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To cite this article: Jonas Grafström, Patrik Söderholm, Erik Gawel, Paul Lehmann & Sebastian Strunz (2023) Government support to renewable energy R&D: drivers and strategic interactions among EU Member States, Economics of Innovation and New Technology, 32:1, 1-24, DOI: 10.1080/10438599.2020.1857499

To link to this article: https://doi.org/10.1080/10438599.2020.1857499
Government support to renewable energy R&D: drivers and strategic interactions among EU Member States

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Abstract

Although the climate challenge requires proactive policies that spur innovation in the renewable energy sector, various countries commit vastly different levels of support for renewable energy R&D. This paper addresses the question why this may be the case. Specifically, the objective is to analyse the determinants of government support to renewable energy R&D in the European Union (EU), and, in doing this, we devote particular attention to the question of whether the level of this support tends to converge or diverge across EU Member States. The investigation relies on a data set of 12 EU Member States and a bias-corrected dynamic panel data estimator. We test for the presence of conditional β-convergence, and the impacts of energy dependence and electricity regulation on government R&D efforts. The findings display divergence in terms of government support to renewable energy R&D, and this result is robust across various model specifications and key assumptions. The analysis also indicates that countries with a low energy-import dependence and deregulated electricity markets tend to experience lower growth rates in government renewable energy R&D. The paper ends by discussing some implications of the results, primarily from an EU perspective.

1. Introduction

The development of renewable and carbon-free energy technologies is central to current efforts to address the challenges of climate change. Both policy makers and scientists have therefore called for significant increases in government (public) R&D commitments in the renewable energy field in order to comply with the existing global climate mitigation pledges (e.g. Witte 2009; Del Río 2004; Reichardt and Rogge 2014). Many governments have acted accordingly. For instance, the so-called ‘Mission Innovation’ pledge that was signed by 20 governments at the 2015 Paris climate meeting (COP 21) promised a doubling of government renewable energy R&D spending to over US$ 30 billion until the year 2021 (Sanchez and Sivaram 2017). Still, even if government support to renewable energy R&D has increased rapidly during the least two decades, not least in Europe and among OECD countries (IEA 2019), various governments commit vastly different levels of R&D support (Sun and Kim 2017). This paper investigates the drivers and the strategic
interactions underlying governments’ support to renewable energy R&D in the empirical context of a number of key European Union (EU) Member States.

This scope of the paper is motivated for at least two reasons. First, the existing research on the economics of innovation in the renewable energy sector has primarily investigated the impacts of government R&D on innovation performance measured through, for instance, patent counts or generation costs. The majority of studies report positive effects of public R&D spending on innovation performance (e.g. Johnstone, Haščič, and Popp 2010; Ek and Söderholm 2010; Verdolini and Galeotti 2011; Peters et al. 2012; Dechezleprêtre and Glachant 2014; Popp 2015; Palage, Lundmark, and Söderholm 2019). Still, considerably less attention has been devoted to the determinants of government R&D support (see, however, Garrone and Grilli 2010; Smith and Urpelainen 2013; Sun and Kim 2017), including the presence or absence of R&D policy coordination across countries.1

Second, our emphasis on government R&D efforts of EU Member States relates to the political economy of overall renewable energy policy within the Union. Even though the EU has been a global forerunner in many areas of renewable energy development (Lema, Sagar, and Zhou 2016), the integration with respect to energy and climate policy currently lingers at a ‘halfway stage’ between national and union-wide approaches. Some consider this untenable, and have called for increased integration (Buchan and Keay 2016) in line with the ambitious official rhetoric about an evolving Energy Union (European Commission 2015). Various top-down policies, such as the renewable energy directive (2009/28/EC), have indeed contributed to an increased integration. For instance, Berk, Kasman, and Kilinc (2020) conclude that since 1990 the shares of the renewable energy sources in primary energy use have tended to converge (among a selection of 14 EU Member States). Conti et al. (2018) suggest that EU policy has reduced fragmentation in renewable energy innovation in terms of patenting, and a similar pattern cannot be observed for the fossil-fuel based energy sources as well as for other emerging technologies (e.g. IT, biotechnology). However, others have emphasized that politico-economic considerations speak against further centralization and top-down policies (Strunz, Gawel, and Lehmann 2015), often stressing the fact that renewable energy policies in the EU Member States are heterogeneous, and with substantial development in some countries and far more modest progress in others. For these reasons, bottom-up processes of convergence, i.e. an independent increase in policy similarity across the Member States, could substitute for the lack of additional supranational harmonization (Kitzing, Mitchell, and Morthorst 2012; Strunz et al. 2018).

In this context, the case of government support to renewable energy R&D merits particular interest from an empirical standpoint, not least since the EU Member States have full discretion when it comes to this type of support to renewable energy R&D. As discussed in greater depth in Section 2, whether or not such domestic efforts will converge or diverge over time remains an empirical question, and the underlying decision-making processes will likely involve various types of strategic considerations. While EU energy policy would provide some top-down drive for convergence in overall renewable energy, the scope of technological development in the renewable energy sector tends to be global, and not all national governments may opt for R&D support in this field. In the EU so far, government R&D efforts in the renewable energy sector have been concentrated to a few leading countries, such as Germany, Finland and Denmark (Dechezleprêtre et al. 2011). These pioneering countries are in part driven by green industrial policy motives (Rodrik 2014), which are reinforced by the presence of agglomeration effects and institutional path dependence (see Section 2). The laggard countries would instead choose to benefit from a ‘wait-and-see’ strategy, and thus await for knowledge spillovers to close the gap between themselves and the pioneering countries (e.g. Stucki and Woerter 2017). Under these circumstances, government R&D efforts would likely diverge over time.

The issue of policy convergence versus divergence in the context of renewable energy R&D may have significant repercussions for the future decarbonisation of the energy system. For instance, policy convergence may raise concerns about overall underinvestment in renewable energy R&D; if so, the EU energy and climate policy targets would become more difficult to achieve (Corradini...
et al. 2015; Garrone and Grilli 2010). Maintaining public acceptance for the financial burdens that consumers need to carry under a period of uncertainty regarding the future energy transformation, could also be more difficult in the presence of diverging efforts.

The objective of the paper is to analyse the determinants of government support to renewable energy R&D in the EU, and, in pursuing this, we devote particular attention to the question of whether or not this support tends to converge or diverge across EU Member States. The analysis accounts for the fact that government R&D expenditures will have long-standing impacts on knowledge accumulation and, ultimately, technological progress. For this reason, we construct country-specific R&D-based knowledge stocks, which acknowledge the presence of knowledge depreciation and time lags between R&D expenditures and additions to these stocks (see further Section 3.1).

The empirical investigation builds on the literature on policy convergence (Strunz et al. 2018; Holzinger, Knill, and Arts 2008; Bennett 1991), the latter understood as the increase in policy similarity over time. Methodologically, however, we depart from approaches and concepts in the so-called green growth literature (Brock and Taylor 2010). Specifically, the analysis relies on a growth path approach, which permits an analysis of the determinants of the changes in the R&D-based knowledge stocks and a test for so-called conditional β-convergence integrated into this analysis. For our purposes, the β-convergence hypothesis states that countries with lower initial R&D-based knowledge stocks will experience higher growth rates in government R&D, and therefore catch-up with the pioneering countries. The reverse relationship displays divergence in terms of such R&D support. The emphasis on conditional convergence or divergence allows for heterogeneous steady state levels across countries. Our analysis includes measures of energy import dependence, the level of electricity regulation, the opportunity cost of government funds as well as country- and time-specific fixed effects. Finally, we also include tests for the presence of interaction effects, which help shed light on the speed of any convergence/divergence.

The econometric investigation relies on a panel data set covering 12 EU Member States over the time-period 1990-2012, and the data are analyzed using a bias-corrected dynamic panel data approach applied to a number of different model specifications. We include several robustness tests, including expanding the sample to include additional OECD (yet non-EU) countries, and tests for the various ways in which the R&D-based knowledge stock may be constructed (i.e. with varying depreciation rates and time lags).

