NBER WORKING PAPER SERIES

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Working Paper 22454
http://www.nber.org/papers/w22454

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
July 2016

Elena Verdolini gratefully acknowledges funding from the European Union's Seventh Framework Programme (FP7/2007-2013) under grant agreement n° 308481 (ENTRACTE) and grant agreement grant agreement n° 308329 (ADVANCE). Francesco Vona gratefully acknowledges funding from the European Union's Seventh Framework Programme (FP7/2007-2013) under grant agreement n°320278 (RASTANEWS). The authors also thank the participants to the IAERE 2015 Conference in Padova, as well as Carolyn Fisher, Giovanni Marin, Giuseppe Nicoletti and Francesco Saraceno for useful comments. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 22454
July 2016
JEL No. O33,Q42,Q48,Q55

ABSTRACT

The diffusion of renewable energy in the power system implies high supply variability. Lacking economically viable storage options, renewable energy integration has so far been possible thanks to the presence of fast-reacting mid-merit fossil-based technologies, which act as back-up capacity. This paper discusses the role of fossil-based power generation technologies in supporting renewable energy investments. We study the deployment of these two technologies conditional on all other drivers in 26 OECD countries between 1990 and 2013. We show that a 1% percent increase in the share of fast-reacting fossil generation capacity is associated with a 0.88% percent increase in renewable in the long run. These results are robust to various modifications in our empirical strategy, and most notably to the use of system-GMM techniques to account for the interdependence of renewable and fast-reacting fossil investment decisions. Our analysis points to the substantial indirect costs of renewable energy integration and highlights the complementarity of investments in different generation technologies for a successful decarbonization process.

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1. Introduction

The ability to match future economic growth with reduced pressure on the environment (through so-called "green growth") is inextricably linked with the deployment and diffusion of low carbon technologies. A crucial sector in this respect is that of energy, which in 2012 accounted for two thirds of global CO2 emissions. Indeed, this sector alone can contribute to more than 40% of the emission reductions needed for a "Two Degree Scenario". To achieve this goal, it will be necessary among other things to deploy renewable energy sources and reduce the carbon intensity of fossil-based generation technologies (IEA 2015).

The widespread diffusion of cleaner technologies in the energy sector is currently hindered for three main reasons. First, renewable technologies recently witnessed dramatic decreases in costs, but they are not yet fully cost-competitive with fossil-based power generation, except in favorable geographical locations. Second, the energy sector is sticky and a change in the paradigm of electricity production faces multiple challenges: the need to upgrade infrastructure (i.e. the electricity grid) and the considerable sunk costs in existing, less efficient power plants. Third, renewable energy sources such as wind and solar, which today are the most cost-competitive options, are intermittent and non-dispatchable. Increasing the penetration of these energy sources in the system is particularly challenging given the current lack of cheap large-scale storage technologies. Indeed, this last issue may prove the most crucial, as it would challenge the deployment of renewables even if these were cost competitive and old fossil-based capital vintages were close to the end of lifetime.

We shed some light on how renewable energy integration has been historically handled. The topic we address is not new to energy system operators and experts: unlike energy produced using fossil fuel sources, generation from the most promising renewables is non-dispatchable and often reaches peak supply in times not coinciding with peak demand.[1] This increases the risk of shortage, and lowers reliability and security of supply. To compensate, much back-up generation capacity needs to be kept in place. For instance, Eon Netz (2004), one of the four grid managers in Germany, indicates that 8 MW of back-up capacity are required for any 10 MW of wind capacity added to the system. Martin Hermann, CEO of 8minutenergy Renewables, argues that only the ability to store solar electricity for three to five hours will eventually "allow a precise overlap between the PV production curve and the demand peak," while 20 hours of storage are necessary for PV to work as a base load resource (REW 2011). Such large scale storage technologies or the dispatch of electricity over long distances are still not possible at

[1] For instance, wind turbines produce most electricity in the early hours of the day and at night and cannot cover daytime peak demand; wind speeds vary significantly from day to day but also between seasons. Solar power plants output is strongly affected by cloud coverage and varies between seasons. Hence, it can cover daytime peak load, but not the residential sector nighttime peak load demand. Both these renewable energy options require a significant amount of backup capacity.

competitive costs at present.[2] Indeed, the issue of how to successfully manage renewable energy integration has attracted increasing attention, especially as their share in the system increases to levels never witnessed before (Carrrara and Marangoni 2015).

To date, back-up capacity has been mostly provided through fossil-based technologies. Importantly, there are different categories of fossil-based technologies. Base-load fossil generation (BLF henceforth), which comprises coal based and low efficiency generation technologies, cannot easily compensate for renewable variability due to slow reacting times and high capital costs. Fast-reacting fossil technologies (FRF henceforth), which includes most gas-generation technologies, Combined Heat and Power and Integrated Gasification Combined Cycle to name a few, are characterized by mid-merit order, quick ramp-up times, lower capital costs and modularity (meaning that efficiency does not fall significantly with size). They are thus particularly suitable to meet peak demand and mitigate the variability of renewables.

A careful consideration of the relationship between renewable capacity and other generation technologies, and especially fast-reacting fossil-based electricity generation, unveils two significant shortcomings of existing empirical and theoretical analyses. First, it highlights that the trade-off between renewable deployment and security of supply is exacerbated as renewable penetration increases. Second, it suggests that unless cheap storage options become widely available in the immediate future, the penetration of renewable energy will increase system costs, as a significant amount of capital-intensive and under-utilized back-up capacity will have to be maintained. Overlooking these two issues leads to an underestimation of the costs of the energy transition. This is particularly troublesome considering that higher renewable penetration rates will further increase system variability and hence require a parallel expansion of back-up resources (NYISO, 2010 and REW 2011).

We contribute to the debate by providing a careful macro-analysis of the historic interplay between the deployment of renewable and fossil electricity generation capacity in a sample of 26 Organization for Economic Cooperation and Development (OECD) countries between 1990 and 2013. As in the related paper by Popp et al. (2011), we focus on installed capacity as our proxy for technology investment and penetration. We complement previous contributions by focusing on the role of fossil-based technologies, and further splitting them into base-load and fast-reacting fossil generation.

Controlling for country fixed effects and the rich dynamics of RE capacity, we show that, all other things equal, a 1% percent increase in the share of fast reacting fossil technologies is associated with a 0.88% percent increase in renewable generation capacity in the long term. This is a sizeable effect, which is attributable to the high persistence of RE capacity in our dynamic specification. To be sure, the short-term effect of a 1% increase in FRF capacity is a modest 0.03% increase in RE. This result is robust to

[2] Electricity transmission operates under a number of significant constraints, among which the interconnections between different regional electricity grids and the capacity constraints of transmission lines that limit movement of energy.

various changes in the specification and in the estimation technique, including the use of system-GMM to account for the fact that investment decisions in renewable and fast-reacting fossil are correlated.

The rest of the paper is organized as follows. Section 2 details some of the challenges of the integration of renewable energy generation in the power system, reviews the available literature on the topic, and highlights our contribution to the debate. Section 3 presents our dependent variable and main variables of interest and provides descriptive statistics. Section 4 details the empirical strategy. Section 5 presents our results, and quantifies them in a detailed way. Section 6 concludes, highlighting the policy implications of our analysis.

2. Managing renewable energy integration in the energy system

Decoupling economic activities from fossil-fuel use (and hence, from anthropogenic carbon emissions) is the only way to avoid severe and pervasive impacts from climate change while sustaining economic growth (IPCC, 2014). As testified by the outcomes of the COP21, all governments are committed to addressing this challenge by implementing policies to promote cleaner technologies and to limit the use of polluting inputs. The integration of renewable sources in the energy system is one of the key components of such decarbonization strategy. However, as argued in the Introduction, this integration raises many challenges in terms of planning, operation, and reliability practice.[3] In particular, renewable technologies are not comparable with fossil-based generation in terms of dispatchability. This translates into high system costs[4] of renewable generation, as it requires holding significant back-up capacity to ensure a balanced energy supply throughout the day. In fact, these challenges will only further increase as the share of renewable energy generation increases to levels never witnessed before. To date these aspects have been only marginally considered in economic analyses of renewable energy deployment.

The issue of how to match demand and supply instantaneously, and in particular to meet peak demand, has always characterized energy systems, since electricity cannot be stored in an economically viable way for extended periods of time or dispatched for long distances without significant loss. This means that even power systems fully based on dispatchable technologies (such as fossil fuels) incur into system costs due to the necessity to hold spinning capacity, namely reserve generation capacity always on hold to offset

[3] For instance, renewables imply a more flexible and decentralized approach to energy generation. In addition, they shift the merit order of power generation options and lower the price of electricity. The merit order is a ranking criterion whereby in a centralized system generation capacity should be brought online in increasing order of marginal costs (considerations are also given to the amount of energy that can be generated). Implementing the merit order ensures that electricity dispatch is done minimizing the cost of production. Sometimes generating units must be started out of merit order, for instance in cases of transmission congestion or system reliability. The high demand for electricity during peak hours pushes up the bidding price for electricity, and the relatively inexpensive base-load power supply mix is supplemented by 'peaking power plants,' which charge a premium for their electricity since their marginal costs are higher. Renewable sources, with high merit, hence reduce the overall costs of electricity, and particularly so in times of peak demand (Sensfuss and Ragwitz 2008).

[4] System costs are the total costs above plant-level to supply electricity at a given load and given level of security of supply.

variations in demand and supply. Generally speaking, peak demand has been met thanks to gas-fired and diesel turbines, which have fast rump-up times and are modular.[5] Conversely, other technologies with higher capital costs, lower operating costs and slower reaction times (such as coal-based or nuclear power plants) have been used to handle base-load production.

The problem of matching demand and supply is magnified in the case of renewables due to their variability vis-à-vis fossil-based generation and to the fact that times of peak production do not necessarily take place at times of high demand. Variability in generation has been identified as a significant barrier to the integration of both wind and solar resources (e.g., GE Energy 2008, Lorenz et al. 2011, Marquez and Coimbra 2011, Mathiesen and Kleissl 2011, Gowrisankaran et al 2016, Sinn 2016). To date, given their relatively low penetration, the integration of renewable sources has not required drastic changes in system operations. Peak-load generation technologies such as gas turbines have been used to compensate for variability, alongside other load-following "mid-merit" generation technologies (such as combined cycle, and specifically combined cycle gas turbines), which have been used to this end as the penetration of renewables increased in the last decades.[6]

As a result, the estimated indirect costs of renewables are at least an order of magnitude greater than those associated with dispatchable fossil-fuel technologies. For the latter, system costs are relatively modest, generally estimated below USD 3 per MWh in OECD countries. For the formers, such costs are as high as USD 40 per MWh for onshore wind, USD 45 per MWh for offshore wind and USD 80 per MWh for solar (IEA 2012). These high estimates are the direct results of the need for additional system reserves and back-up generation to ensure system reliability.[7] Renewable energy system costs will also increase over-proportionally with the amount of variable electricity in the system, with far-fetching implications for the energy markets and security of supply (OECD 2012, NYISO 2010, IEA 2012, Baker et al. 2013, Sinn 2016).[8]Ignoring them can thus lead to a severe underestimation of the social and private costs of any energy transition.

