International expansion of renewable energy capacities: The role of innovation and choice of policy instruments

Erik Hille[a*] and Thomas J. Oelker[a]

[a]HHL Leipzig Graduate School of Management, Jahnallee 59, 04109 Leipzig, Germany

E-Mails: Erik.Hille@hhl.de, Thomas.Oelker@hhl.de

*Corresponding author

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Abstract

Which renewable energy (RE) policy instrument is most effective in expanding the international diffusion of RE and what is the role of innovation? We consider rich policy and patent data for 189 countries and territories to investigate these diversely debated questions for wind and solar photovoltaic capacities. This allows us, firstly, to contribute to the limited evidence on the effect of RE innovation on RE diffusion and its interrelated influence with RE support policies. Secondly, we can evaluate the disentangled individual policies' effectiveness in a broad instrument-country context. Thirdly, we control for the inherent endogeneity of policy instruments and innovation. We find that RE innovation, which appears to be largely policy-induced, is among the most promising ways to increase RE capacities. The most effective policy instruments tend to be quotas with certificate trading, tendering, and fiscal instruments that provide specific investment support, i.e. investment tax credits and capital subsidies. Less tangible and projectable measures, such as the most commonly implemented sales-related tax reductions and RE targets, are least effective. While interactions between instruments influence the composition of a well-designed policy mix, there are also differences in the policies' effectiveness and role of innovation depending on the countries' level of development.

Keywords: Renewable energy capacity; environmental regulation; renewable energy innovation; solar energy; wind energy

JEL classification: H3, Q42, Q48, Q55, Q58

1 Introduction

By signing and ratifying the Paris Agreement, the large majority of countries has officially committed to lowering greenhouse gas emissions, such that average global warming is kept well below 2 °C above pre-industrial levels. Nonetheless, until the COVID-19 pandemic, carbon emissions have not ceased to increase (IEA 2019). One important pillar to sustainably lower anthropogenic emissions – also after the recent crisis – is to shift energy production from carbon-based to renewable energy (RE) sources, such as wind or solar (Balsalobre-Lorente et al. 2018).

In the empirical literature, there is little consensus on the most important determinants of RE growth. Besides regulatory and political determinants, studies have considered environmental and economic factors, energy security, and technological innovation (Bourcet 2020). The focus of our analysis is on regulatory factors as well as technological innovation. Specifically, we analyze rich international data on enacted RE support policies and RE knowledge stocks to specify their respective role in the expansion of wind and solar capacities. We show that the implied policy recommendations depend on the level of detail of and interactions between the policy instruments, the countries' level of development, as well as the control for simultaneity concerns.

Environmental policy, innovation, and installed RE capacities are interrelated, and are expected to influence the expansion of RE capacities in several ways. On the one hand, over time, environmental policy may induce innovation in RE technologies, that reduce the levelized costs of energy, and thus indirectly promote the build-up of RE capacities. The first part of this transmission channel, i.e. the positive effect of environmental regulation on innovation activity, has been popularly framed as the weak Porter Hypothesis and mostly confirmed in the context of both clean technologies in general (Aghion et al. 2016; Calel and Dechezleprêtre 2016) and RE technologies in specific (Böhringer et al. 2017; Johnstone et al. 2010). Interestingly, while several studies analyze a time frame that covers the exponential growth in renewables innovation between 2006 and 2011, the drastic decline in innovation activity thereafter is rarely considered (Hille et al. 2020). The second part of the channel, i.e. the positive effect of innovation activity on energy production and use dimensions, has been analyzed mainly for aggregate energy consumption and the consumption of conventional energy carriers (Alam et al. 2019; Fisher-Vanden et al. 2004; Herrerias et al. 2016). Comparatively few analyses exist on the specific influence of RE innovation on RE diffusion (Hille and Lambernd 2020; Popp et al. 2011), and the interrelated influence of RE innovation and RE support policies has been largely unconsidered.[1] For instance, Popp et al. (2011) find a small but positive effect of knowledge stocks on investments in RE capacities, and point at the more important and immediate role of environmental policy. On the other hand, once RE equipment manufacturers have sufficient technological know-how, environmental policy may also directly promote investments in RE capacity additions. Through exports and international projects, this effect is not limited to countries where those manufacturers and leading innovators are based, but power plants can as well be installed in other countries adopting the technologies (Groba and Cao 2015).

However, not only environmental policy and innovation may influence the expansion of RE capacities, also the reverse can be the case. Reasons for alterations in policy support are manifold and usually related both to the prominent role of public and private interests and to technical constraints. Driven by different policy preferences, reflecting material interests and societal values, key industry stakeholders try to influence policy goals and instruments (Lindberg et al. 2019). This effect of lobbying on RE policy has been documented both theoretically and empirically (Eichner and Pethig 2015; F. Jenner et al. 2013). An increasing share of RE in the energy mix also influences the achievement of

[1] Cross-country studies that consider several policy instruments have usually not controlled for RE innovation (Bento et al. 2020; S. Jenner et al. 2013; Polzin et al. 2015). A recent exception is Verdolini et al. (2018), who, although it is not the focus of their study on 26 OECD countries, also include RE knowledge stocks.

various policy objectives, including energy security (Lehmann and Gawel 2013), greenhouse gas emission reduction (Balsalobre-Lorente et al. 2018), and economic development (Dogan et al. 2020), thereby potentially changing the priority of the respective objective for policymakers and choice of policies over time (Lipp 2007). Similarly, policy instruments need to account for challenges for power systems accompanying RE diffusion, such as the variability of solar and wind power and the need for storage capacities (Helm and Mier 2021). Regarding technological change, it is important to recognize that usually firms, not regulators, decide about the introduction and diffusion of new, cleaner technologies. Hence, regulators need to anticipate the related relative firm-level incentives when constructing proper policy instruments (Milliman and Prince 1989; Requate and Unold 2003). Firms may also intensify R&D activities in promising highly-demanded clean technologies, potentially entailing technology path-dependency (Popp 2019). In other words, the considered relationships are inherently simultaneous, which has frequently not been controlled for in studies on the environmental policy-RE diffusion nexus, in particular in cross-county studies (Bento et al. 2020; Dong 2012; Escoffier et al. 2021).

In order to expand RE supply effectively, the policy design is crucial, especially when there is a policy mix in force. In general, policy instruments can be classified into command-and-control instruments, such as regulatory laws and renewable portfolio standards, market-based instruments, such as feed-in tariffs and carbon taxes, hybrid instruments, such as RE quotas with certificate trading, and voluntary approaches, such as RE targets. Prior research on the effect and effectiveness of environmental policy instruments on RE diffusion mostly detected positive or insignificant associations (Bourcet 2020).

Among the instruments, feed-in-tariffs and renewable portfolio standards have been considered most frequently. Feed-in tariffs tend to positively influence RE diffusion, especially in analyses that consider global sets of countries (Carley et al. 2017; Zhao et al. 2013) or relatively few types of policies (del Río and Tarancon 2012; Escoffier et al. 2021). The effectiveness is more mixed both when the focus is on the specific feed-in tariff's policy design (Alolo et al. 2020) and for relatively advanced instruments, such as tendering and net metering (S. Jenner et al. 2013; Kersey et al. 2021). Evidence on the latter suggests that the policies need to be customized to the local electricity market, for instance by targeting the adoption of small-scale installations in countries with low electricity demand. Similarly, research has detected technology-specific differences in the effectiveness of feed-in tariffs, indicating that such price-based incentives are more supportive during early phases of technological development (Dong et al. 2021; S. Jenner et al. 2013). The estimated effects of renewable portfolio standards are heterogeneous. For example, in single-country studies, such as those on the United States, early evidence of a positive influence on wind energy diffusion (Menz and Vachon 2006) has partly not been confirmed in later studies analyzing longer time frames (Shrimali and Kniefel 2011). Although renewable portfolio standards have in parts also fostered RE growth in cross-country studies (Carley et al. 2017), corresponding empirical evidence indicates that other instruments are more effective (Dong 2012). Among targets negotiated at the international level, the Kyoto Protocol has been analyzed most frequently and often been associated with RE growth (Pfeiffer and Mulders 2013; Popp et al. 2011). In contrast, cross-country studies have rarely considered voluntary national targets.[2] Fiscal incentives can target various aspects of RE diffusion. Accordingly, evidence depends on the specific fiscal instrument. Often studies include fiscal instruments as aggregated binary variables. On this level, fiscal and financial support policies have increased and decreased RE diffusion (Aguirre and Ibikunle 2014; Polzin et al. 2015), which may be explained by the inclusion of varying instruments in the aggregate measures. On the individual instrument level, research has mostly found both positive

[2] More generally, studies have found that voluntary instruments are negatively related with RE diffusion (Aguirre and Ibikunle 2014; Zhao et al. 2013).

and insignificant effects of tax incentives and carbon taxes (Bento et al. 2020; Zhao et al. 2013), subsidies and grants (Aguirre and Ibikunle 2014; Carley et al. 2017), investment incentives (Polzin et al. 2015; Zhao et al. 2013), and loans (Aguirre and Ibikunle 2014). While the estimated effects of individual fiscal policies, such as tax credits, tend to become more pronounced in national-level studies (Bailie et al. 2016; Hitaj 2013), the insignificant results in cross-country studies may originate from the heterogeneous design of fiscal policies across countries (S. Jenner et al. 2013). As with other policy instruments, the effectiveness of fiscal incentives can vary across RE technologies (Polzin et al. 2015; Zhao et al. 2013).

A related research stream has focused on interactions between individual policies, employing mostly qualitative approaches (Fischer and Preonas 2010) as well as partial equilibrium (Andor and Voss 2016), computable general equilibrium (Corradini et al. 2018), and numerical electricity sector models (Malhotra 2022). From a theoretical perspective, implementing a mix of RE support policies can be beneficial for multiple reasons, ranging from different market failures that are seeked to address, to distorted policy choices, to multiple policy objectives (Lehmann and Gawel 2013).[3] However, cross-country empirical evidence is scarce. For instance, S. Jenner et al. (2013) found that feed-in tariffs complement tendering policies, but not tax incentives or investment grants, in fostering wind capacity growth in EU countries. Dong (2012) interacted feed-in tariffs, renewable portfolio standards, and the cumulated number of other policies with each other, and only detected support for complementarities between feed-in tariffs and other policies for wind capacity installations in 53 countries.

Research on the impact of RE policies on RE diffusion has been subject to several constraints. Due to data availability, studies seem to compromise on either the considered number of policy instruments or the geographical scope. That is, the limited number of studies that analyze a broad set of countries, including less-developed economies, tend to differentiate between rather few individual policies (Carley et al. 2017; Zhao et al. 2013). Often cross-country analyses also do not distinguish between specific instruments but consider aggregated clusters of policies, such as fiscal incentives in general (Pfeiffer and Mulder 2013; Polzin et al. 2015). Therefore, when determining the most effective policy tools, the disentangled policy instruments' effects in more diverse policy mixes and interactions with other policy instruments tend to remain unconsidered. The heterogeneity in policy aggregations and definition of policy variables is certainly also one reason why prior research has found varying effects for seemingly similar policy types. Consequently, Bourcet (2020) concludes in her recent literature review that "more research is necessary to assess the impact of diverse national energy or green policies".

In this paper, we investigate the influence of various RE policy instruments and RE innovation on the growth of wind and solar capacities between 2005 and 2018. We contribute to prior research in three main ways. Firstly, by considering the implementation of twelve different policy instruments in 189 countries and territories, we can evaluate the effectiveness of RE support policies in a broader instrument-country context, and further specify the effects of individual policy instruments that are often considered in more aggregated form only. Specifically, besides different feed-in tariffs and renewable portfolio standards, which most previous studies inquired on, we also analyze the role of various fiscal incentives and RE targets. We estimate the policies' effects both individually and as more general groups of policies, and find that the latter can result in misleading findings, as the aggregate effectiveness can be contrary to that of individual policy instruments in the cluster. The most effective individual policy instruments tend to be quotas with certificate trading, tendering, and fiscal instruments that provide specific investment support, i.e. investment tax credits and capital subsidies.

[3] As a consequence, some researchers proposed that regulators should shift their scope from adequate policy design to adequate policy mix design (del Río 2010).

Less tangible and projectable measures, such as the most commonly enacted sales-related tax reductions and RE targets, are least effective. Besides the direct policy effects, complementarities and substitution effects between the instruments are found to influence the composition of well-designed policy mixes. Similarly, we consider a large number of developing and transition economies, whereas most multi-jurisdictional studies have focused on countries from Europe, the OECD, and BRICS (Carley et al. 2017). Interestingly, we detect differences in the policies' effectiveness depending on the countries' level of development, indicating the importance of institutions.

Secondly, as environmental policy and innovation are closely related, we control for technological change and contribute to the scarce knowledge of both its specific influence on RE capacity additions and interdependencies with RE support policies. Utilizing the PATSTAT database (EPO 2018, 2022), we receive a comprehensive list of RE patent applications. This list is used to construct knowledge stocks for wind and solar photovoltaics, representing the respective technological frontier. We find that RE innovation, which appears to be largely policy-induced, has been highly important for the international expansion of RE capacities. This finding complements and may help reconciling the intriguing results of earlier studies, such as Popp et al. (2011), who partly detected only small effects of technological advancement on RE diffusion, but a supposedly more important role of environmental policy. Similar to the differences in the policies' effectiveness, our estimations also indicate that the influence of technological advancement is less pronounced in lower-income countries than in higher-income countries, where most of the high-value innovation activity has taken place.