The remainder of the paper is organized as follows. Section 2 consults the existing literature to discuss the role of government R&D support in renewable energy, and outlines the reasons why the level of such a support may converge or diverge across various countries. Section 3 outlines the methodological approach of the paper; it presents the details of the model specifications and the associated econometric issues. In Section 4, we present and discuss the data employed, i.e. key definitions, sources and descriptive statistics; particular attention is devoted to the data needed to construct the R&D-based knowledge stocks. Section 5 presents the empirical results and provides interpretations. In Section 6, we discuss a few implications of the results, including their relevance for EU energy policy, while a final section concludes the paper and identifies a number of avenues for future research.

2. Government support to renewable energy R&D: convergence vs. divergence

This section addresses the question why government support to renewable energy R&D could converge or diverge across countries. In other words, while our empirical test of convergence versus divergence is simple and straightforward, i.e. investigating the relationship between the growth rate and the initial level of the R&D-based knowledge stock, it is useful to elaborate on the underlying rationales for governments’ strategic decisions on R&D. We note that the answer to the convergence vs. divergence question will be connected to the presence of (inter-country) knowledge spillovers, green industrial policy ambitions, agglomeration effects, and absorptive capacity. In this section, the above concepts are introduced, and their relevance explained; in Section 6, we get back to these when discussing key lessons and implications from the results.
The basic rationale for government support to R&D is well established. A large body of research has argued and shown that economic markets can fail when it comes to providing the socially efficient amount of resources aimed at generating new technological and scientific knowledge (e.g. Nelson 1959; Arrow 1962). This knowledge often has strong public good characteristics, implying that the knowledge spillovers provide benefits to the public as a whole, but not to the innovator. As a result, private firms do not have incentives to provide an efficient level of R&D activity. Government support to R&D thus represents one way of correcting such technology market failures. What is more, from an international perspective, the presence of knowledge spillovers may also influence the level of government R&D support at the national level because some countries may free-ride on others’ development efforts (Corradini et al. 2015; Grafström 2018; Popp 2019).

Innovation in renewable energy largely takes place within the boundaries of common global challenges, not least climate change. Previous research has indicated that the underinvestment problem may be particularly prevalent in the case of R&D targeting environmental technology and low-carbon energy sources, much due to the strong presence of knowledge spillovers across firms and countries in these sectors (Dechezleprêtre, Martin, and Mohnen 2013; Lehmann and Söderholm 2018; Popp 2005; Fischer 2008; Peters et al. 2012). Furthermore, uncertainty about the future returns to energy R&D is often high, e.g. because of policy inconsistencies (Jaffe, Newell, and Stavins 2002), and the capital markets may not provide enough risk management instruments for the immature technologies due to lack of historical data to assess risks (Neuho 2005).

Knowledge spillovers provide one piece of the puzzle when it comes to fully comprehending the strategic interactions among national governments in terms of contributing to government R&D in the renewable energy sector. Substantial R&D efforts by some governments could lead to shrinking incentives to pursue similar R&D investments – and instead engage in free-riding behavior – on the part of other countries (e.g. Corradini et al. 2015). From a global perspective, government R&D support could therefore be overall too low, and this could call for a stronger coordination of R&D efforts at a higher supranational level. Notably, in the EU, the so-called Renewable Energy Directive (2009/28/EC) required all Member States to support renewable energy development. As noted above, this has most likely contributed to a reduction in the fragmentation in EU renewable energy innovation (i.e. patents) (Conti et al. 2018). Even though this and/or other EU directives do not stipulate how much should be spent on domestic government renewable energy R&D, such top-down policy measures may have influenced the willingness to undertake also such investments. One potential advantage of convergence is that the public’s acceptance of the financial burdens associated with the transformation of the energy system could be higher (compared to a divergence scenario).

Other factors, beyond supranational policy measures, could also contribute to converging trends in government renewable energy R&D, including disruptive inventions or failed public R&D programs. For instance, if a former pioneering country is locked-into a stagnant technology, it may face fewer incentives to pursue significant future R&D. In fact, though, the relationship between international knowledge spillovers and convergence/divergence in terms of government renewable energy R&D is a priori not clear. Specifically, in the presence of international knowledge spillovers, national government R&D becomes more ‘efficient’ and can be optimally reduced (Park 1998). In other words, free-riding behavior could reduce all countries’ incentives to pursue own R&D, and this may therefore not alone shed light on whether the resulting allocation across countries is converging or diverging, e.g. why some countries become forerunners and others lag behind. Thus, the rationale for government R&D support has to be understood also in the context of various national sectoral and technological structures. These structures represent the demand for government R&D at the national level.

Thus, even if supranational policy initiatives could induce convergence in terms of government R&D in the renewable energy sector, a relatively strong empirical case can also be made for diverging R&D efforts. One important reason why some countries may choose to be forerunners could be found in green industrial policy motives (Rodrik 2014; Altenburg and Assmann 2017), also linking...
to broader goals of economic development and job creation. Through government R&D, the domestic industry could be offered a leg-up in the international competition; a first-mover advantage in renewable energy technology development could even tilt the future path of technological development in a direction that is closer to the country’s initial comparative advantages. In practice, such green industrial policies often focus on specific renewable energy sources, i.e. wind power, bioenergy, or solar PV. Other countries instead see their competitive advantages materializing in other (non-energy) sectors, and such nations would therefore lag behind in terms of government renewable energy R&D support. In other words, diverging government R&D efforts across various countries could result from varying sectoral structures and capabilities, comparative advantages as well as from heterogeneous political preferences.

The presence of agglomeration effects may reinforce such diverging processes. This means that clustering occurs in the same industry because proximity generates positive externalities (Head, Ries, and Swenson 1995; Rosenthal and Strange 2001). In the case of technological research, there will be increasing returns on investments in areas where other similar research activities already exist. Positive spillovers across complementary R&D activities provide stimulus for agglomeration (e.g. Delgado, Porter, and Stern 2014). In other words, innovative firms in a particular industry will establish themselves geographically in countries and regions in which other inventive companies in the same industry are active. Researchers will, in turn, leave laggard countries and then instead take up employment in countries where there are larger economic returns on new ideas. Moreover, these processes and pathways will often be self-reinforcing – i.e. path dependent – in that they are continuously being influenced by extant infrastructure, institutions, and capabilities (Nelson and Winter 1982) that in turn tend to be highly country-specific (Altenburg and Pegels 2012). Government R&D support to specific technologies or sectors may further such path dependent processes, e.g. by funding basic R&D and permanent test centers, i.e. learning facilities that serve a wide set of incumbent industry actors to make continuous improvements and test new technological options (Hellsmark et al. 2016).

Nevertheless, the presence of forerunning and laggard countries does not necessarily mean that some governments will refrain from investing in renewable energy R&D. Countries often need a minimum level of technological capability in order to be able to appropriate on the knowledge developed in other countries. This demand for so-called absorptive capacity arises due to the desire to improve existing technologies and adapt these to the local conditions (e.g. Cohen and Levinthal 1989, 1990; Hussler 2004; Mancusi 2008). Thus, government support to R&D may be required to secure the country’s ability to make use of external knowledge. In a similar vein, Jovanovic and MacDonald (1994) point out that innovations and imitations are only to a limited extent substitutes. The benefits derived from knowledge spillovers will increase with variations in knowledge, but the catch-up on the part of laggard countries is often conditional on their absorptive capacity. In other words, knowledge spillovers are not equal across countries, and their magnitudes depend on domestic investments in R&D. This may be particularly relevant in the context of renewable energy innovation. The pressures arising from the climate challenge require international deployment of renewable energy innovations. Even though first-mover countries may dominate the emerging markets for such innovations, the laggard countries face incentives to invest in absorptive capacity in order to benefit from technological spillovers. For instance, based on a study of the development of green technology in the manufacturing sectors of 13 countries, Stucki and Woerter (2017) find that international knowledge spillovers may enhance innovation. Still, these spillovers do not appear to enable laggard countries to catch up to the technology leaders. In other words, a pure wait-and-see strategy may not be beneficial.

This section has illustrated that the drivers and strategic interactions underlying government support to renewable energy R&D are complex; there exist rationales for both convergence and divergence across countries in terms of government R&D support to renewable energy sources. Convergence may result in the presence of top-down policy initiatives at the supranational (e.g. EU) level, while the presence of knowledge spillovers in combination with industrial policy motives and
technological cluster theory tend to support the divergence hypothesis. At the same time, the importance of absorptive capacity, and the subsequent need to promote domestic R&D in order to make use of the knowledge developed in other countries, could lend some support to the convergence hypothesis or at least indicate a lower speed of divergence. In other words, the question whether government support to renewable energy R&D will converge or diverge across countries remains an empirical question, which we address in the remainder of this paper. We also, though, return to the above rationales when discussing the results (in Section 6).