[5] Unlike steam turbines, which require a period of 1-1.5 hours for heating after start up, cold gas turbines heat within 6 to15 minutes following the start-up (http://www.eolss.net/sample-chapters/c18/e6-43-33-06.pdf). The most attractive option is to use the most efficient types of gas-fired plants as back-up capacity. These consist of co-generation gas-fired plants, which use gas to produce both electricity and heat for additional applications. Co-generation is an attractive option since back-up capacity is used below peak and often at low levels of capacity. Unfortunately, our data do not allow discerning if gas turbines are used in co-generation mode. Hydro generation has also been traditionally used to meet peak demand, as electricity production can rump up fast. However, hydro is very dependent on endowment and it is unlikely that it can be expanded further (especially in big plants) since most of the resource is already exploited in most of the countries included in our sample. Biomass is also an excellent candidate, but concerns over tradeoffs relating to land use for biomass and biofuel production versus food are high.

[6] Such technologies can respond to changes in load much faster than conventional steam power plants, but slower than gas turbines (see http://www.wartsila.com/energy/learning-center/technical-comparisons/combustion-engine-vs-gas-turbine-part-load-efficiency-and-flexibility and http://iea-etsap.org/web/Highlights%20PDF/E02-gas_fired_power-GS-AD-gct%201.pdf)

[7] Indeed, Baker et al. (2013) argue that new solar PV capacity displaces only a small percentage of already existing dispatchable capacity.

[8] To attenuate such costs, it will be necessary for system operators to alter system infrastructure, introduce demand-side management programs, and change the operating capabilities of conventional generation.

Notwithstanding the importance of this topic, the economic literature focusing on energy innovation and deployment has largely overlooked this issue to date. A first set of contributions focuses on the role of energy and environmental policies in promoting renewable investment and deployment, proxied by installed capacity. Shrimali and Jenner et al. (2013) explore the contribution of different policy instruments to solar PV development in the US commercial and residential sectors over the years 1998-2009, but their analysis does not touch upon the possible role of other generation technologies. Jenner et al. (2013) extend the analysis to the EU and show that solar PV deployment has been driven by feed-in tariffs (FITs). They partially recognize the role of other generation technologies in affecting RE investments (i.e. yearly capacity additions) by conditioning their empirical analysis on the share of power generation from traditional energy sources (nuclear, coal and gas), but they do not distinguish between the roles of different fossil-based technologies (FRF vs. BLF) and they do not discuss the implication of their findings in this respect. Popp et al. (2011) show that technological improvements have a small positive impact on investments in RE generation in OECD countries, but find that policies are not significant. Also in this case, the analysis does not control for the possible interaction between investments in renewable energy and (fast-reacting) fossil generation technologies. Generally speaking, the role of fossil-based generation is overlooked in these studies under the implicit assumption of high substitutability between clean and dirty technologies. This assumption is shared by the theoretical contributions on directed technical change, which assume a relatively high degree of substitutability between the two (Acemoglu et al., 2012). We contribute to this strand of literature by providing the first macro-level empirical analysis of the diffusion of RE generation while accounting for the interaction with investments in other generation capacity, and specifically fossil-based capacity. In addition, our empirical specification takes into account a rich dynamic structure of investments in power generation, improving on the linear technological model of diffusion which is assumed in Popp et al. (2011).

A second strand of empirical literature studies the determinants of renewable energy deployment by focusing on power production (rather than capacity), with no specific attention to the role of energy and environmental policies. Aguirre and Ibikunle (2014) investigate the drivers of country-level RE growth in a broad sample size of countries (including Brazil, Russia, India, China and South Africa). They show that coal, oil and gas contribution to electricity generation is negatively associated with renewable growth (see also Pfeiffer and Mulder, 2013). Narbel (2013) provides evidence that RE generation is inversely related to energy dependency from abroad, proxied by coal imports. Overall, these contributions suggest that renewable and fossil energy are substitutes, as the share of renewable generation is inversely related to the share of fossil generation. However, by focusing on the actual amount of electricity produced, these studies cannot provide any insights on the sunk costs associated with back-up capacity. As argued in Jenner et al. (2013) "generation determines the actual return on investment while capacity reflects the expected return on investment." Our analysis contributes to this strand of literature by exploring the relationship between renewable and other generation technologies using capacity rather than production data. In this way, we are able to capture the investment decision as purely as possible, since capacity informs on investments without being confounded by other forces that investors cannot fully foresee or control, such as weather conditions, equipment performance, and other such factors.

A third strand of literature comprises the contributions which use integrated assessment models (IAMs) to provide insights on the evolution of demand and the generation mix over time. In these models is it of paramount importance to properly account for the constraints imposed by variable renewable energy sources. Carrara and Marangoni (2015) show that several strategies are adopted to this end in IAMs, depending on the granularity of the model and the complexity with which it portrays the energy sector. For instance, some models impose hard upper bounds on variable renewable sources penetration, while others rely on implicit or explicit cost mark-up for renewables, or constraints on the flexibility or installed capacity of the power generation fleet. Our contribution provides insights on the historical interaction between renewable and fossil generation technologies, and can inform the IAMs community regarding the calibration of such constraints. This is particularly true for those models which describe the energy system at the aggregate level and considering that we provide both short-run and long-run estimates.

Our focus is thus on the historic relationship between renewable energy integration and the presence of fossil-based generation technologies which are used as back-up capacity. The core of the paper is devoted to the empirical investigation of whether, absent cost-competitive storage technologies, the successful integration of renewable was possible (and higher) partly due to the availability of fast-reacting fossil-based units. In the next Section, we describe in detail our data sources, while Section 4 presents our empirical approach.

3. Data and Descriptive Statistics

Our sample includes 26 OECD countries betweeen 1990 and 2013.[9] Our dependent variable is the percentage of net installed electrical capacity in RE technologies (Cap_{it}^{RE}) over total electricity capacity ($TotCap_{it}$) in country i, time *t,* which reflects the investment decision as purely as possible (see discussion in Section 2):

[9] The sample is slightly unbalanced due to missing data and includes: Australia, Austria, Belgium, Canada, the Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Poland, Portugal, the Slovak Republic, Spain, Sweden, Switzerland, Turkey, the United Kingdom and the United States. The missing values are concentrated at the end of the sample period for France and Germany, while at the beginning of the sample period for the Czech Republic and the Slovak Republic. These countries account for the majority of worldwide RE investment over the period considered.

$$Share\ Cap_{it}^{RE} = \frac{Cap_{it}^{RE}}{TotCap_{it}} * 100$$

Renewable energy technologies include solar, wind, geothermal, ocean/tide/wave and biomass from the IEA Renewable Energy Information Database (2016a). We exclude hydro from the calculation of RE capacity because, as pointed out by Popp et al. (2011), it is a mature technology for which most of the natural endowment is already exploited. Furthermore, hydro is a fast-reacting dispatchable technology and is often used to meet peak demand. As such, it does not share the same characteristics and limitations of the other RE technologies. Furthermore, since our main argument is that FRF technologies compensate for the variability of RE, we test the robustness of our results by also excluding biomass (which is storable) from the definition of RE capacity.

Fossil technologies are split into base-load fossil generation and fast-reacting fossil technologies, with the latter being the best candidates to compensate for renewable variability, as argued above. The IEA Electricity Information Database (2016b) distinguishes between the following generation technologies: Gas Turbines; Combined Cycle; Internal combustion/diesel; Steam; and Other type of generation. We define FRF as the sum of Gas Turbines and Combined Cycle, as these are mid-merit technologies often used to address peak load. Conversely, we define BLF as Internal combustion/diesel; Steam; and Other type of generation. These are technologies which are generally characterized by lower efficiency levels and slower ramp up times.[10]

Figure 1 shows the development of the shares of installed capacity in RE, FRF and BLF for selected countries and on average in the sample. The share of BLF technologies declined over time except in Japan, with some countries such as Denmark and Italy experiencing a rather sharp decrease. Conversely, both RE and FRF technologies increased significantly, especially in the second part of the sample, albeit with different rates across countries. A sharp and more uniform increase in renewable characterizes EU countries starting around the signing of the Kyoto Protocol. Denmark stands out, with very high investments in RE already in the 1990s, almost entirely due to wind power. We see a similar change in FRF around the year 1996, with some countries, such as Italy and the US, increasing capacity significantly.

[10] IEA (2016b) allows a breakdown based on the energy carrier (gas, oil, coal or other combustible fuels) Unfortunately, it is not possible to distinguish installed capacity along both dimensions (i.e. energy carrier and conversion technology (IEA 2013).

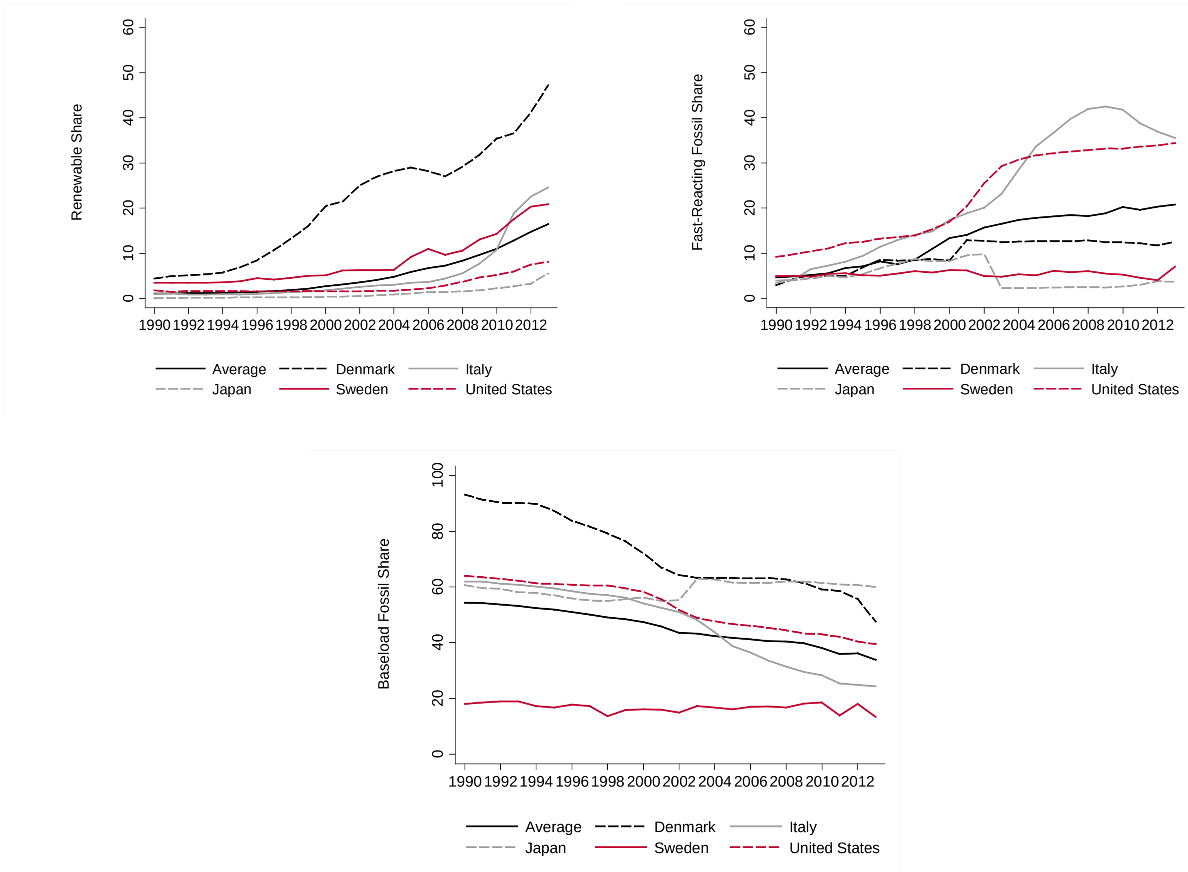

Figure 1: Share of installed capacity in RE, FRF, BLF, average and selected countries.