Lastly, even though several explanatory variables, such as the policy instruments and innovation, are expected to be inherently simultaneous, prior research in the field has mostly not accounted for this issue (Bento et al. 2020; Escoffier et al. 2021; Polzin et al. 2015). We control for potential endogeneity of the policy instruments and innovation by means of a dynamic panel generalized method of moments (GMM) estimator. Our results suggest that omitting simultaneity concerns can change the sign and magnitude of the estimated effects of the RE support policies.

The remainder of this paper is organized as follows: Section 2 introduces the methodology, data sources, as well as descriptive statistics of key variables. In Section 3, we discuss the results of the main model, heterogeneity analyses, and robustness tests. Section 4 concludes.

2 Methodology and data

2.1 Empirical model

To analyze the effect of different RE support policies and innovation on RE capacities, we employ a dynamic panel regression of the following form:

$$Capacity_{i,t} = \alpha_0 + Policy'_{i,t-1}\beta + \alpha_1 Innovation_{i,t-1} + X'_{i,t-1}\theta + \mu_i + \mu_t + \varepsilon_{i,t} \qquad (1)$$

where *Capacity* denotes installed per capita RE capacities in country *i* and year *t*. While *Policy* is a vector of implemented RE support policies at the national and sub-national level, *Innovation* reflects per capita domestic RE knowledge stocks. *X* is a vector of additional control variables. Following prior research, we lag all explanatory variables by one year (del Río and Tarancon 2012; Polzin et al. 2015), because RE capacities are expected to react with a delay, e.g. to newly-enacted RE policies.[4] The intuition is that energy projects tend to be cost-intensive, requiring time to secure funding, and often demand the processing of administrative procedures. Moreover, we include country and time fixed

[4] We tested alternative lag structures and provide examples of results in the robustness checks section 3.3.

effects μ_i and μ_t to capture unobserved heterogeneity across jurisdictions and over time. ε is the error term. Table A1 in Appendix A provides an overview of the variables and regular summary statistics.

As the dependent variable, we focus on installed capacities that produce electricity from the force of wind and solar radiation. Our focus on those technologies has multiple reasons. Most importantly, besides hydroelectricity, wind and solar are the technologies that have contributed most to the international diffusion of RE during the last decades (EIA 2021). Much of this development can be explained by regulatory support and related technological progress, increasing the competitiveness of both technologies and decreasing their levelized costs of energy considerably. In the light of the frequent implementation of policy mixes, wind and solar technologies are therefore particularly interesting to specify the importance of individual RE policies and of (regulation-induced) innovation. In this context, as prior research has analyzed both, we estimate the effects for the RE technologies together (Aguirre and Ibikunle 2014; Bento et al. 2020), and specify the technology-specific influences for wind and solar energy in separate estimations (S. Jenner et al. 2013; Polzin et al. 2015). To capture changes in capacity relative to the potential market size for electricity, we consider per capita RE capacities.

However, the related literature has considered not only RE capacities (Hitaj 2013; Menz and Vachon 2006) but also RE generation (Pfeiffer and Mulder 2013; Zhao et al. 2013). The main weakness of electricity generation data for wind and solar technologies is their dependence on unpredictable factors, such as weather fluctuations or technical performance, which are in the case of the former difficult to control for. At best, country fixed effects can account for fluctuations across countries but not within countries. While capacity data is relatively independent from weather fluctuations, it has been criticized for also including weakly maintained capacities, potentially generating no electricity (Carley et al. 2017). Overall, we prefer the reasoning of studies focusing on investments in RE (Popp et al. 2011; Verdolini et al. 2018), that investments are necessary to facilitate RE diffusion, and that changes in RE capacities more accurately reflect initial policy- and innovation-induced investment decisions. As will be shown in the robustness tests in Section 3.3, our findings remain unchanged when using generation instead of capacity data.

As the first main determinants, we consider the implementation status of twelve different RE support policies, listed in Table 1. Each policy is coded as a binary variable with a value of 1 if the respective policy is adopted, and 0 otherwise. This approach is regularly employed in international studies, where the heterogeneous nature of implemented policies across countries restricts the use of continuous measures (Carley et al. 2017; Johnstone et al. 2010; Zhao et al. 2013). Continuous indicators have mostly been based on specific characteristics of the adopted policy instruments, such as guaranteed price levels, contract durations, or shares of eligible technologies in the energy production. Besides the availability of accurate data, this requires a sufficiently similar policy design of the same instrument type across all jurisdictions, which is not the case for our broad sample of 189 countries and territories. In other words, while we consider comprehensive data on adopted policies, our estimations cannot attribute regulation-induced changes in RE capacities to specific adjustments in the design of policy instruments, such as lower guaranteed feed-in tariffs.

We consider the RE support policies both individually and in clusters of policy instruments.[5] This allows us to compare our results to those of studies that considered policies in more aggregated form, to further specify the effects of individual policy instruments, and to detect differences between the coefficients of both approaches, indicating potentially misleading findings. At the same time, given the limited space, we can use a less complex base model to show compact examples of results of various heterogeneity and robustness checks. The policy instruments are grouped based on similarities

[5] Similar to the individual policy instruments, the policy clusters are binary variables, which are 1 if at least one of the instruments of the respective policy cluster has been implemented, and 0 otherwise.

in their economic characteristics. Specifically, we consider four policy clusters, namely targets, feed-in tariffs, quotas, and fiscal incentives. The targets cluster only comprises RE targets or strategies, which are meant to signal the political commitment to RE growth, sending positive signs to market participants. While targets can refer to different goals, such as RE shares in the electricity production or RE capacities, they do not have to directly translate into environmental regulations and incentives. In the feed-in tariffs cluster, we analyze classic fixed-rate or premium feed-in tariffs as well as more advanced instruments, such as net metering and tendering that have become increasingly important in recent years (REN21 2020). The classic fixed-rate feed-in tariffs incentivize investors by providing certainty about future electricity prices for a predetermined number of years through the subsidy of electricity fed into the general grid. The quotas cluster consists of RE quota schemes with and without certificate trading. The latter instrument is commonly referred to as renewable portfolio standards, which set a fixed or increasing share of RE in the overall energy mix. The data on fiscal incentives comprises the largest number of individual instruments with partly varying incentive mechanisms. This is important, because the reward of some instruments, such as capital subsidies or investment tax credits, is closely linked to the initial investment. Other instruments, like sales-related tax reductions or energy production payments, only come into play during the years of operation and are therefore less projectable for investors. Moreover, we analyze fiscal incentives related to public activities, i.e. RE public investments and procurement. Based on the approach of several prior cross-country studies, which have often been restricted by data availability or focused on policies from other clusters, we aggregate the different fiscal policies rather broadly into one cluster in the main estimations. In the heterogeneity analysis, we group the instruments by incentive mechanisms.

Table 1: Individual and clustered RE support policies

Policy cluster	Policy instrument
Targets	RE targets or strategies
Feed-in tariffs	Fixed-rate or premium feed-in tariffs
	Tendering (Public competitive bidding)
	Net metering
Quotas	Renewable portfolio standards (RE quotas without certificate trading)
	Tradable certificates (RE quotas with certificate trading)
Fiscal incentives	Investment tax credits
	Capital subsidies and grants
	Public investment
	Public procurement
	Sales-related tax reductions
	Production payments

The second focus of our analysis is on the role of innovation. Following a growing number of clean innovation studies, we measure the technological frontiers by determining knowledge stocks based on patenting activity (Aghion et al. 2016; Groba and Cao 2015; Verdolini et al. 2018).[6] Specifically, we adapt the approach of Popp (2002), used among others in Popp (2005), Lovely and Popp (2011), and Hille et al. (2020), and also normalize the technology-specific knowledge stock by the population size:

$$Innovation_{i,t} = \left[\sum_{s=0}^{t} e^{-\delta_1(s)} \left(1 - e^{-\delta_2(s+1)}\right) Patent_{i,t-s}\right] / Population_{i,t} \qquad (2)$$

[6] RE knowledge stocks have also been estimated using alternative measures of innovation, such as R&D expenditures (Bointner 2014; Ek and Söderholm 2010) and technology adoption (Qui and Anadon 2012). These approaches are not viable for our analysis because of limited data availability, especially for lower-income countries. For instance, contrary to patenting data, consistent information on energy-related R&D expenditures tends to be restricted to few IEA member states (Bointner 2014).

While *Patent* represents the size-weighted number of RE patent families grouped by the country of the inventor, δ_1 and δ_2 are the rate of decay and rate of diffusion, respectively. We focus on patent families, which are each a collection of patent applications for a single invention in different countries, in order to account for quality differences between patents. In this context, we follow Popp et al. (2011), who extended this approach of counting patents by suggesting two additional filters. Accordingly, we weight patent families by their family size, i.e. the number of countries a patent has been filed in, and consider only patents filed in multiple countries. In the robustness checks, we relieve these restrictions and estimate specifications using alternative patent counts. For the knowledge stock calculation, we consider patent applications from 1980 onwards. Prior patenting activity in wind and solar technologies was comparatively low (EPO 2018) and the implementation of RE support policies was limited to less than a handful of policies (REN21 2020). We set the rate of decay to 0.10 and the rate of diffusion to 0.25. These rates have been commonly used in the technological change literature (Hille et al. 2020; Lovely and Popp 2011; Popp et al. 2013) and imply a delayed flow of knowledge that peaks four years after the patent application.

In the main model, we include the RE knowledge stock directly, in addition to the RE policy binaries. This allows us to distinguish between the policy and innovation effects, which related analyses have mostly not considered together. Besides explaining the direct effects of innovation and policy instruments on RE capacities, the direct coefficients will each partly capture the indirect regulation-induced effects of innovation on RE capacities, but only to the extent that they are linked to the respective variable and not to the others. To separate these direct and induced effects, we tested alternative specifications where additional interaction terms of the policy instruments and the RE knowledge stock are included, and show examples of results in the heterogeneity analyses in Section 3.2.

Besides the main variables of interest, we control for a number of confounding factors. Firstly, similar to prior research (Carley et al. 2017; Pfeiffer and Mulders 2013), we complement our model with a compound index capturing overall regulatory quality. With twelve different policy instruments under scrutiny, it is difficult to compare their effectiveness across countries, especially if specific regulatory design data is unavailable. The regulatory quality index measures governments' general ability to enact elaborate policies and regulations that promote private sector development. Its inclusion allows us to reduce the possibility of erroneous clustered country effects. Secondly and thirdly, GDP per capita and trade openness account for general economic conditions. In a global context, it is important to control for countries' income levels, as richer economies typically possess more means to invest into RE (Zhao et al. 2013), and to capture unconsidered demand-side factors (Verdolini et al. 2018). We measure trade openness using trade intensities, i.e. the sum of exports and imports relative to the GDP. While a higher trade openness may accelerate the diffusion of knowledge and thus promote RE diffusion (Pfeiffer and Mulders 2013), capital-intensive exporting industries can also demand less RE due to cost pressures in international competition (Hille and Lambernd 2021). Fourthly and lastly, to account for energy market characteristics, we include per capita electricity net consumption as well as the share of fossil fuel exports in the total GDP. The former reflects changes in the demand and supply structure of a country's electricity market (Dong 2012).[7] The latter is an indicator for the political influence of fossil fuel-producing firms, which may slow down national energy transition efforts, and is motivated by the inclusion of energy trade measures in the literature (Carley et al. 2017; Escoffier et al. 2021). Further control variables are considered in the robustness checks.

As discussed in the introduction, the relationship between environmental policy, innovation, and RE diffusion is inherently simultaneous. Consequently, we treat the RE support policies and the

[7] Because of this characteristic and the partial evidence that energy prices are not a significant driver of RE diffusion (Yin and Powers 2010), research has also included electricity net consumption as an alternative to electricity prices (Dong 2012).

knowledge stock as endogenous. As this implies the use of multiple instrumental variables, we employ the system GMM estimator (Arellano and Bover 1995; Blundell and Bond 1998), where such conditions can be implemented relatively easily. That is, as GMM-type instruments, system GMM uses both the lagged levels and lagged differences of the potentially endogenous regressors in the transformed equation and levels equation, respectively. We restrict the instruments to two lags per variable to avoid overfitting the model, and apply the standard orthogonality conditions. In the main estimations, the remaining control variables are treated as exogenous and serve as standard instruments.[8] Besides addressing endogeneity concerns in the form of simultaneity and omitted variable bias, system GMM is especially suitable for panels with more individuals than time periods, which is the case for our sample, and allows controlling for unobserved fixed effects as well as heteroskedastic and correlated idiosyncratic disturbances within individuals (Roodman 2009). We apply the two-step standard error correction by Windmeijer (2005) to improve the estimator's efficiency and avoid downward-biased standard errors.

2.2 Data

Our analysis is based on strongly balanced panel data of 189 countries between 2005 and 2018. The outset of our work was the policy database by REN21 (2020), which includes detailed information on implemented RE policies in 198 countries. Nine countries were dropped, because data for our dependent variables was not available. A detailed country overview is given in Table A2 in Appendix A.

We collected the data from various sources. Most raw data on energy measures was obtained from the EIA (2021). The only exception are energy prices from BP (2020), which we used to transform the fossil fuel export and expenditure volumes from the EIA into monetary units. The implementation status of the RE support policies stems from REN21 (2020), who, upon request, provided us with updated policy tables of their annual global status reports. The base reports are a popular source in RE policy research (Bento et al. 2020; Dong 2012). To ensure the reliability of the policy data, we compared it with the IEA's (2021) policies database as well as the respective national administration websites. Our RE knowledge stock is based on patent application information from the global PATSTAT database (EPO 2018, 2021). Specifically, we used the novel Y02 classification that was particularly developed to classify climate change mitigation technologies and is increasingly considered the international standard in clean innovation analyses (Calel and Dechezleprêtre 2016; Hille et al. 2020). While Beck et al. (2019) provided supplementary data on private credits for the robustness tests, the raw data of the remaining control variables, the national GDP and population sizes, as well as monetary deflators were downloaded from the World Bank's WDI (2021) database.

