the mediator (i.e. RE policies). To conduct the analysis, we used the "medeff" routine by Hicks and Tingley (2011) in Stata.

5. Preliminary data analysis and descriptive statistics

Figure 2 presents linear plots for panel data for the dependent and independent variables. The variables are shown in the way they are entered in the regression equations (i.e. log transformed, where applicable). A general feature of the variables is that they all exhibit a smooth upward trend, except for RE R&D, which shows some volatility. Generally, energy R&D expenditure is as volatile as the energy market itself. The plot of the RE policy index fits the most common feature of the RE policy landscape: in the 1990s, RE policies were in place in only a handful of countries, but they grew exponentially after 2000. The log of RE share depicts an interesting trend of convergence in RE sources across the EU-15 countries. However, the logs of real per capita GDP—widely recognized as being unit root processes—show country variation in income among the EU-15 nations.

Figure 2 about here

Further details about these variables emerge from Table 2, which presents mean and standard deviation for the dependent and independent variables. For the sake of greater comparability, these descriptive statistics have been obtained using the original data. A few remarks are in order. Among the EU15 countries in the period of our analysis most of the innovation in RE industry took place in Germany, which displays the highest number of patent applications in the sample (nearly 45% of total). Moreover, the innovation process appears to be highly concentrated too: four countries (Denmark, France, Germany, and the UK) account for over 70% of invention in the renewable industry in the EU15. The RE diffusion pattern is also worth discussing. Over the full sample, the average share of RE in most countries is low (5% or less), with the exception of Denmark, Finland, and Portugal. However, since 2000, the diffusion of RE has increased noticeably in countries such as Finland, Germany, and Spain, with a RE share of 10% or more. France remains an outlier, with a negligible contribution of RE to total energy (less than 2%). This is because nuclear energy accounts for over three-fourths of electricity production in France. Denmark, which has nearly zero hydroelectric resources, is really a forerunner in clean energy generation among the EU-15. RE sources in Denmark rely solely on wind energy and biomass, and have maintained an average share of 25% in the post-2000 period. Other countries in which the adoption of RE significantly increased in the new millennium are Austria, Ireland, Italy, the Netherlands and Sweden; with an average RE share of 7% or higher.

Table 2 about here

Income per capita ranges from $16,940 (Portugal) to $69,966 (Luxembourg), with the majority of the countries showing a per capita income above the $30,000 threshold. To make an individual country's RE position conditional on its income level, Figure 3 depicts a matrix that maps countries according to two dimensions. The first dimension is the country's position regarding renewable development relative to the rest of the group. Hence, a country has a lower (higher) RE share if its average level is lower (higher) than the median level of the EU-15 over the observation period. Similarly, the second dimension, which reflects a country's economic strength, identifies a country as having lower (higher) GDP per capita if its average income level is lower (higher) than the median income level of the EU-15 over the sample period. This perspective serves as a proxy for the relative ability to deploy the necessary measures to foster renewable energy development. The information in Figure 3 speaks for itself. Italy, Portugal, and

Spain are clearly the champions in fostering the growth of nonhydro RE sources. In contrast, Belgium and the UK trail other nations in their effort to hit the energy targets set for 2020[15].

Figure 3 about here

Turning to the share of RE RD&D spending as a percentage of the total RD&D spending in the fossil and renewable sectors, we find that (barring France) a large fraction of energy R&D spending in the EU-15 countries is devoted to RE. This is not surprising, given that these countries are a net importer of fossil fuels (particularly oil), so that developing alternative energy sources such as RE sources are considered as a national priority to improve the respective countries' energy security position, among other goals. In the EU-15, Germany spends much more than the other nations on renewable R&D and has a large stock of R&D personnel. In terms of the share of RE in total national R&D budgets, Denmark and the Netherlands have the highest ratios. On the other hand, for the ratio of the share of RE R&D to GDP, the leading countries are Denmark, Finland, the Netherlands and Sweden.

The average levels of the REP index also differ markedly among the EU-15, including their volatility (measured by the standard deviation). Although, in general, it is tempting to conclude that countries with a higher REP index have a greater number of policies devoted to RE sources, the limitation of this argument is that it ignores the associated volatility or policy uncertainty. For example, the average REP index in the UK is the highest, but its standard deviation is also very high (coefficient of variation higher than 1), which makes the UK (after Spain) very vulnerable to policy uncertainty. Within the RE policy arena the situation of Spain and Portugal is very fragile. In these countries, there were few and unstable accumulated policies (with the coefficient of variation for the REP index exceeding 1). By contrast, in Germany and Denmark, RE policies are numerous and are stable, compared to their EU peers.

Finally, Figure 4 presents the distribution of the regression variables in descending order based on the median. The median share, represented by a line subdividing the box, is not very different between countries for RE share. On the other hand, with the exception of Ireland and Luxembourg, the distribution of per capita income is quite symmetric across the EU-15.

Figure 4 about here
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[15] According to the Renewable Energy Directive, the EU countries are required to fulfil at least 20% of their total energy needs through renewable energy sources by 2020. Source: https://ec.europa.eu/energy/en/topics/renewable-energy

6. Discussion of results

Tables 3 and 4 present the estimation results for RE innovation and RE diffusion, respectively. Two remarks are in order. First, for the RE innovation model (where the dependent variable is represented by a count of patents in the renewable energy industry) we apply both Poisson and negative binominal estimators, incorporating fixed effects. Although the results are roughly similar, below we only discuss the results obtained by applying the fixed effects negative binomial model (Table 3), as it is robust to overdispersed count data.[16] Likewise, for the RE diffusion model, where the dependent variable contains a unit root (see Appendix A for further discussion), we will discuss the results obtained by the CCEMG estimator, which is robust to both nonstationarity of variables and cross-sectional dependence. The estimates of the alternative econometric methods are available from the authors on request.