To explore the relationship between RE and FRF capacity, we estimate a regression model where the capacity share in FRF technology ($Share\ Cap_{it}^{FRF}$) is the main explanatory variable of interest, and is included in a regression alongside other determinants previously explored in the literature. This allows us to quantify the relationship between $Share\ Cap_{it}^{RE}$ and $Share\ Cap_{it}^{FRF}$ *ceteris paribus*, namely conditioning our estimates on several other confounding factors affecting the level of RE generation capacity in country *i* at time *t*.

Among the most important drivers of renewable deployment previously identified in the literature are public policies, which pertain to two realms: environmental policy and market regulation. On the one hand, environmental policies such as feed-in tariffs, tax credits, emission targets and investment incentives are specifically designed to accelerate the diffusion of RE technologies by reducing the cost wedge with fossil generation. Their role in supporting the development and diffusion of renewable technologies has been widely explored in the theoretical and empirical literature (see Popp et al 2010 for a review). As such, our analysis necessarily includes them among the key determinants of renewable investments.

On the other hand, the liberalization of the electricity market had the effect, among the other things, of shifting the balance of power from centralized, large and regulated providers to smaller actors specialized in cleaner technologies (Nicolli and Vona, 2016). While it is theoretically well established that the degree of competition in the energy market affects the incentives to innovate in renewable energy technologies (Nesta et al. 2014; Nicolli and Vona, 2016), this is to the best of our knowledge the first paper to consider the effect of market competition on the deployment of both renewable and fossil energy technologies. Conditioning our analysis on the level of market liberalization is particularly important given the significant changes that characterized OECD countries in the last decades.

Regarding environmental policies, we use data from the OECD Environmental Policy Stringency (EPS) database (Botta and Koźluk 2014). This data includes information 15 environmental policy instruments for OECD countries over the years 1990-2012, and rates their stringency on a scale from 1 and 6.[11] Among the policy instruments included in the EPS database, we select the ones that are more relevant for the power sector. In line with the findings of Johnstone et al. (2010), we include in our preferred specification feed-in tariffs (FITs) and renewable energy certificates as the most important policies supporting RE deployment. FITs promote the integration of renewable in the power system by guaranteeing a fixed remuneration to RE generation. Our underlying assumption is that feed-in-tariffs are particularly effective in supporting new and small producers in the power market. Conversely, renewable energy certificate promote RE deployment by requiring that utilities produce or purchase a certain share of renewable power as part of their portfolio. In this respect, certificates are expected to be particularly effective. We define the variable "FIT" as the average of a country's score for the solar and wind FITs from the EPS database. The variable "Certificates" is defined as the average of the score for White, Green and CO2 certificates.

We also test also the effects of other two policy instruments in additional empirical specifications: "Taxes" (defined as the average of CO2, SOx, NOx and Diesel taxes scores) and "Limits" to pollutants (defined as the average of SOx, NOx, and Particulate Matters limits scores). Unlike FITs and Certificates, these do not provide a direct incentive to invest in RE and thus are expected to have smaller effect on the deployment of RE.

Regarding the level of market regulation, we include the OECD index capturing the level of entry barriers in the electricity market, which accounts for both freedom of access to the grid by producers and freedom of choice by consumers. The index varies on a 1-6 scale, with the highest values indicating a higher level of entry barrier (Conway et al., 2005). The scale of production for RE installation is usually

[11] The OECD EPS database contains information on 15 different environmental policy instruments implemented in OECD countries, which include Non-Market Based (NMB) and Market Based (MB) instruments. NMB policies are limits to pollutants (SOx, NOx, Particulate Matters and Sulphur Content of Diesel) and Government energy-related R&D expenditures as a percentage of GDP. MB policies are feed in tariffs (FITs - Solar and Wind), taxes (on CO2, SOx, NOx and Diesel), certificates (White, Green and CO2) and the presence of deposit and refund schemes (DRS).

much smaller than the one of traditional fossil plants (e.g. rooftop PV) and more suitable for a decentralized market composed of several producers. Therefore, we expect that the diffusion of both RE and small scale FRF technologies will be favored by the reduction of entry barriers.

Hence, the basic vector of policy controls **POL** in our analysis is defined as follows:

$$\mathbf{POL}_{it-1} = [\mathrm{FIT}_{\mathrm{it-1}}; \mathrm{Certificates}_{\mathrm{it-1}};\ \mathrm{PMR}_{\mathrm{it-1}}]$$

To capture the optimal lag between all variables in the **POL** vector and our dependent variable, we use a moving average of the policy variables between $t-1$ and $t-3$. We limit ourselves to this time window, rather than considering all lags of the policy proxies between $t-1$ and $t-k$, to be parsimonious, given that, as we will explain more in detail below, our empirical strategy already takes into account a rich dynamic structure of the dependent variable.

Figure 2 shows the evolution of the policy variables on average in our sample and for selected countries. FITs increased steadily over time, indicating that more and more countries relied on this policy instrument to promote renewable energy capacity and generation. However, countries like Italy or Denmark experience high fluctuations. The use of Certificates started around the year 2000, and increased very fast after 2005, but with some heterogeneity across countries. Japan and the US score rather low on this specific policy instrument. The deregulation of the power sector (PMR) led to a rather sharp increase in entry (i.e. a decrease of entry barriers) in all countries since the mid-1990s. The use of Taxes in the sample has increased, but at a much lower speed than other policy instruments, including Limits to pollutants.

To isolate the true relation between installed capacity in the different power generation technologies, our model controls for additional confounding factors likely to affect RE investments. Details on the data source for each variable are presented in Table 1.

First, GDP per capita and electricity consumption are included to capture overall economic well-being, expectations about future demand and as well as all other demand-side factors not captured by the policy indicators and related to country or economy size. All these forces are expected to increase the need for new generation capacity irrespective of the technology considered.

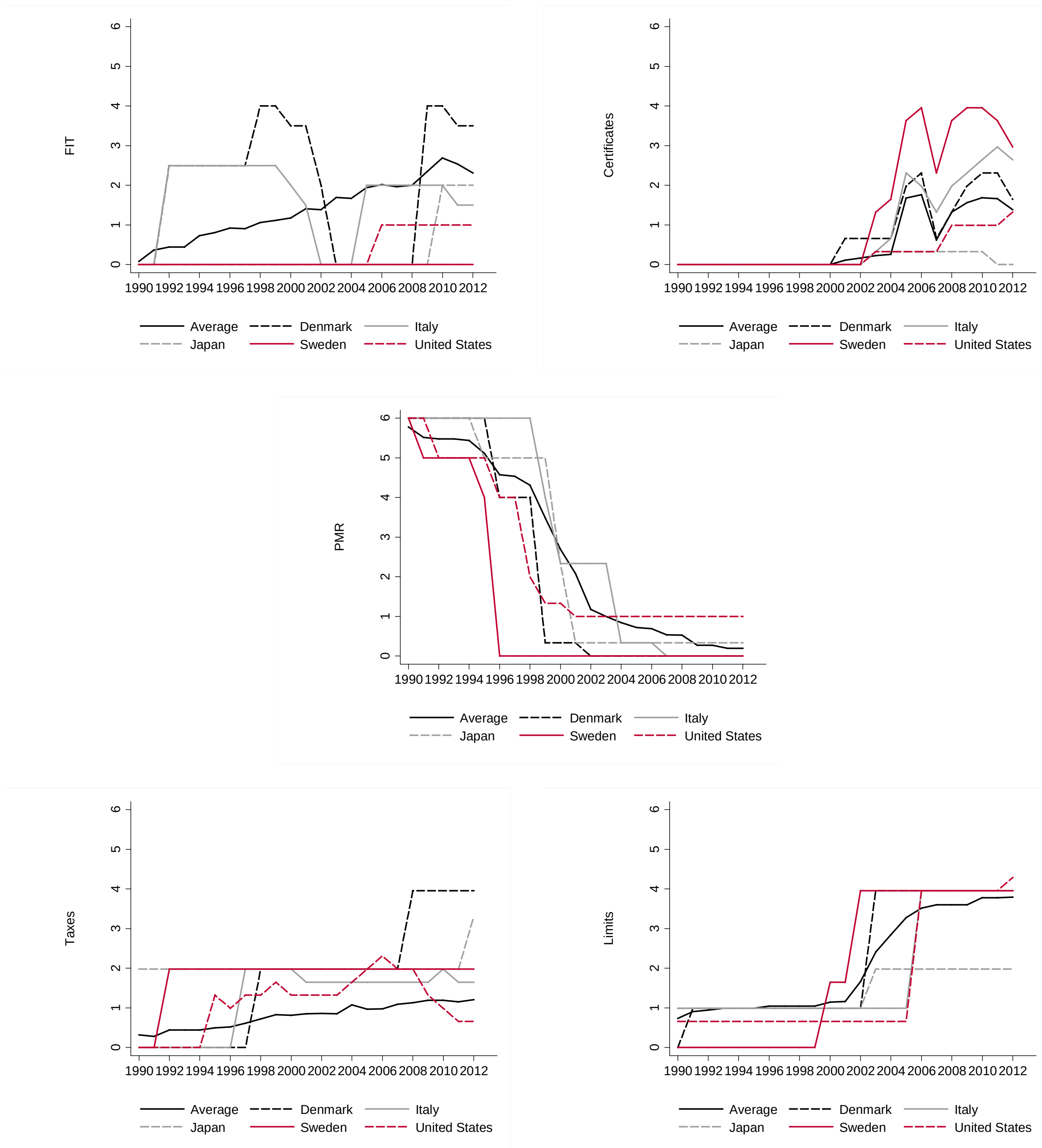

Figure 2: Indexes of policy stringency - FITs, Certificates, PMR, Taxes, Limits -- average and selected countries.