2.3 Descriptive statistics of key variables

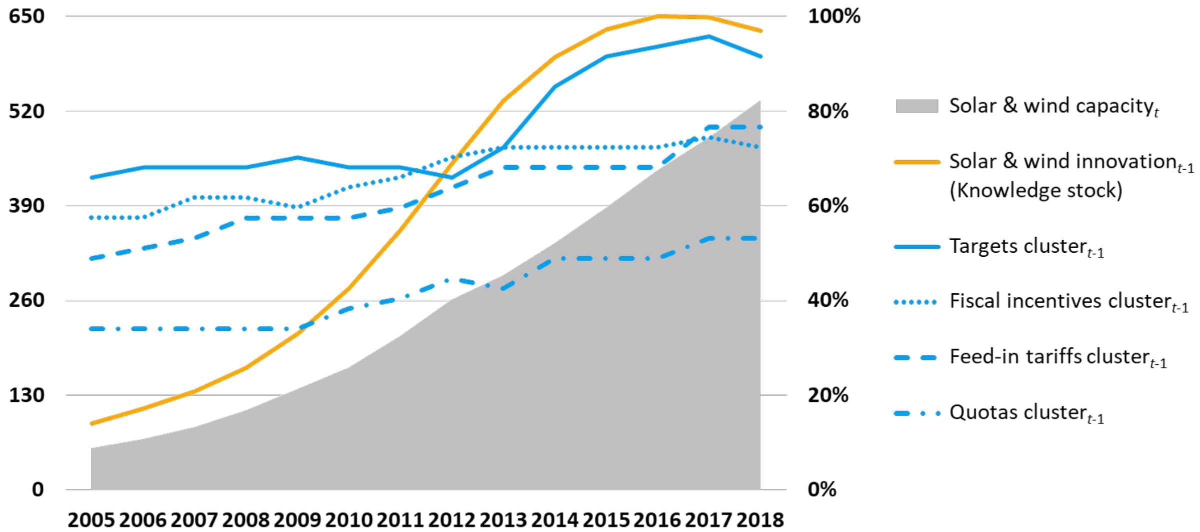
The international diffusion of solar and wind technologies has strongly increased during recent years. While both technologies made up 7.2% of global RE capacities and 1.6% of overall electricity capacities in 2005, by 2018, these figures have risen to 44.9% and 15.5%, respectively (EIA 2021).[9] During the period, nominal and per capita solar and wind capacities have grown by an average 24% and 23% per year, respectively. This growth was mainly driven by additional wind capacities in the first half of the period. In recent years, annually-installed solar capacities have picked up and exceeded those of wind

[8] Our findings remain unchanged when we relieve this strict exogeneity assumption. In the robustness checks, we show an example of results.

[9] The remaining statistics in this section refer to the database introduced in Section 2.2.

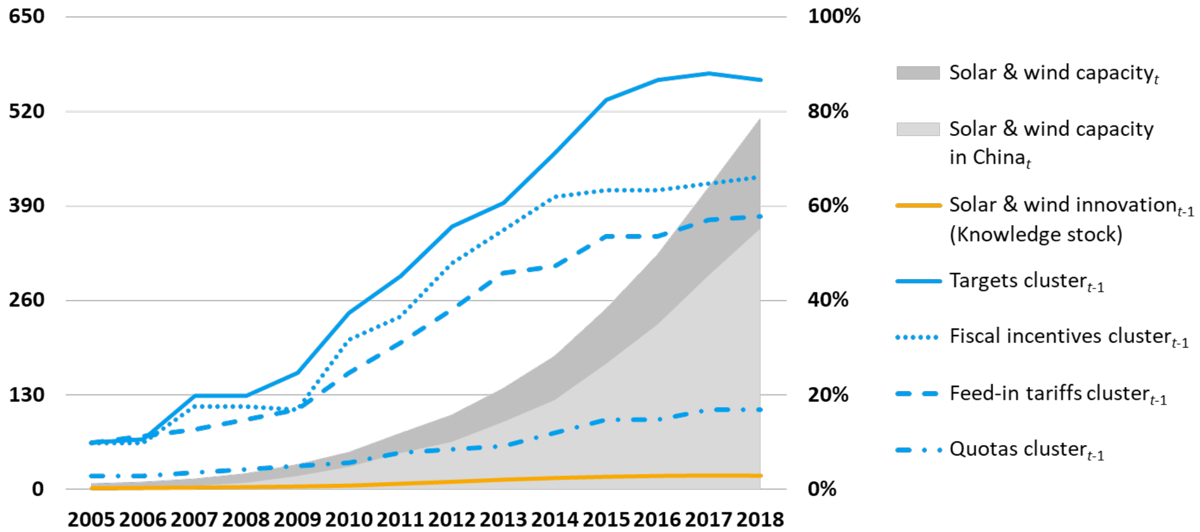
energy. As a consequence, while wind capacities were more than 13 times the size of solar capacities in 2005, installed capacities are nowadays comparable with a corresponding ratio of 1.17 in 2018.

Figure 1: Development of solar and wind capacities, enacted RE support policies, and RE knowledge stocks across the 25% countries with the highest GDP per capita[a]



[a]On the left y-axis, the capacity in million kW and knowledge stock in thousand patent applications are displayed. The right y-axis shows the share of countries with at least one policy instrument enacted from the respective policy cluster. Following the empirical model, the contemporaneous capacities are shown, and all other variables are lagged by one year.

Figure 2: Development of solar and wind capacities, enacted RE support policies, and RE knowledge stocks across the 75% countries with the lowest GDP per capita[a]



[a]On the left y-axis, the capacity in million kW and knowledge stock in thousand patent applications are displayed. The right y-axis shows the share of countries with at least one policy instrument enacted from the respective policy cluster. Following the empirical model, the contemporaneous capacities are shown, and all other variables are lagged by one year.

In order to detail the dynamics within our vast dataset, we group the countries with respect to GDP per capita quartiles. Figures 1 and 2 depict the development of solar and wind capacities, enacted RE support policies, and RE knowledge stocks for both the 25% highest-income countries and the remaining 75% lower-income countries. As can be seen, solar and wind capacities have been mostly installed in higher-income countries as well as China. The former accounted for 51% and the latter for 34% of global capacities in 2018, amounting to 85% in total. In contrast, in 2005, the higher-income countries only were responsible for 87%. This highlights China's catching-up process, not only making it currently the country with the largest nominal solar and wind capacities, but also driving the exponential growth of RE capacities among lower-income countries. Nevertheless, despite comparable nominal capacities, per capita capacities in the 25% highest-income countries were still six times larger than in lower-income countries in 2018.

One potential driver of solar and wind technology diffusion is the strongly increased implementation of RE support policies at the national and sub-national level. In 2004, in only 29% of the countries at least one policy instrument was enacted, whereas until 2017 the figure rose to 92%. During the same period, the median number of policy instruments per country has increased from zero to four, implying that the majority of countries had a mix of policies in 2017. This also holds true when policies at the national level are considered only, which accounted for 97% of the policies in 2017. The remaining sub-national policies have been set predominantly at the state level in a few higher-income countries, in particular the United States, Canada, and more recently the United Arab Emirates. An exception is India.

Overall, targets have been the most frequently implemented policy cluster, followed by fiscal incentives, feed-in tariffs, and quotas. Except for the quotas cluster, the increased implementation rates have been largely driven by new policies in lower-income countries. That is, in 2004 higher-income countries already had comparatively high implementation rates for the policy clusters, which rose moderately by further 15 to 26 percentage points until 2017. In contrast, in lower-income countries, RE support was rather the exception in 2004. As a result, the low implementation rates of 10% for targets, fiscal incentives, and feed-in tariffs have increased strongly between 48 and 77 percentage points until 2017. Quotas are an exception, as the share of countries with such a policy increased by 19 percentage points in higher-income countries compared to 14 percentage points in other countries.

Regarding the individual policy instruments, in all but seven lower-income countries, at least one of the policy instruments analyzed was in effect at some point in time of our analysis. Conversely, no country had all twelve policies implemented in one year. Three countries concurrently implemented eleven different types of policies, namely the United States (until 2008), Italy (2010), and India (2012, 2014-2017).[10] Targets are often the starting point of governments' commitment and were implemented in 88% of the countries by 2017. Both in 2004 and in 2017, only eleven countries had implemented a policy from the remaining clusters without a national target. That means, having introduced a target policy, countries tend to enact further policy instruments to substantiate the RE strategy, amounting to four additional policies in the median for the entire sample. However, targets seem to play an ambiguous role. We observe countries, in particular with a lower income, which have officially committed to RE diffusion with a target policy, but did not or only with a long delay introduce other RE support policies. Overall, 54 countries merely enacted RE targets for three consecutive years or longer, and half of them even for at least five years. Examples of countries range from small island states like Samoa (since 2008),[11] to heavily populated countries like Nigeria (2005-2011), to few developed countries like Singapore (until 2009).

[10] At the national level, only Italy (2010) and India (2012) concurrently set eleven different types of policies, followed by several countries with up to ten enacted policy types, i.e. Albania, Greece, the Netherlands, and the Philippines.

[11] Arguably, for countries with relatively low aggregate energy consumption, the successful transition to RE may not require the implementation of a sophisticated mix of support policies. Instead, it may be sufficient that the domestic (public) utility implements public orders and favors RE plants when replacing existing or installing new capacities. In line with that reasoning, in 2017, 74% of the countries in the decile with the lowest total electricity consumption had implemented a RE target, whereas only 16% of the jurisdictions enacted additional policies. These instruments were either net metering or a combination of sales-related tax reductions with a policy from the feed-in tariffs cluster, i.e. a classic feed-in tariff or net metering.

Among the fiscal incentives, sales-related tax reductions (52%) and public investments (51%) were most frequently implemented in 2017, followed by measures directly supporting the build-up of RE capacities, i.e. capital subsidies and grants (31%) and investment tax credits (23%). The high implementation rate of sales-related tax reductions has been driven by lower-income countries. In higher-income countries, public investments and capital subsidies were more popular, whereas the frequency of the former has strongly increased, passing the latter in 2015. Within the feed-in tariffs cluster, classic fixed-rate feed-in tariffs were historically the most widespread policy instrument. Since 2009, tendering and net metering have seen increasing popularity, such that the implementation rate of tendering (43%) was for the first time higher than that of fixed-rate feed-in tariffs (41%) in 2017. In the same year, the importance of the individual quota instruments was comparatively low for both renewable portfolio standards (17%) and tradeable RE certificates (16%), yet there were large differences between higher- and lower-income countries (53% vs. 17% for quotas cluster). This is one of the reasons why the policy mix in lower-income countries has, on average, been less diversified. Specifically, with four different policy instruments implemented in 2017, the median policy mix in lower-income countries consisted of two policies less than in higher-income countries.

Similar to RE capacities and enacted RE support policies, nominal and per capita aggregate knowledge stocks in solar and wind technologies have seen a strong increase between 2004 and 2017, namely by an average 16% and 15% per year, respectively. However, high-quality RE knowledge tended to be concentrated, in particular in few leading higher-income countries. While inventors from 38% of the countries have not filed a single patent in solar and wind technologies since 1980, the five leading countries accounted for 76% of the nominal knowledge stock in 2017. In descending order, these five countries were the United States, Germany, Japan, South Korea, and Denmark, which also belonged to the economies with the corresponding highest per capita knowledge (12th, 3rd, 5th, 7th, and 1st, respectively). However, as can be seen in Figure 1, the knowledge stock in high-income countries has been stagnating and started declining in recent years. This can be explained by strongly decreased patenting activity, which peaked in 2011 for solar and wind energy, indicating that the technologies have become more mature and making significant efficiency improvements increasingly difficult (Hille et al. 2020). In lower-income countries, nominal and per capita RE knowledge stocks have been relatively low, amounting to 3.1% and 0.5% only of that of higher-income countries. The small knowledge stocks contrast with the strong growth in RE capacities. Together both provide a first indication that, in the light of regulatory support or competitive levelized costs of electricity, smaller and lower-income countries will also adopt RE technologies, even if the countries lack innovation activity. Nonetheless, some emerging economies, such as China and India, have increased their efforts to become important players in the field of RE technologies. As a result, even though at a low level, knowledge stocks in lower-income countries grew by an average 3 percentage points faster each year than the global aggregate, both nominally and in per capita terms.

3 Results and discussion

3.1 Results of the main model

In the first part of the empirical analysis, we estimate specifications of our main model in order to specify the influence of RE support policies and innovation and to reveal differences depending on the level of detail of the policy instruments. While Table 2 presents the effects on aggregate wind and solar capacities, Tables 3 and 4 show the respective technology-specific influences for wind and solar energy. In each table, we estimate six different specifications. Firstly, we regress the RE capacities on the clustered policies and innovation. Secondly, we include the vector of additional control variables and refer to these estimations as our base specification. Thirdly to fifthly, we disaggregate each cluster of policies separately to specify the policy instruments driving the cluster effect. Lastly, we include all individual policy instruments simultaneously.[12]

Regarding the RE support policies, we estimate mostly significantly negative coefficients for targets, in particular for aggregate RE and solar capacities. In other words, the mere existence of RE strategies does not suffice as an unambiguous signal for investors to build up RE capacities. This appears reasonable as RE targets and strategies usually only represent jurisdictions' first structured declaration to support energy transition and do not yet provide specific incentives for market participants. While we would not expect a negative influence if targets were subsequently substantiated with other RE policy instruments, the descriptive statistics indicated that a number of countries did not behave in this way or only with a long delay. Moreover, the negative coefficient may partly reflect that countries have missed or scaled back their RE targets, which we however cannot measure with the binary policy variable.