3. Model specification and econometric issues

3.1. R&D-based knowledge stocks and the conditional convergence model

Government R&D expenditures in the energy field, including support to specific technology groups, tend to be volatile over time (Schuelke-Leech 2014), but these expenditures could also have long-lasting impacts on knowledge accumulation and technical change. For these reasons, it is necessary to abstain from a sole focus on yearly changes in government renewable energy R&D. In line with previous work (e.g. Ek and Söderholm 2010; Krammer 2009), we instead assume that lagged government R&D expenditures add to a knowledge stock. For our purposes, we are interested in the development of this R&D-based stock in per capita terms. We have:

$$y_{it} = (1 - \delta)y_{i(t-1)} + R&D_{i(t-x)}$$

where $y_{it}$ denotes the per capita government R&D-based knowledge stock ($i$ indexes the sample countries and $t$ time). Equation (1) builds on the perpetual inventory model approach, where a certain share of the previous year’s stock adds to this year’s stock. This is in turn determined by the size of the depreciation rate of the stock, (where $0 \leq \delta \leq 1$). Moreover, $R&D_{i(t-x)}$ denotes the per capita annual government support to renewable energy R&D, and $x$ denotes the number of years it takes before these expenditures generate results and thus add to the knowledge stock. This formulation builds on the reasonable assumptions that: (a) government R&D expenditures on renewable energy technologies do not have instantaneous effects on the generation of new knowledge; and (b) the acquired knowledge depreciates in that the effects of previous public R&D expenditures gradually become outdated (see also Hall and Scobie 2006).

It should be noted that while government R&D in itself represents an input to the technological development process, the knowledge stock approach introduced above is implied to reflect the output of R&D investment in terms of knowledge generated, and (in part) maintained over time. Clearly, though, this is merely an assumption and throughout the paper, we do not emphasize and/or draw heavily on the distinction between R&D input and output.

The literature review in Section 2 suggested that the presence of divergence versus convergence in the context of government renewable R&D efforts largely remains an empirical question. In order to study this specific policy convergence/divergence case (see also Strunz et al. 2018), we build on methodological approaches and concepts developed in the green growth literature. For instance, Brock and Taylor (2010) and Ordás Criado, Valente, and Stengos (2011) expand on Solow (1956), and outline theoretical models, which predict that growth in carbon dioxide emissions depends on the initial level of these emissions as well as on economic output (see Brännlund, Karimu, and Söderholm 2017 for an empirical application).

Given our focus on R&D policy convergence, we instead investigate how the initial level of the government renewable energy R&D stock per capita is related to the growth rate of that same stock. It should be noted that this approach is in line with existing research on green innovation economics. For instance, due to scale, learning and network economies, companies typically build on accumulated knowledge when developing new and better-performing technologies, in turn giving rise to path dependence in the technological development process (Acemoglu et al. 2012). We assume a corresponding relationship in the context of national governments’ R&D support decisions.
For instance, investments in government R&D may be positively related to how much knowledge that has been accumulated in the past, i.e. implying policy divergence.

The empirical analysis relies on the conditional $\beta$-convergence model. This implies that, in the case of policy convergence, the countries are permitted to converge to different steady-state levels rather than to the same level. In a panel data setting, we can test for conditional $\beta$-convergence versus divergence through a transformed growth equation (Barro and Sala-i-Martin 1992). We have:

$$\ln(y_{it}/y_{it-\tau}) = \alpha + \beta_c \ln(y_{i,t-1}) + \beta X_{it} + \rho_i + \eta_i + \epsilon_{it}$$

(2)

where $\ln(y_{it}/y_{it-\tau})$ is the growth rate in the public renewable energy R&D stock per capita over the time period $t - \tau$ ($\tau = 1$) and $t$. The first two terms on the right hand side of equation (2) are the intercept term $\alpha$, and the logarithm of the initial level of thestit per capita knowledge stock, $\ln(y_{i,t-\tau})$. A negative – and statistically significant – estimate of $\beta_c$ implies support for the conditional $\beta$-convergence hypothesis (e.g. Strazicich and List 2003), while a positive estimate instead would instead suggest divergence in terms of government R&D in the renewable energy field. The magnitude of the $\beta_c$ coefficient will in turn influence the speed of policy convergence or divergence (see further below). Moreover, represents the country-specific fixed effects, $\eta_i$, represents period-specific fixed effects, while $\epsilon_{it}$ is the error term.

The vector $X_{it}$ contains three exogenous variables that can be assumed to influence the growth rate of the R&D knowledge stock, and these thus help control for differences in the steady states across countries (e.g. Barro and Sala-i-Martin 1992; Barro 2015). First, $RIR_{it}$ represents the opportunity cost of government R&D, here measured by the real rate of return on long-term treasury bonds. We anticipate that increases in this variable will have a negative influence on annual government support to renewable energy R&D, and thus also on the growth rate of the corresponding knowledge stock, i.e. $\ln(y_{it}/y_{it-\tau})$.

Second, we also include a variable, $EI_{it}$, indicating the degree of energy import dependence in country $i$ and time-period $t$. Energy imports into the EU are heavily dominated by fossil fuels such as oil and natural gas. Increased energy import dependence could therefore have a positive influence on the willingness of governments to invest in renewable energy R&D (e.g. Baccini and Urpelainen 2012). As noted above, in this analysis, we focus on the aggregate support to renewables, as have indeed most of the relevant EU policies (e.g. Directive 2009/28/EC). Still, it should be clear that individual countries will typically respond differently with respect to the specific energy sources receiving most support, e.g. forest biomass in northern Europe, solar PV in southern Europe (see further Section 4.1).

Third, $ER_{it}$ is a variable measuring the degree of regulation of the electricity sector where high values indicate a more regulated sector, i.e. with respect to the presence of public ownership, entry barriers, vertical integration, etc. (see Section 4.2 for details). Since the turn of the century, many of the most important renewable energy sources, e.g. wind power and solar PV, have increasingly been penetrating the electric power sector. Still, at the same time, previous research indicates that as the OECD and EU countries have deregulated their electricity sectors from the 1990s and onwards, national governments have tended to reduce the budget appropriations for energy R&D (e.g. Nemet and Kammen 2007; Sanyal and Cohen 2009). Smith and Urpelainen (2013) argue that, in the absence of government control, electricity companies may have weaker incentives to internalize the social benefits of knowledge generation in their decision-making.

It is important to note that this reduction in government energy R&D has not been compensated by an increase in private R&D. On the contrary, the deregulation of the electricity markets has coincided with a significant decline in private R&D investment (Jamasb and Pollitt 2008; Kim, Kim, and Flacher 2012). On the one hand, deregulation would mean more competition, and therefore, some would argue, more companies in the market potentially investing in renewable energy R&D. However, the intense competition primarily implies lower profit margins, as well as more cost conscious companies facing a reduced ability to pass on any cost increases to the consumers (Jamasb
and Pollitt 2008; Söderholm 1999). In addition, electricity being a highly homogenous good also makes it difficult for companies to get out of the price-competition mechanisms.

The fixed effect approach implies that our model estimates take both country – and time-specific unobserved impacts into account. For instance, the country-specific effects will address factors such as climate, including sunshine, ocean access, and arable land. This implies in turn that any convergence or divergence results cannot be traced back to these natural endowments, which are essentially fixed over time. The country-specific effects will also capture the fact that some countries host long-standing non-renewable energy sectors, which deter government support to renewable energy R&D (following lobbying activity) (Wang, Li, and Pisarenko 2020; Furlan and Mortarino 2018). Moreover, the profitability of the fossil fuel sectors will be influenced by global fossil fuel prices, and such common influences are captured by the time-specific effects.