Second, we include a set of controls specific to the country's energy system. For instance, France relies heavily on nuclear power, which is a carbon free source of electricity, and this should decrease its need to invest in either renewable or fossil-based technologies. We hence include the share of capacity in nuclear as a control variable. Conversely, as shown in Narbel (2013), investments in alternative energy sources are lower in countries which are less dependent on energy imports. The same can be argued with respect to investments in higher efficiency fossil-based power production. We control for energy dependence by including a variable defined as net energy imports over total energy use. A variable controlling for rents associated with the extraction of coal, oil and gas is also included as a way to capture in-house resource advantages in fossil fuel endowments and profitability, which likely affect the incentives to invest in any type of additional generation capacity. We also add the average age of each installed megawatt of electricity capacity to proxy for the fact that countries with older capital stock are more likely invest in new capacity.

Third, although large scale storage technologies for power production are not available in the market at cost-competitive prices during our sample period, expectations about the fast deployment of such technologies may influence investment decisions. Therefore, we control for the technological evolution of storage technologies by including in our specification a variable measuring the knowledge stock in storage and smart grids technologies. This is built using the perpetual inventory method, as in Verdolini and Galeotti (2011).

Table 1: Descriptive Statistics

Variable	Mean	Median	Quartile_1	Quartile_3	SD	Minimum	Maximum	Data Source
Share of REN capacity (excl. hydro, waste)	0.05	0.02	0.00	0.07	0.08	0	0.47	*IEA 2016a*
Share of REN capacity *(excl. hydro, waste, biomass)*	0.04	0.01	0.00	0.04	0.07	0	0.40	*IEA 2016a*
Share of FRF capacity	0.13	0.09	0.03	0.21	0.12	0	0.49	*IEA 2016b*
Share of BLF capacity	0.46	0.47	0.28	0.62	0.23	0.005	0.93	*IEA 2016b*
Share of NUKE capacity	0.12	0.11	0.00	0.19	0.14	0	0.55	*IEA 2016b*
Share of HYDRO capacity	0.27	0.19	0.08	0.37	0.25	0.001	1.00	*IEA 2016a*
Limits	2.14	0.99	0.99	3.96	1.64	0	5.94	*Botta and Koźluk 2014*
Taxes	0.80	0.00	0.00	1.65	1.03	0	3.96	*Botta and Koźluk 2014*
PMR	2.65	2.00	0.00	6.00	2.64	0	6.00	*Conway et al. 2005*
FIT	1.39	0.00	0.00	2.50	1.78	0	6.00	*Botta and Koźluk 2014*
Certificates	0.54	0.00	0.00	0.66	0.97	0	5.28	*Botta and Koźluk 2014*
Knowledge stock *(storage/grid)*	83.40	7.96	1.52	35.49	239.10	0	2022.00	*OECD 2015*
Knowledge stock *(storage/grid/FC/H2)*	188.40	17.23	3.52	78.34	516.20	0	3963.00	*OECD 2015*
Fossil Fuel Rents	1.03	0.11	0.01	0.86	2.78	0	21.22	*WDI 2016*
GDP per capita	10.33	10.41	10.15	10.60	0.39	9.15	11.09	*WDI 2016*
Energy Dependence	0.08	0.06	0.02	0.12	0.09	0	0.59	*WDI 2016*
Energy Consumption	1215	472	218	1171	2457	43	14494.00	*WDI 2016*

Table 2: Descriptive Statistics, by country

Country	*Share of REN capacity (excl. hydro, waste)*	*Share of REN capacity (excl. hydro,waste,biomass)*	*Share of FRF capacity*	*Share of BLF capacity*	*Share of NUKE capacity*	*Share of HYDRO capacity*	*Limits*	*Taxes*	*PMR*	*FIT*	*Certificates*	*Stock of knowledge (storage/grid)*	*Stock of knowledge (storage/grid/FC/hydrogen)*	*Fossil Fuel Rents*	*GDP per capita*	*Average age of installed MW*	*Energy Dependence*	*Energy Consumption*
Average	**0.05**	**0.04**	**0.13**	**0.46**	**0.12**	**0.27**	**2.14**	**0.80**	**2.65**	**1.39**	**0.54**	**83.40**	**188.40**	**1.03**	**10.33**	**2.72**	**0.08**	**1215**
Australia	0.03	0.02	0.13	0.67	0.00	0.18	0.32	0.65	1.64	0.46	0.47	7.69	26.79	1.98	10.47	2.60	0.00	654
Austria	0.08	0.03	0.11	0.24	0.00	0.63	3.63	0.00	2.78	2.39	0.53	9.58	21.73	0.14	10.55	2.70	0.19	245
Belgium	0.05	0.03	0.19	0.34	0.36	0.09	2.67	0.00	3.01	0.00	0.90	5.10	12.42	0.00	10.50	2.83	0.13	295
Canada	0.02	0.01	0.05	0.24	0.11	0.58	2.18	1.08	2.96	0.89	0.03	53.69	137.30	3.43	10.51	2.63	0.03	1812
Czech Republic	0.03	0.02	0.02	0.68	0.16	0.12	3.96	1.58	3.01	1.44	0.42	3.30	3.80	0.14	10.03	2.83	0.08	330
Denmark	0.21	0.18	0.10	0.72	0.00	0.00	2.24	1.72	2.13	2.04	0.75	7.34	17.14	1.72	10.60	3.16	0.11	215
Finland	0.10	0.01	0.15	0.49	0.17	0.19	3.17	0.00	1.42	0.17	0.55	7.10	17.68	0.00	10.43	2.80	0.11	409
France	0.02	0.02	0.01	0.21	0.54	0.22	2.15	1.23	2.81	2.65	0.82	127.30	253.50	0.03	10.43	2.96	0.01	1572
Germany	0.13	0.12	0.06	0.64	0.17	0.08	3.42	0.00	2.61	3.57	0.43	197.90	551.40	0.10	10.52	2.71	0.06	2224
Greece	0.05	0.05	0.14	0.56	0.00	0.25	1.65	0.00	3.41	3.52	0.49	0.45	1.88	0.04	10.14	2.44	0.07	164
Hungary	0.03	0.01	0.17	0.59	0.23	0.01	1.85	1.15	3.29	1.54	0.42	3.23	4.29	0.77	9.84	3.04	0.18	177
Ireland	0.07	0.07	0.30	0.53	0.00	0.10	2.02	0.00	3.29	0.30	0.40	0.88	1.80	0.12	10.49	2.81	0.02	73
Italy	0.05	0.04	0.23	0.47	0.00	0.26	1.89	1.22	2.97	1.67	0.83	20.57	68.15	0.17	10.45	2.80	0.15	1075
Japan	0.01	0.01	0.05	0.59	0.17	0.18	1.42	2.04	2.67	0.26	0.12	1019	2005	0.01	10.39	2.46	0.00	3329
Korea, Rep.	0.01	0.00	0.23	0.45	0.20	0.23	2.33	0.98	3.91	2.15	0.01	215.90	387.20	0.01	9.97	2.19	0.00	1112
Netherlands	0.06	0.04	0.33	0.59	0.02	0.00	2.25	0.00	2.41	1.41	0.82	11.50	36.98	1.39	10.61	2.69	0.14	451
Norway	0.01	0.01	0.01	0.01	0.00	0.98	2.32	0.52	0.26	0.00	0.63	5.06	15.79	13.45	10.95	2.55	0.05	399
Poland	0.02	0.01	0.01	0.91	0.00	0.07	1.87	2.93	3.59	0.50	0.92	1.91	2.85	0.48	9.61	2.95	0.02	821
Portugal	0.10	0.08	0.13	0.41	0.00	0.39	2.15	0.00	2.51	2.94	0.45	0.06	1.00	0.00	10.12	2.48	0.12	148
Slovak Republic	0.02	0.01	0.06	0.32	0.28	0.31	0.99	1.56	3.81	0.52	0.39	0.66	0.89	0.08	9.78	2.92	0.18	122
Spain	0.11	0.10	0.05	0.44	0.12	0.28	2.12	0.98	2.12	3.30	0.46	5.31	11.29	0.02	10.30	2.63	0.03	715
Sweden	0.08	0.02	0.05	0.17	0.28	0.48	2.04	1.81	1.30	0.00	1.35	16.01	26.40	0.00	10.51	3.00	0.07	625
Switzerland	0.01	0.00	0.01	0.04	0.17	0.78	2.53	0.34	4.80	2.85	0.00	17.94	39.35	0.00	10.81	2.74	0.38	205
Turkey	0.01	0.01	0.22	0.39	0.00	0.39	0.78	0.00	3.29	0.61	0.00	0.21	1.74	0.21	9.52	2.12	0.01	411
United Kingdom	0.04	0.03	0.27	0.50	0.15	0.05	2.28	0.00	0.38	0.67	1.59	71.78	186.10	1.40	10.39	2.73	0.03	1218
United States	0.03	0.02	0.23	0.53	0.11	0.11	1.68	1.11	2.46	0.30	0.30	359.20	1067.00	0.87	10.71	2.87	0.01	12799

Tables 1 and 2 provide descriptive statistics for our variables of interest on average across the sample and by country. Overall, the share of RE capacity is rather low (5 percent and 3.5 percent when including or excluding biomass from the calculation, respectively). However, this share spans from 0 up to 47 percent. The share of FRF technologies is about two and a half times higher on average, but the maximum penetration rate is very similar to that of renewables (49 percent). Overall, the distribution of RE investments in much more skewed to the left than that of FRF technologies. BLF technologies, on the other hand, provided the bulk of generation capacity over the sample period, while the share of nuclear generation is comparable to that of FRF. Germany, Spain and the Nordic countries (excluding Norway) are leaders in non-hydro RE deployment and generally have high FITs, high Certificates and low entry barriers in the electricity markets. Interesting for the purpose of this paper, eight countries are above the median in both RE and in FRF; in particular, Ireland, Netherland, Italy and Finland are leaders in both.