Second, Tables 3 and 4 present results of the various nested models. This allows us to examine the incremental role of demand-pull and technology-push policies in spurring innovation and fostering the diffusion of RES. For example, column [1] in Tables 3 and 4 indicate that analyzing exogenous demand-pull instruments without taking endogenous mechanisms into account tends to overestimate the impact of RE policies. Furthermore, with this nested structure, we are able to observe that the sign on each variable remains unaffected by the inclusion of additional regressor(s), suggesting the robustness of the results. While the discussion below is based on the results of the full models (column [5] in Tables 3 and 4), where it is necessary we will make connection between the full and nested models. The full model (represented by column [5]) includes a country-specific linear time trend, which may be correlated with both policy implementation and RE development. Specifically, a time trend is often included to capture the common technological trend towards lower costs in the RE industry.[17]

Table 2 and table 3 about here

Let us now turn to the analysis of the empirical results pertaining to our main hypotheses. Hypotheses 1a and 1b consider the impact of exogenous technology-push policies. As expected, in the innovation model, the coefficient for R&D spending is positive and significant at the 1% level (see column [5] in Table 3), supporting the hypothesis that exogenous technology-push mechanisms foster innovation in the renewable industry. This is consistent with previous empirical studies that demonstrated the positive effect of technology-push R&D spending on innovation in the RE sector (see, e.g. Watanabe et al., 2000; Klaasen et al., 2005; Johnstone et al., 2010). Results also support hypothesis 1b. Notice that

[16] The regression results remain broadly the same across different specifications with bootstrapped standard errors.
[17] Braun et al. (2010) argues that time trends "are important for capturing general changes in the propensity to patent and strategic patenting behaviour across countries" (p. 12).

public R&D spending has an even larger effect on RE diffusion than on innovation (the estimated coefficient is 0.21 for diffusion versus 0.002 for innovation). However, while R&D spending has a rather instantaneous effect on innovation, its impact on diffusion becomes visible only after a non-negligible time lag (the effect is maximized for a five-year lag). This is consistent with previous findings[18]: innovation produced by R&D efforts needs an initial "gestation" period before becoming commercially available and, therefore, being able to exert an impact on technology diffusion. Thus, the relationship between R&D spending and RE diffusion is not direct. Instead, the impact comes from higher innovations in the form of cost reduction and the resulting learning activities, which in turn should lead to increased market penetration of RE technologies.

In Hypothesis 2a and 2b, we argue that exogenous demand-pull policies have a positive impact on both innovation and diffusion in the RE industry. The empirical results clearly support these hypotheses, as the estimated coefficient for the REP index is positive and statistically significant in both models (see column [5] in Tables 3 and 4). This result echoes the findings of various studies arguing that government policies have played a crucial role in accelerating the deployment of RE sources (see IPCC 2011 and the works cited there). However, the results also indicate that analyzing exogenous demand-pull instruments without taking endogenous mechanisms into account tends to overestimate the impact of RE policies. The estimated impact of RE policies on innovation is higher when the variable is analyzed as a stand-alone driver of innovation than when it is combined with other covariates (see columns [1] and [5] in Table 3). Essentially, when the dependent variable is regressed only on RE policies, some of the mediation effect of economic growth on innovation (more details on this are discussed below) is spuriously captured by demand-pull policies. The empirical results also lend support to a widely accepted proposition that R&D research complemented with deployment policies are very effective in inducing RE technologies (Mowery and Rosenberg, 1979; Johnstone et al., 2010; Zachmann et al., 2014). Both effects are individually significant with economically plausible signs (see column [5] in Tables 3 and 4). Together, R&D and deployment policies create a positive feedback cycle (Watanabe et al., 2000), where the resulting benefits give positive feedback to the policy cycle (IPCC 2011, p. 888). The rapid development of RE in Germany is a case in point (IPCC 2011).

Hypothesis 3a and 3b consider the impact of public policy uncertainty. Our results reveal a negative impact of policy uncertainty (proxied here by policy variability, σ_{REP}) on RE diffusion, lending support to Hypothesis 3b. This is consistent with the general perception that policy uncertainty poses a serious threat to the development of low-carbon technologies (IEA, 2007). Like businesses in other industries, those within the RE industry adopt a 'wait and see' attitude in the face of uncertainty and delay

[18] For example, Zachmann et al. (2014) found that the impact of R&D spending on wind technology seemed to be most effective between the second and sixth year.

their investments until policy direction becomes clearer (Stern, 2007). For example, Meyer and Koefoed (2003) looked at the impact of delayed implementation of the new policy in Demark and found that it caused a well-established wind industry to stall. Likewise, in the context of Canada and Norway, White et al. (2013) discuss how large, unexpected changes in public policies increased uncertainty, eventually leading to a fall in investments in RE sector. In 2013 installation of solar panels fell by nearly 60% in Germany and by 70% in Italy following a decision by the European Commission to phase out subsidies for RE by 2017 (Creyts and Stuchtey, 2015). In its latest report, the IEA (2013) warned that growth of RE in OECD markets is under threat due to ongoing uncertainty over policy framework in the EU and the US. The cloud of policy uncertainty is particularly damaging at a time when renewables are becoming a cost-competitive option in the global energy market. Conversely, results do not support hypothesis 3a as the impact of public policy uncertainty on RE innovation is not statistically significant and positive (see model [5] in Table 3). Interestingly, policy uncertainty seems to affect only decisions pertaining to the deployment of commercially available technologies (i.e. those affecting RE diffusion), but not much to the innovation creation process. Indirectly, these findings reinforce the view that demand-pull policies favor the exploitation of those technologies closest to grid parity, but are relatively ineffective at producing technological breakthroughs (of course, the other facet of this coin is that the innovation process is more resilient to short-term policy variability). This apparently counter-intuitive result is consistent with recent contributions suggesting that companies may carry on with their innovation efforts, even in face of high regulatory uncertainty, if they need to secure scarce resources, leverage complementary assets, or alleviate institutional pressure (Hoffman et al., 2009).

