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Bridging the gap: Do fast-reacting fossil technologies facilitate renewable energy diffusion?☆

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ABSTRACT

The diffusion of renewable energy in the power system implies high supply variability. Lacking economically viable storage options, renewable energy integration is possible thanks to the presence of modern mid-merit fossil-based technologies, which act as back-up capacity. This paper discusses the role of modern 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 moving from the first to the third quartile of the distribution of modern fossil technologies is associated with an increase in yearly renewable energy investment of between 6 and 14 kW per thousand people, on average and ceteris paribus. This is a sizeable effect, considering that average yearly renewable capacity addition in our sample are around 12 kW per thousand people. These findings are robust to different econometric specifications, various definitions of modern fossil technologies and are stronger for wind, which is more intermittent and for which the mismatch between supply and demand is more marked. 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.

1. Introduction

Electricity generation is one of the key sectors for decarbonization. In 2014, electricity production satisfied 18% of final energy demand, but contributed to more than 40% of energy-related CO_2 emissions. Indeed, the IEA estimates that this sector alone could contribute to more than two thirds the energy-related emission reductions in a "Two Degree Scenario", mostly through the deployment of renewable technologies (IEA, 2017).[1] One of the major barriers to the large scale deployment of the most renewables is that they are variable and non dispatchable, with peaks in generation not fully coinciding with peaks in demand.[2]

Historically, the variability of renewable generation has been accommodated within the energy system by relying on fossil-based technologies as back-up capacity, since cheap, large-scale storage options do not currently exist (see discussion in Section 3). Importantly, there are different categories of fossil-based technologies. Traditional fossil generation, which comprises coal-based and low efficiency generation technologies, cannot easily compensate for renewable variability due to slow reacting times, high capital costs and little modularity (meaning that the efficiency of smaller units is significantly lower than that of larger units). Modern fossil technologies, which include most gas generation technologies, Combined Heat and Power and Integrated Gasification Combined Cycle to name a few, are characterized by mid-

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[1] Generally speaking, renewable energy technologies include hydro, wind, solar, geothermal, ocean and wave technologies and biomass. See Section 4.1 for the specific definition of renewable energy technologies in the context of our analysis.

[2] Additional important barriers to the large scale deployment of renewable energy sources are that (1) renewables are not yet fully cost-competitive with fossil-based power generation, even though they recently witnessed significant decreases in costs and that (2) the energy sector is sticky and modifying the paradigm of electricity production implies multiple challenges: the need to upgrade infrastructure (i.e. the electricity grid) and the considerable sunk costs in existing, less efficient and more polluting power plants.

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merit order,[3] quick(er) ramp-up times, lower capital costs and modularity. These latter technologies are particularly suitable to meet peak demand and mitigate the variability of renewables.

We contribute to the debate on the determinants of renewable generation capacity by extending the analysis of Popp et al. (2011) and discussing the role of traditional and modern fossil-based technologies as back-up capacity to compensate renewable energy variability. We focus on a sample of 26 OECD countries, which account for the majority of renewable capacity additions between 1990 and 2013.

Controlling for country-level fixed effects and a host of factors affecting renewable energy investments, we show that the deployment of renewable energy sources did not decouple from that of fossil-based technologies in our sample, and specifically from a modern sub-set of these technologies using gas as primary input. Moving from the first to the third quartile of the distribution of modern fossil technologies capacity is associated with an increase in yearly renewable energy investments of roughly 6–14 kW per thousand people, on average and ceteris paribus. This is a sizeable effect, given that the average yearly renewable capacity addition in our sample is just below 12 kW per thousand people. These findings are robust to different econometric specifications, and two definitions of modern fossil technologies. Moreover, they are stronger for wind, which is more intermittent and for which the mismatch between supply and demand is more marked.

Our contribution suggests that overlooking the complementarity between renewable and modern fossil technologies leads to an underestimation of the costs of the energy transition. Given the large uncertainty regarding the availability of cost-competitive storage options in the immediate future, increasing the penetration of renewable energy as implied by global targets will most likely result in significantly higher system costs because it will require a parallel expansion of back-up resources, which are capital-intensive and will be largely underutilized. This gives rise to important policy implications related to (1) the need to account for such complementarity when making investment decisions; (2) the fact that system costs of renewables may be underestimated, especially as renewable penetration increase and (3) that investment in other non-fossil back-up technologies (i.e. storage) is a crucial component of the effort to decarbonize the energy system.

The rest of the paper is organized as follows. Section 2 discusses the related literature and highlights our contribution to the debate, while Section 3 details some of the challenges of the integration of renewable energy generation in the power system. Section 4 presents our data sources, the definition of our variables and provides descriptive statistics. Section 5 details the empirical strategy. Section 6 presents our results and quantifies them. Section 7 concludes with a discussion of the policy implications of our analysis.

2. Related literature

This paper focuses on the relationship between renewable energy generation and the presence of fossil-based back-up capacity. The core of the paper is devoted to the empirical investigation of whether the successful integration of renewable was possible partly due to the availability of modern, fast reacting fossil-based units. This topic has received little attention in the literature on the development and diffusion of renewable energy technologies.

A first set of contributions focuses on the role of energy and environmental policies in promoting renewable investment and deployment, which is proxied using information on installed capacity. Shrimali and Jenner (2013) explore the impact of different policy instruments on solar photovoltaics (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 renewable 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 (modern vs. traditional) nor do they 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 renewable generation in OECD countries, but find that the effect of renewable energy policies is often not significant. Also in this case, the empirical analysis does not account for the possible complementarity between investments in renewable energy and (modern) 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 technologies (Acemoglu et al., 2012). We contribute to this strand of literature by providing the first macro-level empirical analysis of the diffusion of renewable generation while accounting for the interaction with investments in other generation capacity, and specifically modern and traditional fossil.