4. Empirical Strategy

In this Section we illustrate our empirical strategy, which is designed to address, to our best, the econometric issues which characterize the identification of the effect of FRF capacity on RE capacity. As explained above, we assume that the percentage of RE capacity ($Share\ Cap_{it}^{RE}$) is a function of the percentage of FRF capacity ($Share\ Cap_{it}^{FRF}$), of the policy variables and of all other controls. Because capacity is a stock and thus is highly persistent, we consider a dynamic econometric model. Specifically, we estimate variants of the following equation:

$$ShareCap_{\mathrm{i,t}}^{\mathrm{RE}} = \sum_{\mathrm{s}=1}^{\mathrm{k}} \rho_{\mathrm{s}} Share\ Cap_{\mathrm{i,t-s}}^{\mathrm{RE}} + \beta Share\ Cap_{\mathrm{i,t-1}}^{\mathrm{FRF}} + \theta \boldsymbol{POL}_{i,t-1} + \alpha \mathbf{X}_{\mathrm{i,t-1}} + \mu_{\mathrm{i}} + \mu_{\mathrm{t}} + \varepsilon_{\mathrm{i,t}}, \quad (1)$$

where $Share\ Cap_{\mathrm{i,t}}^{\mathrm{RE}}$, $Share\ Cap_{\mathrm{i,t-1}}^{\mathrm{FRF}}$ and $\mathbf{POL}_{\mathrm{i,t-1}}$ are as explained in the previous Section; μ_{i} and μ_{t} are country and time effects, respectively, with the former capturing time-invariant country characteristics and the latter absorbing the influence of global shocks; $\varepsilon_{\mathrm{it}}$ is an error term and $\mathrm{X}_{\mathrm{it-1}}$ is the vector of other controls. This empirical specification improves on that of the closely related paper of Popp et al. (2011), which uses the change in Cap_{it}^{RE} (ΔCap_{it}^{RE}) as dependent variable, because it accounts in a flexible way for the rich dynamics of capacity. Our approach is more general as it nests the one where the dependent variable is in first difference (i.e. $s = 1$ and $\rho_1 = 1$)[12] and provides two advantages. On the one hand, the inclusion of more than one lag portrays rich and technology-specific dynamics, allowing to retrieve both the short- and long-term effects of our variables of interest. Specifically, the latter is equal to the short-term effect multiplied by $1/(1 - \sum_{s=1}^{k} \hat{\rho}_s)$. On the other hand, we can take advantage of GMM estimation methods to lower endogeneity concerns regarding the main explanatory variable of interest ($\mathrm{Cap}_{\mathrm{it-1}}^{\mathrm{FRF}}$). We briefly discuss these two advantages in turn here, and present detailed results in the next Section.

First, investments in RE are likely planned to structurally reduce energy dependence and carbon emissions in the long run, and therefore they are expected to be highly persistent. The potentially rich dynamics of RE capacity requires the *ex-ante* choice of the appropriate lag length for the lagged terms of the dependent variable in equation (1). Following Acemoglu et al. (2014) and Popp (2016), we use a practical approach to determine the optimal number of lags required to correctly specify such dynamics. We estimate a basic model which includes only the lagged dependent variable alongside time and country fixed effects and we add lagged terms up to the point where the additional lag is not statistically significant. These estimates are presented in Table A1 in the Appendix and discussed in next Section. To show the robustness of our results, we also presents estimates for the specification in first difference used in Popp et al. (2011).[13]

Second, and most importantly, we need to choose the appropriate estimator to obtain an unbiased coefficient for our variables of interest. It is well known in the literature that a simple within-transformation fails to provide accurate estimates in dynamic panels (Nickell, 1981). This bias is due to the mechanical correlation between the within-transformed error term and the right-hand side variables, and it decreases with $1/T$, where T is the number of periods considered. In our case $T = 24$, hence the bias should be small and a fixed effect estimator is a good starting point. While the debate regarding the best estimator for dynamic panels is still open, the system-GMM estimator has gained some consensus especially in the case of highly persistent series (Arellano and Bover, 1995; Blundell and Bond, 1998). The basic rationale underpinning this estimator is to instrument the lagged terms of the dependent variable with lags and lagged differences. Compared to the difference-GMM estimator proposed by Arellano and Bond (1991), the system GMM approach mitigates the weak instrument problem using moment conditions both for the equation in levels and in first-differences (Bond, 2002). This problem exists because, by definition, lagged levels are weak instrument of the subsequent first-differences when a variable is highly persistent.

[12] This is evident from the fact that a model as: $\Delta y_{it} = \beta X_{it} + \varepsilon_{it}$ is equivalent to $y_{it} = \rho y_{it-1} + \beta X_{it} + \varepsilon_{it}$ under the constraint that $\hat{\rho} = 1$. If the series y_{it} is highly persistent, Δy_{it} is near a pure random disturbance and the estimates of our effects of interest $\hat{\beta}$ are more likely to be estimated imprecisely.

[13] The specification used by Popp et al. (2011) is: $\Delta Share\ Cap_{\mathrm{it}}^{\mathrm{RE}} = \beta Share\ Cap_{\mathrm{it-1}}^{\mathrm{FRF}} + \theta \mathbf{POL}_{\mathrm{i,t-1}} + \alpha X_{i,t-1} + \mu_{\mathrm{i}} + \mu_{\mathrm{t}} + \varepsilon_{\mathrm{it}}$.

The flexibility of the system-GMM approach is especially useful to mitigate bias in the estimation of the effect of the share of capacity in FRF on RE investments. In our context, the coefficient associated with the variable $Share\ Cap_{\mathrm{it-1}}^{\mathrm{FRF}}$ and estimated using an OLS approach cannot be interpreted as causal because unobservable shocks are likely correlated with investments decisions. Of particular concern is the fact that actual investments in both FRF and RE result from long-term planning of utilities under environmental and "dispatchability" constraints. Instrumenting $Share\ Cap_{\mathrm{it-1}}^{\mathrm{FRF}}$ with the history of both capacities in RE and FRF reduces endogeneity concerns because the predicted $\widehat{Share\ Cap}_{\mathrm{it-1}}^{\mathrm{FRF}}$ reflects a given country's past long-term investment strategies in both RE and FRF investments. This arguably smoothens the influence of time varying shocks, such as unobserved changes in energy policy or the entry of a new large player, affecting both RE and FRF investments. We are aware that our estimation strategy does not fully succeed in dealing with the endogeneity of FRF capacity. Indeed, a full test of the role played by FRF technologies as backup capacity for intermittent RE would require convincing external instruments or an exogenous variation in FRF capacity. Such a thorough test is left for future research, but the robustness of our results to different specifications reassures with respect to the validity of our results, given the data constraints we face.

5. Estimation Results

Table 3 presents the main results of our analysis using variations of Equation (1) presented above. An important initial insights provided by our estimates is that there is a sizeable amount of persistence in the RE dynamics, thus supporting our choice of a rich dynamic model. More specifically, if we consider only one or two lags, RE capacity behaves similarly to a random walk with a drift (see Table A1). Adding the third lag (which is significant in the base specification presented in Table A1), the dynamics of RE capacity becomes less persistent. The cumulative effect of past RE capacity on current RE capacity is estimated at 0.972 in our favorite specification (Model 3 in Table 3). This implies that the short-term effect of FRF capacity on RE capacity is small compared to the long-term effect. For this reason, it is important to distinguish between the two effects using a general dynamic framework, as is the case in this analysis.

Table 3: Empirical results, Share of renewable installed capacity

Dependent variable: **Share of REN capacity**	excl. hydro, waste	excl. hydro, waste	excl. hydro, waste	excl. hydro, waste, biomass	excl. hydro, waste
	Model 1	Model 2	Model 3	Model 4	Model 5
Dependent variable, t-1	1.303***	1.286***	1.293***	1.340***	1.414***
	(0.06)	(0.06)	(0.06)	(0.08)	(0.09)
Dependent variable, t-2	-0.221**	-0.215**	-0.247**	-0.264**	-0.391***
	(0.09)	(0.09)	(0.10)	(0.12)	(0.11)
Dependent variable, t-3	-0.095	-0.090	-0.074	-0.107	-0.069
	(0.07)	(0.07)	(0.08)	(0.09)	(0.08)
Share in FRF capacity, t-1			0.029**	0.027**	
			(0.01)	(0.01)	
Share in FRF capacity, t+1					-0.013
					(0.02)
Share in FRF capacity, t+2					0.016
					(0.02)
Share in FRF capacity, t+3					-0.007
					(0.01)
PMR (moving average)	-0.082***	-0.091**	-0.092**	-0.062*	-0.054*
	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)
FIT (moving average)	0.097	0.118*	0.118*	0.081	0.092*
	(0.06)	(0.07)	(0.06)	(0.06)	(0.05)
Certificates (moving average)	0.305***	0.284***	0.311***	0.238***	0.173**
	(0.07)	(0.07)	(0.07)	(0.06)	(0.07)
Limits (moving average)		0.043			
		(0.07)			
Taxes (moving average)		-0.120			
		(0.10)			
FFS rents, t-1		-0.005	-0.010	-0.008	-0.014
		(0.04)	(0.03)	(0.02)	(0.04)
GDP per capita, t-1		-1.209	-1.175	-1.107	-0.295
		(0.84)	(0.86)	(0.78)	(0.81)
Average age of capital, t-1		-0.478	0.173	0.278	-0.521
		(0.63)	(0.67)	(0.59)	(0.57)
Energy Dependence, t-1		0.114	0.67	0.998	-0.677
		(1.36)	(1.55)	(1.60)	(0.84)
Electricity Consumption, log, t-1		0.043	-0.546	-0.332	-0.166
		(0.37)	(0.38)	(0.36)	(0.52)
Share NUKE capacity, t-1		-0.015	-0.024	-0.021	0.009
		(0.02)	(0.03)	(0.03)	(0.01)
Knowledge stock (grid/storage), t-1			0.248	0.213*	-0.051
			(0.15)	(0.12)	(0.12)
Observations	541	527	498	498	417
R-squared	0.981	0.981	0.976	0.975	0.970

Notes: Standard errors clustered at the level of country in parentheses. *, ** and * indicate p-values of <.1, <.05 and <.01, respectively. All models include year dummies.**

Moving to more detailed comments, Model 1 presents a basic specification where we consider only FITs, Certificates and PMR as determinants of RE deployment. Two main considerations emerge from this model, which shed light on previous results in the literature. First, in line with recent studies on the effect of competition on RE innovation (Nesta et al., 2014; Nicolli and Vona, 2016), lowering entry barriers promotes the deployment of RE. Second, environmental policies have a positive impact on the diffusion of RE capacity. This last result goes in the direction of confirming that environmental policies are indeed key drivers of renewable energy generation. Previous empirical evidence in this respect was rather mixed. For instance, Popp et al (2011) finds only a modest and often statistically insignificant effect, while other contributions point to the effectiveness of FITs but not of other policies (Jenner et al., 2013). The difference between the results put forward in these contributions and our analysis can be ascribed to several factors which we are not in a position to test directly, including the choice of econometric approach, the choice of policy proxies and the time frame and geographical focus of the analysis.

Furthermore, the effects of both environmental policy and market regulation are economically relevant. On the one hand, the short-term effects appear small. An inter-quartile change in the policy variables is associated with an increase in $ShareCap_{\mathrm{i,t}}^{\mathrm{RE}}$ of 0.2% for FITs and Certificates and 0.5% for PMR. On the other hand, the long-term effects are 77 times larger in the base specification (Model 1) and 35 times larger in our favorite specification (Model 3, see discussion below). Notice that for PMR an interquartile change is equivalent to going from "no freedom of access and choice for producers and consumers" to "full opening up of the market", while the interquartile changes in Certificates and FIT entail less extreme variations. The large long-term effect of PMR (i.e. 17.5% in our favorite specification) reflects the key role of independent power producers and decentralized generation in the deployment of key RE technologies, such as Wind and Solar.