The last set of hypotheses, from 4a to 5b, discusses the impact of endogenous drivers on RE innovation and RE diffusion. In the diffusion model, the estimated coefficients for income and income squared are, respectively, negative and positive, and statistically significant, validating our hypothesis that the relationship between RE diffusion and income is U-shaped. According to this result, up to a certain income threshold, the contribution of RE to a country's total electricity generation is nil. However, once the threshold income level is crossed, driven by increased environmental awareness and greater affluence, the diffusion of RE sources increases. More concretely, after a certain threshold a 1% increase in real GDP per person (or about $340 per head) leads to a nearly 18% increase in RES's contribution to electricity generation. A specific example may be illustrative here. Using the estimates of income and income squared in the RE diffusion model, the turning point income threshold is estimated at $34,391.[19] Our sample has an average per person income of $33,990, which is close to the turning point income threshold. Over the period 1990-2012, per capita real GDP in EU15 countries grew at an average annual

[19] The turning point is obtained using the following formula: $\tau = \exp\left(-\beta_1/2\beta_2\right)$, where β_1 and β_2 are the estimates income and income squared in column [5] in Table 4.

rate of 1.42%; whereas the average annual contribution of RES to electricity generation in the EU15 countries was about 19%. Our results, therefore, suggest that, in the future, a similar level of RE diffusion could be maintained with an even lower per capita income growth, since the observed income level is close to the turning point income threshold (i.e. from that point onwards, the diffusion of RE will increase faster than any increase in the income level).[20]

Conversely, results of the innovation model do not provide support to hypothesis 4a. The number of patents in the RE industry seem to be unrelated to economic growth. Taken together, our results shed new light on the critical role that endogenous demand-pull mechanisms play in supporting technological change and the diffusion of RE sources. Above a certain income level, greater environmental awareness does produce a demand for more renewable energies. However, alike to what observed for exogenous demand-pull policies, such demand does not stimulate the exploration of new technologies and tends to be satisfied through commercially available system (i.e. it supports exploitation rather than exploration). Finally, the results of the mediation model on innovation diffusion indicate that the total effect is estimated at 1.64, of which the estimate of the direct effect (β_1) is equal to 1.64 (i.e. nearly 80% of the total effect). This suggests that only 20% of the effect of economic growth on RE diffusion is transmitted through RE policies (the mediating variable). To investigate this finding further, we also test for the possibility of reverse causality running from RE share to GDP growth, as documented in Marques and Fuinhas (2012). Based on Granger causality test, we find that for 11 out of 15 countries RE share does not cause GDP growth, indicating that reverse causality is an unlikely confound behind our results. These results, along with the evidence already reported, strongly support our hypothesis regarding the role of economic growth as an endogenous demand-pull driver of RE diffusion. The results of the mediation model on RE patents are insignificant and are not reported here.

7. Conclusions

This paper aims to study the mechanisms that support innovation creation and diffusion in the renewable energy sector. We applied panel data models to estimate the impact of public R&D investments, RE support policies and per capita income on RE patents (a measure of innovation creation) and RE share (a measure of innovation diffusion) in 15 EU countries from 1990 to 2012. By focusing on both exploration and exploitation mechanisms and on endogenous and exogenous drivers of innovation, our study sheds

[20] These results clearly nest the prediction of the prosperity or affluence hypothesis of Baumol and Oates (1979), which assumes that the demand for the quality of the environment rises with income, an argument typically advanced in environmental economics (e.g. Field 1994). In addition, these results have important implications for the debate over economic growth versus environmental quality. For instance, in the standard neoclassical environment growth model (e.g. Nordhaus, 1994), higher environmental quality is achieved through reducing capital accumulation, which, in turn, reduces GDP and economic growth. However, recent growth models with endogenous and directed technical change have shown that environmental goals can be achieved with simple environmental policies such as research subsidies and "without sacrificing (much or any) long-run growth" (Acemoglu et al., 2012, p. 133).

new light on the long discussed technology-push vs. demand-pull debate and it contributes to the literature on RE policy assessment.

We argue that in addition to the traditional push-pull dichotomy, the drivers of technological change must be differentiated based on whether they are exogenous or endogenous to the economic system. Building on that observation, we propose a taxonomy of support mechanisms and we maintain that a specific type of endogenous demand-pull mechanism (i.e. economic growth) is an important and much underrated driver of innovation diffusion (but not creation), with both a direct and an indirect impact. We further suggest innovation support mechanisms have to be assessed with respect to whether they facilitate the creation or the diffusion of innovations.

Our results provide further empirical support to the idea that innovation policies should be carefully balanced. Among the various drivers examined, exogenous technology-push measures have a stronger impact on innovation creation than diffusion; although, while their effect on innovation creation is almost immediate, their impact on diffusion becomes visible only after significant time lag. Exogenous demand-pull policies also have a stronger positive impact on innovation creation than diffusion; although, their contribution becomes less important after controlling for economic growth. The variability of support mechanisms also has a negative impact on innovation diffusion but not on innovation creation (i.e. it hurts exploitation but not exploration).

Most importantly, our results show that economic growth is a much stronger driver of innovation diffusion than either technology-push or exogenous policy-driven demand-pull mechanisms, whereas it is relatively ineffective at stimulating innovation creation. The effect of endogenous growth on RE diffusion is both direct and indirect (through its impact on RE policies) although the direct effect is largely predominant. Thus, the relationship between economic growth and RE diffusion exhibits a nonlinear, U-shaped pattern. At low levels of economic growth, investments are allocated to the least expensive (but least environmentally friendly) technologies. After income per capita has reached a given threshold, the demand for environmental quality rises and investments are eventually redirected to less polluting, but more expensive technologies. However, the demand for better environmental quality is satisfied through the exploitation of commercially available technologies and it does not produce any significant effect on the exploration of new technologies.

In passing, the paper also makes some methodological contributions. We note that both the direction and the magnitude of the estimated impacts are dependent on the choice of the correct panel data estimator, which must take into account the presence of both cross-sectional dependence (CSD) and nonstationarity in the panel data.

Our results have a number of policy implications. First, they reinforce the view that different innovation support instruments should be deployed together. The EKC hypothesis suggests that for RE diffusion to increase, government action should be directed at stimulating aggregated demand and economic growth rather than at shielding renewables from competition with fossil fuel technologies. However, such efforts should be coupled with innovation technology-push policies that stimulate radical innovation, because the latter is not induced by economic growth. Furthermore, our findings that RE companies may carry on with their innovation efforts despite high levels of regulator uncertainty should not imply overconfidence and complacency when designing RE policies. In particular, policy makers must be wary of unintended consequences of regulatory uncertainty, which could lead to a bifurcation in manufacturing in the sense that firms may find it profitable to produce PV cells (a higher-value manufacturing activity) in China and assemble them (a lower-value, lower-technology manufacturing activity) in, say, Germany[21]. Finally, our methodological findings also have important implications. The finding that renewable energy contains a unit root implies that policies designed to induce permanent changes in RE such as FITs or TGCs will be more effective than policies such as tax incentives designed to induce temporary changes.