A second set of analyses uses data on power production (rather than capacity) as a proxy for renewable energy deployment. Aguirre and Ibikunle (2014) investigate the drivers of country-level renewable growth in a broad sample 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) finds that fossil-fuel reserves (proxied by the quantity of electricity generated per capita from domestic fossil fuel reserves) are a barrier to the diffusion of renewable technologies in a sample of 107 countries over the years 2007–2009. Overall, these contributions seem to suggest that renewable and fossil electricity generation technologies are substitutes. However, this conclusion is reached by focusing on electricity generation rather than on the amount of installed capacity. This is a relevant distinction, because, as argued in Jenner et al. (2013) "generation determines the actual return on investment while capacity reflects the expected return on investment." Moreover, for a given unobservable distribution of capacities in different technologies, it is purely mechanical to observe a negative correlation between the share of renewable and fossil electricity generation, as demand is met with either one or the other input. However, it may be indeed the case that to support a given level of renewable energy generation, a country needs to install back-up capacity in other (fossil) technologies on top of the capacity installed in renewable generation. This is due to the high variability of the most promising renewable energy sources (see discussion in the next Section). By choosing to focus on the amount of electricity produced one cannot provide any insights on the sunk costs associated with back-up capacity.[4] Our analysis contributes to this strand of literature by exploring the relationship between renewable and fossil generation technologies using capacity rather than production data. In this way, we are able to capture the investment decision as

[3] 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 and the speed at which each system can be brought online). Implementing the merit order ensures that electricity dispatch is done minimizing the cost of production. Generally speaking and focusing on fossil-fuel generation, coal power plants are characterized by high-merit order, as they have low marginal costs of production (in addition to slow reacting times). Gas-fired power plants, on the other hand, are characterized by mid-merit order as they have higher marginal costs than coal power plants (in addition to faster reacting times). Note that renewable energy sources are generally characterized by high merit order since their marginal cost of production is (close to) zero (Sensfuss and Ragwitz, 2008).

[4] Note also that the contributions just discussed pay no specific attention to the role of energy and environmental policies.

purely as possible, since capacity informs on the full (direct and indirect) cost paid to produce a given amount of electricity.

A third strand of literature uses integrated assessment models (IAMs) to provide insights on the evolution of the electricity 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 (2017) 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 upper bounds (i.e., an exogenous ceiling) on variable renewable sources penetration, while others rely on implicit or explicit cost mark-up for renewables (i.e. they assume higher-than-observed costs of renewable generation to account for variability), or impose constraints on the flexibility or installed capacity of the power generation fleet. Our country-level analysis provides insights on the historical interaction between renewable and fossil generation technologies, and can inform the IAMs community regarding the calibration of such constraints.

We argue that recognizing the complementarity between renewable and fossil-based generation both in terms of system costs and of decarbonization process is crucially important to assess if and at what cost economic activities can be decoupled from fossil-fuel use (and hence, from anthropogenic carbon emissions) to avoid severe and pervasive impacts from climate change while sustaining economic growth (IPCC et al., 2014). In the next section, we briefly discuss the challenges of managing a large share of renewable energy generation in terms of planning, operation, and reliability practices (NYISO, 2010; Baker et al., 2013). This discussion provides insights on the importance of our research question, as well as on how the management of variable sources of electricity impacts the social and private costs of an energy transition.

3. Managing renewable variability in the energy system

The issue of how to match demand and supply instantaneously, and in particular how 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 back-up capacity, namely reserve generation capacity always on hold to offset variations in demand and supply. Generally speaking, peak demand has been met mostly 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 (Bhattacharyya, 2011).

The problem of matching demand and supply is exacerbated in the case of renewables because the power system needs to adapt not only to decentralized generation but also to variable supply. Variability characterizes the most promising and most used of these technologies (i.e. wind and solar), which often reach peak supply in times not coinciding with peak demand (Carrara and Marangoni, 2017).[6] This consequently increases the risk of shortage, and lowers reliability and security of supply. The problem is further compiled by the lack of cheap, large-scale storage options. Indeed, while the costs of storage for transport applications and of small-scale storage for electricity generation have witnessed significant decreases over the last decade,[7] large-scale storage for stationary applications remains significantly costlier due to the more challenging charge/discharge cycles, which require more expensive battery management systems and hardware (IRENA 2017). Potentially large cost reductions could emerge as a result of improvements in transport and small-scale storage, but significant uncertainty remains around the size and speed of future costs decreases for large-scale, stationary options (Nykvist and Nilsson, 2015).

Hence, the only currently viable and certain option available for the integration of renewable energy sources in the energy systems is to have a significant amount of fossil-based back-up generation capacity, which is unused for the large majority of time, but which can be brought online at times of need and of peak demand. For instance, E.ON Netz (2004), one of the four grid managers in Germany as of 2004, indicated that 8 MW of back-up capacity were required for any 10 MW of wind capacity added to the system. Similar concerns are voiced in recently commissioned studies on the feasibility of the British renewable energy targets (e.g. Aurora Research, 2016; Strbac and Aunedi, 2016). Indeed, it has been noted that some traditional load-following “mid-merit” generation technologies (i.e. combined cycle, and specifically combined cycle gas turbines) have been increasingly used to compensate for renewable variability in the last decade, alongside the traditional, peak-load generation technologies, such as gas turbines.[8] This problem has also been discussed in several academic contributions, which, however, do not empirically examine how the availability of modern fossil back-up capacity affects the diffusion of renewable energy technologies. We discuss here few representative papers to which the reader can refer for a comprehensive review of this active literature. Anderson and Leach (2004) discuss the several technological options to deal with intermittency focusing on a comparison between gas and hydrogen. Their main conclusion is that increasing the penetration of zero-emission hydrogen-based storage requires complementary innovations in the domains of decentralized generation and combined heat and power production. Steinke et al. (2013) notice that dealing with intermittency can be done with either storage technologies or grid extensions, which reduce the risk of energy shortages. The authors develop a simple physical model to gauge the additional requirement of back-up capacity in a hypothetical 100% renewable scenario for Europe and the key role played by grid extensions in reducing this requirement. Similar conclusions regarding the importance of grid extensions and demand-side management are reached in another model developed by Brouwer et al.

[5] Unlike steam turbines, which require a period of 1–1.5 hours for heating after start up, cold gas turbines heat within 6–15 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] 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, solar can cover daytime peak load, but not the residential sector nighttime peak load demand. Both these renewable energy options require a significant amount of back-up capacity.

[7] Nykvist and Nilsson (2015) argue that industry-wide cost estimates declined by approximately 14% annually between 2007 and 2014, from above US$1000 per kWh to around US$410 per kWh, and that the cost of battery packs used by market-leading BEV manufacturers are even lower, at US$300 per kWh, and has declined by 8% annually. More recently, IRENA (2017) reports that Li-on batteries for transport applications saw a 73% cost reduction between 2010 and 2016. Small-scale Li-ion storage options for electricity generation (i.e. options for households and small distributed generation) have seen a 60% decrease in total installed costs in Germany between 2014 and 2017. Other battery storage technologies (e.g. flow batteries) also offer large cost reduction potential. Please see IRENA (2017) for a thorough discussion.

[8] 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).

(2014). Finally, the ambitious paper of Gowrisankaran et al. (2016) quantifies the social costs and benefits in terms of CO2 emissions from a scenario of large-scale renewable generation, accounting for the costs of intermittency in terms of back-up capacity, forecastable output and correlation between demand and supply variability. In a scenario of 10% penetration of solar energy, on which they calibrate the model, the increased social cost of higher renewable energy penetration is justified by an environmental cost of a ton of CO_2 as high as $275, which is much higher than the figure provided by the US government, i.e. $39.