Model 2 adds both the vector of relevant controls $X_{i,t-1}$ and the other policy variables (Limits and Taxes). These additional regressors fail to reach acceptable levels of significance and their inclusion does not affect in a major way the coefficients associated with the main policy variables. Given the lack of significance of the coefficients for the Taxes and Limits variables, we exclude them from our specification and focus on the FIT, Certificates and PMR variables.

Model 3 presents our preferred specification, which includes our variable of interest $ShareCap_{\mathrm{i,t-1}}^{\mathrm{FRF}}$ alongside all controls $X_{i,t-1}$ and the proxy indicating the stock of knowledge related to storage technologies. Our results indicate that the presence of FRF technologies favors investment in RE, conditional on all other covariates. Once again, the estimated short-term effects of the policy variables are small, but their high persistence gives rise to significantly larger long-term effects. In the short-term, a one percent increase in FRF capacity brings to a 0.028% increase in the share of RE. In the long term, the effect becomes nearly a one-to-one increase (i.e. 1.02%). Indeed, the large long-run point estimates we present are consistent with the insights from technical assessments made by practitioners and international institutions, as explained in Section 2. For instance, Baker et al. (2013) argue that new solar PV capacity displaces only a small percentage of dispatchable capacity. Our results also confirm the insights from Eon Netz (2004) and REW (2011) indicating that wind and solar are in need of close to a one-to-one back-up capacity. We discuss the implications of these results in the concluding Section.

As mentioned in the previous Section, our econometric model nests the model used in Popp et al. (2011). Table A2 in the Appendix presents the estimation of our favorite specification using the first-difference transformation of the dependent variable as in Popp et al. (2011) to show the robustness of our results.[14] While the short-term effect of FRF on RE capacity is very similar to the one we obtain, our approach has the advantage of allowing the assessment of long-term effects.

A possible concern regarding the estimated effect of FRF capacity on RE diffusion is represented by the fact that RE include biomass, which differs from other renewable energy sources in two respects. First, it is dispatchable, namely it can be stored and burned when needed. Second, biomass can be fed into many burners which also burn fossil fuels, and can be co-fired by mixing it with coal and gas. Therefore, including biomass in the definition of RE could lead to biased estimates. To gauge the strength of our results, we re-estimate our favorite specification subtracting biomass capacity from our definition of dependent variable (Model 4). Our general conclusion is that the enabling role of FRF technologies with respect to RE investment is not driven by any mechanical correlation between FRF investments and biomass. Specifically, we observe a small decline in the effect of FRF on RE, which is however still close to unity in the long-run: a 1% increase in FRF capacity is associated with a 0.88% increase in RE capacity. It is interesting to stress that in the specification without biomass the policy effects become weaker and more similar to that estimated in Popp et al. (2011), while PMR remains the most important policy driver. Finally, the effect of storage technologies becomes statistically significant at conventional level, pointing to the importance of complementary technologies which improve the dispatchability of intermittent RE technologies such as wind and solar. It is indeed well known that the speed of technical change in storage technologies will be as important as the direct speed of technical change in RE technologies to make RE autonomous and thus fully substitutable to fossil fuel technologies.

As an additional step to improve the identification of the effect of FRF capacity, Model 5 replaces $ShareCap_{\mathrm{i,t-1}}^{\mathrm{FRF}}$ with leads of the same variable, from $t+1$ to $t+3$. This allows us to test the robustness of our results to the assumptions regarding the way in which agents form expectations. Indeed, by using lags of the variable of interest, our estimation strategy so far implicitly assumed that agents follow an adaptive rule to form expectations. On the contrary, positive significant coefficients associated with the leads of

[14] That is: $\Delta Share\ Cap_{\mathrm{it}}^{\mathrm{RE}} = \beta Share\ Cap_{\mathrm{it-1}}^{\mathrm{FRF}} + \theta \mathbf{POL}_{\mathrm{i,t-1}} + \alpha X_{i,t-1} + \mu_{\mathrm{i}} + \mu_{\mathrm{t}} + \varepsilon_{\mathrm{it}}$.

FRF capacity would indicate that agents are forward-looking. This would undermine our estimation strategy and point to reverse causality issues which would be difficult to address in an appropriate way with the data at hand. It is thus reassuring to observe that the coefficients associated with the leads of $ShareCap_{\mathrm{i}}^{\mathrm{FRF}}$ are never significant, suggesting that our model is well specified.

Nonetheless, the results presented so far do not fully resolve all the endogeneity concerns regarding the estimated effect of FRF capacity. Because FRF and RE investments are the outcomes of a joint decision of power producers, unobservable time varying shocks can affect both types of investments. As illustrated in the previous Section, system GMM represents the best option to identify the effect at stake, absent a clear exogenous policy change affecting either FRF or RE capacity. Note that system GMM can be criticized because, as Roodman (2009) points out, when N is small the method has ‘too many instruments’ compared with the number of observations. This leads to an overfitting of the endogenous regressions, which in the second stage will give results nearly identical to those obtained without instrumenting. To solve this problem, Roodman (2009) proposes to collapse the instrument matrix to retain only the relevant information and to reduce the number of lags used to build the instruments. This correction should in theory allow to obtain reliable standard specification tests such as the Hansen’s test of overidentifying restrictions. In our case, however, given that N is particularly small (26 countries), the p-value associated with the Hansen’s test is implausibly good. We thus present the Hansen’s test and the estimated coefficients obtained using a simplified equation, where we replace year effects with a linear and a quadratic time trend.

Results of the system-GMM estimates are shown in Table 4, which show the estimates of our preferred specification with and without biomass (Model 1 and Model 3) and the estimates obtained replacing year fixed effects with a time trend to obtain plausible values of the Hansen’s test (Model 2 and Model 4). Three conclusions emerge from this table. First, standard tests validate our specification: the Hansen’s test does not reject the null hypothesis of instruments’ exogeneity, while the Arellano-Bond tests always fails to reject the alternative hypothesis of second-order autocorrelation. This latter test is particularly important for a consistent estimation of the coefficients of interest. Second, the system GMM results indicate that the combined effect of the lagged terms is close to one and thus is larger than that presented in Table 3. The combined effect of the lagged terms remains high, but smaller than one when we add a fourth lag in the dependent variable, as shown in Table A3 of the Appendix. Third, the coefficients associated with our variable of interest $Share\ Cap_{\mathrm{it-1}}^{\mathrm{FRF}}$ are roughly half the size of those presented in Table 3. While this indicates that not addressing the issues of endogeneity leads to an overestimation of the role of FRF in supporting RE generation, the higher persistency in the series of RE makes it difficult to compute a reasonable long-term effect in this case.

Table 4: Empirical results, endogeneity and system-GMM estimation

Dependent variable: **Share of REN capacity**	excl. hydro, waste	excl. hydro, waste, biomass	excl. hydro, waste	excl. hydro, waste, biomass
	Model 1	Model 2	Model 3	Model 4
Dependent variable, t-1	1.374***	1.391***	1.419***	1.430***
	(0.07)	(0.06)	(0.08)	(0.09)
Dependent variable, t-2	-0.286**	-0.307***	-0.308**	-0.311**
	(0.10)	(0.09)	(0.13)	(0.12)
Dependent variable, t-3	-0.072	-0.074	-0.104	-0.113
	(0.08)	(0.07)	(0.09)	(0.08)
Share in FRF capacity, t-1	0.012	0.016**	0.018**	0.014*
	(0.01)	(0.01)	(0.01)	(0.01)
PMR (moving average)	-0.031	-0.021	-0.015	-0.001
	(0.03)	(0.03)	(0.02)	(0.02)
FIT (moving average)	0.107**	0.109**	0.097**	0.091**
	(0.05)	(0.05)	(0.05)	(0.04)
Certificates (moving average)	0.139**	-0.024	0.117**	0.053
	(0.06)	(0.08)	(0.05)	(0.04)
FFS rents, t-1	-0.007	-0.010	0.005	-0.004
	(0.02)	(0.02)	(0.02)	(0.02)
GDP per capita, t-1	-0.013	0.0765	-0.008	0.074
	(0.20)	(0.22)	(0.21)	(0.20)
Average age of capital, t-1	0.348	0.585**	0.339	0.375
	(0.21)	(0.24)	(0.25)	(0.22)
Energy Dependence, t-1	-0.823	-1.518*	-0.486	-0.954
	(0.72)	(0.87)	(0.64)	(0.73)
Electricity Consumption, log, t-1	-0.083	-0.109	-0.064	-0.065
	(0.07)	(0.10)	(0.07)	(0.08)
Share NUKE capacity, t-1	-0.001	-0.001	-0.002	-0.002
	(0.00)	(0.01)	(0.00)	(0.00)
Knowledge stock (grid/storage), t-1	0.015	0.010	0.013	0.002
	(0.06)	(0.06)	(0.06)	(0.05)
Observations	498	498	498	498
Adjusted R2	0.3268	-0.0117	0.8758	0.7322
Adjusted R2 crit. prob.	0.7438	0.9906	0.3811	0.4640
Hansen J	0	11.00	0	8.91
Hansen crit. prob.	1	0.53	1	0.71
Instruments	79	29	79	29

Notes: Standard errors clustered at the level of country in parentheses. *, ** and * indicate p-values of <.1, <.05 and <.01, respectively. Models 1 and 3 include year dummies, Models 2 and 4 include a quadratic time trend.**

To give a clearer interpretation to our results of the feedback of FRF capacity on RE diffusion, we also study the determinants of FRF diffusion (Table 5). This exercise allows showing to what extent the decisions regarding FRF investments are affected by RE capacity as well as by other common drivers. Our main argument is based on the assumption of no effect of RE investments on FRF investments, and on the further assumption that the drivers of FRF investments are different from the ones of RE investments. Indeed, Table 5 shows that RE capacity has no effect on FRF capacity, both when using lags and leads of the dependent variable in our estimation. Similarly, environmental policies have no effect on the change in FRF capacity, except for the negative effect of emission limits. This highlights the fact that to date investors in FRF plants seem to have paid little attention both to the installed capacity in RE and to environmental policies. It also provides some evidence that there is a sort of "asymmetric" complementarity between RE and FRF investment, where the latter are key support technologies for the former, but not *viceversa*.

Results of the drivers of FRF capacity are also interesting *per se*, given the importance of these technologies for decarbonization. Table 5 highlights the fact that the main drivers of FRF are related to the size of the economy (GDP per capita) and to the growth rate of energy consumption as well as to the rents associated with fossil fuels. Notice that in this case, we include only one lag to account for the dynamics of the dependent variable (see Table A1 in the Appendix). Overall, our results indicate that FRF investments are more volatile than RE investments, and that they respond more to demand shocks than to policy shocks.