The empirical analysis also involves two alternative, and more general, model specifications in which we include interaction effects. We allow the speed of convergence or divergence to differ with the levels of energy-import dependency and electricity regulation, respectively.\textsuperscript{11} The following alternative model specifications are introduced:

\[
\ln(y_{it}/y_{i,t-1}) = \alpha + \beta_1 \ln(y_{i,t-1}) + \beta_2 X_{it} + \mu \ln(y_{i,t-1}) \ln(E_{it}) + \rho_i + \eta_t + \varepsilon_{it} \quad (3)
\]

\[
\ln(y_{it}/y_{i,t-1}) = \alpha + \beta_1 \ln(y_{i,t-1}) + \beta_2 X_{it} + \phi \ln(y_{it-1}) \ln(E_{it}) + \rho_i + \eta_t + \varepsilon_{it} \quad (4)
\]

In these specifications, the speed of $\beta$-convergence will be determined by the terms $\beta_2 + \mu E_{it}$ and $\beta_1 + \mu E_{it}$, respectively.

In the case of energy import dependence, it can be hypothesized that countries with relatively high energy-import dependence levels will have (ceteris paribus) stronger incentives to develop renewable energy sources, and therefore to maintain a high growth rate in $y_{it}$. For this reason, $\mu$ should have a positive sign, suggesting either a lower speed of convergence or, alternatively, a higher speed of divergence (depending on the estimated sign and magnitude of $\phi$). Moreover, the specified interaction between $\ln y_{i,t-1}$ and $E_{it}$ allows us to investigate how the degree of electricity market regulation influences the speed of convergence/divergence. As noted above, countries with a highly regulated electricity sector (e.g. strong public ownership and vertical integration) are more likely to (ceteris paribus) maintain a high growth rate in $y_{it}$.\textsuperscript{12} Hence, we expect a positive sign for the parameter $\phi$ in equation (4), implying in turn that a move towards more deregulated electricity markets would be associated with a higher speed of convergence (or, alternatively, a lower speed of divergence).

Equations (2)-(4) represent our base specifications, i.e. models I-III, which are estimated using a panel data set comprising 12 EU countries over the time-period 1990-2012. However, in order to test the robustness of the empirical results we also consider an extended data sample in which five OECD, yet non-EU, countries are included as well. These model specifications are referred to as models IV-VI. Furthermore, the Appendix presents the results from a number of additional robustness tests (Tables A1–A2). In this case, we test whether the results are robust to different assumptions concerning the construction of the R&D-based knowledge stock, i.e. the time lag ($x$) and the depreciation rate ($\delta$) (see Section 4.1 for details). As noted in section 3.2 below, we also challenge the robustness of the results by including a (deterministic) time trend.

### 3.2. Econometric issues

The main usefulness of a panel approach lies in it allowing for heterogeneity across countries in the sample (Islam 1995). When using lagged dependent variables in traditional models, such as pooled OLS, fixed- or random-effects models, there is a risk that these yield biased estimates due to correlation and endogeneity issues. Kiviet (1995) therefore proposed the use of a least squares dummy variable approach (LSDV) that has been corrected for bias. This is found to be more efficient than the various instrumental variable (IV) and generalized method of moments (GMM) estimators,
such as Arellano and Bond (1991), who adopt a two-step method in which lags of explanatory variables in levels are used as instruments. Moreover, the GMM estimators were originally designed for large cross-sectional units $N$ and long time periods $T$. Kiviet (1995) however demonstrated that the bias-corrected LSDV approach has a relatively small variance compared to most IV and GMM estimators. In our model estimations, $N$ is either 12 or 17 while $T$ equals 23. For these reasons, we estimate our dynamic panel data models employing the bias-corrected LSDV approach. We build on Bruno (2005a) in which the bias approximations are extended to accommodate unbalanced panels, as well as on Bruno (2005b) who introduces the routine \texttt{xtlsdv} that implements the LSDV model in the statistical software Stata. In total 200 bootstrap iterations were employed.

We also need to address the potential problem of non-stationarity. The Im-Pesaran-Shin unit-root test for panel data indicate that we cannot reject the null hypothesis of unit root for the initial level of the per capita knowledge stock (while all the remaining variables, including the dependent variable, appear to be stationary). It is however not straightforward how to address this. First, non-stationarity is less of concern when the time-series is short, and the standard tests are not entirely reliable because of the unit root tests’ asymptotic characteristics (Baltagi 2005). The unit root problem is a matter of time dimension, and a 23-year-long time series does not necessarily convey the time-series feature for the variables, not least for our (initial) R&D stock where the transformation is relatively slow over time. Second, taking the first difference of the initial R&D stock does not make sense for theoretical reasons, this since the test of R&D convergence versus divergence builds on this. Third, our use of period-specific fixed effects will take a stochastic trend common to all units of the data into account, but not the country-specific unit-root processes. Given the above, we keep the standard panel-data analysis based on the bias-corrected LSDV approach (thus assuming stationary data). Still, in order to address any concerns about spurious correlation, we added a simple (deterministic) time trend to models I-III. As noted in Section 5, our results were robust to this inclusion.

4. Data sources, definitions and descriptive statistics

Our data set consists of a balanced panel including 12 of the 15 first EU Member States during the period 1990-2012. These include Austria, Belgium, Denmark, Finland, France, Germany, Italy, the Netherlands, Portugal, Spain, Sweden, and the United Kingdom. The early 1990s involved a number of important geopolitical changes, such as the reunification of Germany and the EU expansion. Sweden, Finland and Austria, who all joined the EU in 1995, were not EU members from the starting year of the period. The early 1990s were also characterized by an increased focus on climate change, and many of the early support schemes to renewable energy were introduced (e.g. the German feed-in tariff for wind power). Since the introduction of two renewable energy directives in 2001 and 2009, respectively, all EU Member States have implemented support schemes that help promote the adoption of renewable energy sources (e.g. feed-in tariffs, quota schemes, tendering procedures). However, while this has led to some amount of policy convergence in terms of renewable energy shares, innovation and policy instrument choices (Strunz et al. 2018; Conti et al. 2018), the Member States have full discretion when it comes to deciding how much government expenditures should be spent on encouraging R&D in the renewable energy sector.

As was noted above, in order test the robustness of the empirical results we also extend the data set to include five OECD countries that are not EU Member States: Canada, Japan, Switzerland, Norway and the USA.

4.1. The calculation of the R&D-based knowledge stock

The dependent variable, $\ln(y_{it}/y_{i,t-1})$, is the growth rate in the per capita knowledge stock of government funded renewable energy R&D, and the initial (lagged) level of this stock is one of the independent variables. The data needed to calculate this stock in line with equation (1) were collected from the Energy Technology RD&D Statistics database of the International Energy Agency (IEA).
These IEA data are known as possibly the best available data source of public R&D expenditures in the energy sector (Garrone and Grilli 2010). They also permit us to distinguish between R&D support to renewable energy sources and other energy R&D (e.g. energy efficiency, nuclear power, fossil fuels). Nevertheless, this does not mean that the data do not raise any concerns (Bointner 2014). Some scholars argue that these data provide an incomplete representation of government support to energy R&D (e.g. Arundel and Kemp 2009). There are also concerns with respect to the geographical coverage over time; e.g. Germany was reunified in 1991 but reports some missing data for the new Bundesländer (i.e. states formerly associated with the German Democratic Republic) prior to 1992. Moreover, all countries may not report data concerning R&D funded by regional governments (IEA 2012).

In order to construct the knowledge stock variables, in the baseline case we assume a time lag of two years (\(x=2\)) and a depreciation rate of 10 percent. Our choice of time lag is constrained by the limited data set. However, since Popp (2015) shows that the time lag between public R&D expenses and private energy patents can be extended, up to 5–6 years (see also Popp 2006), we also consider alternative estimations based on a five-year time lag. Our choice of a ten percent knowledge depreciation rate builds on Griliches (1998) and Nordhaus (2002), and in part, this reflects the relatively rapid development of renewable energy technology since the oil crises in the 1970s. The magnitude of this parameter is, however, also uncertain. For this reason, we also adopt alternative assumptions, and estimate models based on depreciation rates of 5 and 15%, respectively.

The IEA provides government R&D data for renewable energy sources from the year 1974 and onwards (IEA 2019). Although the respective domestic R&D expenditures were low in this year, we need to somehow account for the fact that there was accumulation of government R&D spending before 1974. In order to account for previous R&D expenditures, an initial knowledge stock, \(y_0\), is
estimated as:

\[ y_0 = \frac{R&D_0}{g + \delta} \]  

(5)

where \( R&D_0 \) is the amount of government renewable energy R&D spending per capita in the first year for which data are available (1974), and \( g \) is the average geometric growth rate for each country's R&D expenditures by country over the first ten-year period (see also Hall and Scobie 2006; Madsen and Farhadi 2016).