These findings resonate the concern that larger back-up capacity translates into higher renewable "whole-system costs".[9] In OECD countries, estimates of such costs for dispatchable fossil-fuel technologies are relatively modest and estimated below USD 3 per MWh. Conversely, the whole-system costs of renewables are significantly higher, ranging from USD 40 per MWh for onshore wind, USD 45 per MWh for offshore wind and USD 80 per MWh for solar (NEA, 2012).

The above discussion points to how handling variable generation is a significant barrier to the decarbonization of the power sector (e.g. Carrara and Marangoni, 2017; Lorenz et al., 2011; Marquez and Coimbra, 2011; Mathiesen and Kleissl, 2011; GE Energy, 2008,). For this reason, it is of paramount importance to analyze the interplay between renewable energy generation and fossil-based generation.

In the remaining of the paper, we tackle to this issue studying the determinants of investments in renewable energy capacity in cross-country regressions.

4. Data and descriptive statistics

Our analysis is based on a sample of 26 OECD countries between 1990 and 2013.[10] Our dependent variable is (1) a measure of investments in renewable energy generation capacity. Our main explanatory variables of interest are (2) proxies for the availability of modern fossil and traditional back-up capacity, and (3) a vector of policy indexes, which capture the stringency of environmental policy and the level of market regulation. We also condition our estimates on (4) a set of control variables which likely affect the decision to invest in renewable technologies above and beyond our explanatory variables of interest. We now describe each of these variables in turn. Tables 1 and 2 provide descriptive statistics for all variables on average across the sample and by country, respectively.

4.1. Dependent variable: investment in renewables

We extract data on renewable installed capacity from the IEA Renewable Energy Information Database (IEA, 2016a), which provides country-level information for OECD countries on solar, wind, hydro, geothermal, biomass and ocean/tide from the 1990s.[11] In the context of our paper, renewable energy (RE) technologies include solar, wind, geothermal and ocean/tide/wave. 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 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. We exclude biomass because this type of energy source is also dispatchable, and is generally burned alongside fossil fuels in power plants.

As in the related paper of Popp et al. (2011), our dependent variable is the net installed electrical capacity in RE technologies ($\Delta Cap\_pc_{it}^{RE}$) per capita in country i, time t, which, as argued in Section 2, reflects the investment decision as purely as possible:

$$\Delta Cap\_pc_{it}^{RE} = \frac{Cap_{it}^{RE} - Cap_{it-1}^{RE}}{Pop_{it}}$$

As in Popp et al. (2011), we use population as a rescaling variable in order to capture the change in capacity compared to the potential market size for electricity. Hence, the main capacity variables are normalized by population, and are measured in kW per thousand people.[12]

In our main specification, we consider all RE technologies together. We however test the robustness of our results separately for different renewable energy sources. We specifically consider solar and wind on the one hand and biomass on the other. The former are considered the most promising RE technology options. Both have witnessed an impressive decrease in costs over the past decade, and consequently experienced rapid increases in installed capacity. While both are variable electricity sources, they differ because electricity production from solar tends to be more aligned with the schedule of electricity demand, whereas wind's electricity production is highest in the very early hours of the day, when demand for electricity is low.

Table 1 shows that average RE installed capacity in the sample is roughly 65 kW per thousand people, with a median of 12.5 kW. Yearly capacity additions are on average 11.5 kW per thousand people, with a median of just above 2 kW per thousand people. Both these variables have standard deviations which are more than twice the average value, indicating wide heterogeneity in our sample (see also Table 2). Denmark leads by far in terms of average per capita RE investment, followed by Portugal, Italy, Sweden and Ireland. Countries like Hungary, Turkey, South Korea, but also Finland lag behind in terms of per capita investments. Overall, RE capacity has been increasing in the sample since around the year 2000 (see Fig. A1 in the Appendix).

4.2. Fossil-based energy generation

We collect information on country-level fossil-based installed capacity from IEA Electricity Information Database (IEA, 2016b). Importantly, this database allows us to distinguish between different types of fossil generation technologies. Recall from the introduction that fossil technologies can be separated into traditional fossil (TF henceforth) generation and modern fossil technologies (MF henceforth), with the latter being the best candidates to compensate for renewable variability. To explore the relationship between renewable investments and fossil installed capacity, we estimate a regression model where per capita capacity in MF and TF technology ($Cap\_pc_{it}^{MF}$ and $Cap\_pc_{it}^{TF}$) are the main explanatory variables of interest.

Specifically, we use the IEA (2016b) data to create two different proxies for both traditional and modern fossil technologies.

The first approach we use is to focus on the input used for electricity production, namely gas or coal. Gas is an efficient input in electricity production than coal and gas-based technologies are more modular and characterized by faster rump-up times than coal technologies. Following this reasoning, a first way to proxy MF versus TF is to use

[9] Whole system costs include the levelized cost of energy (LCOE) of a given technology, but also other system integration costs, i.e. the additional cost at the system level required to securely integrate a unit of generation of that specific technology (Strbac and Aunedi, 2016).

[10] 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, Korea, the Netherlands, 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. The countries included in our sample account for the majority of worldwide RE investment over the period considered.

[11] Indeed, our time span is dictated by the fact that the IEA (2016a) detailing renewable energy capacity starts in 1990. Conversely, data on fossil capacity generation from IEA (2016b) is available also for earlier years.

[12] In our main specification, hydro and nuclear capacities are in percentage terms (see discussion on control variables). However, in Appendix A, Table A1, we show that results remain unchanged if we rescale all capacity variables using total capacity (i.e. we consider variables in percentage terms), or if we rescale also the hydro and nuclear controls using population.

Table 1
Descriptive statistics.