Our study is not exempt from some limitations, although these indicate avenues for future research. First, while we used quantitative measures for assessing the level of exogenous technology-push mechanisms (public R&D spending) and endogenous demand-pull mechanisms (GDP per capita), we could only use qualitative indicators for measuring exogenous demand-pull instruments (RE deployment policies). Our approach is fully consistent with the extant empirical literature in the field. However, it would be interesting to replicate the analysis after obtaining detailed quantitative data on the budgets allocated to RE support policies by each of the countries in our sample. Second, although our results are robust to different assumptions and different test specifications, the analysis was conducted on a relatively small sample that only included EU countries. Compared to some emerging economies, the countries in our sample have a higher awareness of environmental problems and a higher willingness to pay for tackling them. This may have amplified the impact of endogenous demand-pull mechanisms we observed.

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[21] Some evidence favouring this hypothesis can be found in Haley and Schiler (2011).

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TABLES AND FIGURES

Table 1. A taxonomy of studies on innovation support mechanisms for RE or environmental technologies

		Outcome of the innovation process	
Type of support	*Locus of support*	**Innovation creation (patents)**	**Innovation diffusion (deployment)**
Technology push	**Exogenous**	Peters et al. (2012) Costantini et al. (2015) Hoppman et al. (2013) Nemet (2009) Watanabe et al. (2000) Klaassen et al. (2005)	Polzin et al. (2015) Hoffman (2009) Hoppman et al. (2013) Jager-Waldau (2007) Watanabe et al. (2000) Klaassen et al. (2005)
	Endogenous	N.A.	N.A.
Demand pull	**Exogenous**	Peters et al. (2012) Costantini et al. (2015) Corradini et al. (2014) Hoppman et al. (2013) Hoppman et al. (2014) Nemet (2009) Soderholm and Klaassen (2007)	Polzin et al. (2015) White et al. (2012) Hoffman et al. (2009) Borghesi et al. (2015) Hoppman et al. (2013) Hoppman et al. (2014) Jager-Waldau (2007) Fouquet and Johansson (2008) Soderholm and Klaassen (2007)
	Endogenous (EKC)	N.A.	Mazzanti and Musolesi (2013) (indirectly, through impact on emissions)

Table 2. Descriptive statistics

	Patent counts in the renewable industry		Share of RE in electricity production (%)		GDP per person ($2005 constant prices)		Share of RE RD&D in total share		REP index	
	μ	σ	μ	σ	μ	σ	μ	σ	μ	σ
Austria	14	13.92	0.05	0.03	$34,478	4131.85	0.87	0.08	6	5.83
Belgium	10	11.03	0.02	0.03	$33,313	3349.07	0.61	0.20	18.52	12.55
Denmark	53	74.51	0.17	0.13	$43,757	4133.07	0.86	0.11	11.34	4.98
Finland	6	7.02	0.12	0.02	$32,975	5382.05	0.65	0.17	7.43	4.73
France	39	48.44	0.01	0.01	$31,689	2561.53	0.24	0.14	18.21	16.14
Germany	206	207.08	0.05	0.06	$32,615	2885.88	0.84	0.10	17.30	7.24
Greece	2	1.59	0.02	0.02	$18,713	2864.42	0.79	0.14	9.73	4.50
Ireland	4	6.04	0.04	0.05	$36,709	11522.27	0.88	0.12	8.34	8.08
Italy	27	33.58	0.04	0.04	$28,710	1816.59	0.84	0.17	16.95	14.47
Luxembourg	1	1.01	0.05	0.03	$69,966	11757.77	0.99	-	7.43	4.29
Netherlands	24	24.77	0.05	0.04	$36,385	4431.14	0.73	0.10	7.34	6.19
Portugal	2	2.73	0.09	0.08	$16,940	1764.31	0.73	0.16	5.04	5.38
Spain	27	36.25	0.06	0.07	$23,281	2931.49	0.84	0.08	6.39	9.07
Sweden	11	11.84	0.05	0.04	$36,684	5371.15	0.94	0.06	14.39	10.59
UK	41	41.87	0.03	0.03	$33,631	5047.23	0.64	0.16	20.30	22.40
EU-15 (1990–2012)	**31**	**77.65**	**0.05**	**0.06**	**$33,990**	**12988**	**0.75**	**0.21**	**11.65**	**11.45**
EU-15 (2000–2012)	**52**	**100**	**0.08**	**0.07**	**$37,521**	**13909**	**0.80**	**0.18**	**19.01**	**11.03**

The sample period is 1990–2012. Average patent counts are rounded to the nearest whole number. Renewable sources do not include hydro power. See the text for details. Source: *World Energy Balance*, IEA (2013).

Table 3. Negative binomial panel regression with fixed effects for RE innovation

	(1)	(2)	(3)	(4)	(5)
REP index	0.077***	0.076***	0.070***	0.057***	0.043***
	(0.003)	(0.003)	(0.004)	(0.005)	(0.006)
σ_{REP}		-0.0005	0.008	0.010	0.005
		(0.014)	(0.015)	(0.015)	(0.014)
R&D			0.001**	0.002***	0.002***
			(0.0009)	(0.0008)	(0.0008)
GDP				-20.51	-6.12
				(17.10)	(17.22)
GDP^2				1.083*	0.429
				(0.832)	(0.834)
Trend					0.005***
					(0.001)
Log-likelihood	-972.53	-937.69	-840.02	-828.88	-822.13
Observations	330	315	269	269	269

The dependent variable patent counts in the renewable industry. The REP index is a measure of RE policies; σ_{REP} is a measure of policy uncertainty surrounding renewable support policies; RE R&D is the log share of renewable R&D spending; GDP and GDP^2 are log of real GDP per person and squared counterpart; Trend is a linear time trend. Constant terms were included but not reported. The values in parentheses are standard errors. All models are estimated by fixed effects negative binominal panel data models. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively (one-tailed test).