On the cluster level, the adoption of feed-in tariffs has influenced aggregate RE and solar capacities mostly positively, but had no effect on wind capacities. While the general positive effect confirms prior research looking at aggregate RE (Aguirre and Ibikunle 2014; Carley et al. 2017), the differential effect on solar and wind energy may be explained by the argumentation that price-based policies are particularly effective during earlier phases of technological development (Johnstone et al. 2010). The technology-specific differences vanish when the individual feed-in tariff instruments are considered. This is also the case for instruments from the other clusters, where we only find smaller differences, if at all, between solar and wind energy. Hence, similar policy incentives seem to be effective for both technologies. Among the feed-in tariff instruments, tendering schemes are especially influential. For instance, the coefficient in column (3) suggests that if a country implemented a tendering scheme, it experienced an average per capita increase of 0.110 kW in wind and solar capacity. For a country like Germany, this would amount to 4% of the total per capita electricity capacity in 2018 (EIA 2021; WDI 2021). In contrast, the other feed-in tariff instruments have no significant effect. This is interesting, because past research partly did not find an increased induced innovation activity from advanced feed-in tariff instruments, like tendering, compared to classic fixed-rate feed-in tariffs (Hille et al. 2020). However, while tendering schemes have been increasingly implemented mostly after the peak innovation activity in solar and wind technologies, this timing corresponds with the strong growth in international RE capacities. The relatively high effectiveness of tendering suggests that RE diffusion can be achieved cost-efficiently, e.g. through auction formats. Compared to other cross-country studies, our findings for fixed-rate feed-in tariffs and tendering are analogous to those of Bento et al. (2020) but mostly different to S. Jenner et al. (2013). The latter may stem from differences in their sample, in particular the earlier analysis period from 1992 to 2008.

[12] Dynamic panel models can potentially yield inconsistent results due to weak instruments. The statistics of several diagnostic tests suggest that this is not an issue in this paper. Specifically, while insignificant Hansen tests of overidentifying restrictions imply joint exogenous instruments, Arellano-Bond tests confirm the absence of serial correlation in the disturbances at an order higher than one, indicating that the moment conditions are valid. Separate difference-in-Hansen statistics that confirm the validity of the individual instruments are available upon request.

Table 2: Estimates for the aggregate capacity of solar and wind energy

Solar & Wind Capacity	(1)	(2)	(3)	(4)	(5)	(6)
	Policies and innovation only	Controls included (Base)	Detailed FIT instruments	Detailed quota instruments	Detailed fiscal instruments	All detailed policy instruments
c.Targets and *i.Targets*	0.025	-0.092**	-0.075**	-0.066*	-0.123***	-0.123***
	(0.057)	(0.039)	(0.030)	(0.039)	(0.047)	(0.041)
c.FIT	0.068**	0.057**		0.061*	-0.003	
	(0.030)	(0.027)		(0.034)	(0.031)	
c.Quotas	0.116**	0.076*	0.038		0.042	
	(0.049)	(0.045)	(0.041)		(0.054)	
c.Fiscal	-0.079**	-0.130***	-0.138***	-0.107***		
	(0.035)	(0.037)	(0.034)	(0.031)		
i.FIT			0.023			0.005
			(0.027)			(0.051)
i.Tendering			0.110***			0.092**
			(0.028)			(0.047)
i.Net Metering			-0.001			-0.029
			(0.032)			(0.028)
i.RPS				0.032		-0.016
				(0.042)		(0.072)
i.Tradable Certificates				0.186***		0.165**
				(0.066)		(0.068)
i.Investment Tax Credits					0.126**	0.103**
					(0.051)	(0.047)
i.Capital Subsidy					0.089	0.080
					(0.062)	(0.067)
i.Public Investment					-0.028	-0.027
					(0.030)	(0.034)
i.Public Procurement					0.167	0.109
					(0.367)	(0.504)
i.Sales Tax Reductions					-0.115***	-0.137***
					(0.041)	(0.050)
i.Production Payments					0.026	0.002
					(0.068)	(0.070)
Innovation Solar & Wind	0.251***	0.204***	0.200***	0.185***	0.203***	0.195***
	(0.077)	(0.040)	(0.043)	(0.044)	(0.036)	(0.041)
Electricity Consumption		-5.219***	-5.672***	-2.894**	-4.059***	-3.562**
		(1.812)	(1.340)	(1.347)	(1.488)	(1.789)
GDP per capita		1.544	2.048**	-0.099	0.641	-0.084
		(1.042)	(1.020)	(1.011)	(1.025)	(1.194)
Trade Openness		-0.298*	-0.252	-0.122	-0.232	-0.136
		(0.162)	(0.169)	(0.168)	(0.152)	(0.186)
Regulatory Quality		0.059***	0.060***	0.0430***	0.048***	0.041***
		(0.019)	(0.014)	(0.014)	(0.017)	(0.014)
Fossil Fuel Exports		-0.010	-0.019	-0.010	-0.017	-0.019
		(0.017)	(0.022)	(0.020)	(0.022)	(0.021)
Constant	0.037*	0.067**	0.063***	0.043*	0.050**	0.040*
	(0.022)	(0.026)	(0.021)	(0.023)	(0.020)	(0.023)
Observations	2,600	2,409	2,409	2,409	2,409	2,409
Wald	67.58***	132.6***	155.7***	137.5***	257.6***	229.6***
AR(1)	0.680	-1.573	-1.945*	-1.325	-2.246**	-2.357**
AR(2)	-1.199	-1.557	-1.487	-0.958	0.750	0.405
Hansen	58.05	102.0	90.18	62.42	81.50	88.24

*** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$; Heteroscedasticity-corrected standard errors are in parentheses; In all estimations, country and year fixed effects are included.

Table 3: Estimates for wind energy capacity

Wind Capacity	(7)	(8)	(9)	(10)	(11)	(12)
	Policies and innovation only	Controls included (Base)	Detailed FIT instruments	Detailed quota instruments	Detailed fiscal instruments	All detailed policy instruments
c.Targets and *i.Targets*	-0.018	-0.028	-0.025	-0.037	-0.080**	-0.087**
	(0.016)	(0.018)	(0.035)	(0.030)	(0.040)	(0.035)
c.FIT	0.044	0.013		0.037	-0.022	
	(0.028)	(0.023)		(0.024)	(0.032)	
c.Quotas	0.103***	0.075**	0.026		0.011	
	(0.038)	(0.034)	(0.036)		(0.033)	
c.Fiscal	-0.066**	-0.057**	-0.108***	-0.070**		
	(0.026)	(0.023)	(0.033)	(0.028)		
i.FIT			0.004			0.004
			(0.024)			(0.035)
i.Tendering			0.074**			0.038
			(0.037)			(0.041)
i.Net Metering			0.000			-0.010
			(0.019)			(0.028)
i.RPS				0.012		-0.006
				(0.025)		(0.043)
i.Tradable Certificates				0.129***		0.110**
				(0.044)		(0.056)
i.Investment Tax Credits					0.110**	0.068*
					(0.050)	(0.036)
i.Capital Subsidy					0.091**	0.061
					(0.044)	(0.041)
i.Public Investment					-0.027	-0.017
					(0.029)	(0.026)
i.Public Procurement					0.237	-0.011
					(0.320)	(0.419)
i.Sales Tax Reductions					-0.109***	-0.107***
					(0.039)	(0.032)
i.Production Payments					0.047	0.042
					(0.070)	(0.062)
Innovation Wind	0.217***	0.188***	0.173***	0.184***	0.180***	0.174***
	(0.027)	(0.017)	(0.016)	(0.016)	(0.014)	(0.019)
Electricity Consumption		-3.206**	-4.358***	-1.730	-3.545**	-2.508*
		(1.433)	(1.483)	(1.426)	(1.805)	(1.499)
GDP per capita		1.128	1.717*	0.292	0.553	-0.127
		(0.854)	(0.899)	(0.943)	(1.005)	(1.052)
Trade Openness		-0.220**	-0.323**	-0.208*	-0.211*	-0.097
		(0.103)	(0.126)	(0.125)	(0.111)	(0.132)
Regulatory Quality		0.030***	0.046***	0.028**	0.042**	0.036***
		(0.009)	(0.013)	(0.012)	(0.017)	(0.011)
Fossil Fuel Exports		-0.008	-0.021	-0.005	-0.012	-0.014
		(0.012)	(0.026)	(0.013)	(0.025)	(0.023)
Constant	0.003	0.035***	0.057***	0.034*	0.047**	0.032**
	(0.004)	(0.013)	(0.019)	(0.018)	(0.019)	(0.015)
Observations	2,600	2,409	2,409	2,409	2,409	2,409
Wald	218.2***	353.5***	422.1***	395.5***	541.1***	564.1***
AR(1)	0.687	1.078	-1.182	-0.774	-2.161**	-2.958**
AR(2)	-0.148	0.522	-0.776	-0.287	1.413	0.917
Hansen	84.55	83.37	101.3	61.28	76.49	124.8

∗∗∗ $p < 0.01$, ∗∗ $p < 0.05$, and ∗ $p < 0.1$; Heteroscedasticity-corrected standard errors are in parentheses; In all estimations, country and year fixed effects are included.

Table 4: Estimates for solar energy capacity

Solar Capacity	(13)	(14)	(15)	(16)	(17)	(18)
	Policies and innovation only	Controls included (Base)	Detailed FIT instruments	Detailed quota instruments	Detailed fiscal instruments	All detailed policy instruments
c.Targets and *i.Targets*	-0.039**	-0.056***	-0.048**	-0.069**	-0.066***	-0.072***
	(0.017)	(0.019)	(0.021)	(0.030)	(0.020)	(0.022)
c.FIT	0.040*	0.033*		0.042*	0.000	
	(0.020)	(0.019)		(0.025)	(0.022)	
c.Quotas	0.031*	0.013	0.002		0.002	
	(0.018)	(0.018)	(0.018)		(0.022)	
c.Fiscal	-0.032	-0.034	-0.043**	-0.024		
	(0.021)	(0.021)	(0.020)	(0.025)		
i.FIT			0.019			0.004
			(0.014)			(0.015)
i.Tendering			0.034*			0.020
			(0.020)			(0.024)
i.Net Metering			-0.007			-0.007
			(0.017)			(0.014)
i.RPS				-0.038		-0.031
				(0.023)		(0.021)
i.Tradable Certificates				0.089***		0.058***
				(0.034)		(0.022)
i.Investment Tax Credits					0.018	0.005
					(0.019)	(0.020)
i.Capital Subsidy					0.043**	0.037*
					(0.020)	(0.020)
i.Public Investment					-0.011	-0.007
					(0.020)	(0.017)
i.Public Procurement					0.009	-0.049
					(0.147)	(0.257)
i.Sales Tax Reductions					-0.034*	-0.025*
					(0.018)	(0.014)
i.Production Payments					0.024	0.011
					(0.018)	(0.027)
Innovation Solar	0.296***	0.269**	0.290**	0.229**	0.263***	0.255***
	(0.077)	(0.112)	(0.128)	(0.112)	(0.090)	(0.089)
Electricity Consumption		-1.971*	-1.864*	-1.279	-1.913**	-1.337
		(1.101)	(1.015)	(1.044)	(0.867)	(1.259)
GDP per capita		0.327	0.382	-0.094	0.045	-0.300
		(0.677)	(0.602)	(0.791)	(0.456)	(0.519)
Trade Openness		-0.012	-0.002	0.031	0.040	0.044
		(0.097)	(0.102)	(0.112)	(0.089)	(0.116)
Regulatory Quality		0.017**	0.019**	0.013*	0.019**	0.018**
		(0.007)	(0.009)	(0.007)	(0.008)	(0.009)
Fossil Fuel Exports		-0.003	-0.013	-0.008	-0.008	-0.011
		(0.010)	(0.013)	(0.014)	(0.011)	(0.013)
Constant	0.002	0.016	0.018	0.011	0.014	0.014
	(0.003)	(0.013)	(0.014)	(0.013)	(0.014)	(0.015)
Observations	2,600	2,409	2,409	2,409	2,409	2,409
Wald	119.9***	82.70***	231.0***	134.5***	107.2***	135.9***
AR(1)	1.556	0.568	0.306	-0.873	-0.743	-0.803
AR(2)	0.522	0.0777	0.170	-0.692	0.156	-0.290
Hansen	97.69	96.01	75.38	124.8	92.18	95.57

∗∗∗ $p < 0.01$, ∗∗ $p < 0.05$, and ∗ $p < 0.1$; Heteroscedasticity-corrected standard errors are in parentheses; In all estimations, country and year fixed effects are included.