Variable	Mean	Median	First Quartile	Third Quartile	Standard deviation	Minimum	Maximum
Renewable Energy Capacity (kW per thousand people)							
Capacity in renewables (RE)	65.03	12.53	1.591	65.24	126.8	0	960.1
Investments in RE (ΔCap_RE)	11.56	2.031	0.145	11.01	22.11	−2.197	175.6
Fossil-based Capacity (kW per thousand people)							
Capacity in modern fossil (MF1)	241.2	184.9	63.34	338.3	230.4	0	1157
Capacity in traditional fossil (TF1)	762.9	657.1	480.9	1028	460.2	18.70	1861
Capacity in modern fossil (MF2)	381.8	346.5	110.6	555.9	317.4	0	1345
Capacity in traditional fossil (TF2)	573.5	517.9	219.2	768.5	434.4	0	1702
Policy Variables							
Feed in Tariffs (FIT)	1.332	0	0	2.500	1.840	0	6
Certificates	0.566	0	0	0.660	0.990	0	4.950
Limits	2.175	1.320	0.990	3.960	1.686	0	5.940
Tax	0.688	0	0	1.320	0.913	0	3.960
PMR - Entry	2.574	2	0	6	2.600	0	6
Additional Control Variables							
Growth Rate of Electricity Consumption	0.0181	0.0164	−0.00276	0.0376	0.0397	−0.151	0.287
GDP per capita (constant 2005 US$)	30259	31758	18115	39726	14666	4411	69095
Share of Nuclear capacity (%)	19.02	16.12	0	33.60	20.34	0	78.94
Share of Hydro capacity (%)	19.87	8.218	1.445	25.60	25.62	0.0355	99.62
Share of energy imports (%)	0.0878	0.0589	0.0157	0.129	0.0955	0	0.585
Share of fossil fuel rents in GDP (%)	.427	0.122	0.00665	0.685	0.640	0	3.101
Stock of Knowledge in RE (patents)	212.8	52.17	14.75	134.4	453.7	0	3329

installed capacity in gas for the former, and installed capacity in coal for the latter. We call these two proxies MF1 and TF1, respectively.[13]

The second approach we use is to consider the type of technology used for production. Specifically, the IEA (2016b) distinguishes between the following generation technologies: Gas Turbines; Combined Cycle; Internal combustion/diesel; Steam; and Other type of generation. We define MF2 as the sum of Gas Turbines and Combined Cycle, as these are often used to address peak load. Conversely, we define TF2 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.

Note that not all countries report the information under both classifications for all years in our sample.[14] This gives rise to both an unbalanced sample and to samples which are not overlapping when using the first rather than the second definition of fossil fuel technologies.

Descriptive statistics from Table 1 and Table 2 provide largely consistent insights independent on whether we focus on MF1 and TF1 or MF2 and TF2. From Table 1, we observe that modern fossil installed capacity is larger than installed capacity in renewables, with MF1 and MF2 representing on average roughly one third and one half of TF capacity, respectively (240 and 380 kW per thousand people). The distribution of MF capacity across the countries in the sample is more heterogeneous than that of TF, as the standard deviation is almost as wide as the mean. In the case of TFl technologies, on the contrary, the distribution is more tightly centered. Interesting for the purpose of this paper, roughly two fifths in the countries in our sample have above the median both in terms of yearly RE investments and in terms of MF installed capacity, as shown in Table 2.[15]

4.3. Policy variables

To quantify the relationship between $\Delta Cap\_pc_{it}^{RE}$, $Cap\_pc_{it}^{MF}$ and $Cap\_pc_{it}^{TF}$ ceteris paribus we condition our estimates on several other confounding factors affecting the level of RE investments 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 policies (e.g. such as feed-in tariffs, tax credits, emission targets and investment incentives) and market regulation (Popp et al., 2011). We discuss each of them in turn.

We use the OECD Environmental Policy Stringency (EPS) database (OECD, 2015; Botta and Koźluk, 2014) to create several indexes measuring environmental policy stringency in our sample. The database includes information on 15 environmental policy instruments for OECD countries starting from 1990, and rates their stringency on a scale from 1 and 6.[16] Specifically, we create the following variables: “FIT” is the average of a country's score for the solar and wind feed in tariffs; “Certificates” is the average of the score for White, Green and CO2 certificates; “Taxes” is the average of CO2, SOx, NOx and Diesel taxes scores and “Limits” is the average of SOx, NOx, and Particulate Matters limits scores. In line with the findings of Johnstone et al. (2010), we expect feed-in tariffs and certificates to play a strong role in supporting the deployment of RE capacity and the integration of renewable in the power system. Indeed, FITs guarantee a fixed remuneration to RE generation and are expected to be particularly effective in supporting new and small producers in the electricity market. Conversely, certificates promote RE deployment either directly (green certificates) by requiring that utilities produce or purchase a certain share of renewable power as part of their portfolio, or indirectly, by requiring permits for CO2 emissions (CO2 certificates) or establishing energy saving obligations (White certificates). Taxes and limits are expected to be less effective, as they only provide indirect incentives for RE deployment.

[13] Specifically, MF1 is constructed by summing capacity in natural gas or a combination of gas, solid and liquid fuels. Conversely, TF1 is constructed by summing capacity in coal and coal products, peat, liquid fuels and other combustible fuels.

[14] For instance, Sweden reports installed capacity for gas and coal only for one year in our sample period. Hence, Sweden cannot be included in an analysis using this definition of modern fossil technologies (see Section 5 for more details).

[15] See Fig. A1 in the Appendix for information on how modern fossil and traditional fossil capacity developed over time.

[16] The EPS database represents the most comprehensive available indicator on environmental policy instruments in OECD countries, and is developed following a statistics methodology that allows for comparison across countries and over time. The major shortcoming of this database is that it considers policy instruments which are primarily related to supporting renewable energy generation technologies. This has two implications. First, it means that the database does not reflect environmental policy stringency in the whole economy, but rather in the energy generation sector. Second, it implies that any indicator built using the EPS data would not include information regarding policy support to fossil fuels. In the context of our analysis, the first implication is actually a plus, since we specifically focus on electricity generation. On the contrary, the second implication is relevant because fossil fuel subsidies are estimated to be very high across countries. Not accounting for this aspect may lead to an imprecise estimation of the impact of policy stringency in certain countries. However, it is reasonable to assume that fossil fuels subsidies are relatively stable over time in each country, i.e. they did not significantly change in the period under consideration.

Table 2
Descriptive statistics, by country.