Table 4. Common correlated effect mean group (CCEMG) panel regression for RE diffusion

	(1)	(2)	(3)	(4)	(5)
REP index	0.003	0.003	0.035*	0.032**	0.023*
	(0.015)	(0.016)	(0.027)	(0.019)	(0.015)
σ_{REP}		0.004	-0.016	-0.014**	-0.012*
		(0.013)	(0.017)	(0.007)	(0.007)
R&D(*t*-5)			0.156	0.069	0.219*
			(0.234)	(0.165)	(0.154)
GDP				-411.44*	-378.04*
				(313.13)	(257.37)
GDP^2				19.44*	18.09*
				(15.00)	(12.42)
Trend					0.020
					(0.056)
RMSE	0.245	0.211	0.10	0.051	0.046
Observations	345	330	215	195	195

The dependent variable is log RE share. The REP index is a measure of RE policies; σ_{REP} is a measure of policy uncertainty surrounding renewable support policies; RE R&D is the log share of renewable R&D spending; GDP and GDP^2 are log of real GDP per person and squared counterpart; Trend is a linear time trend. Constant terms were included but not reported. The values in parentheses are standard errors. All models are estimated by fixed effects negative binominal panel data models. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively (one-tailed test).

Figure 1. A taxonomy of RE support instruments

Demand-pull	Economic growth	Demand-oriented policies (FIT, TGC, etc.)
Technology-push	Corporate R&D investments	Public R&D investments
	Endogenous mechanisms	*Exogenous mechanisms*

Figure 2. Plots of economic variables

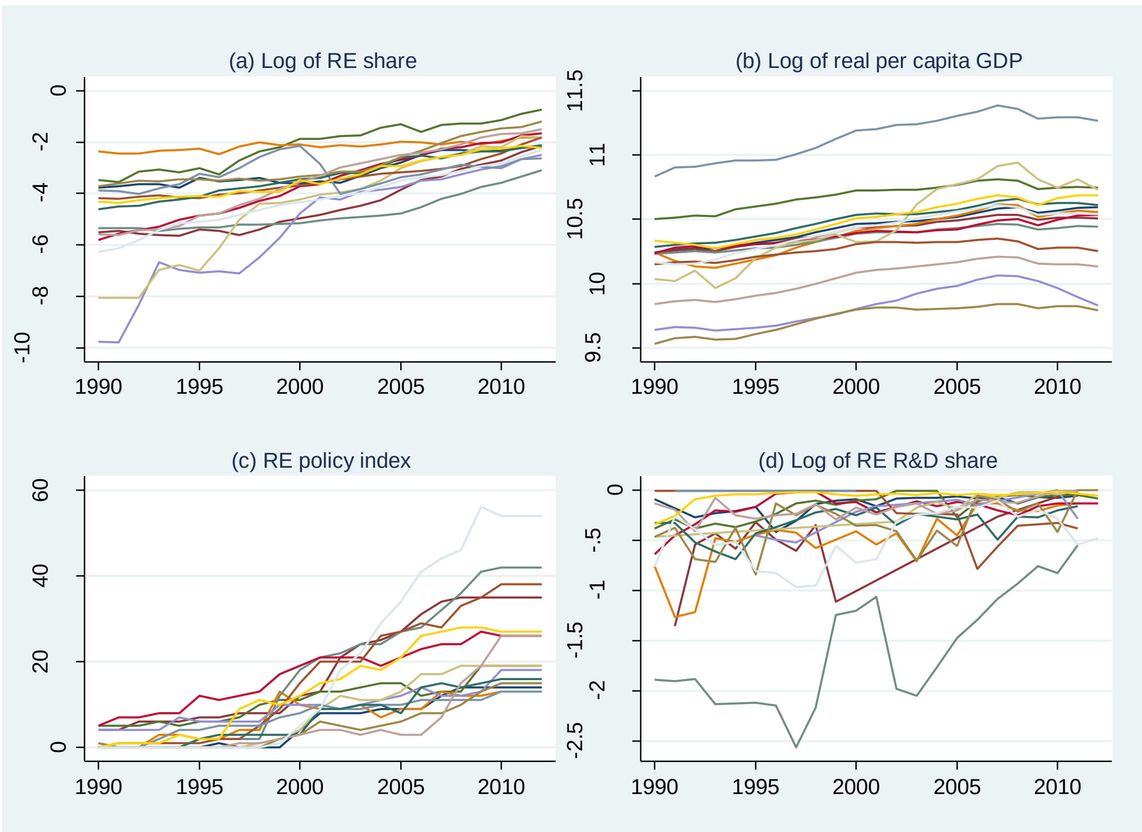
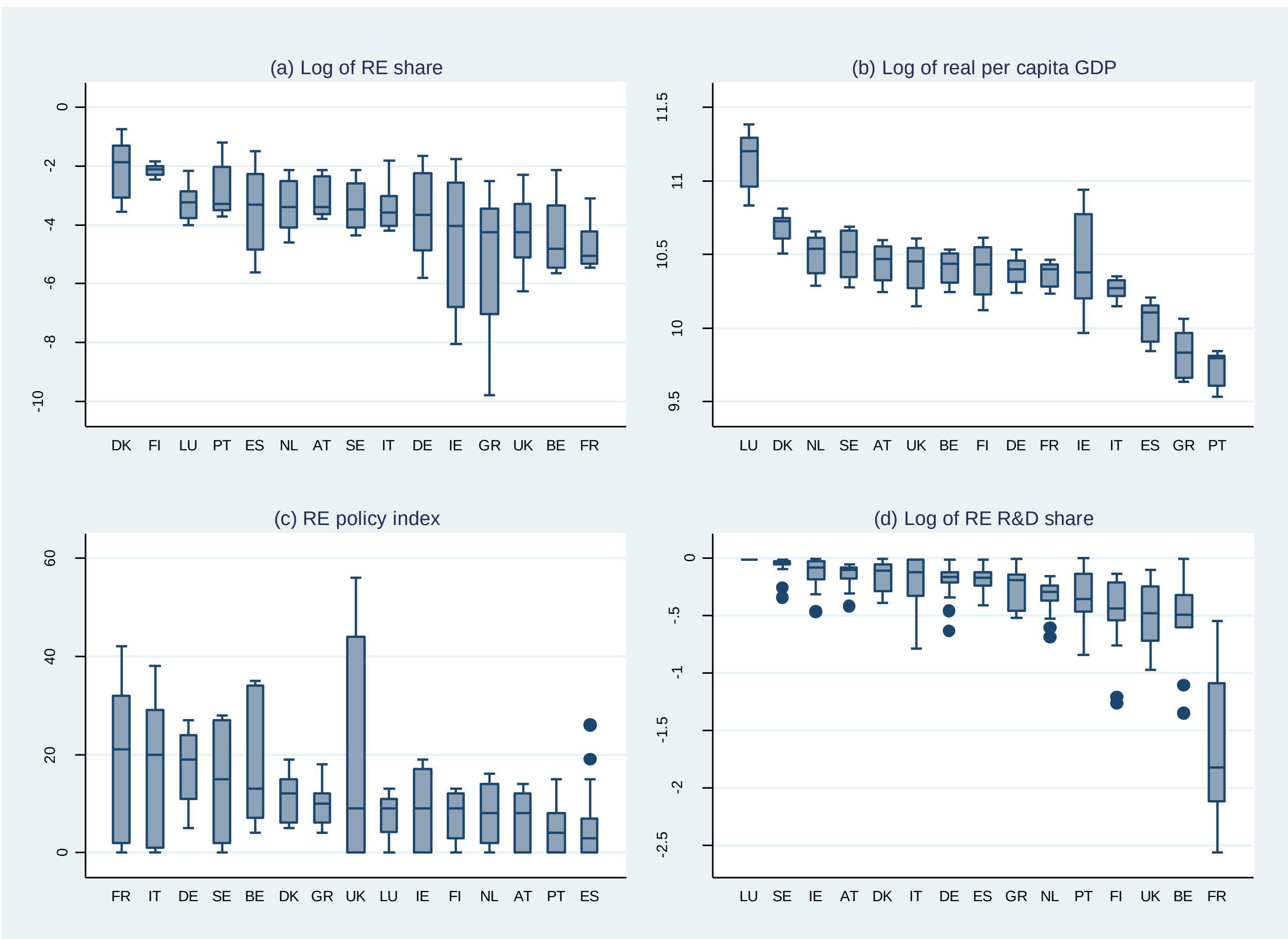