Figure 1 illustrates the results of the calculation of the government renewable energy R&D-based knowledge stock (per capita). This stock is reported for the period 1990–2012 and for 12 EU Member States. It is evident that in per capita terms the R&D-based knowledge stock differs across countries as well as over time. For some of the countries (e.g. Sweden), we see periods of decline, thus indicating that new spending on government R&D has not always been able to offset the depreciation of the stock (as well as any increases in the country's total population). Germany and Denmark represent the two countries that have had the highest knowledge stock per capita since 2000, in part reflecting their promotion of wind power and (later on) solar PV. Over time, there appears to be an increased focus on government support of renewable energy R&D in most countries. This reflects in part a shift away from support to other energy sources (e.g. nuclear power) (IEA 2019). In total for our 12 EU Member States, the R&D budgets for renewables increased from 7% of the total energy R&D expenses in 1980 to approximately 25% in 2012.

The Appendix provides detailed information on how the selected countries prioritized among the different renewable energy sources in per capita terms: on average over the 2000–2012 period (Figure A1) and in the single year 2012 (Figure A2). These figures show, for instance, that in northern Europe (Finland and Sweden), a lion share of government R&D expenditures has been invested in bioenergy, while Denmark and Germany have tended to prioritize wind power R&D. Instead, solar PV has dominated the government R&D support to renewables in parts of southern Europe, e.g. Italy. In the discussion section, we get back to the issue of country heterogeneity in terms of the type of renewable energy sources supported by governments.

4.2. Independent variables

Table 1 provides variable definitions and descriptive statistics for the per capita knowledge stock variables, and the remaining independent variables used in the empirical investigation. The initial government R&D knowledge stock enters the regression models in logarithmic form, but the

<table>
<thead>
<tr>
<th>Variables</th>
<th>Definitions</th>
<th>Mean</th>
<th>S.D.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent variable</td>
<td>The growth rate in the knowledge stock of renewable energy R&amp;D support per capita ( \ln(y_{it}/y_{i,t-1}) ).</td>
<td>Knowledge stock calculated based on equation (1) and the parameter assumptions that are outlined in Section 4.1.</td>
<td>0.06</td>
<td>0.13</td>
<td>−0.10</td>
</tr>
<tr>
<td>Independent variables</td>
<td>The initial public R&amp;D-based stock ( y_{i,t-1} )</td>
<td>The one period lag of the knowledge stock, calculated based on equation (1) and the parameter assumptions that are presented in Section 4.1</td>
<td>12.13</td>
<td>1.34</td>
<td>8.15</td>
</tr>
<tr>
<td></td>
<td>Real interest rate ( RIR_{it} )</td>
<td>Rate-of-return in percent on government bonds with 10-year maturity (inflation-adjusted)</td>
<td>4.53</td>
<td>2.99</td>
<td>−2.77</td>
</tr>
<tr>
<td></td>
<td>Energy import dependence ( EI_{it} )</td>
<td>Energy use less production, both measured in tons of oil equivalents (toe)</td>
<td>9.36</td>
<td>152.87</td>
<td>−842.43</td>
</tr>
<tr>
<td></td>
<td>Electricity regulation ( ER_{it} )</td>
<td>The OECD PMR index of regulation in the electricity sector. Scaled between 6, the highest, and zero (0) the lowest.</td>
<td>3.35</td>
<td>1.64</td>
<td>0.87</td>
</tr>
</tbody>
</table>
descriptive statistics reported in Table 1 build on the original data. The real interest rate on government bonds ($RIR_{it}$) is employed as proxy for the opportunity cost of public R&D expenses; these rates were collected from the Strunz, Gawel, and Lehmann (2016) and the OECD statistical database (2016b).

We define energy import dependence ($EI_{it}$) as total primary energy use less domestic production measured in tons of oil equivalents. The relevant data source was the IEA’s data series on total primary energy balances. Energy use refers to use of primary energy before transformation to other end-use fuels, which is equal to indigenous production plus imports and stock changes, minus exports as well as fuels supplied to ships and aircraft engaged in international transport. A negative value indicates that the country is a net exporter, and high positive values therefore suggest a high energy-import dependence. As was noted above, a country with high levels of (fossil fuel) energy imports will be induced to invest in the development of renewable energy sources, since this would reduce the country's exposure to international fuel price fluctuations. It also increases the ability to address future supply interruptions caused by political instability and/or resource constraints (Neuhoff 2005; Rübbelke and Weiss 2011; Sun and Kim 2017).

Finally, electricity regulation ($ER_{it}$) refers to the level of regulation of the electric power sector in terms of public ownership, entry restrictions, vertical integration, and price regulation of the wholesale market. We here employ OECD data on product market regulation (PMR) in the electricity sector (OECD 2016a). The PMR contains annual data for several countries, and the PMR scores range from zero (0) to six (6) (Jamasb and Pollitt 2008; Kim, Kim, and Flacher 2012). Again, high scores indicate the presence of an intensively regulated electricity sector while low values indicate liberalization.

### 5. Empirical results

Table 2 presents the estimated coefficients for models I-VI, i.e. the models building on the time period 1990-2012, and where models I-III involve the EU 12 countries and models IV-VI the 17 OECD countries. For the EU 12 sample, the convergence/divergence results are overall very robust, and show a positive relationship between the initial levels of the R&D-based knowledge stock and the growth rate in this same stock. These results therefore indicate clear evidence of divergence across the 12 EU Member States in terms of government R&D knowledge build-up in the renewable energy sector.

<table>
<thead>
<tr>
<th>Models Coefficients</th>
<th>I 12 EU countries</th>
<th>II 12 EU countries</th>
<th>III 12 EU countries</th>
<th>IV 17 OECD countries</th>
<th>V 17 OECD countries</th>
<th>VI 17 OECD countries</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_1$ Initial public R&amp;D-based stock</td>
<td>0.394*** (0.068)</td>
<td>0.383*** (0.0685)</td>
<td>0.167** (0.065)</td>
<td>0.409*** (0.06)</td>
<td>0.409*** (0.0616)</td>
<td>0.083 (0.056)</td>
</tr>
<tr>
<td>$\beta_2$ Real interest rate</td>
<td>0.005 (0.003)</td>
<td>0.006 (0.003)</td>
<td>0.005 (0.003)</td>
<td>0.005** (0.002)</td>
<td>0.006** (0.002)</td>
<td>0.006** (0.002)</td>
</tr>
<tr>
<td>$\beta_3$ Energy import dependence</td>
<td>0.001** (0.0004)</td>
<td>0.001** (0.0004)</td>
<td>0.001** (0.0004)</td>
<td>0.0005*** (0.0001)</td>
<td>0.001*** (0.00024)</td>
<td>0.0005*** (0.0001)</td>
</tr>
<tr>
<td>$\beta_4$ Electricity regulation</td>
<td>0.010 (0.007)</td>
<td>0.010 (0.008)</td>
<td>0.011 (0.007)</td>
<td>0.012** (0.006)</td>
<td>0.012** (0.006)</td>
<td>0.012** (0.006)</td>
</tr>
<tr>
<td>$\beta_5$ Interaction – energy import dependence</td>
<td>0.0001 (0.001)</td>
<td>0.068*** (0.019)</td>
<td>0.0002 (0.0002)</td>
<td>0.104*** (0.016)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Country-specific effects: Yes, Yes, Yes, Yes, Yes, Yes
Time-specific effects: Yes, Yes, Yes, Yes, Yes, Yes
Number of observations: 252, 252, 252, 362, 362, 362
Number of countries: 12, 12, 12, 17, 17, 17
Number of years: 23, 23, 23, 23, 23, 23
Number of iterations: 200, 200, 200, 200, 200, 200

Note: The standard errors are in parenthesis, while ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.
As shown in the Appendix, our finding of divergence holds also in the cases where we assume a longer time lag of five years (Table A1) and/or use alternative knowledge depreciation rates (Table A2). This applies also for the extended OECD sample; the only exception is model VI based on a two-year time lag and a ten percent depreciation rate (Table 2). Finally, the results from the model estimates including deterministic time trends are shown in the Appendix (Table A3). These illustrate that although the time trend coefficients are all statistically significant our results are overall robust also to this inclusion.