Country	Renewable Capacity (kW per thousand people): Capacity in renewables	Investments in RE	Fossil-based Capacity: Capacity in modern fossil (MF1)	Capacity in traditional fossil (TF1)	Capacity in modern fossil (MF2)	Capacity in traditional fossil (TF2)	Policy Variables: Feed in Tariffs (FIT)	Certificates	Limits	Tax	PMR - Entry	Additional Control Variables: Growth Rate of Electricity Consumption	GDP per capita	Share of Nuclear capacity	Share of Hydro capacity	Share of Energy Imports	Share of fossil fuel rents in GDP	Stock of Knowledge in RE
Australia	48.51	12.77	479.3	1512	354.5	1637	0.522	0.660	1.693	0.646	1.439	0.0212	31483	0	7.519	0	1.063	60.23
Austria	66.17	11.88	494.8	317.9	264.3	548.3	2.591	0.570	3.630	0	2.636	0.0202	36150	0	63.35	0.196	0.134	104.5
Belgium	60.25	18.62	633.2	104.1	303.6	504.4	0	0.885	2.745	0	2.924	0.0151	34459	56.34	0.411	0.137	3.20e − 05	57.78
Canada	47.95	11.54	284.6	647.8	208.8	912.4	1.935	0.0574	2.439	1.191	2.818	0.00732	33114	14.97	59.31	0.0239	1.435	97.66
Czech Republic	40.39	9.669	.	.	50.35	1058	1.295	0.435	1.980	1.065	2.879	0.000772	12053	26.25	2.620	0.0765	0.123	9.324
Denmark	441.5	40.54	498.0	1324	233.7	1589	2.227	0.780	2.340	1.575	1.955	0.00673	45165	0	0.0645	0.111	0.959	139.0
Finland	17.10	3.692	718.8	1191	455.9	1454	0.205	0.570	3.300	0	1.212	0.0197	34723	30.66	18.75	0.107	0	41.00
France	41.06	5.172	50.20	357.4	22.15	381.6	1.400	0.561	1.980	0.330	5.333	0.0179	30743	76.20	13.39	0.0107	0.0265	317.8
Germany	31.16	9.855	377.7	627.1	92.25	912.6	3.545	0	2.310	0	4.636	0.00276	31636	29.39	3.534	0.0571	0.0690	741.7
Greece	69.51	17.21	146.9	626.3	176.2	597.1	3.250	0.510	1.500	0	3.288	0.0236	19426	0	7.777	0.0740	0.0328	16.63
Hungary	8.158	1.653	418.3	199.1	148.8	468.6	1.714	0.456	2.027	0.754	3.032	0.00169	9691	40.19	0.542	0.189	0.546	12.31
Ireland	121.4	19.43	610.5	539.4	460.3	689.6	0.318	0.420	2.115	0	3.167	0.0302	41285	0	3.408	0.0261	0.101	15.22
Italy	84.83	19.95	630.2	374.6	378.2	623.4	1.891	0.890	2.109	1.119	2.833	0.0186	30078	0	15.90	0.150	0.154	212.4
Japan	25.21	5.621	277.1	763.9	98.33	1209	0.565	0.115	1.636	2.009	2.515	0.00909	34613	24.86	8.291	0	0.0114	1619
Korea, Rep.	7.301	2.092	284.9	491.1	307.0	585.0	2.152	0.0430	2.410	1.090	3.818	0.0744	16659	36.43	1.355	0	0.00699	366.3
Netherlands	69.09	9.049	582.0	36.60	492.4	790.6	1.568	0.855	2.310	0	2.242	0.0241	39028	4.093	0.108	0.140	0.853	132.5
Norway	41.94	7.392	73.31	50.38	73.08	47.04	0	0.660	2.430	0.540	0	0.00695	60955	0	98.39	0.0575	2.644	71.35
Poland	12.42	3.918	11.72	739.4	10.91	740.0	0	0.960	1.920	1.830	3.485	−0.0151	7428	0	1.405	0.0222	0.371	11.26
Portugal	128.1	20.36	213.5	430.9	183.8	460.6	2.932	0.465	2.250	0	2.348	0.0306	17626	0	24.86	0.124	0	16.26
Slovak Republic	21.19	7.118	292.8	200.7	93.99	478.8	0.923	0.685	0.838	1.371	2.128	−0.00354	12324	54.68	15.16	0.211	0.0551	6.820
Spain	28.52	10.08	104.8	491.6	62.57	533.9	2.958	0	0.990	0.632	3.556	0.0426	21811	31.50	15.50	0.0391	0.0157	40.24
Sweden	89.21	19.64	.	.	208.5	642.2	0.205	1.410	2.130	1.890	1.091	0.00898	39096	45.24	45.26	0.0651	1.94e − 05	99.20
Switzerland	12.38	4.454	49.36	71.81	20.68	100.5	1.682	0	2.535	0.360	4.742	0.00988	53233	40.52	54.87	0.379	4.06e − 05	97.67
Turkey	6.353	1.823	151.3	160.8	135.3	176.8	1.152	0	0.947	0	3.167	0.0681	6570	0	29.48	0.0127	0.184	6.259
United Kingdom	39.25	9.737	356.3	665.0	378.6	642.7	0.891	1.707	2.497	0	0.333	0.00772	35943	22.23	1.304	0.0341	0.866	311.8
United States	63.52	10.01	1114	1248	742.4	1619	0.500	0.545	2.425	1.133	2.303	0.0136	40482	19.46	7.135	0.0111	0.597	1084
Sample Average	**65.03**	**11.56**	**241.2**	**762.9**	**381.8**	**573.5**	**1.332**	**0.566**	**2.175**	**0.688**	**2.574**	**0.0181**	**30259**	**19.02**	**19.87**	**0.0878**	**0.427**	**212.8**

We use the OECD index capturing the level of entry barriers in the electricity market (OECD, 2013) to measure the level of deregulation of the power sector (PMR), which accounts for both freedom of access to the grid by producers and freedom of choice by consumers (see Conway et al., 2005 for details). The index varies on a 1–6 scale, with the highest values indicating a higher level of entry barrier. Conditioning our estimates on the level of market liberalization is important because there is evidence that 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). It is well established that the degree of competition in the energy market affects the incentives to innovate in renewable energy technologies (Nicolli and Vona, 2016; Nesta et al., 2014). Following these insights, we expect that the diffusion of both RE and small scale MF 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:

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

where the policy proxies are lagged to capture time-to-build of new capacity.

Table 1 and Table 2 show that the policy variables are used heterogeneously in our sample of countries. All policy variables except limits have standard deviations which are higher than the sample mean. All the countries in our sample rely on an heterogeneous mix of policy instruments, with some scoring high in Certificates and Limits (e.g. the UK and Sweden) while others relying more heavily on FITs and Taxes (e.g. Denmark).[17]

4.4. Additional control variables

We condition our estimates on a large set of control variables, which account for additional confounding factors likely to affect RE investments and relate to (1) demand-side factors not captured by the policy indicators, (2) characteristics of a country's energy system and (3) a stock of knowledge in RE technologies. We discuss each of them in turn below.

The growth rate of electricity consumption and GDP per capita (in constant 2005 US$ per person) capture demand-side factors related to country or economy size. The former captures expectations about future demand, as new generation capacity is expected to be higher in those countries where the demand for electricity increases faster. The latter captures overall economic well-being and, more generally, all other demand-side factors not captured by the policy indicators or the growth in electricity demand. We use the World Development Indicators database (WDI, 2016) to compute both variables.