Figure 3. The renewable energy-income matrix

	Lower GDP per capita	Higher GDP per capita
Lower RE share	France, Greece	Belgium, UK
Higher RE share	Italy, Portugal, Spain	Austria, Denmark, Finland, Germany, Ireland, Luxemburg, the Netherlands, Sweden

Figure 4. Box plots of economic variables



AT, Austria; BE, Belgium; DK, Denmark; FI, Finland; FR, France; DE, Germany, GR, Greece, IE, Ireland; IT, Italy; LU, Luxemburg; NL, the Netherlands; PT, Portugal, ES, Spain; SE, Sweden; UK, United Kingdom;

Appendices

This Appendix is divided into three parts. In the first part, we summarize the various panel data tests that are used as a pretest to select the appropriate econometric method to estimate the RE diffusion model. It also reports the findings of the various panel tests. In the second part, we briefly describe the econometric methods, namely the negative binomial regression for the RE innovation model, and the common correlated effect mean group (CCEMG) estimator for the RE diffusion model. The third part discusses the results of various robustness tests of our baseline results presented in Tables 3 and 4.

Appendix A: Panel Data Tests and Results

A.1 Cross-sectional dependence (CSD) tests

It has now become customary to test for the presence of CSD in panel data models because the individual units in the panel (countries, in our case) are likely to exhibit strong correlations due to their exposure to common macroeconomic, technological, legal/institutional, political, environmental, health and sociological shocks. Our panel data comprising the EU-15 countries are expected to be affected by similar shocks, albeit in different magnitude, making the panel highly prone to CSD. For example, one may expect, *a priori*, a high level of CSD in RE deployment due to the implementation of common RE policies across the EU (i.e. the EU directive). Likewise, the increased business cycle correlation across the EU economies makes the case for CSD more compelling. As such, neglecting CSD could lead to significant size distortions in the panel unit root and cointegration tests that assume cross-sectional independence (Baltagi and Pesaran 2007). To this end, we use the test of error cross-dependence (the CD test) developed by Pesaran (2004). The CD test statistic is based on the average of the pairwise Pearson's correlation coefficients $\hat{\rho}_{ij}$ of the residual obtained from the panel data model and it is given by:

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right), \tag{A1}$$

under the null hypothesis of no CSD (i.e. $\hat{\rho}_{ij} = \hat{\rho}_{ji} = corr\left(u_{it}, u_{jt}\right) = 0$ for $i \neq j$). The test has a mean exactly at zero for fixed values of T and N under a wide range of panel data models, including nonstationary models. In addition, we also make use of the tests proposed by Friedman (1937) and Frees (1995). The Friedman (1937) test is based on the average Spearman's correlation and is given by:

$$R_{AVE} = \frac{2}{N(N-1)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{r}_{ij}, \tag{A2}$$

where $\hat{r}_{ij}$ is the simple estimate of the rank correlation coefficient of the residuals. In comparison, the Frees (1995) test is based on the sum of the squared rank correlation coefficients and equals:

$$R_{AVE}^2 = \frac{2}{N(N-1)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{r}_{ij}^2\ . \tag{A3}$$

Unlike the CD and R_{AVE} tests, the R_{AVE}^2 test is robust to the alternating sign of the correlation.

A.2 Panel unit root test

The panel unit root test considered in our application is the test proposed by Pesaran (2007), which follows the correlated common effects (CCE) approach and filters out the CSD by augmenting the ADF regressions with cross-section averages. The cross-section augmented ADF (CADF) regressions, carried out separately for each country, are given by:

$$\Delta\omega_{it} = a_i + \varphi_i t + b_i\omega_{i,t-1} + c_i\overline{\omega}_{t-1} + \sum_{j=0}^{p} d_{ij}\Delta\,\overline{\omega}_{t-j} + \sum_{j=1}^{p}\delta_{ij}\Delta\,\omega_{i,t-j} + v_{ij} \qquad \text{(A4)}$$

where $\overline{\omega}_t$ denotes the cross-section mean of ω_{it}. The CIPS statistic is a simple-cross section average of $\tilde{t}_i$ defined by:

$$CIPS = N^{-1}\sum_{i=1}^{N}\tilde{t}_{i,} \qquad \text{(A5)}$$

where $\tilde{t}_i$ is the ordinary least squares *t*-ratio of b_i in the CADF regression above.