The implementation of quotas tends to foster RE diffusion, both on the aggregate and on the technology-specific level. That is, we mostly estimate significantly positive coefficients for the quotas cluster in the first and second specifications that do not yet include individual policy instruments. The cluster effect is driven by the strong influence of tradable certificates, making it the most effective policy instrument in our analysis. This is intriguing, because the quotas cluster and tradable certificates have been the respective least and second least frequently implemented cluster and policy instrument. The high effectiveness indicates the importance of a command-and-control component for the policy instruments. In the heterogeneity analyses, we will attribute this importance to our sample composition, including a large number of lower-income countries with potentially weaker institutions. In contrast to tradable certificates, renewable portfolio standards are not significant. This confirms studies, such as Bento et al. (2020) and Dong (2012), whose results reveal that renewable portfolio standards are not as effective as other instruments. Similar to tendering, the higher effectiveness of tradable certificates relative to renewable portfolio standards also suggests a responsiveness of RE capacities to market mechanisms that can elicit the most cost-efficient RE projects.

With the partial exception of solar energy, the fiscal incentives cluster has a significant negative effect on RE capacities. This result lies in the broad spectrum of values found in cross-country studies for fiscal policies on a more aggregated level, ranging between positive (Polzin et al. 2015) and negative effects (Aguirre and Ibikunle 2014). Interestingly, the decomposition of the relatively strong negative cluster effect results in diverse effects for the individual fiscal instruments. A corresponding significantly negative influence is only estimated for sales-related tax reductions, which have however been the second most commonly enacted policy instrument, only exceeded in their frequency by RE targets. In contrast, while investment tax credits are highly effective for aggregate RE and wind energy, capital subsidies have significantly fostered the installation of solar capacities and partially of wind capacities.[13] The difference in the effects may be explained by the implied uncertainties for investors. For investment tax credits and capital subsidies, the financial support is relatively easy to determine, as it usually depends on the amount of the initial investment and is granted in the course of the investment or the beginning of operation. Sales-related tax reductions can only be made use of during the years of operation. Consequently, the financial benefits are more difficult to project, because they are linked to the generation and retail of energy that depend on unpredictable factors, such as weather fluctuations and changes in political support. The diverse effects of fiscal policies also show the importance of analyzing detailed data on enacted policy instruments or, as will be suggested in the heterogeneity analysis, to aggregate policies more consistently, for instance by incentive mechanisms. Focusing on very general groups of policies, which has often been done in cross-country studies, can result in misleading policy advice, because the effectiveness of individual policies may differ from that of the aggregate cluster.

Overall, quotas with certificate trading, tendering, investment tax credits, and capital subsidies tend to be most effective, whereas RE targets and sales-related tax reductions are least effective. As countries have predominantly implemented packages of RE support policies, the simultaneous effectiveness of different policy instruments indicates that a policy mix can foster the expansion of solar and wind capacities. As will be shown in the heterogeneity analyses, the composition of such a well-designed policy mix depends on the countries' level of development, affecting national energy markets, and also needs to consider complementarities and substitution effects between instruments. Nonetheless, the estimations also reveal that the portfolio should comprise tangible and projectable investment support, in particular for fiscal instruments.

[13] It is important to mention that the coefficient estimates of public procurement often have equal magnitudes, but are insignificant. This can be explained by the instrument's implementation rate, being the lowest among the individual policies, and the comparatively high corresponding standard deviation. Hence, more experience with RE-related public procurement is needed to judge its role for international RE diffusion.

Besides different RE policy instruments, our results suggest that technological progress is among the most promising ways to increase RE capacities. Across all estimations, the coefficient for innovation is positive and significant. In light of the achieved cost efficiency increases during the last two decades, the persistent effect is in line with researchers' expectation. Nevertheless, the result may appear surprising given the insignificant (Verdolini et al. 2018) or only small positive effects (Popp et al. 2011) estimated in studies that also controlled for RE knowledge stocks. Our heterogeneity analyses will help reconciling these seemingly different estimates. Moreover, the results indicate technology-specific differences, i.e. innovation appears to be more important for solar capacities than wind capacities. This may be explained by the later maturity of solar energy, increasing the necessity of innovation activity to reduce levelized costs of electricity and thus induce capacity growth.

With regard to the additional control variables, we find significant positive effects on RE capacities of regulatory quality and partly through increased GDP per capita as well as negative effects of electricity net consumption and partly of trade openness. Changes in fossil fuel exports have not played a significant role for the diffusion of solar and wind energy. The persistently positive influence of the regulatory quality highlights the importance of the political environment for a successful energy transition. The estimates are in line with expectations and supplement the results of prior cross-country analyses (Carley et al. 2017; Pfeiffer and Mulders 2013). Regarding GDP per capita, other studies in the field have detected mixed results, including the estimated positive (Zhao et al. 2013) and insignificant effects (Verdolini et al. 2018). Interestingly, although not only partially, S. Jenner et al. (2013) also found that higher incomes accelerate the diffusion of wind energy but not of solar energy, and attributed this to differences in the size of the installations and hence required initial investments. The result of a delayed RE diffusion because of growth in electricity consumption and trade openness is similar to that in Pfeiffer and Mulders (2013) and Hille and Lambernd (2021), respectively. Both effects may indicate that countries with energy-intensive (exporting) industries have tended to cover their additional electricity demand with non-RE sources, so as to have internationally competitive cost structures.

3.2 Heterogeneity analyses

In the second part of the empirical analysis, we study alterations of the main model and split our sample in order to specify the roles of interactions between policy instruments, countries' level of development, and induced innovation, and to suggest a more customized clustering of fiscal incentives. Given the limited space, in Appendix B, we mostly show the estimates for alterations of the base specification and consider both RE technologies together. Further results are available upon request.

Firstly, we analyze interactions between different policies. For this reason, we interact the individual policy intervention binaries with each other and estimate alterations of the disaggregated specification in column (6) by including one respective interaction term at a time. We consider all pairs of policy instruments from the feed-in tariff, quotas, and fiscal incentives clusters, that are meant to provide specific incentives to market participants and translate RE targets and strategies.[14] Figure B1 graphs the largest and smallest coefficient estimates of the interaction terms, highlighting complementarities and few substitution effects between policy instruments. Besides the direct policy effects discussed in the prior section, these are of relevance when constructing a policy mix to foster

[14] We do not consider interactions with RE targets and strategies as they usually only represent the first structured declaration to support RE diffusion. Out of the 55 possible combinations of policy interventions, the ten pairs related to public procurement have either not been implemented or only implemented in up to three data points. Because of this weak validity, the respective estimates are not discussed.

energy transition. Overall, we estimate 31 positive coefficients, of which eight are significant, and 14 negative coefficients, of which only one is significant. Among the pairs with the lowest coefficients, we predominantly find combinations of policies from the quotas cluster with either those from the feed-in tariffs cluster or fiscal incentives other than public investments. This suggests that the burden of the command-and-control component for market participants to foster RE diffusion tends to be reduced by incentive-based policies that provide financial support for the initial investment or energy production, albeit mostly not significant. An exception is the combination of quotas with certificate trading and tendering, including both a trading and an auction component. While this combination belongs to the less frequently implemented combinations and has gained increasing popularity only rather recently, it is found to be highly complementary.

Public investments in combination with other policy interventions as well as feed-in tariff policies in combination with the remaining fiscal incentives account for most of the remaining largest coefficients of the interaction terms. The former combinations suggest that public investments in RE have not significantly crowded out policy-induced private activities, but instead may have counteracted market failures, such as restrained investments of incumbent utilities. The latter provides an indication that the combination of financial support policies with different incentive mechanisms can increase the attractiveness for market participants to support energy transition, for instance by reducing the perceived risk of RE investments. Interestingly, for all of the most frequent policy combinations, i.e. combinations of sales-related tax reductions, public investments, classic feed-in tariffs, and capital subsidies, we also estimate positive coefficients. Yet, none of them are among the largest coefficients. In other words, from a global perspective, the most frequently implemented policy combinations tend to be rather weak complements. A significant complementarity is only estimated for the combination of classic feed-in tariffs and capital subsidies, a combination that was already in place comparatively often during the early years of our sample. In contrast, combinations of policies, which were identified as those with the highest individual effectiveness in the prior analyses, are among the combinations with the highest and lowest complementarities. Hence, policymakers need to carefully consider both the direct policy effects and interactions between policy instruments.

Secondly, to determine differences between higher- and lower-income countries, we split our sample analogously to the descriptive statistics section, i.e. based on countries' average GDP per capita into the first and second to fourth income quartiles. The results in columns (19) and (20) in Table B1 reveal a variety of differences for our main determinants. While the coefficient estimates of innovation are both still significantly positive, the one of higher-income countries is 2.5 times larger. Hence, innovation has been an important driver of RE diffusion for higher- and lower-income countries, but the effect is especially pronounced in the former, where most innovation leaders are located and large parts of RE knowledge has accumulated. Regarding the RE support policies, the results reveal significant effects for targets and quotas in lower-income countries and for fiscal incentives in higher-income countries. That is, the initial negative effect of targets in the main estimations appears to be predominantly driven by enacted RE strategies in lower-income countries. As RE strategies, particularly in these economies, have partly not been substantiated with other policy instruments, the result seems intuitive. The detected differences in the effectiveness of quotas and fiscal incentives depending on the countries' level of development is interesting, and may contribute to the discussion about the most appropriate policy at a particular development stage. A precondition for the successful implementation of market-based policy instruments are strong institutions and efficient energy markets, which often do not exist in lower-income countries (Tang et al. 2020). Our results seem to reflect this aspect indirectly. Quotas with and without certificate trading include an important command-and-control component. Their positive effect for lower-income countries indicate that this type of instruments may be easier to implement and enforce, thus making them more effective than sole market-based instruments given institutional restrictions. Likewise, the estimates point at the importance of developing strong institutions in order to be able to reap the potential benefits of the full set of the comprehensive policy toolbox.

Thirdly, we analyze interrelations between innovation and the RE policies. That is, we interact the RE support policies with the knowledge stock to get a first indication whether the strong effect of innovation on RE diffusion is driven by intrinsically motivated innovation activity of market participants or is in fact regulation-induced. The empirical evidence on the weak Porter Hypothesis may speak in favor of the latter (Hille et al. 2020; Johnstone et al. 2010), but, by its mere research design, cannot establish the link to the international expansion of RE capacities. In column (21), we observe that once the interaction terms are included, the direct effect of innovation becomes insignificant. Instead, the indirect effect of innovation through quotas becomes positively significant. These intriguing estimates suggest that the previously identified growth of RE capacities associated with innovation activity has been primarily induced through RE support policies, in particular through quotas. When specifying the results for higher-and lower-income countries in columns (22) and (23), it becomes obvious that the inducement through quotas can be explained by our sample, consisting of mostly lower-income countries where quotas are estimated to play a major role for RE diffusion. In contrast, for higher-income countries, we find that feed-in tariffs have been of highest relevance for the expansion of RE capacities through regulation-induced innovation. This is in line with the partial evidence that feed-in tariffs have driven patenting activity in RE technologies, in particular in solar photovoltaics, in developed countries (Böhringer et al. 2017; Johnstone et al. 2010). Our results stress the importance of regulation, and as such may complement the interesting findings of prior analyses, such as Popp et al. (2011), who estimated that technological advances lead to relatively small increases in RE diffusion compared to environmental policy. It clearly appears that without policy incentives, investments in solar and wind capacities, related to technological progress and increasing cost efficiencies, would not have reached today's scales.

Fourthly, we suggest an alternative clustering of the fiscal policy instruments, i.e. we group them by incentive mechanisms. As introduced before, prior research has analyzed the effects of feed-in tariffs and renewable portfolio standards most frequently. In cross-country studies, additional policies in general and fiscal incentives in specific have often received less attention and been controlled for in a less consistent way. For instance, studies have included the cumulated number of (remaining) policies (Dong 2012; Marques and Fuinhas 2012) or relied on data that does not specify individual instruments but general policy groups only, such as fiscal and financial support (Aguirre and Ibikunle 2014; Polzin et al. 2015). Harmonizing various data sources can also lead to the aggregation of different policies, e.g. of subsidies for RE investors and RE producers (Carley et al. 2017). This implies that instruments have been frequently grouped together although they have different incentive mechanisms, i.e. the instruments apply at different stages and potentially affect other decision makers. Our results in the prior section clearly show that this can entail misleading policy advice as the estimated aggregate policy effect is partly contrary to that of individual instruments. Intuitively, we therefore test whether the problem remains when the fiscal policies are clustered according to their incentive mechanism. Specifically, we differentiate between direct public activities (Public investment, public procurement) and two groups of fiscal policies with direct incentives for market participants, namely fiscal support of the initial investment (Investment tax credits, capital subsidy) and fiscal support of RE sale and generation (Sales tax reductions, production payments). The example of results of the base model in column (24) indicates that this approach solves the issue of misleading policy implications for our sample. While the direct public activities do not significantly influence RE capacities, fiscal incentives related to the initial investment and to RE sale and generation have a significantly positive and negative effect, respectively. Likewise, the importance of regulation-induced innovation remains unchanged in column (25), displaying insignificant interaction effects of the new fiscal incentives clusters as well as a direct innovation coefficient and interaction effects of the remaining policy clusters that are analogous to those in column (21). Hence, the clustering of fiscal policies by incentive mechanisms may represent a rather simple, more consistent alternative for future researchers that want to balance the trade-off between identifying attributes of specific RE policies and analyzing less complex specifications despite heterogeneous policies.