The set of controls specific to the country's energy system includes the shares of nuclear and hydro power generation, the share of net energy imports in total energy use and the share of rents associated with the extraction of coal, oil and gas over GDP. All these variables are built using data from the WDI (2016). The first variable controls for the fact that countries which can rely on alternative carbon free source of electricity such as hydro and nuclear may not need to invest in either renewable or fossil-based technologies. The second variable accounts for the fact that investments in alternative energy sources may be influenced by dependency on energy imports, and more specifically, as shown in Narbel (2013), RE investments are lower in countries which are less dependent on energy imports. The third variable captures in-house resource advantages in fossil fuel endowments and profitability, which likely affect the incentives to invest in any type of additional generation capacity.

Finally, we add a control variable which measures the stock of knowledge in renewable energy technologies in any given country. This variable is build using data on patents in renewable technologies (OECD, 2016) and using the perpetual inventory method, as in Verdolini and Galeotti (2011). Specifically, we apply the perpetual inventory method on the count of RE patents by inventors in country *i* at time *t* which are protected in at least two countries. We follow this approach, and consider only patents with a family equal or larger than two because, as suggested by Migotto and Haščič (2015), these represent higher value patents.

5. 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 TF and MF capacity on RE investments. Recall from the discussion above that per capita investments in RE capacity ($\Delta Cap\_pc_{it}^{RE}$) are assumed to be a function of TF and MF capacity per capita ($Cap\_pc_{it}^{MF}$ and $Cap\_pc_{it}^{TF}$), of the policy variables and of all other controls. As already mentioned, our main specification resembles that of Popp et al. (2011), augmented by the inclusion of the fossil capacity proxies MF and TF and the fact that the knowledge stocks of renewable energy are country-specific. In addition to focusing on the relationship between fossil and renewable technologies, extending the analysis of Popp et al. (2011) to 2013 allows also to re-evaluate the effects of policies on technology diffusion after the boom of public support to renewable in the years after 2004. Specifically, we estimate several variations of the following equation:

$$\Delta Cap\_pc_{i,t}^{\mathrm{RE}} = \beta Cap\_pc_{i,t-1}^{\mathrm{MF}} + \gamma Cap\_pc_{i,t-1}^{\mathrm{TF}} + \theta \boldsymbol{POL}_{i,t-1} + \alpha \mathbf{X}_{i,t-1} + \mu_i + \mu_t + \varepsilon_{i,t}, \tag{1}$$

where $\mathbf{POL}_{i,t-1}$ is the vector of policy proxies 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; ε_{it} is an error term and $\mathbf{X}_{it-1}$ is the vector of other controls previously discussed. We estimate our models using an OLS panel fixed effects estimator, as customary in the literature.

According to our discussion in Section 2, we expect the coefficient associated with $Cap\_pc_{i,t-1}^{\mathrm{MF}}$ to be positive, i.e. $\hat{\beta}>0$, while that associated with $Cap_{i,t-1}^{\mathrm{TF}}$, i.e. $\hat{\gamma}\leq 0$, to be zero or negative. Importantly, we should also expect that the effect of policies may be biased without properly accounting for the degree of compatibility of RE technologies and fossil technologies. Notice that our specification also accounts for the feedbacks from hydro and nuclear technologies included in the set of controls $\mathbf{X}_{i,t-1}$. These two additional feedbacks are measured in terms of effective electricity production rather than of installed capacity to rule out a strong collinearity with our two variables of interest, $Cap_{i,t-1}^{\mathrm{MF}}$ and $Cap_{i,t-1}^{\mathrm{TF}}$. Indeed, because total capacity is limited by the size of the market that is in turn proportional to population, a greater per capita capacity in nuclear will mechanically entail a lower fossil capacity. Our results are however robust to the inclusion of nuclear and hydro capacities (see Table A1 in the Appendix).

The fossil capacity variables (MF and TF) capture long-term persistent investments stretching over several years. These total capacities are thus composed of cumulative investments in both traditional and modern technologies. To be sure that our estimates truly capture the association between newer energy investments, we should minimize the measurement error that stems the inclusion of older vintages of both traditional and modern fossil into the stocks $Cap_{i,t-1}^{\mathrm{MF}}$ and $Cap_{i,t-1}^{\mathrm{TF}}$. We therefore check the robustness of our results by re-computing both variables accounting only the investments in fossil technologies carried

[17] See Fig. A2 in the Appendix display the evolution of the policy indexes. Observe that the policy proxies increased significantly after 2004, which is the last year of analysis in Popp et al. (2011). Note also that the countries which lead in RE investments are also those which generally have higher than average scores in the environmental policy indexes and which are characterized by medium-to-low entry barriers in the electricity markets (Table 2).

Table 3
Main empirical results, per capita investment in renewables.

	(1)	(2)	(3)	(4)	(5)
MF1 Capacity, per capita			0.0207***		
			(0.0065)		
TF1 Capacity, per capita			−0.0046		
			(0.0107)		
MF2 Capacity, per capita				0.0207*	0.0334***
				(0.0119)	(0.0117)
TF2 Capacity, per capita				0.0037	0.0066
				(0.0117)	(0.0124)
Feed-in-Tariffs		1.4197	2.2667**	1.5537	1.9579*
		(1.1402)	(1.0521)	(1.1242)	(1.0720)
Certificates		5.6872**	4.3836**	5.9584**	4.0219**
		(2.5036)	(2.0367)	(2.3698)	(1.7534)
Limits		1.4407	0.8630	1.3079	0.6603
		(1.2259)	(1.3678)	(1.1661)	(1.4587)
Taxes		−2.5677	−2.6889	−2.3847	−0.9657
		(2.1854)	(1.8409)	(2.2784)	(2.0492)
PMR - Entry		−1.6858***	−1.7992**	−1.7519***	−1.6766**
		(0.5880)	(0.6886)	(0.6031)	(0.6774)
Growth Rate in Electricity Consumption	−0.8921	8.0078	−7.3272	17.3770	9.1982
	(18.9822)	(20.9740)	(19.6238)	(21.3296)	(25.1535)
GDP per capita, log	−26.5846	−31.9423	−31.1167	−32.4680	−33.2130
	(23.1053)	(21.9293)	(22.9801)	(21.9445)	(22.7268)
Share of Nuclear	−0.3383	−0.3101	0.1328	−0.3540	−0.0629
	(0.3322)	(0.2651)	(0.2054)	(0.2939)	(0.3081)
Share of Hydro	0.3487	0.3105	0.4234	0.3401	0.3538
	(0.3509)	(0.3456)	(0.3702)	(0.3489)	(0.3901)
Share of Fossil Imports in GDP	−24.5394	−9.9662	3.4840	1.6815	19.7965
	(32.4169)	(29.3420)	(31.0795)	(32.9693)	(32.6975)
Share of fossil rents in GDP	−5.3433	−3.6178	−1.4919	−2.0584	0.7172
	(7.6585)	(7.7889)	(9.4429)	(7.2145)	(8.3328)
Stock of RE knowledge, log	−2.8991	−0.7360	0.7906	−1.3268	1.3805
	(3.7279)	(3.3925)	(3.4382)	(3.3021)	(3.6774)
Observations	552	552	494	543	485
R-squared	0.4336	0.4676	0.4760	0.4758	0.4707
Number of countries	26	26	24	26	24

Robust standard errors in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

out in the most recent years. To this end, we recalculate the MF and TF proxies by cumulating only the installed capacity of the previous 5 or 10 years.