While we would expect that a high opportunity cost of public funds should lead to lower growth rates in government renewable energy R&D, our results are not entirely robust in this respect. For instance, when assuming a five-year time lag in the knowledge stock, we find statistically significant and negative coefficients (Table A1 in the Appendix), but in most of the other model specifications, the results suggest statistically insignificant and even positive (and statistically significant) coefficients (e.g. Table 2 and Table A2). One reason for these ambiguous results could be that the real interest rate on government bonds could be positively correlated with upswings in the domestic economy. Clearly, for the EU and OECD countries, the domestic business cycle will be closely influenced by the global economy in general, and such common influences will be captured by our use of time-specific fixed effects. However, the economic development in each country may also differ due to heterogeneities in industry structure, trading partners, etc.

Table 2 also displays that positive growth in the government R&D-based knowledge stock tends to be induced by higher energy import dependence levels. Thus, governments in countries with high energy-use levels but low levels of domestic energy production generally have a stronger focus on maintaining a relatively high support to renewable energy R&D. As noted above, renewable energy is an important substitute to fossil fuels such as natural gas and oil, which dominate the energy imports in the EU and OECD countries. When consulting also the outcome of the robustness tests (see Appendix), we find that this result appears to be robust for the EU 12 sample, but less so for the extended sample including a few additional OECD countries. However, we find no evidence whatsoever of an interaction effect suggesting that the speed of β-divergence would be affected by the magnitude of energy import dependence.

Finally, the results in Table 2 display a positive and statistically significant relationship between the degree of electricity market regulation and the growth rate of the R&D-based knowledge stock. This result is expected, but overall, it does not appear to be particularly robust (see also Tables A1-A2). For the EU 12 sample, the electricity regulation effect is particularly manifested in the interaction with the initial knowledge stock, i.e. the β5 coefficient. In other words, a more regulated electricity sector implies a higher growth rate in the R&D-based knowledge stock, and the speed of divergence thus increases.

This last result thus suggests that the deregulations of the European electricity markets over the last decades have helped slow down the growth in government support to renewable energy R&D, as well as the speed of divergence in terms of the accumulation of such R&D. Similar findings are shown for the extended OECD sample, but these results are not entirely robust when considering the various time lags and depreciation rates used when calculating the R&D-based knowledge stock (see the Appendix, Tables A1-A2).

6. Discussion

6.1. Diverging government commitments to renewable energy R&D

Our results show divergence across the EU Member States (and OECD countries) in terms of government support to renewable energy R&D. How can we interpret this? To begin with, recall that, in general, convergence does not equate good and divergence does not equate bad (or vice versa). In addition, our empirical tests do not address the exact drivers and strategic interactions involved. Still, combining our econometric results with relevant lessons from the literature that we reviewed
and discussed in Section 2 will permit us to shed some additional light on a few of the most pertinent issues.

First, Conti et al. (2018) show that policy support for renewables has led to less, and not more, fragmentation in renewable energy innovation across the EU Member States. Specifically, they conclude that the probability of (renewable energy) patent citations across these countries has increased over time, thus suggesting converging instead of diverging processes. Verdolini and Galeotti (2011) report some related results, and report that international knowledge spillovers (in the form of patenting activity in other countries) have had particularly important impacts on innovation. However, the main difference between our study and those cited above is that we focus not on renewable energy innovation in general (i.e. based on private patenting), but on one specific type of input to the technology development process.

Government energy R&D support plays a particularly important role in the case of long-term and risky research endeavors, in turn accompanied by additional R&D policy measures such as tax breaks for private R&D (Garrone and Grilli 2010). Still, the implementation of public R&D programs is far from straightforward. For instance, governments may try to avoid criticism of wasting public funds by allocating R&D support to technologies and projects with lower risk profiles. This could end up in crowding-out private R&D, e.g. if the government interventions translate into higher costs of research inputs in the form of scientists (David and Hall 2000). In the light of these risks and difficulties, some nation states could opt for a free-riding strategy, and limit their R&D expenditures to the levels needed to maintain a decent level of absorptive capacity.

Second, while the empirical findings are to some extent consistent with free-riding behavior on the part of a selection of EU Member States, it is also important to consider why some countries opt for another strategy, and take the lead in terms of government R&D support to renewable energy sources. An important answer to this question relates to the presence of industrial policy motives where some governments attempt to pursue first-mover advantages in the renewable energy industry. Any potential comparative advantages are often path dependent, and may be fueled by the presence of agglomeration effects. In other words, technology development tends to cluster in certain regions and industries; this gives rise to positive externalities, not least due to geographical proximity (Head, Ries, and Swenson 1995; Rosenthal and Strange 2001). In fact, industrial policy motives tend to be prominent within several EU Member States’ energy policies, notably Germany (Strunz, Gawel, and Lehmann 2016) and Denmark (Rasmussen 2001; Hansen, Jensen, and Madsen 2003). Such policy goals are consistent with our empirical results indicating divergence in government renewable energy R&D among EU Member States.

Furthermore, even though EU policy goals address renewable energy development in general, the efforts made in separate countries to pursue industrial policy ambitions will typically focus on specific renewable energy technologies in which the country has comparative advantages. As noted in Section 2, such ambitions may be spurred by existing infrastructure, institutions and research capability. Government support can help private companies build on accumulated technology-specific knowledge in developing new or better-performing products and processes (Acemoglu et al. 2012). Figures A1 and A2 in the Appendix show how the Nordic countries tend to specialize in bioenergy (Finland and Sweden) as well as wind power (Denmark), while the governments in Italy and Spain instead prioritize support to solar PV R&D. Support to these technologies may be viewed as a vehicle for economic growth, job creation and export potential.

Third, what are the implications for energy and climate policy at the EU-level? Even though a normative assessment is beyond the scope of this paper, there might be some reason for concern. Our discussion above could be interpreted to suggest that the diverging government R&D support for renewable energy represents a stable – and perhaps even economically efficient – allocation of efforts across EU Member States. This is not necessarily the case! Clearly, in the presence of strong industrial policy motives, there is likely to be continued investment in public renewable energy R&D. Even if these efforts would be highly biased towards a few selected countries, there may be little concerns about free-riding and unfair burden-sharing. The main challenges lie instead in
designing institutional frameworks that can help counter the political and informational risks associated with green industrial policies (e.g. Rodrik 2014).

However, if major government R&D programs fail, extensive criticism of wasting public funds could emerge in the forerunning countries, and their roles as engines in renewable energy R&D wane. In the worst scenario, the transition to a zero-carbon energy system would become much more costly to achieve. As a remedy, top-down supranational policy measures contesting any existing diverging trends could be considered. For instance, an EU-wide agreement on R&D funding, i.e. analogous to the internationally agreed greenhouse gas emission targets for each Member State, might be contemplated. Another option, of course, is to rely on direct funding from the European Commission. Any such EU-level policy initiatives, though, come with many challenges. In 2010, the Commission adopted the so-called Strategic Energy Technology (SET) Plan, approved by all Member States (e.g. Centre for European Policy Studies 2011). It has however remained difficult to ramp up R&D spending in significant ways, in part because of the desire among Member States to keep the development of new technologies with potential scope for competitiveness under national control (Witte 2009).

In sum, the overall implication from the above discussion suggests a somewhat weakened case for further harmonization and centralization within an ‘Energy Union’; there exists substantial national interest in developing renewable energy technologies and solutions. Unless free-riding complaints should figure eminently in future climate and energy policy deliberations, the scope for very ambitious EU-level approaches to government energy R&D is probably limited.

### 6.2. Energy independence and electricity regulation

The empirical results show that both energy import dependence and electricity regulation tend to be correlated with the growth in EU government R&D support to renewable energy, although the latter relationship was not robust across all model specifications.

The result that energy import dependence is a driver of government renewable energy R&D is consistent with other studies. These include Sun and Kim (2017), who show that among OECD countries, domestic output in the petroleum-refining sector has been positively linked to overall government energy R&D but negatively correlated with government R&D support to renewable energy sources. Moreover, Baccini and Urpelainen (2012) find a clear relationship between oil price movements and government R&D expenditures. In this respect, it is important to note that the incentives to reduce the exposure to fossil fuel energy imports will be related to both price movements and import dependence in terms of volumes (in toe). Our energy import dependence variable addresses the latter influence, while the inclusion of time-specific fixed effects captures the former (since the global crude oil price are the same across all countries for a given year).