As a final robustness exercise, we perturb our main specification adding the shares of capacity in technologies other than FRF on the right hand side of equation (1). While ideally we would like to control for all other technologies at the same time, this is impossible due to the high collinearity which characterizes these variables: by definition all shares sum to 1. For this reason, we add the share of another technologies one at a time to our base specification. Results are presented in Table 6. Models 1 and 2 include the share of capacity in Hydro in the estimation of the share of RE with and without biomass, respectively. Along the same lines, Models 3 and 4 the share of capacity in coal-burning technologies and Models 5 and 6 the share of capacity in Base Load Fossil technologies. The perturbations we implement are motivated by the role that these technologies have in the energy system: Hydro is often used to compensate fluctuations in demand and supply, while the inclusion of Coal and BLF capacity is meant to test our assumption that only FRF technologies (which are gas-burning rather than coal-burning) contribute to increasing the share of RE capacity. Overall, this table confirms previous results: the inclusion of additional variables does not change the estimates associated with the FRF capacity and confirms that there is no feed-back effect between variable renewables and capacity in other generation technologies.

Table 5: Empirical results, Share of fast-reacting fossil installed capacity

Dependent variable: **Share of FRF capacity, t**	Model 1	Model 2	Model 3	Model 4
Dependent variable, t-1	0.911***	0.875***	0.855***	0.849***
	(0.02)	(0.04)	(0.04)	(0.06)
Share in REN capacity, t-1			0.0194	
			(0.04)	
Share in REN capacity, t+1				0.019
				(0.13)
Share in REN capacity, t+2				-0.048
				(0.21)
Share in REN capacity, t+3				0.026
				(0.13)
PMR (moving average)	0.013	0.022	0.049	0.021
	(0.08)	(0.10)	(0.11)	(0.13)
FIT (moving average)	-0.026	-0.101		
	(0.08)	(0.11)		
Certificates (moving average)	-0.187	0.119		
	(0.11)	(0.23)		
Limits (moving average)		-0.241*	-0.292**	-0.344***
		(0.13)	(0.11)	(0.12)
Taxes (moving average)		0.0600		
		(0.19)		
FFS rents, t-1		0.137	0.165*	0.218**
		(0.09)	(0.09)	(0.10)
GDP per capita, t-1		2.627*	2.910**	3.600*
		(1.40)	(1.35)	(2.10)
Average age of capital, t-1		-2.246	-2.790	-2.826
		(1.80)	(1.96)	(2.49)
Energy Dependence, t-1		3.348	0.991	1.067
		(3.34)	(2.74)	(3.15)
Electricity Consumption, log, t-1		2.326*	3.007***	3.930***
		(1.19)	(0.80)	(1.25)
Share NUKE capacity		0.001	-0.012	-0.069
		(0.06)	(0.05)	(0.14)
Stock of knowledge			-0.855**	-0.857*
(grid/storage/FC/H2), t-1			(0.35)	(0.42)
Observations	541	525	525	456
R-squared	0.927	0.928	0.930	0.921

Notes: Standard errors clustered at the level of country in parentheses. *, ** and * indicate p-values of <.1, <.05 and <.01, respectively. All models include year dummies.**

Table 6: Empirical results, Additional share variables

Dependent variable: **Share of REN capacity**	excl. hydro, waste	excl. hydro, waste, biomass	excl. hydro, waste	excl. hydro, waste, biomass	excl. hydro, waste	excl. hydro, waste, biomass
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Dependent variable, t-1	1.281***	1.330***	1.291***	1.333***	1.289***	1.360***
	(0.06)	(0.0757)	(0.0663)	(0.0876)	(0.0607)	(0.0761)
Dependent variable, t-2	-0.251**	-0.269**	-0.272***	-0.336***	-0.247**	-0.269**
	(0.10)	(0.12)	(0.10)	(0.10)	(0.10)	(0.12)
Dependent variable, t-3	-0.062	-0.097	-0.057	-0.031	-0.076	-0.096
	(0.08)	(0.09)	(0.06)	(0.06)	(0.07)	(0.09)
Share in FRF capacity, t-1	0.023*	0.023*	0.029**	0.027**	0.023	0.053**
	(0.01)	(0.01)	(0.01)	(0.0113)	(0.03)	(0.02)
Share in HYDRO capacity, t-1	-0.040	-0.028				
	(0.03)	(0.02)				
Share in COAL capacity, t-1			-0.027	-0.029		
			(0.02)	(0.02)		
Share in BLF capacity, t-1					-0.007	0.030
					(0.04)	(0.02)
PMR (moving average)	-0.088**	-0.060*	-0.104***	-0.070*	-0.093**	-0.060*
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)
FIT (moving average)	0.122**	0.083	0.152***	0.119**	0.117*	0.083
	(0.06)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)
Certificates (moving average)	0.319***	0.244***	0.269***	0.193***	0.312***	0.245***
	(0.07)	(0.06)	(0.07)	(0.05)	(0.07)	(0.05)
FFS rents, t-1	-0.011	-0.007	0.004	-0.004	-0.009	-0.007
	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
GDP per capita, t-1	-0.938	-0.953	-1.638**	-1.559**	-1.208	-0.946
	(0.88)	(0.81)	(0.77)	(0.68)	(0.88)	(0.80)
Average age of capital, t-1	0.056	0.204	0.690	0.868	0.182	0.199
	(0.73)	(0.63)	(0.67)	(0.59)	(0.67)	(0.63)
Energy Dependence, t-1	0.887	1.142	0.737	0.887	0.661	1.149
	(1.56)	(1.60)	(1.37)	(1.44)	(1.56)	(1.60)
Electricity Consumption, log, t-1	-0.845***	-0.537*	-0.464	-0.228	-0.498	-0.550*
	(0.29)	(0.31)	(0.43)	(0.39)	(0.37)	(0.31)
Share NUKE capacity	-0.034	-0.027	0.012	0.014	-0.029	0.0024
	(0.032)	(0.031)	(0.02)	(0.02)	(0.04)	(0.03)
Knowledge stock (grid/storage), t-1	0.264*	0.226*	0.262	0.250*	0.241	0.227*
	(0.14)	(0.12)	(0.16)	(0.13)	(0.15)	(0.12)
Observations	498	498	466	466	498	498
R-squared	0.976	0.975	0.977	0.976	0.976	0.975

Notes: Standard errors clustered at the level of country in parentheses. *, ** and * indicate p-values of <.1, <.05 and <.01, respectively. All models include year dummies.**

6. Conclusions

This paper presents an econometric analysis of the determinants of the diffusion of renewables in a sample of 26 OECD countries over the years 1990-2013, with a specific focus on the role of fast-reacting fossil technologies. We contribute to the literature with one key result. We show that absent economically viable storage options, countries where FRF capacity was available were more likely, *ceteris paribus*, to invest in renewable energy generation. While short-run effects are low, in the long run the relation between FRF and RE capacity has been almost a one-to-one increase (i.e. 0.88%). This result holds in a series of demanding robustness checks, including system-GMM estimators, different definitions of RE capacity and the inclusion of other technologies besides FRF technology.

The evidence presented here supports the conclusion that to date FRF technologies have enabled RE diffusion by providing reliable and dispatchable back-up capacity to hedge against variability of supply. Our paper calls attention to the fact that renewables and fast-reacting fossil technologies appear as highly complementary and that they should be jointly installed to meet the goals of cutting emissions and ensuring a stable supply. In this respect, our analysis complements recent attempts to systematically assess the grid-level system costs for different technologies. Our long-run estimations of the relation between FRF and RE point indeed to the high indirect costs of the latter.

These considerations must be appropriately recognized and internalized in the policy debate to avoid serious challenges to the security of electricity supply in the coming years. As the share of RE increases, so will the requirements for increased back-up capacity and serious stresses will be put on the energy system unless the relationship and the complementarity between FRF and RE technologies are appropriately acknowledged. Our analysis thus draws attention to the fact that the technical and pecuniary system costs are of such magnitude that they will have to be acknowledged, and can't be borne in a diffuse manner. A particularly thorny issue is linked with the need to take a long-term perspective and to consider the future need of replacing existing mid-merit/load following capacity as they reach the end of their lifetime. Indeed, while not paying the external cost of pollution, FRF technologies provide the unremunerated positive externality of long-term flexible capacity for back-up (OECD 2012). Pricing both back-up services and greenhouse gas emissions appears as a key priority of a sound energy policy.

We thus argue that a policy and academic debate centered on the juxtaposition of renewable (clean) and fossil (dirty) technologies misses this important point, leads to an underestimation of the costs of renewable energy integration, and does not contribute to stressing the importance of funding and developing solid alternative options such as cheap storage technologies. Overstating the ability to substitute fossil generation with renewable energy generation may lead to a poor support of alternative enabling technologies. Conversely, our analysis suggests the need for a systemic perspective and the coordination of different types of investments (in storage technologies, RE and FRF) to successfully pursue sustainable development through the integration of large shares of RE energy in the power system.

While our results are robust to a series of modifications in the empirical strategy, a fruitful avenue for future research will be a thorough test of our conclusions based on a convincing external instruments or exogenous variation in FRF capacity. This will further lower any concerns linked with the possible endogeneity of the share of FRF capacity.

References

Acemoglu, D., S Naidu, P. Restrepo, and J. A. Robinson (2014). "*Democracy does cause growth*", NBER Working Paper No. 20004

Acemoglu, D., P. Aghion, L. Bursztyn, and D. Hemous (2012). "The Environment and Directed Technical Change". American Economic Review 102 (1), pp. 131-166.

Aguirre, M and G. Ibikunle (2014). "Determinants of renewable energy growth: A global sample analysis", Energy Policy 69, pp. 374–384

Arellano, M. and S. Bond (1991) "Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations". Review of Economic Studies 58(2), pp. 277-97.

Arellano, M. and O. Bover (1995). "Another look at the instrumental variable estimation of error-components models", Journal of econometrics 68(1), pp. 29-51.

Baker, E., M. Fowlie, D. Lemoine, and S. Reynolds (2013). "The Economics of Solar Electricity", Annual Review of Resource Economics 5, pp.387- 426

Bhattacharyya, S. (2011), *Energy Economics. Concepts, Issues, Markets and Governance*, Springer, London

Blundell, R. and S. Bond (1998). "Initial conditions and moment restrictions in dynamic panel data models". Journal of Econometrics, 87(1), pp. 115-143.

Bond, S. (2002). "Dynamic panel data models: a guide to micro data methods and practice" Portuguese Economic Journal 1, pp. 141-162.

Botta, E. and T. Koźluk (2014). "Measuring environmental policy stringency in OECD countries: a composite index approach", OECD Economics Department Working Papers No. 1177, OECD Publishing, http://dx.doi.org/10.1787/5jxrjnc45gvg-en.