The estimates of β and γ can be interpreted as causal only if investments in renewable energy and the past fossil capacity are not correlated with unobservable features of the energy system that will be absorbed by the error term ε_{it}. While controlling for country and time fixed effects mitigates this concern, we cannot rule out the possibility that there may be an unobservable country-specific trend correlated with both renewable energy and fossil fuel investments. This is due to the fact that such investments are co-determined within a country's energy strategy, raising endogeneity concerns. Particularly, actual investments in both MF and RE result from long-term planning of utilities under environmental and "dispatchability" constraints.

A full test of the role played by MF technologies as back-up capacity for intermittent RE would require convincing external instruments or an exogenous variation in MF capacity. Unfortunately, such test is not feasible in our context due to data constraints, and is therefore left for future research. Nonetheless, to partially address these concerns, we present two alternative specifications meant to at least reassure us regarding the fact that any potential endogeneity bias is relatively small.

First of all, we estimate an alternative specification where we explore the determinants of investments in modern fossil installed capacity ($\Delta Cap\_pc_{it}^{MF}$). In this specification, we include the stock of renewable energy capacity as a main explanatory variable, with the expectation of an insignificant coefficient. This exercise, which is similar to a Granger causality test, is meant to rule out extreme cases of reverse causality by showing that the complementarity between certain fossil technologies and renewable energy technologies is not symmetric. This should indeed at least enable us to establish the direction of the causality nexus between renewable and modern fossil technologies.

Second, both investments in RE and in new fossil technologies are likely planned to structurally reduce energy dependence and carbon emissions in the long run, and, thus, are expected to be highly persistent. To tackle this issue more directly than in our main specification, we present a robustness check which fits a dynamic model that we estimate using the difference-GMM estimator proposed by Arellano and Bond (1991).[18] The use of GMM method also allows us to instrument the two fossil fuel capacities. Instrumenting $Cap\_pc_{it-1}^{MF}$ and $Cap\_pc_{it-1}^{TF}$ with the history of capacities in RE, MF and TF reduces endogeneity concerns because the predicted levels of these variables reflect a country's long-term investment strategies. This arguably smoothens the influence of time varying shocks, such as unobserved changes in energy policy or the entry of a new large player, which affect both RE and fossil investments.

[18] The basic rationale underpinning the difference-GMM estimator is to instrument the lagged terms of the dependent variable with its lagged differences. 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, but we prefer to resort to the standard difference-GMM methodology (see, e.g., Bond, 2002).

Table 4
Empirical results, Recent fossil capacity stock.

Model	(1)	(2)	(3)	(4)
Proxies for fossil fuel capacity	MF1 and TF1		MF2 and TF2	
Time window	5 years	10 years	5 years	10 years
MF Capacity, per capita	0.0162*	0.0153***	0.0264**	0.0273**
	(0.0079)	(0.0038)	(0.0115)	(0.0120)
TF Capacity, per capita	−0.0081	0.0103	−0.0015	0.0120
	(0.0060)	(0.0127)	(0.0166)	(0.0126)
Feed-in-Tariffs	1.9245*	1.9124*	1.6218	1.8272
	(1.0778)	(0.9997)	(1.1935)	(1.1349)
Certificates	5.6996**	5.5724**	6.7930**	6.5175**
	(2.3078)	(2.1400)	(2.4717)	(2.3535)
Limits	1.4041	1.6970	1.9980*	1.7276
	(1.5089)	(1.4708)	(1.1515)	(1.1727)
Taxes	−1.3577	−1.8414	−2.8647	−3.4957
	(2.2708)	(2.0482)	(2.3720)	(2.4609)
PMR - Entry	−1.8644***	−1.9250**	−1.8515***	−1.6682**
	(0.6089)	(0.7442)	(0.6484)	(0.7256)
Growth Rate in Electricity Consumption	−4.0420	−11.2845	16.9995	25.1028
	(22.2627)	(22.3254)	(25.7526)	(26.4675)
GDP per capita, log	−37.3911	−46.3225*	−40.8852*	−40.8692
	(21.9030)	(25.0692)	(23.1336)	(24.3768)
Share of Nuclear	0.0941	0.1449	−0.3127	−0.3145
	(0.1942)	(0.2515)	(0.2830)	(0.3017)
Share of Hydro	0.3369	0.2926	0.3194	0.1844
	(0.3912)	(0.3501)	(0.3716)	(0.3221)
Share of Fossil Imports in GDP	−4.1309	6.9103	−7.9224	4.8905
	(30.5542)	(31.1867)	(30.6860)	(35.4672)
Share of fossil rents in GDP	−4.5380	−1.8685	−4.3443	−5.6116
	(10.5002)	(8.9974)	(7.9801)	(8.7628)
Stock of RE knowledge, log	1.4924	1.6434	−0.6518	0.5554
	(3.6656)	(3.8004)	(3.4696)	(4.4123)
Observations	483	461	516	469
R-squared	0.4678	0.4619	0.4820	0.4940
Number of countries	24	24	26	26

Robust standard errors in parentheses.
*** $p < 0.01$.
** $p < 0.05$.
* $p < 0.1$.

6. Estimation results

Table 3 presents the main results of our analysis using variations of Eq. (1) presented above. Model 1 only includes the vector of controls $\mathbf{X}_{i,t-1}$ and represents a benchmark model. Model 2 adds the policy variable and is the most similar set up to that of Popp et al. (2011). These two models suggest that the coefficients on the set of controls are not precisely estimated. This can be accounted for by the fact that country- and time-fixed effects capture the bulk of the variation of slow moving variables such as fossil fuel dependence, per capita GDP or the share of nuclear or hydro power.