Our electricity regulation results are not robust, but primarily the interaction effect suggests a positive relationship between a more regulated electricity sector and investments in government renewable energy R&D. This finding is consistent with previous research concluding that the deregulation of electricity markets has implied a reduction in government energy R&D (Smith and Urpelainen 2013; Wiesenthal et al. 2012; Dooley 1998). Smith and Urpelainen (2013) suggest that one way to deal with this dilemma could be to build up new coalitions of industrial support for government R&D, e.g. around producers of new energy technologies, and possibly also supported by new types of energy users (e.g. data centers, electric battery producers).

As noted in Section 3.1, there appears to be relatively meagre scope that this decline will be compensated through a corresponding increase in corresponding private R&D. The willingness of private companies to commit resources towards energy R&D is affected by market structure, and a higher degree of competition and less state control will typically imply lower profit margins, and thus less scope for investing in long-term energy technology innovation (Jamasb and Pollitt, 2008). Electricity is a homogenous good, therefore providing companies with very meagre opportunities to get out of the price-cost competition (Neuhoff 2005).
Finally, this potentially grim outlook for government R&D in the renewable energy field could also have repercussions for overall EU energy and climate policy. With the finalization of the internal market being the main pillar of EU energy policy (one that gives the EU Commission substantial legal competences\(^\text{22}\)), a hitherto neglected trade-off between this internal market agenda and climate policy comes into view: if deregulation lowers government R&D efforts (particularly by fore-running countries), this may insufficiently internalize knowledge spillover effects and not correspond to the levels of public R&D support implied by the EU’s climate policy pledges. In other words, under-investment in government renewable energy R&D support could well be an undesired side-effect of the internal market agenda.

7. Concluding remarks and implications

This paper contributed with increased empirical understanding of the dynamics of government R&D efforts in the renewable energy sector, and with an emphasis on key drivers and strategic interactions. Specifically, we analysed the development of government support to renewable energy R&D across selected EU countries over time, and particular attention was devoted to the presence of conditional β-convergence. The empirical results suggested divergence in terms of government R&D support to renewable energy, and these results were overall very robust to the use of various model specifications, variable constructions, and data samples. Moreover, the results showed a positive relationship between energy import dependence and the growth rate in the R&D-based knowledge stock, while the trend towards deregulated electricity markets appear to have contributed to a decline in this stock.

Our analysis also opens new opportunities for future empirical research. For instance, future research on public R&D support to environmental and green technology should in more detail address the complex – and often conflicting – forces behind national governments’ decisions to allocate funding to such R&D. Furthermore, the global distribution of domestic energy R&D efforts is changing, thus making it important to also investigate the drivers (and the impacts) of government energy R&D in the emerging economies, not least China. As noted by Popp (2019), in this context, most research attention has been devoted to technology transfer in solar PV and wind power (e.g. Lam, Branstetter, and Azevedo\(^\text{2017}\); Groba and Cao\(^\text{2015}\)), while fewer studies have studied the link between government policy and energy innovation in the emerging economies.

Notes

1. The few studies that do address coordination and fragmentation in terms of R&D efforts and innovation activity across countries either adopt a national innovation system perspective (e.g. Hammoud, Paty, and Savona\(^\text{2014}\)), thus focusing on the interactions between private firms, industrial sectors, universities and government, or investigate the role of knowledge spillovers by studying patent citations regardless of whether these patents stem from government or private R&D (e.g. Conti et al.\(^\text{2018}\)).

2. Nevertheless, even though the concepts of convergence and divergence are useful starting points for empirical analyses of the drivers and strategic interactions underlying government support to renewable energy R&D across countries, this paper does not explicitly address the question of whether one particular development path should be preferred over another.

3. Breyer et al. (2010) report that 85–90 percent of global energy R&D have taken place in the OECD countries.

4. Close economic integration, through trade and geographical closeness, does increase the likelihood that countries tend to have access to – more or less – the same pool of knowledge, even considering the fact that technological knowledge is not always fully codified and remains tacit and informal.

5. The convergence process could also be facilitated by the simple fact that laggard countries can grow faster (in percentage terms) than the more technologically advanced countries, this since growing from something small will result in comparatively large growth rates. This should in turn lead to a catch-up with the more developed countries, at least in the long-run (Keefer and Knack\(^\text{1997}\)).

6. Schmidt and Huenteler (2016) note, though, that this does not preclude that even laggard countries could benefit from the formation of local industries in specific stages of the value chains. These include installation, operation and maintenance, and simple production steps (e.g., the assembly of PV cells into modules).
7. One such example is the establishment of the Danish Wind Turbine Test Station in 1978, which helped position Denmark as a key knowledge and innovation hub in the wind power industry (Garud and Karnoe 2003). As shown in the Appendix, Figures A1-A2, Denmark has maintained high per capita expenditures on government wind power R&D compared to other EU Member States.

8. According to Antonelli, Patrucco, and Quatraro (2011) and Boschma and lammarino (2009), the diffusion of knowledge is more likely to occur when the competences and knowledge stocks of the inventors and the adopters are closely related, i.e., when there is a high level of technological proximity (see also Fischer, Scherngell, and Jansenberger 2006).

9. One special issue of the journal *Energy Economics* illustrates a broad set of tests with respect to convergence in the energy sector, e.g., relating to energy productivity, intensity etc. (Apergis, Ewing, and Payne 2017).

10. Tsai, Wang, and Chiou (2016) illustrate that in a duopoly market setting, privatization cannot induce both public and private firms’ environmental R&D efforts and it may even lower the efforts of both types of firms.

11. A related approach is employed by Brännlund, Lundgren, and Söderholm (2015) but in a different empirical convergence context.

12. Put differently, according to equation (2), two countries with identical initial levels of the per capita knowledge stock, would (ceteris paribus) have the same growth rate in $y_{i,t}$, but in equation (4) this growth rate is allowed to vary depending on differences in electricity regulations.

13. Greece, Ireland and Luxembourg are not included due to a lack of data on renewable energy R&D expenditures, in particular prior to the year 2000. Due to data availability and quality reasons, we also limit the investigation to the time-period 1990-2012.

14. While the analysis in this paper focuses on the development of the R&D-based knowledge stock per capita, we also tested alternatives where the size of the stock and its growth rate were instead related to the gross domestic product (GDP) and to total energy use in the respective countries. However, using these alternative specifications of the dependent variable generated (qualitatively) similar results to those presented in this paper.

15. Griliches (1998) suggests that the appropriate knowledge depreciation rate for private R&D spending would be higher, basically leaving hardly any of the R&D spent 10 years ago to the present day.

16. Arthur (1989) points out that technology choices are likely to be particularly self-reinforcing if investments are characterized by high upfront costs and increasing returns from technology adoption.

17. Following electricity market liberalization, the budget of the Electric Power Research Institute in the USA was reduced to a third, making it more difficult for industry to attract funding for R&D (Nemet and Kammen, 2007). This is exemplified by the EU Commission’s Guidelines on state aid for environmental protection and energy 2014-2020 (2014/C 200/01), which strongly influence national renewable energy policies.

**Acknowledgements**

Financial support from the Swedish Research Council Formas (Grant 254-2013-100) and the German Helmholtz Association (Grant HA-303) is gratefully acknowledged, as are valuable comments from Francesco Nicolli, Luis Mundaca and Paul Nightingale, and two anonymous reviewers on earlier versions of the manuscript. Any remaining errors reside solely with the authors.

**Disclosure statement**

No potential conflict of interest was reported by the author(s).

**Funding**

This work was supported by the Swedish Research Council Formas (Grant 254-2013-100) and the German Helmholtz Association (Grant HA-303).
References


Appendix


Figure A2. Per capita public R&D spending in 2012 (USD in 2014 prices and exchange rates). Source: IEA (2019).
### Table A1. Bias-corrected LSDV estimation results: 5-year knowledge stock time lag.