A.3 Panel cointegration test(s)

Following Holly et al. (2010), we adopt a two-stage procedure to assess the possibility of cointegration between log of contribution of the renewable share and its determinants as shown in equation (2). In both stages, the procedure allows for unobserved common factors that could be potentially correlated with the observed regressors. Using the CCE estimator, we first estimate Equation (2) and obtain the residuals. We then apply the CIPS panel unit root test discussed above to these residuals:

$$\hat{u}_{it} = ln\ RE\ share_{it} - \hat{\beta}_{i,CCE}\ lnX_{it} - \hat{\alpha}_i. \qquad \text{(A6)}$$

If the presence of a unit root in $\hat{u}_{it}$'s can be rejected, we can conclude that the variables are cointegrated.

A.4 Results of Cross-sectional dependence tests

We apply three alternative tests to examine the extent of CSD in our panel data. All three tests test the null hypothesis of cross-sectional independence against the alternative hypothesis of CSD. The CD test statistic of Pesaran (2004) is 15.94 with a *p*-value of 0.00, which clearly rejects the null hypothesis of cross-sectional independence in the panel. The results for Friedman's (1937) R_{AVE} test also yield a similar conclusion: the test statistic 103.76 (p = 0.00), suggesting that strong CSD is present in the data. However, both the CD and R_{AVE} tests share a common weakness in that they miss out cases of CSD where correlations sign alternates (De Hoyos and Sarafidis 2006). The test statistic (R_{AVE}^2) of Frees (1995) is, however, not subject to this drawback. The R_{AVE}^2 test statistic is 3.29 (p = 0.00), which also rejects the null hypothesis of cross-sectional independence. Moreover, the average absolute value of the off-diagonal elements of the cross-sectional correlation matrix of the residual is 0.47, which is very high. Overall, the results indicate that there is enough evidence to suggest the presence of CSD in the data.

A.5 Results of the panel unit root test Given the strong presence of CSD in the data, we have employed the CIPS panel unit root test of Pesaran (2007), which allows for CSD. The CIPS statistic is based on the cross-section average of the individual ADF *t*-statistics of each unit in the panel. Under the null hypothesis, the CIPS assumes that a series is nonstationary. Given the short length of the individual units (T=23), we consider a maximum of two lags and allow both constant and deterministic trends in the test regression. For the dependent variable (RE share), the results of the CIPS test statistic with lags p=1 and 2 are -1.75 and -1.37 (intercept only) and -1.74 and -1.24 (with intercept and trend). At the 5% significance level, the critical values of the CIPS statistic for N=20 and T in the range of 20–30 are about -2.25 and -2.76 with a constant and constant and trend, respectively. Therefore, according to the CIPS statistic, the null hypothesis of a unit root cannot be rejected at the 5% level.

Likewise, for the log of real GDP per capita, the CIPS test statistics are -1.83 and -1.92 (intercept) and -2.32 and -2.36 (intercept and trend) for lag lengths of 1 and 2, respectively. These test statistics are lower than the 5% critical values reported just above, suggesting that the series is nonstationary. Note that nonstationarity in the log of GDP per capita implies that its quadratic form (i.e. the square of the log of GDP per capita) is also nonstationary.[22] Park and Phillips (1999) have shown that the usual I(1) asymptotics hold for regressions with a nonlinear transformation (such as power) of the time series. However, we could not test for the presence of a unit root in the log of R&D spending, as some observations were missing. Nonetheless, the plots of R&D spending (see Figure 2(c) in the text) indicate that the series are trending upwards over time, leading us to conclude that a unit root might be present in the R&D spending data.

Given the presence of stochastic trends in the data, a practical implication for inference is that the least squares estimation of the model in Equation (1) cannot reliably distinguish between a true long-run relationship and a spurious regression (Granger and Newbold 1974). A panel time series estimator can address this concern over spurious regression, as discussed below. Another implication is that nonstationarity in time series poses a serious problem for forecasting the future path of the contribution of RE in the energy mix as a function of income, as current shocks have permanent effects on their levels. For a further discussion, see Basher et al. (2015).

Our next task is to test for the existence of the long-run equilibrium relationships of Equation (1) for the panel as a whole.

[22] Since y is I(1), $y_t^2 = (y_{t-1} + e_t)^2 = y_{t-1}^2 + e_t^2 + 2y_{t-1}e_t$. Since y_t is orthogonal to e_t, this implies that y_t^2 is also I(1). We thank Stefano Fachin for pointing this out to us.

A.6 Results of the panel cointegration test Finally, we apply the CIPS(*p*) panel unit root test described above to the estimated residuals as shown in Equation (A6), including an intercept and with lag orders *p*=1,2, and 3. We obtained the results -3.617, -2.687, and -2.30, respectively. These test statistics exceed the 5% critical value (around -2.25) of the CIPS statistic for the intercept case and for panel dimensions similar to ours. The results suggest rejection of a unit root in the residuals of Equation (A6), indicating that the variables in question are indeed cointegrated.

Appendix B: Panel Data Estimators

B.1 Negative binomial regression

As the dependent variable y_{it} have a Poisson distribution with parameter μ_{it}, which in turn depends on a vector of exogenous variables x_{it}, the fixed-effects Poisson regression model for panel data is given as (Cameron and Trivedi, 1998):

$$\ln \mu_{it} = \alpha_i + \beta X_{it} + e_{it} \tag{B1}$$

where α_i is the fixed effects.