3.3 Robustness tests

In the last part of the empirical analysis, we perform a number of robustness checks to ensure the validity of results. Firstly, our results are fairly robust to the inclusion of additional control variables. Specifically, in Table B2, we consider private credits per GDP, secondary school enrollment rate, CO_2 intensity, policy stability, as well as coal, oil, and natural gas expenditures per GDP. The intuition to control for financial sector development in the form of the share of private credits in GDP is that RE projects often entail large investment costs, requiring sufficient access to capital (Pfeiffer and Mulder 2013). The secondary school enrollment rate is included to control for increasing cost efficiencies of RE technologies through learning effects. In this context, we adopt the approach of Zhao et al. (2013) to proxy human capital accumulation, yet acknowledging that the annual enrollment rate can only be considered as a weak stock measure compared to other approaches, such as educational attainment (Barro and Lee 2013), which cannot be applied because of limited data availability. Measures based on CO_2 emissions have frequently been used in cross-country studies to account for environmental commitments in the electricity sector and differences in energy use (Escoffier et al. 2021; Polzin et al. 2015). Using emissions to measure policy stringency is however contentious, because high levels have been interpreted as both stringency and laxity (Costantini and Crespi 2008; McConnell and Schwab 1990). Moreover, related research has considered various dimensions of the political environment (Carley et al. 2017; Pfeiffer and Mulder 2013). Therefore, we analyze the inclusion of a political stability index, besides the regulatory quality variable. To further specify energy consumption patterns and market characteristics, we lastly control for net expenditures of the most important fossil fuels (Carley et al. 2017). As can be seen in Table B2, while secondary school enrollment is the only significant newly-included variable, there is no consistent change in results of the priorly-included variables compared to column (2). That is, among all coefficient estimates of the priorly-included variables, four become insignificant, most notably those of the policy clusters of quotas, feed-in tariffs, and targets in columns (26) to (28), respectively.

Secondly, as discussed in Section 2.1, related research has also used generation instead of capacity data (Carley et al. 2017; Pfeiffer and Mulder 2013). When we consider the effects on per capita RE electricity generation in Table B3, our findings largely remain unchanged, in particular for the individual policy instruments. This may appear a bit surprising, because policies that are, in terms of the support mechanism, closer to the generation and retail of energy, such as energy production payments, did not become significantly more effective. However, it may be explained by the fact that RE capacities first need to be installed before they can generate electricity, and hence policy instruments that foster investments in RE capacities in the end support the growth of RE generation in a similar way. Moreover, the results indicate that (expected) future costs that are relevant for RE generation, e.g. for maintenance, are already considered in the prior investment decision.

Thirdly, we analyze the implementation of national policies only. In our main estimations, we consider sub-national policies as well, because in some countries, such as the United States and Canada, RE policies are often set at the state rather than federal level. Certainly, few, if any, market participants in those countries may face the whole set of policy instruments at one point in time. The estimates in columns (37) and (38) in Table B4 suggest that our findings, particularly on the effectiveness of individual policy instruments, remain robust despite the change in the policy measure.

Fourthly, research has considered alternative lag structures, especially for RE support policies, to capture potential longer time delays for triggering and building capacity additions (Polzin et al. 2015). Therefore, in columns (39) and (40), we lag the policies by two and three years, respectively. In column (41), we analyze RE capacities as a moving average of the years t and $t + 1$, thus considering possible lagged effects rather generally. As expected, we find that the negative effect of targets becomes insignificant, indicating that the mere announcement of a RE strategy does not have a lasting effect on capacity additions. For the other policies, our results reveal analogous effects as in column (2), which are strongest for the feed-in tariffs and fiscal incentives after two years. For the quotas, the effect is strongest in column (41), i.e. after a one- to two-year lag, and declines most after three years. Hence, quotas appear to quickly provide a large incentive to install RE capacities, but once RE shares get closer to regulatory compliance over time, these incentives decrease.

Fifthly, we analyze changes related to the measurement of the knowledge stocks. On the one hand, we control for heterogeneity in the quality of patents. One motivation is that our focus on high-value patents, i.e. on size-weighted patent families with a family size ≥ 2, certainly reduces the relevance of innovation activity in lower-income countries, because, with the exception of China, high-value innovation has been relatively concentrated in few developed economies. Therefore, we relieve the two restrictions suggested in Popp et al. (2011), and analyze the effect of knowledge stocks, which either are not size-weighted or also include patents filed in one country only. Moreover, instead of the family size, we utilize the number of citations in subsequent patents as an alternative, frequently used weight to control for the quality of patents (Calel and Dechezleprêtre 2016; Harhoff et al. 2003). On the other hand, we consider an alternative allocation of patents to countries. Typically, firms first protect an innovation in their countries of origin (Breyer et al. 2013), which is reflected in the approach taken in our main estimations. In order to expand their business, firms also tend to file patents in the countries where the product will be manufactured and commercialized. Assigning patents to the latter countries, i.e. to the individual application authorities, may better reflect the respective technology used in the market and hence entailed levelized costs of electricity. Therefore, as a robustness check, we use knowledge stocks based on the patent count by the intellectual property office as opposed to the inventor country. As can be seen in columns (42) to (45) in Table B5, the relevance of both innovation and the RE policies for RE diffusion tend to remain unchanged despite the alterations in the knowledge stock measurement.

Lastly, we test changes in the estimator related to the control for endogeneity. On the one hand, other explanatory variables than the RE policies and innovation can potentially be endogenous. For instance, although not controlling for it, Dong's (2012) results indicate endogeneity issues for electricity net consumption. This appears intuitive as more RE capacities, ceteris paribus, entail a higher energy supply, which potentially influences consumption patterns. Therefore, we ran several robustness checks, treating other regressors, which may arguably not be strictly exogenous, as endogenous in the GMM estimations, and detect that our findings remain robust. As an example of results, column (46) shows the corresponding estimates for electricity net consumption. On the other hand, related studies have frequently applied estimators that cannot control for simultaneity, such as panel fixed-effects estimators (Bento et al. 2020; Carley et al. 2017; Dong 2012). To analyze the implications for our findings, we re-estimated the models using the fixed-effects estimator that can only account for omitted variable bias as a source of endogeneity. As can be seen in column (47) for the base model, besides influencing the coefficient estimates of several of the additional confounding factors, in particular the estimated effects of the RE support policies change. That is, while the implementation of targets is now associated with significantly higher RE capacities, being the opposite of the estimate in column (2), the effects of feed-in tariffs, quotas, and fiscal incentives are significantly lower and potentially downward-biased. In other words, the estimator appears to wrongly attribute some positive influences of the three policy clusters to the mostly priorly-implemented but nonbinding targets. Hence, omitting simultaneity concerns can drastically change the entailed policy advice.

4 Conclusion and policy implications

In this paper, we wanted to gain new insights into the relationship between RE support policies, RE innovation, and the international diffusion of RE. In particular, we specified the interrelated effects of enacted policy instruments and knowledge stocks on solar and wind capacities. Besides analyzing rich cross-country data on both main determinants, our study advances prior research by showing that the effects on RE diffusion depend on the level of detail of the policy instruments, the countries' level of development, and the control for simultaneity.

Our results have important policy implications. With regard to the ongoing discussion of the higher suitability of market-based instruments over command-and-control instruments to foster RE diffusion, we find mixed evidence. Analogous to the heterogeneous set of countries considered, comprising almost all states that have ratified the Paris Agreement, we detect a heterogeneous set of RE support policies to be most effective. These policy instruments include quotas with certificate trading, tendering, and fiscal instruments that provide specific investment support, i.e. investment tax credits and capital subsidies. Less concrete and projectable measures, such as sales tax reductions and RE targets, which have been implemented most frequently, are least effective. Given that the majority of countries have enacted packages of RE support policies, the simultaneous effectiveness of different policy instruments indicates that, if well-crafted, a policy mix can be beneficial to drive energy transition. In light of the ambitious goal to limit global warming well below 2°C, these policy packages need to comprise especially tangible and projectable incentives for investors. Likewise, they need to carefully take interactions between policies into account, as the most effective individual policy instruments can be both complements and substitutes.

The diverse results for the fiscal incentives also highlight the importance of deducting policy advice from detailed data on enacted policy instruments and of considering policies' incentive mechanisms to avoid misleading suggestions. That is, our overall effect of aggregate fiscal policies differs in parts from the influence of individual policy instruments, ranging from highly effective instruments to others that are even estimated to slow down RE capacity growth. Similarly, our results suggest that the control for simultaneity concerns of RE support policies and innovation is crucial, as the omission can change not only the size of the determined policy effects but also their direction. Simultaneity seems to make it more difficult for basic panel estimators to correctly assign the effects to interrelated policies that have often been implemented at different times. Lastly, the conclusion to the discussion on the most effective policy instruments is likely to be influenced by the country's level of development as well as specific local regulatory and energy market characteristics. For instance, given potentially weaker market institutions in lower-income countries, we find that quota instruments, which always include a command-and-control component, are more effective in these countries than sole market-based instruments. This implies that the development of strong institutions is an important precondition to be able to make use of all prospective benefits of well-designed policy mixes.

While we find that technological advances are also highly relevant for RE diffusion, the corresponding coefficient estimates provide interesting implications related to the RE policies. On the one hand, without policy support, innovation activity, that has entailed remarkable cost efficiency increases and is a prerequisite for the long-term success of RE, would not have developed as dynamically and therefore driven solar and wind capacities as persistently. In other words, our results indicate that the effect of innovation has been largely policy-induced. On the other hand, even without strong innovation activity, but with enacted RE support policies, smaller and lower-income countries can foster energy transition through the adoption of solar and wind technologies. The herein lying policy recommendations are particularly relevant given the ongoing debate about the implementation of fiscal incentives to tackle the economic shock entailing the COVID-19 pandemic, and may provide guidance in prioritizing packages of individual instruments of the comprehensive policy toolbox.

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Appendix A: Overviews

Table A1: Variables overview and summary statistics

Variable	Description	Unit	Obs.	Mean	SD	Min.	Max.
Energy and emission measures							
Solar & Wind Capacity	Per capita solar and wind capacity installed	kW	2,600	0.048	0.132	0.000	1.268
Wind Capacity	Per capita wind capacity installed	kW	2,600	0.033	0.101	0.000	1.063
Solar Capacity	Per capita solar capacity installed	kW	2,600	0.015	0.051	0.000	0.556
Solar & Wind Generation	Per capita electricity generation from solar and wind	Thousand kWh	2,486	0.093	0.270	0.000	2.711
Wind Generation	Per capita electricity generation from wind	Thousand kWh	2,539	0.075	0.240	0.000	2.580
Solar Generation	Per capita electricity generation from solar	Thousand kWh	2,495	0.016	0.056	0.000	0.559
Electricity Consumption	Per capita electricity net consumption	Million kWh	2,596	0.003	0.005	0.000	0.054
Fossil Fuel Exports	Fossil fuel exports per GDP	Share	2,548	0.060	0.171	0.000	2.941
CO_2 Intensity	CO_2 emissions per GDP	kg per USD (2010 prices)	2,353	0.510	0.453	0.053	4.307
Coal Expenditures	Net coal expenditures per GDP	Share	2,548	0.001	0.009	-0.024	0.174
Oil Expenditures	Net oil expenditures per GDP	Share	2,364	0.031	0.148	-1.239	0.981
Natural Gas Expenditures	Net gas expenditures per GDP	Share	2,548	0.010	0.106	-0.161	2.935
Policy instruments and clusters at the national and sub-national level							
c.Targets and *i.Targets*	Implementation of renewable energy targets or strategies	[0; 1]	2,646	0.565	0.496	0.000	1.000
c.FIT	Implementation of at least one policy instrument from the feed-in tariffs cluster	[0; 1]	2,646	0.410	0.492	0.000	1.000
c.Quotas	Implementation of at least one policy instrument from the quotas cluster	[0; 1]	2,646	0.172	0.377	0.000	1.000
c.Fiscal	Implementation of at least one policy instrument from the fiscal incentives cluster	[0; 1]	2,646	0.468	0.499	0.000	1.000
i.FIT	Implementation of fixed rate or premium feed-in tariffs	[0; 1]	2,646	0.314	0.464	0.000	1.000
i.Tendering	Implementation of public competitive bidding (tendering)	[0; 1]	2,646	0.193	0.396	0.000	1.000
i.Net Metering	Implementation of net metering	[0; 1]	2,646	0.144	0.352	0.000	1.000
i.RPS	Implementation of renewable portfolio standards or quota obligations	[0; 1]	2,646	0.107	0.309	0.000	1.000
i.Tradable Certificates	Implementation of tradable renewable certificates	[0; 1]	2,646	0.120	0.325	0.000	1.000
i.Investment Tax Credits	Implementation of investment or production tax credits	[0; 1]	2,646	0.187	0.390	0.000	1.000
i.Capital Subsidy	Implementation of a capital subsidy, grant or rebate	[0; 1]	2,646	0.253	0.435	0.000	1.000
i.Public Investment	Implementation of public investment, loans or grants	[0; 1]	2,646	0.280	0.449	0.000	1.000
i.Public Procurement	Implementation of public procurement	[0; 1]	2,646	0.002	0.039	0.000	1.000
i.Sales Tax Reductions	Implementation of reductions in sales, energy, CO_2, value-added or other taxes	[0; 1]	2,646	0.322	0.467	0.000	1.000
i.Production Payments	Implementation of energy production payments	[0; 1]	2,646	0.078	0.269	0.000	1.000

Table A1 cont.:

Variable	Description	Unit	Obs.	Mean	SD	Min.	Max.
Policy instruments and clusters cont.							
c.Fiscal - Initial Investment	Implementation of *i.Investment Tax Credits* and/or *i.Capital Subsidy*	[0; 1]	2,646	0.316	0.465	0.000	1.000
c.Fiscal - Public Activity	Implementation of *i.Public Investment* and/or *i.Public Procurement*	[0; 1]	2,646	0.280	0.449	0.000	1.000
c.Fiscal - Energy Sale & Generation	Implementation of *i.Sales Tax Reductions* and/or *i.Production Payments*	[0; 1]	2,646	0.344	0.475	0.000	1.000
Innovation measures							
Innovation Solar & Wind (FCw)	Per capita stock of domestic patent families in solar and wind technologies with family size ≥ 2 (size-weighted)	Patent applications	2,612	0.071	0.297	0.000	4.565
Innovation Wind (FCw)	Per capita stock of domestic patent families in wind technologies with family size ≥ 2 (size-weighted)	Patent applications	2,612	0.045	0.258	0.000	4.503
Innovation Solar (FCw)	Per capita stock of domestic patent families in solar technologies with family size ≥ 2 (size-weighted)	Patent applications	2,612	0.026	0.095	0.000	0.862
Innovation Solar & Wind (FC)	Per capita stock of domestic patent families in solar and wind technologies with family size ≥ 2	Patent families	2,612	0.011	0.048	0.000	0.814
Innovation Solar & Wind (SCw)	Per capita stock of all domestic patent families in solar and wind technologies (size-weighted)	Patent applications	2,612	0.072	0.302	0.000	4.640
Innovation Solar & Wind (Citations)	Per capita stock of all domestic patent families in solar and wind technologies (size-weighted by patent citations)	Patent families × patent citations	2,612	0.004	0.021	0.000	0.355
Innovation Solar & Wind (IP Office)	Per capita stock of domestic patent families in solar and wind technologies with family size ≥ 2 grouped by IP office (size-weighted)	Patent applications	2,612	0.062	0.221	0.000	2.885
Miscellaneous control variables							
GDP per capita	GDP per capita	Million USD (2010 prices)	2,548	0.013	0.018	0.000	0.112
Trade Openness	Sum of exports and imports per GDP	Thousand %	2,430	0.089	0.051	0.000	0.437
Regulatory Quality	Regulatory quality index	Index [Standard normal distribution]	2,618	-0.088	0.979	-2.645	2.261
Private Credit	Private credit by deposit banks per GDP	Thousand %	2,426	0.048	0.051	0.000	0.972
Secondary Education	Ratio of secondary school enrollment to the population of the age group that corresponds to this level of education	Thousand %	1,877	0.081	0.029	0.006	0.164
Policy Stability	Political stability index	Index [Standard normal distribution]	2,609	-0.126	0.982	-3.315	1.620

Table A2: Country overview

Africa (53 countries and territories)	
	Algeria, Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Cape Verde, Central African Republic, Chad, Comoros, Congo (Brazzaville), Congo (Kinshasa), Cote d'Ivoire (Ivory Coast), Djibouti, Egypt, Equatorial Guinea, Eritrea, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Libya, Madagascar, Malawi, Mali, Mauritania, Mauritius, Morocco, Mozambique, Namibia, Niger, Nigeria, Rwanda, Sao Tome and Principe, Senegal, Seychelles, Sierra Leone, Somalia, South Africa, Sudan and South Sudan, Swaziland, Tanzania, Togo, Tunisia, Uganda, Zambia, Zimbabwe
Asia (46 countries and territories)	
	Afghanistan, Armenia, Azerbaijan, Bahrain, Bangladesh, Bhutan, Burma (Myanmar), Cambodia, China, Georgia, India, Indonesia, Iran, Iraq, Israel, Japan, Jordan, Kazakhstan, Korea (North), Korea (South), Kuwait, Kyrgyzstan, Laos, Lebanon, Malaysia, Maldives, Mongolia, Nepal, Oman, Pakistan, Palestinian Territories, Philippines, Qatar, Saudi Arabia, Singapore, Sri Lanka, Syria, Tajikistan, Thailand, Timor-Leste (East Timor), Turkey, Turkmenistan, United Arab Emirates, Uzbekistan, Vietnam, Yemen
Australia and Oceania (12 countries and territories)	
	Australia, Cook Islands, Fiji, Kiribati, Nauru, New Zealand, Niue, Papua New Guinea, Samoa, Solomon Islands, Tonga, Vanuatu
Europe (41 countries and territories)	
	Albania, Austria, Belarus, Belgium, Bosnia and Herzegovina, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Kosovo, Latvia, Lithuania, Luxembourg, Macedonia, Malta, Moldova, Montenegro, Netherlands, Norway, Poland, Portugal, Romania, Russia, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Ukraine, United Kingdom
North America (23 countries and territories)	
	Antigua and Barbuda, Bahamas, Barbados, Belize, Canada, Costa Rica, Cuba, Dominica, Dominican Republic, El Salvador, Grenada, Guatemala, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Panama, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, Trinidad and Tobago, United States
South America (13 countries and territories)	
	Argentina, Aruba, Bolivia, Brazil, Chile, Colombia, Ecuador, Guyana, Paraguay, Peru, Suriname, Uruguay, Venezuela
Dropped countries	
	Andorra, Brunei Darussalam, Liechtenstein, Marshall Islands, Micronesia, Monaco, Palau, San Marino, Tuvalu

Note: With the exception of Russia, the countries between Asia and Europe have been assigned to Asia.

Appendix B: Heterogeneity analyses and robustness checks

Figure B1: Largest and smallest coefficient estimates and corresponding 95% confidence intervals of additional policy interactions estimated based on alterations of the specification in column (6)

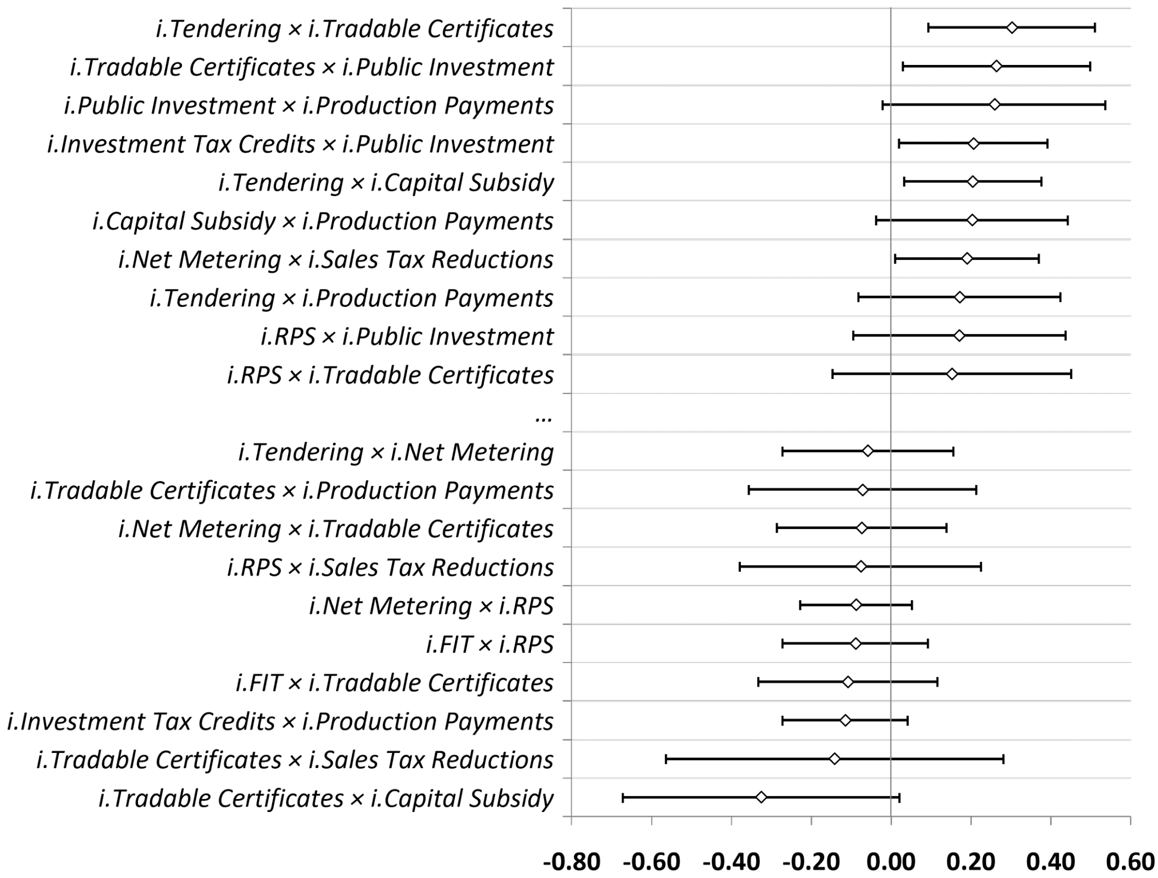

Table B1: Income percentiles, induced innovation, and alternative fiscal clusters

Solar & Wind Capacity	(19)	(20)	(21)	(22)	(23)	(24)	(25)
	Base		Induced innovation			Alternative fiscal clusters	
	Poorest 75% countries	Richest 25% countries	All countries	Poorest 75% countries	Richest 25% countries	Base	Induced innovation
c.Targets	-0.093**	-0.023	-0.105**	-0.038**	-0.072	-0.155**	-0.089***
	(0.040)	(0.234)	-(0.042)	(0.017)	(0.195)	(0.062)	(0.023)
c.FIT	0.021	-0.177	0.068**	0.020	-0.305	-0.018	-0.021
	(0.043)	(0.116)	(0.034)	(0.028)	(0.186)	(0.037)	(0.033)
c.Quotas	0.158***	-0.078	0.007	-0.020	0.051	0.100**	0.045
	(0.054)	(0.050)	(0.032)	(0.025)	(0.153)	(0.043)	(0.045)
c.Fiscal	0.008	0.103*	-0.108***	-0.015	0.270**		
	(0.030)	(0.055)	(0.031)	(0.011)	(0.137)		
c.Fiscal - Initial Investment						0.177***	0.064**
						(0.067)	(0.032)
c.Fiscal - Public Activity						-0.050	0.031
						(0.052)	(0.031)
c.Fiscal - Energy Sale & Generation						-0.125**	-0.083**
						(0.059)	(0.034)
Innovation Solar & Wind	0.112*	0.280***	-0.637	-0.048	4.121	0.195***	-0.670
	(0.061)	(0.095)	(0.544)	(0.037)	(5.227)	(0.035)	(0.422)
Innovation × c.Targets			0.637	0.102	0.294		0.680
			(0.428)	(0.120)	(2.070)		(0.493)
Innovation × c.FIT			-0.004	-0.049	1.140*		-0.070
			(0.159)	(0.104)	(0.682)		(0.230)
Innovation × c.Quotas			0.264***	11.60*	0.372		0.228**
			(0.086)	(6.005)	(0.285)		(0.110)
Innovation × c.Fiscal			-0.021	-0.051	-5.672		
			(0.381)	(0.113)	(3.698)		
Innovation × c.Fiscal - Initial Investment							-0.061
							(0.070)
Innovation × c.Fiscal - Public Activity							-0.080
							(0.082)
Innovation × c.Fiscal - Energy Sale & Generation							0.219
							(0.261)

Table B1 cont.:

Solar & Wind Capacity	(19)	(20)	(21)	(22)	(23)	(24)	(25)
	Base		Induced innovation			Alternative fiscal clusters	
	Poorest 75% countries	Richest 25% countries	All countries	Poorest 75% countries	Richest 25% countries	Base	Induced innovation
Electricity Consumption	-5.598	-7.665	-5,613***	-1.541	-12.57*	-4.520***	-7.161**
	(6.594)	(4.817)	(1.837)	(2.390)	(7.376)	(1.671)	(3.423)
GDP per capita	3.811*	0.068	2.755*	2.438*	1.221	0.412	2.533**
	(2.200)	(1.978)	(1.456)	(1.383)	(3.837)	(0.868)	(1.270)
Trade Openness	0.048	-0.851***	-0.163	-0.005	-0.273	-0.112	0.077
	(0.143)	(0.207)	(0.131)	(0.093)	(0.571)	(0.237)	(0.143)
Regulatory Quality	0.000	0.101**	0.056***	0.010*	0.064	0.053***	0.041***
	(0.010)	(0.046)	(0.017)	(0.006)	(0.050)	(0.018)	(0.015)
Fossil Fuel Exports	-0.017	-0.132	-0.026	-0.006	-0.010	-0.030	-0.033
	(0.027)	(0.247)	(0.033)	(0.010)	(0.295)	(0.021)	(0.048)
Constant	-0.006	0.136	0.053**	0.005	0.035	0.052*	0.018
	(0.015)	(0.129)	(0.023)	(0.011)	(0.108)	(0.027)	(0.017)
Observations	1,770	639	2,409	1,770	639	2,409	2,409
Wald	70.37***	604.3***	157.5***	95.56***	2,102***	249.2***	286.3***
AR(1)	-1.209	1.702	-1.472	0.347	-0.616	-2.266**	-0.830
AR(2)	-1.604	1.543	-1.072	-0.276	-1.211	-0.578	0.643
Hansen	62.94	9.546	71.04	81.31	0.140	47.42	126.6

∗∗∗ $p < 0.01$, ∗∗ $p < 0.05$, and ∗ $p < 0.1$; Heteroscedasticity-corrected standard errors are in parentheses; In all estimations, country and year fixed effects are included.