<table>
<thead>
<tr>
<th>Models</th>
<th>Coefficients</th>
<th>I (5-year lag)</th>
<th>II (5-year lag)</th>
<th>III (5-year lag)</th>
<th>IV (5-year lag)</th>
<th>V (5-year lag)</th>
<th>VI (5-year lag)</th>
<th>VII (5-year lag)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>12 EU countries</td>
<td>17 OECD countries</td>
<td>12 EU countries</td>
<td>17 OECD countries</td>
<td>12 EU countries</td>
<td>17 OECD countries</td>
<td>12 EU countries</td>
</tr>
<tr>
<td>$\beta_1$ Initial public R&amp;D-based stock</td>
<td>0.447***</td>
<td>0.458***</td>
<td>0.451***</td>
<td>0.531***</td>
<td>0.533***</td>
<td>0.517***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.047)</td>
<td>(0.049)</td>
<td>(0.046)</td>
<td>(0.043)</td>
<td>(0.044)</td>
<td>(0.043)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_1$ Real interest rate</td>
<td>$-0.007^{**}$</td>
<td>$-0.007^{**}$</td>
<td>$-0.008^{**}$</td>
<td>$-0.005^{***}$</td>
<td>$-0.006^{***}$</td>
<td>$-0.006^{***}$</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_2$ Energy imports</td>
<td>0.0006***</td>
<td>0.0011***</td>
<td>0.0003</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0002)</td>
<td>(0.0003)</td>
<td>(0.0003)</td>
<td>(0.00021)</td>
<td>(0.0002)</td>
<td>(0.0002)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_3$ Electricity regulation</td>
<td>0.0027</td>
<td>0.0001</td>
<td>0.0019</td>
<td>$-0.0013$</td>
<td>$-0.0018$</td>
<td>$-0.0021$</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.009)</td>
<td>(0.008)</td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.006)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_4$ Interaction – Energy import dependence</td>
<td>$-0.000$</td>
<td>$-0.000$</td>
<td>$-0.000$</td>
<td>$-0.000$</td>
<td>$-0.000$</td>
<td>$-0.000$</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_5$ Interaction – Electricity regulation</td>
<td>0.023</td>
<td>(0.016)</td>
<td>0.033*</td>
<td>(0.018)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Country-specific effects | Yes | Yes | Yes | Yes | Yes | Yes |
Time-specific effects | Yes | Yes | Yes | Yes | Yes | Yes |
Number of observations | 252 | 252 | 252 | 362 | 362 | 362 |
Number of countries | 12 | 12 | 12 | 17 | 17 | 17 |
Number of years | 22 | 22 | 22 | 22 | 22 | 22 |
Number of iterations | 200 | 200 | 200 | 200 | 200 | 200 |

Note: The standard errors are in parenthesis, while ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.

### Table A2. Bias-corrected LSDV estimation results: 5 and 15% depreciation rates.

<table>
<thead>
<tr>
<th>Models</th>
<th>Coefficients</th>
<th>I (5%)</th>
<th>II (5%)</th>
<th>III (5%)</th>
<th>I (15%)</th>
<th>II (15%)</th>
<th>III (15%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>12 EU countries</td>
<td>12 EU countries</td>
<td>12 EU countries</td>
<td>12 EU countries</td>
<td>12 EU countries</td>
<td>12 EU countries</td>
</tr>
<tr>
<td>$\beta_1$ Initial public R&amp;D-based stock</td>
<td>0.432***</td>
<td>0.381***</td>
<td>0.151**</td>
<td>0.338***</td>
<td>0.390***</td>
<td>0.173**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
<td>(0.06)</td>
<td>(0.06)</td>
<td>(0.07)</td>
<td>(0.07)</td>
<td>(0.06)</td>
<td></td>
</tr>
<tr>
<td>$\beta_1$ Real interest rate</td>
<td>0.003</td>
<td>0.003</td>
<td>0.003</td>
<td>0.008*</td>
<td>0.009*</td>
<td>0.008*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.004)</td>
<td>(0.005)</td>
<td>(0.004)</td>
<td></td>
</tr>
<tr>
<td>$\beta_2$ Energy imports</td>
<td>0.0006**</td>
<td>0.0006**</td>
<td>0.0005**</td>
<td>0.001*</td>
<td>0.001*</td>
<td>0.001*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0003)</td>
<td>(0.0003)</td>
<td>(0.0003)</td>
<td>(0.0005)</td>
<td>(0.0006)</td>
<td>(0.0006)</td>
<td></td>
</tr>
<tr>
<td>$\beta_3$ Electricity regulation</td>
<td>0.007*</td>
<td>0.007*</td>
<td>0.007*</td>
<td>0.014</td>
<td>0.013</td>
<td>0.015</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td></td>
</tr>
<tr>
<td>$\beta_4$ Interaction – Energy import dependence</td>
<td>0.0007</td>
<td>(0.001)</td>
<td>$-0.0009$</td>
<td>(0.001)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.013)</td>
<td>(0.028)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_5$ Interaction – Electricity regulation</td>
<td>0.062***</td>
<td>(0.013)</td>
<td>0.066**</td>
<td>(0.028)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Country-specific effects | Yes | Yes | Yes | Yes | Yes | Yes |
Time-specific effects | Yes | Yes | Yes | Yes | Yes | Yes |
Number of observations | 252 | 252 | 252 | 252 | 252 | 252 |
Number of countries | 12 | 12 | 12 | 12 | 12 | 12 |
Number of years | 22 | 22 | 22 | 22 | 22 | 22 |
Number of iterations | 200 | 200 | 200 | 200 | 200 | 200 |

Note: The standard errors are in parenthesis, while ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.
### Table A3. Bias-corrected LSDV estimation results: Models I-VI with deterministic time trend.

<table>
<thead>
<tr>
<th>Models Coefficients</th>
<th>I (time) 12 EU countries</th>
<th>II (time) 12 EU countries</th>
<th>III (time) 12 EU countries</th>
<th>IV (time) 17 OECD countries</th>
<th>V (time) 17 OECD countries</th>
<th>VI (time) 17 OECD countries</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\beta_1$: Initial public R&amp;D-based stock</td>
<td>0.396*** (0.063)</td>
<td>0.448*** (0.063)</td>
<td>0.190** (0.061)</td>
<td>0.411*** (0.059)</td>
<td>0.413*** (0.060)</td>
<td>0.095* (0.055)</td>
</tr>
<tr>
<td>$\beta_2$: Real interest rate</td>
<td>0.010 (0.003)</td>
<td>0.010 (0.003)</td>
<td>0.010 (0.003)</td>
<td>0.008** (0.003)</td>
<td>0.009** (0.003)</td>
<td>0.009** (0.003)</td>
</tr>
<tr>
<td>$\beta_3$: Energy import dependence</td>
<td>0.001** (0.0005)</td>
<td>0.001** (0.0005)</td>
<td>0.001** (0.0005)</td>
<td>0.0005*** (0.0002)</td>
<td>0.001*** (0.0002)</td>
<td>0.0015*** (0.0002)</td>
</tr>
<tr>
<td>$\beta_4$: Electricity regulation</td>
<td>0.012 (0.008)</td>
<td>0.012 (0.008)</td>
<td>0.012* (0.008)</td>
<td>0.014** (0.006)</td>
<td>0.014** (0.006)</td>
<td>0.015** (0.006)</td>
</tr>
<tr>
<td>$\beta_5$: Interaction – energy import dependence</td>
<td>0.0001 (0.0001)</td>
<td>0.0001 (0.0001)</td>
<td>0.0001 (0.0001)</td>
<td>0.0003 (0.0003)</td>
<td>0.0003 (0.0003)</td>
<td>0.0003 (0.0003)</td>
</tr>
<tr>
<td>$\beta_6$: Interaction – electricity regulation</td>
<td>0.009*** (0.002)</td>
<td>0.009*** (0.002)</td>
<td>0.009*** (0.002)</td>
<td>0.009*** (0.002)</td>
<td>0.009*** (0.002)</td>
<td>0.104*** (0.017)</td>
</tr>
<tr>
<td>$B_6$: Time trend</td>
<td>0.009*** (0.021)</td>
<td>0.009*** (0.021)</td>
<td>0.009*** (0.021)</td>
<td>0.009*** (0.021)</td>
<td>0.009*** (0.021)</td>
<td>0.104*** (0.021)</td>
</tr>
</tbody>
</table>

Country-specific effects: Yes, Yes, Yes, Yes, Yes, Yes
Time-specific effects: No, No, No, No, No, No
Number of observations: 252, 252, 252, 362, 362, 362
Number of countries: 12, 12, 12, 17, 17, 17
Number of years: 23, 23, 23, 23, 23, 23
Number of iterations: 200, 200, 200, 200, 200, 200

Note: The standard errors are in parenthesis, while ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.