One way to estimate the above model is by means of conventional Poisson regression using maximum likelihood. However, the Poisson model is known to suffer from overdispersion problem and an excess in zeros. Efficient estimation of overdispersed model can be achieved by assuming that y_{it} have a negative binomial distribution, which generalizes Poisson regression by accounting for cross-sectional heterogeneity. The negative binominal model of Hausman, Hall and Griliches (1984) is given as:

$$f(y_{it}|\lambda_{it}, \theta_i) = \frac{\Gamma(\lambda_{it} + y_{it})}{\Gamma(\lambda_{it})\Gamma(y_{it} + 1)}\left(\frac{\theta_i}{1 + \theta_i}\right)^{y_{it}} (1 + \theta_i)^{-\lambda_{it}} \tag{B2}$$

where Γ is the gamma function, θ_i is assumed to be constant over time for each individual and λ_{it} is defined as:

$$\ln \lambda_{it} = \beta X_{it} \tag{B3}$$

The mean and variance of y_{it} are given by $E(y_{it}) = \theta_i \lambda_{it}$ and $var(y_{it}) = (1 + \theta_i)\theta_i \lambda_{it}$. Therefore, the variance to mean ratio is $(1 + \theta_i)$. Thus, the negative binomial model allows for overdispersion with the original Poisson a limiting case as $\lambda \to \infty$.

B.2 CCEMG estimator

The results of the above panel tests suggest that we cannot exclude the presence of either CSD or cointegration in our data. Thus, to estimate equation (1), we used the Common Correlated Effects (CCE) estimator of Pesaran (2006), which is robust to the presence of CSD and can handle cointegrated relationships.

Besides CSD, there are other forms of interaction among variables that are either unobservable or difficult to measure. Pesaran (2006) solved this problem by augmenting equation (1) with the cross-section averages of the independent and dependent variables:

$$\ln Y_{sit} = \alpha_i + \varphi_i t + \beta_{1t} X_{it} + + \delta_{1i}\bar{Y} + \delta_{2i}\bar{X} + u_{it} \tag{B4}$$

where δ_i are the individual specific loading coefficients of the cross-sectional averages of all observable variables in the model. The $\widehat{\beta_i}$ coefficient estimates the effect of income on RE's contribution after controlling for common factors in the data. The dynamics and common unobserved factors are modeled in the error terms ε_{it}, which are assumed to have the following structure:

$$u_{it} = \lambda_i^{'}\boldsymbol{f}_t + \epsilon_{it}, \tag{B5}$$

where $\boldsymbol{f}_t$ is an $m \times 1$ vector of unobserved common effects and ϵ_{it} represents the country-specific (idiosyncratic) errors that are assumed to be distributed independently of the regressors $\boldsymbol{x}_{it}$ and $\boldsymbol{f}_t$. However, ϵ_{it} is allowed to be weakly dependent across i. The CCE estimator is based on the assumption that $\boldsymbol{x}_{it}$ is generated as:

$$x_{it} = a_i + \lambda_i^{'}\boldsymbol{f}_t + v_{it}, \tag{B6}$$

where a_i is a $k \times 1$ vector of individual effects, λ_i is a $m \times k$ factor of loading matrices with fixed components and v_{it} represents the specific components of $\boldsymbol{x}_{it}$ distributed independently of the common effects and across *i*. The CCE estimator is equivalent to ordinary least squares technique applied to an auxiliary regression such as Equation (2). The CCE mean group (CCEMG) estimator, which has been adopted in our application, is a simple average of the individual CCE estimators, β_i:

$$\hat{\beta}_{CCEMG} = \frac{1}{N}\sum_{i=1}^{N}\hat{\beta}_i. \tag{B7}$$

As pointed out by Eberhardt and Teal (2013), the CEE estimator is robust when the cross-section dimension *N* is small; when variables are nonstationary (cointegrated or not), subject to structural breaks; and/or in the presence of "weak" unobserved common factors (spatial spillover) and global/local business cycles.

Appendix C: Robustness tests

Our analysis stood up to a good number of robustness experiments, including alternative specifications or estimation techniques. Note that these sensitivity analyses were conducted for the RE diffusion model only. The first sensitivity analysis was conducted by adding hydropower to the contribution of RE. An interesting result that emerged was that across countries, hydro RE was more variable than nonhydro RE. This challenges the commonly held view that only wind and solar energy are variable;, hydro power can be subject to even greater fluctuations of energy supply (e.g. drought or rainfall variability). For brevity, the estimation is conducted on the full specification by applying the CCEMG estimator (i.e. column [5] in Table 4). The time series properties (unit root, cointegration) of hydro RES are almost identical to those of nonhydro RE. This suggests a long-run equilibrium relationship between the log of RE share and its determinants. The estimated parameters of the variables have the correct sign (as in the baseline CCEMG case in Table 2) but not statistically significant. Thus, our results are robust to the inclusion of hydro power in the data, although better results (in statistical terms) are obtained using the nonhydro RE.[23]

Second, we also consider cumulative nonhydro RE capacity (as a percentage of total capacity) as an alternative dependent variable. As pointed out by Jenner et al. (2013), the choice of cumulative capacity is appropriate if the objective is to examine links between FIT policies and the decision to invest in solar or wind capacity. This is because, unlike generation or supply, cumulative capacity reflects expected (not actual) returns on investment. The estimation results are almost similar to those of the original model. Except for RE R&D share, which shows a negative sign, all other variables have the correct sign. But, once again, the estimates are not statistically significantly different from zero. Thus our results also survive the choice of RES capacity as an alternative dependent variable in the model.

Third, we conducted an experiment allowing first and second lags of the REP index separately in the regression model, since there might be a time lag between the implementation of RE policies and the resulting diffusion of RE sources. However, these changes did not improve the results relative to the baseline findings reported in Table 2. The estimated lag coefficients are negative but insignificant, whereas the coefficients of income and income retained their expected signs, losing some significance. Finally, we augmented equation (1) with an interaction term between our RE policy variable and GDP per capita to see how these two variables work together in explaining the variation in RE. In this case, the estimated coefficients for RE policy are negative and that for GDP is positive. However, the coefficient of the interaction term has a positive sign, implying that an additional increase in GDP per capita yields a higher increase in RE. This supports the notion that in a market economy, demand-pull approaches encourage firms to generate clean energy through market signals and creating incentives. Finally, we have also considered the pooled version of the CCE estimator of Pesaran (2006) in order to gain efficiency in the parameter estimates by restricting the individual slope coefficients β_i to be the same across the cross-section units. However, the results are once again no better than those of the CCEMG estimator reported in column [5] of Table 4. These results are not discussed here to conserve space.

[23] These unreported results are available from the corresponding author on request.