Table B2: Additional control variables

Solar & Wind Capacity	(26) Add private credit	(27) Add education	(28) Add carbon intensity	(29) Add policy stability	(30) Add fossil fuel expenditures
c.Targets	-0.085**	-0.043*	-0.043	-0.086**	-0.055*
	(0.041)	(0.025)	(0.035)	(0.039)	(0.031)
c.FIT	0.061**	-0.009	0.074**	0.057*	0.075**
	(0.028)	(0.040)	(0.031)	(0.030)	(0.033)
c.Quotas	0.071	0.106**	0.080***	0.078*	0.082***
	(0.047)	(0.044)	(0.030)	(0.045)	(0.031)
c.Fiscal	-0.124***	-0.066*	-0.130***	-0.130***	-0.132***
	(0.039)	(0.036)	(0.039)	(0.037)	(0.038)
Innovation Solar & Wind	0.206***	0.200***	0.210***	0.204***	0.205***
	(0.042)	(0.039)	(0.043)	(0.041)	(0.043)
Electricity Consumption	-5.813**	-6.134***	-3.448**	-4.932***	-3.716**
	(2.682)	(2.152)	(1.491)	(1.777)	(1.475)
GDP per capita	1.561	1.667	0.817	1.581	1.053
	(1.208)	(1.166)	(0.902)	(1.055)	(0.928)
Trade Openness	-0.327*	-0.303*	-0.205	-0.272*	-0.240*
	(0.194)	(0.175)	(0.132)	(0.150)	(0.142)
Regulatory Quality	0.051***	0.044***	0.041***	0.060***	0.042***
	(0.019)	(0.013)	(0.013)	(0.018)	(0.013)
Fossil Fuel Exports	-0.007	-0.030	-0.014	-0.009	0.009
	(0.018)	(0.042)	(0.019)	(0.017)	(0.051)
Private Credit	0.255				
	(0.270)				
Secondary Education		0.562*			
		(0.311)			
CO_2 Intensity			0.001		
			(0.013)		
Policy Stability				-0.008	
				(0.007)	
Coal Expenditures					-0.366
					(0.329)
Oil Expenditures					-0.043
					(0.043)
Natural Gas Expenditures					0.000
					(0.051)
Constant	0.057**	0.010	0.042**	0.060**	0.046**
	(0.028)	(0.022)	(0.019)	(0.024)	(0.020)
Observations	2,277	1,760	2,237	2,409	2,241
Wald	114.8***	270.5***	154.0***	143.3***	196.7***
AR(1)	-1.000	1.823	-0.954	-1.511	-1.086
AR(2)	-0.950	1.391	-0.802	-1.512	-1.032
Hansen	102.5	128.7	72.01	99.34	76.75

∗∗∗ $p < 0.01$, ∗∗ $p < 0.05$, and ∗ $p < 0.1$; Heteroscedasticity-corrected standard errors are in parentheses; In all estimations, country and year fixed effects are included.

Table B3: Electricity generation as the dependent variable

Electricity Generation	Solar & Wind		Wind		Solar	
	(31) Clustered policies (Base)	(32) Detailed policy instruments	(33) Clustered policies (Base)	(34) Detailed policy instruments	(35) Clustered policies (Base)	(36) Detailed policy instruments
c.Targets and *i.Targets*	-0.138	-0.191**	-0.050	-0.186**	-0.089***	-0.094***
	(0.101)	(0.094)	(0.056)	(0.081)	(0.025)	(0.025)
c.FIT	0.201**		0.066		0.050	
	(0.079)		(0.058)		(0.041)	
c.Quotas	0.192*		0.161**		0.026*	
	(0.105)		(0.079)		(0.014)	
c.Fiscal	-0.327***		-0.234***		-0.040	
	(0.107)		(0.071)		(0.041)	
i.FIT		0.000		0.008		-0.002
		(0.078)		(0.072)		(0.029)
i.Tendering		0.207**		0.046		0.030
		(0.104)		(0.092)		(0.023)
i.Net Metering		0.019		-0.006		0.018
		(0.073)		(0.055)		(0.024)
i.RPS		0.055		0.011		-0.038
		(0.119)		(0.098)		(0.024)
i.Tradable Certificates		0.268*		0.215*		0.061***
		(0.145)		(0.112)		(0.021)
i.Investment Tax Credits		0.171*		0.157**		0.012
		(0.092)		(0.079)		(0.020)
i.Capital Subsidy		0.088		0.061		0.044*
		(0.099)		(0.108)		(0.027)
i.Public Investment		-0.070		-0.040		-0.007
		(0.077)		(0.060)		(0.025)
i.Public Procurement		0.217		0.154		0.112
		(0.281)		(0.307)		(0.258)
i.Sales Tax Reductions		-0.256***		-0.203***		-0.032*
		(0.091)		(0.078)		(0.017)
i.Production Payments		-0.047		0.070		0.018
		(0.147)		(0.139)		(0.032)
Innovation[a]	0.424***	0.414***	0.441***	0.435***	0.224***	0.213**
	(0.064)	(0.054)	(0.038)	(0.045)	(0.081)	(0.088)
Electricity Consumption	-7.338**	-4.899**	-7.105**	-5.555	-1.899**	-1.293
	(3.711)	(1.954)	(3.029)	(3.515)	(0.862)	(1.266)
GDP per capita	1.251	-1.394	1.677	-0.342	0.104	-0.403
	(2.266)	(1.671)	(1.849)	(2.142)	(0.473)	(0.566)
Trade Openness	-0.698**	-0.325	-0.733***	-0.407	-0.022	0.011
	(0.309)	(0.335)	(0.235)	(0.286)	(0.099)	(0.099)
Regulatory Quality	0.104***	0.090***	0.107***	0.099***	0.024***	0.022*
	(0.035)	(0.027)	(0.029)	(0.025)	(0.008)	(0.012)
Fossil Fuel Exports	-0.028	-0.019	-0.018	-0.023	-0.010	-0.007
	(0.044)	(0.042)	(0.038)	(0.054)	(0.013)	(0.015)
Constant	0.133***	0.093**	0.123***	0.097***	0.025*	0.021
	(0.049)	(0.039)	(0.036)	(0.029)	(0.013)	(0.018)
Observations	2,311	2,311	2,353	2,353	2,320	2,320
Wald	177.1***	315.6***	461.2***	862.3***	133.5***	150.2***
AR(1)	-2.191**	-2.248**	-1.018	-2.638*	-0.354	-1.098
AR(2)	-1.263	0.928	0.142	1.581	-0.755	-0.758
Hansen	104.2	89.95	134.8	123.6	62.95	122.1

∗∗∗ $p < 0.01$, ∗∗ $p < 0.05$, and ∗ $p < 0.1$; Heteroscedasticity-corrected standard errors are in parentheses; In all estimations, country and year fixed effects are included.

[a] Depending on the RE type analyzed, the knowledge stock changes accordingly. That is, we use knowledge stocks based on wind and solar patenting in (24) and (25), wind patenting only in (26) and (27), and solar patenting only in (28) and (29).

Table B4: National policies only and different lag structures

Solar & Wind Capacity[a]	(37) National policies - Base	(38) National policies - Detailed instruments	(39) Policies in t-2	(40) Policies in t-3	(41) Capacity as 2-year moving average
c.Targets[b]	-0.115***	-0.125***	-0.059	-0.025	-0.036
	(0.027)	(0.030)	(0.042)	(0.031)	(0.037)
c.FIT[b]	0.049		0.109**	0.072**	0.074*
	(0.030)		(0.044)	(0.031)	(0.038)
c.Quotas[b]	0.069*		0.088**	0.058*	0.103**
	(0.042)		(0.038)	(0.030)	(0.045)
c.Fiscal[b]	-0.109***		-0.165***	-0.129***	-0.129***
	(0.027)		(0.046)	(0.034)	(0.045)
i.FIT		-0.011			
		(0.040)			
i.Tendering		0.070*			
		(0.043)			
i.Net Metering		-0.008			
		(0.028)			
i.RPS		-0.047			
		(0.063)			
i.Tradable Certificates		0.166**			
		(0.077)			
i.Investment Tax Credits		0.113**			
		(0.051)			
i.Capital Subsidy		0.050			
		(0.048)			
i.Public Investment		-0.014			
		(0.037)			
i.Public Procurement		0.011			
		(0.278)			
i.Sales Tax Reductions		-0.094**			
		(0.038)			
i.Production Payments		0.009			
		(0.049)			
Innovation Solar & Wind	0.203***	0.190***	0.207***	0.212***	0.214***
	(0.041)	(0.038)	(0.044)	(0.041)	(0.042)
Electricity Consumption	-5.138***	-3.681**	-4.439***	-4.205***	-4.211***
	(1.687)	(1.592)	(1.474)	(1.604)	(1.561)
GDP per capita	2.008*	0.005	1.327	1.572	1.126
	(1.105)	(1.062)	(1.008)	(1.081)	(0.958)
Trade Openness	-0.361**	-0.090	-0.293**	-0.315**	-0.207
	(0.154)	(0.166)	(0.145)	(0.150)	(0.132)
Regulatory Quality	0.058***	0.045**	0.050***	0.048***	0.040***
	(0.017)	(0.019)	(0.014)	(0.014)	(0.014)
Fossil Fuel Exports	-0.006	-0.011	-0.016	-0.018	-0.015
	(0.022)	(0.038)	(0.023)	(0.023)	(0.018)
Constant	0.073***	0.036*	0.058***	0.142***	0.040**
	(0.022)	(0.019)	(0.022)	(0.037)	(0.019)
Observations	2,409	2,409	2,242	2,075	2,069
Wald	145.5***	280.2***	127.7***	128.1***	109.3***
AR(1)	-1.663*	-2.543**	-1.692	-0.302	-0.672
AR(2)	-1.628	0.707	-1.460	-0.299	-1.052
Hansen	110.3	149.2	79.86	87.43	80.98

∗∗∗ $p < 0.01$, ∗∗ $p < 0.05$, and ∗ $p < 0.1$; Heteroscedasticity-corrected standard errors are in parentheses; In all estimations, country and year fixed effects are included.

[a] While we analyze the average capacity of periods *t* and *t*+1 as the dependent variable in column (41), the capacity in period *t* is used in the remaining columns.

[b] In columns (39) and (40), the policies are lagged by two and three years, respectively. In the other columns, the policies remain lagged by one year.

Table B5: Alternative knowledge stock measures and changes in the estimator

Solar & Wind Capacity	(42)	(43)	(44)	(45)	(46)	(47)
	Only patent family size ≥ 2	All patent families, size-weighted	Citations as weight	Patents by IP office	Electricity consumption as endogenous	Fixed effects estimator
c.Targets	-0.075**	-0.078**	-0.090**	-0.107***	-0.072**	0.010**
	(0.035)	(0.038)	(0.036)	(0.029)	(0.032)	(0.004)
c.FIT	0.078*	0.074*	0.036	0.002	0.060**	0.019***
	(0.044)	(0.039)	(0.027)	(0.027)	(0.024)	(0.006)
c.Quotas	0.081*	0.073*	0.054*	0.061**	0.069*	0.029*
	(0.046)	(0.042)	(0.032)	(0.028)	(0.040)	(0.015)
c.Fiscal	-0.139***	-0.154***	-0.108***	-0.067***	-0.133***	-0.013*
	(0.047)	(0.052)	(0.036)	(0.026)	(0.031)	(0.007)
Innovation[a]	1.202***	0.202***	2.577***	0.181***	0.203***	0.227***
	(0.259)	(0.037)	(0.405)	(0.070)	(0.041)	(0.057)
Electricity Consumption	-5.468***	-5.774***	-6.818***	-8.876***	-5.843***	-5.677
	(1.501)	(1.364)	(1.968)	(1.848)	(1.678)	(4.077)
GDP per capita	2.108*	1.688*	2.430**	3.801***	1.739	10.80***
	(1.134)	(0.957)	(1.156)	(1.047)	(1.068)	(3.728)
Trade Openness	-0.265*	-0.352**	-0.337*	-0.250*	-0.365**	0.448**
	(0.151)	(0.138)	(0.189)	(0.129)	(0.160)	(0.184)
Regulatory Quality	0.048***	0.061***	0.059***	0.049***	0.059***	-0.023
	(0.018)	(0.018)	(0.019)	(0.014)	(0.017)	(0.014)
Fossil Fuel Exports	-0.018	0.012	-0.022	-0.043	-0.028	-0.013
	(0.026)	(0.025)	(0.031)	(0.041)	(0.030)	(0.010)
Constant	0.056**	0.074***	0.073***	0.052***	0.070***	-0.140***
	(0.026)	(0.022)	(0.028)	(0.018)	(0.024)	(0.043)
Observations	2,409	2,409	2,409	2,409	2,409	2,409
Wald	132.9***	146.2***	149.2***	166.8***	140.7***	
AR(1)	-1.319	-1.690	-0.889	-0.314	-1.137	
AR(2)	-1.492	-1.624	-0.823	-0.389	-1.105	
Hansen	82.23	134.2	100.4	126.9	126.6	
F						8.878***
R^2 within						0.366
R^2 between						0.492
R^2 overall						0.423

∗∗∗ $p < 0.01$, ∗∗ $p < 0.05$, and ∗ $p < 0.1$; Heteroscedasticity-corrected standard errors are in parentheses; In all estimations, country and year fixed effects are included.

[a] Different knowledge stock estimates are used in the columns. Specifically, they are based on patent families with a family size ≥ 2 (*FC*) in (42) and on all patent families weighted either by their family size (*SCw*) in (43) or by patent citations (*Citations*) in (44). Size-weighted patent families with a family size ≥ 2 are used in the remaining estimations, grouped either by IP office (*IP Office*) in (45) or, as in the main estimations, by the country of the inventor (*FCw*) in (46) and (47).