Carrara, S. and G. Marangoni, (2015), 'Including System Integration of Variable Renewable Energies in a Constant Elasticity of Substitution Framework: the Case of the WITCH Model', Nota di Lavoro 109.2015, Milan, Italy: Fondazione Eni Enrico Mattei

Conway, P., V. Janod and G. Nicoletti (2005). "Product Market Regulation in OECD Countries: 1998 to 2003", OECD Economics Department Working Papers 419, OECD Publishing.

EON NETZ, (2004) Wind Report 2004. http://www.aweo.org/windEon2004.html

GE Energy (2008) "Analysis of Wind Generation Impact on ERCOT Ancillary Services Requirements" http://www.uwig.org/attcha-ercot_a-s_study_exec_sum.pdf

Gowrisankaran, G., S. Reynolds, M. Samano (2016) "Intermittency and the Value of Renewable Energy", Journal of Political Economy. DOI 10.1086/686733

IEA (2013) Electricity Information, available at
http://www.iea.org/media/training/presentations/statisticsmarch/electricityinformation.pdf

IEA (2015). Energy Technology Perspectives, Paris

IEA (2016a). "OECD - Net capacity of renewables", IEA Renewables Information Statistics (database). DOI: http://dx.doi.org/10.1787/data-00467-en (Accessed on 29 February 2016)

IEA (2016b). "OECD - Net electrical capacity", IEA Electricity Information Statistics (database). DOI: http://dx.doi.org/10.1787/data-00460-en (Accessed on 02 March 2016)

IPCC (2014). Climate Change 2014: Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland, 151 pp.

Jenner, F., G. Chan, R. Frankenberger, and M. Gabel (2013). "What Drives States to Support Renewable Energy?" The Energy Journal 33 (2), pp. 1-12

Johnstone, N., I. Haščič, and D. Popp (2010). "Renewable Energy Policies and Technological Innovation: Evidence Based on Patent Counts", Environmental & Resource Economics 45 (1), pp. 133-155.

Lanzi E., E. Verdolini and I. Haščič (2011). "Efficiency Improving Fossil Fuel Technologies for Electricity Generation: Data Selection and Trends", Energy Policy 39(11), pp. 7000-7014

Lorenz, E., T. Scheidsteger, J. Hurka, D. Heinemann and C. Kurz (2011). "Regional PV power prediction for improved grid integration", Prog. Photovolt. Res. Appl. 19, pp. 757–71

Marquez. R. And C.F. Coimbra (2011). "Forecasting of global and direct solar irradiance using stochastic learning methods, ground experiments and the NWS database", Sol. Energy 85, pp. 746–56

Mathiesen. P. And J. Kleissl (2011). "Evaluation of numerical weather prediction for intra-day solar forecasting in the continental United States", ol. Energy 85, pp. 967–77

Narbel. P. (2013). "What is really behind the adoption of new renewable electricity generating technologies?", Energy for Sustainable Development 17, pp.386-390

Nesta, L., F. Vona and F. Nicolli (2014). "Environmental policies, competition and innovation in renewable energy", Journal of Environmental Economics and Management 67, pp. 396–411

Nickell, S. (1981). "Biases in dynamic models with fixed effects". Econometrica 49(6), pp. 1417-1426.

Nicolli, F. and F. Vona (2016). "Heterogeneous policies, heterogenous technologies: the case of renewable energy". Energy Econmics forthcoming.

NYISO, New York Independent System Operator (2010). "Growing Wind Final Report of the NYISO 2010 Wind Generation Study", http://www.uwig.org/growing_wind_-_final_report_of_the_nyiso_2010_wind_generation_study.pdf

OECD (2012). Nuclear Energy and Renewables: System Effects in Low-carbon Electricity Systems, https://www.oecd-nea.org/ndd/reports/2012/system-effects-exec-sum.pdf

Platts (2013), Platts Power Plant Database.

Pfeiffera B. and P. Mulder, (2013). "Explaining the diffusion of renewable energy technology in developing countries," Energy Economics, Elsevier, vol. 40(C), pages 285-296.

Popp D. (2016). "Economic analysis of scientific publications and implications for energy research and development", Nature Energy forthcoming.

Popp, D., I. Haščič, and N. Medhi (2011). "Technology and the diffusion of renewable energy", Energy Economics 33 (4), pp. 648–662

Popp, D., R. G. Newell, and A. B. Jaffe, (2010). 'Energy, the Environment, and Technological Change', In Bronwyn H. Hall and and Nathan Rosenberg: Handbook of the Economics of Innovation- Volume-II, Burlington: Academic Press, 2010, pp.873-938.

REW Renewable Energy World (2011). "Solar Intermittency: How Big is the Problem?", available at http://www.renewableenergyworld.com/articles/2011/11/solar-intermittency-how-big-is-the-problem.html

Roodman, D. (2009). "A Note on the Theme of Too Many Instruments". Oxford Bulletin of Economics and Statistics, 71(1), pp. 135-158

Shrimali, G. and S. Jenner (2013). "The impact of state policy on deployment and cost of solar photovoltaic technology in the U.S.: A sector-specific empirical analysis", Renewable Energy 60, pp. 679-690

Sensfuss, F. and M. Ragwitz (2008). "The merit-order effect: A detailed analysis of the price effect of renewable electricity generation on spot market prices in Germany". Energy Policy 36, pp. 3076–3084.

Sinn, H. (2016) "Buffering Volatility: A Study on the Limits of Germany's Energy Revolution", CESIFO Working Paper No.5950

Verdolini E. and M. Galeotti (2011). “At home and abroad: An empirical analysis of innovation and diffusion in energy technologies”, Journal of Environmental Economics and Management 61(2), pp.119-134

WDI (2013). World Development Indicators Database

Appendix

Table A1. Appropriate lag structure, RE and FRF technologies

Dependent variable	excl. hydro, waste	excl. hydro, waste, biomass	excl. hydro, waste	excl. hydro, waste, biomass		
	Share of REN capacity				Share of FRF capacity	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Dependent variable, t-1	1.041***	1.400***	1.351***	1.340***	0.911***	0.889***
	(0.015)	(0.06)	(0.06)	(0.06)	(0.01)	(0.05)
Dependent variable, t-2		-0.400***	-0.223**	-0.226**		0.008
		(0.07)	(0.10)	(0.09)		(0.05)
Dependent variable, t-3			-0.143**	-0.098		
			(0.07)	(0.10)		
Dependent variable, t-4				-0.039		
				(0.07)		
Observations	593	567	541	515	541	513
R-squared	0.979	0.981	0.980	0.979	0.927	0.920

Notes: Standard errors clustered at the level of country in parentheses. *, ** and * indicate p-values of <.1, <.05 and <.01, respectively. All models include year dummies.**

Table A2. Additional Results, Popp et al. (2011) specification

Dependent variable: Δ Share of REN capacity	excl. hydro, waste	excl. hydro, waste, biomass
	Model 1	Model 2
Share in FRF capacity, t-1	0.0272*	0.0270*
	(0.02)	(0.0150)
PMR (moving average)	-0.115***	-0.0927**
	(0.04)	(0.0382)
FIT (moving average)	0.171**	0.130*
	(0.08)	(0.0754)
Certificates (moving average)	0.429***	0.348***
	(0.08)	(0.0798)
FFS rents, t-1	-0.0127	-0.00983
	(0.04)	(0.0301)
GDP per capita, t-1	-1.148	-1.101
	(1.09)	(1.052)
Average age of capital, t-1	-0.137	0.0460
	(0.70)	(0.618)
Energy Dependence, t-1	0.403	0.681
	(1.60)	(1.651)
Electricity Consumption, log, t-1	-0.406	-0.217
	(0.49)	(0.493)
Share NUKE capacity, t-1	-0.0342	-0.0404
	(0.04)	(0.0443)
Knowledge stock (grid/storage), t-1	0.296	0.269*
	(0.18)	(0.155)
Observations	545	545
R-squared	0.403	0.424

Notes: Standard errors clustered at the level of country in parentheses. *, ** and * indicate p-values of <.1, <.05 and <.01, respectively. All models include year dummies.**

Table A3. Additional GMM models

Dependent variable: **Share of REN capacity**	excl. hydro, waste	excl. hydro, waste, biomass	excl. hydro, waste	excl. hydro, waste, biomass
	Model 1	Model 2	Model 3	Model 4
Dependent variable, t-1	1.374***	1.388***	1.419***	1.428***
	(0.069)	(0.067)	(0.092)	(0.092)
Dependent variable, t-2	-0.284***	-0.312***	-0.306**	-0.306**
	(0.100)	(0.093)	(0.123)	(0.118)
Dependent variable, t-3	-0.062	-0.018	-0.097	-0.098
	(0.107)	(0.119)	(0.099)	(0.083)
Dependent variable, t-4	-0.036	-0.081	-0.021	-0.036
	(0.099)	(0.109)	(0.094)	(0.094)
Share in FRF capacity, t-1	0.011	0.014*	0.016*	0.012
	(0.007)	(0.008)	(0.009)	(0.010)
PMR (moving average)	-0.045*	-0.039	-0.016	-0.008
	(0.023)	(0.025)	(0.019)	(0.017)
FIT (moving average)	0.103*	0.101**	0.095*	0.089*
	(0.050)	(0.049)	(0.048)	(0.045)
Certificates (moving average)	0.151***	-0.017	0.118**	0.055
	(0.054)	(0.072)	(0.049)	(0.034)
FFS rents, t-1	-0.018	-0.022	0.002	-0.012
	(0.018)	(0.017)	(0.020)	(0.018)
GDP per capita, t-1	0.042	0.140	0.005	0.112
	(0.216)	(0.232)	(0.229)	(0.208)
Average age of capital, t-1	0.460**	0.743***	0.390	0.435*
	(0.212)	(0.261)	(0.273)	(0.223)
Energy Dependence, t-1	-0.948	-1.667*	-0.583	-1.103
	(0.774)	(0.955)	(0.655)	(0.735)
Electricity Consumption, log, t-1	-0.132	-0.167	-0.091	-0.096
	(0.080)	(0.114)	(0.077)	(0.074)
Share NUKE capacity, t-1	-0.004	-0.004	-0.004	-0.005
	(0.004)	(0.005)	(0.004)	(0.004)
Knowledge stock (grid/storage), t-1	0.032	0.032	0.026	0.014
	(0.062)	(0.068)	(0.062)	(0.054)
Observations	474	474	474	474
Adjusted R2	0.585	0.561	0.875	0.841
Adjusted R2 crit. prob.	0.559	0.575	0.382	0.401
Hansen J	0.000	9.067	0.000	9.964
Hansen crit. prob.	1.000	0.768	1.000	0.697
Instruments	79	31	79	31

Notes: Standard errors clustered at the level of country in parentheses. *, ** and * indicate p-values of <.1, <.05 and <.01, respectively. Models 1 and 3 include year dummies, Models 2 and 4 include a quadratic time trend.**