Regarding the policy variables, two main considerations emerge from Model 2. First, in line with recent studies on the effect of competition on RE innovation (Nicolli and Vona, 2016; Nesta et al., 2014), lowering entry barriers promotes the deployment of RE. Second, certificates have a positive impact on the diffusion of RE capacity, but the impact of all other policy variables is estimated very imprecisely. This last result is somewhat in line with the rather mixed evidence in this respect from the available literature. For instance, Popp et al. (2011) finds only a modest and often statistically insignificant effect of the policy variables, while other contributions point to the effectiveness of FITs but not of other policies (Jenner et al., 2013). Focusing on Certificates and PMR, their effect is economically relevant. An interquartile change in the former and the latter variable, respectively, is associated with an increase in $\Delta Cap\_pc_{it}^{RE}$ of roughly 4 and 10 kW per thousand people. 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 entail less extreme variations (Table 1).

Models 3 and 4 presents results of the estimation which includes our variables of interest $Cap\_pc_{i,t-1}^{MF}$ and $Cap\_pc_{i,t-1}^{TF}$ alongside all controls $X_{i,t-1}$. Model 3 uses the first definition of fossil capacity (MF1 and TF1), while Model 4 uses the second (MF2 and TF2). Recall that the samples used in these two models are different because some countries only report fossil installed capacity using the MF1 and TF1 definitions, others only the MF2 and TF2 definitions, and others both. For this reason, Model 5 presents the result of the estimation when using the MF2 and TF2 proxies, but considering only the subset of countries which also report information on MF1 and TF1.

Our results indicate that the presence of MF technologies favors investment in RE, conditional on all other covariates. An interquartile change in per capita installed capacity of MF1 and MF2, which is equal to approximately to 275 and 445 kW per thousand people, is associated with an increase in RE yearly investment per capita of 6 and 14 kW per thousand people, respectively. This is a sizeable effect, considering that investments in RE capacity are just less than 12 kW per thousand people on average in our sample, with a median of 2. Furthermore, our results are particularly significant because they are conditional on the inclusion of the proxy for TF capacity. Indeed, the coefficient associated with the TF proxies is not statistically different from zero.

These results confirm 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. Conversely, our results indicate that a larger endowment of MF capacity makes it easier for the system operator to integrate RE technologies, and thus implicitly enhances the incentives to invest in RE. This interpretation should be, however, taken with caution as we are not able to identify a causal effect of MF capacity on the incentives to invest in RE. The skeptical reader can interpret the coefficient associated with MF capacity as an interesting correlation to explore in future research using more fine-grained data at both the regional and the utility level.

Importantly, the inclusion of the proxies for per capita fossil capacities leaves the coefficients associated with the Certificates and PMR variable roughly unchanged, but in Model 3 and Model 5 the inclusion of the MF proxies makes the coefficient associated the FIT variable significant. Indeed, these models suggests that an interquartile change of the FITs variable is associated with an increase in RE investment of roughly 6 and 5 kW per thousand people, respectively. This implies that including MF capacity improves the precision in the estimates of the policy variables.

In Table 4 we present the results associated with building the proxies for MF and TF only the more recent cumulative additions in capacity, and specifically those in the last 5 (Models 1 and 2) to 10 years (Models 3 and 4). This is done to lower the measurement error associated with the inclusion of older vintages of both MF and TF technologies in the proxies for fossil capacity. In the case of MF1, the coefficients are slightly lower than those presented in Table 3, while in the case of MF2 they are slightly higher, and more precisely estimated. Indeed, we confirm the positive association between MF and renewable investments when using a more restrictive definition for modern fossil capacity.

Table 5 tests the robustness of our results to changes in the definition of the dependent variable $\Delta Cap\_pc_{i,t}^{RE}$. Specifically, Model 2 includes biomass in the definition of the dependent variable. Models 3, 4 and 5 define the dependent variable as investments in wind, solar and biomass, respectively. A few interesting insights emerge from this Table. First, when including biomass in the definition of our dependent variable, the positive association between MF and investments in RE is confirmed, and the coefficient is slightly higher. This is consistent with our observation that biomass is often co-fired with fossil technologies and particularly so for modern ones. Second, the positive impact of MF capacity on investments is confirmed in the case of wind, but not precisely estimated for solar. This last result suggests that the availability

Table 5
Empirical results, changes in the definition of renewables.

Model	(1) Renewables	(2) Renewables and biomass	(3) Wind	(4) Solar	(5) Biomass
MF1 Capacity	0.0207***	0.0228***	0.0105***	0.0102	0.0022
	(0.0065)	(0.0076)	(0.0032)	(0.0061)	(0.0018)
TF1 Capacity	−0.0046	−0.0042	−0.0077	0.0029	0.0004
	(0.0107)	(0.0130)	(0.0075)	(0.0073)	(0.0063)
Feed-in-Tariffs	2.2667**	2.7350**	1.9956*	0.3007	0.4681
	(1.0521)	(1.0685)	(1.0191)	(0.3855)	(0.4051)
Certificates	4.3836**	6.0742***	3.1012**	1.3196	1.6902*
	(2.0367)	(1.9949)	(1.2043)	(1.6433)	(0.8828)
Limits	0.8630	1.0991	1.6594	−0.8215	0.2362
	(1.3678)	(1.3682)	(1.2593)	(0.6624)	(0.5192)
Taxes	−2.6889	−2.1214	−1.8413	−0.8342	0.5676
	(1.8409)	(2.1563)	(1.1461)	(1.5837)	(0.7052)
PMR - Entry	−1.7992**	−2.2673***	−0.7586	−1.0537*	−0.4681**
	(0.6886)	(0.6964)	(0.4919)	(0.5471)	(0.1868)
Growth Rate in Electricity Consumption	−7.3272	0.1678	−7.6192	0.9044	7.4965
	(19.6238)	(22.9930)	(13.0219)	(19.8740)	(11.0758)
GDP per capita, log	−31.1167	−36.2815	1.5009	−32.9883*	−5.1652
	(22.9801)	(24.7246)	(13.9108)	(18.0980)	(3.6937)
Share of Nuclear	0.1328	0.0965	0.3512*	−0.2123	−0.0363
	(0.2054)	(0.2671)	(0.2040)	(0.2019)	(0.1422)
Share of Hydro	0.4234	0.3162	−0.0996	0.5316*	−0.1072
	(0.3702)	(0.4071)	(0.2082)	(0.2943)	(0.1594)
Share of Fossil Imports in GDP	3.4840	3.3923	8.4851	−5.2577	−0.0922
	(31.0795)	(29.7025)	(26.9740)	(12.6427)	(8.7992)
Share of fossil rents in GDP	−1.4919	0.2025	−1.5846	0.0024	1.6945
	(9.4429)	(10.1783)	(7.1221)	(5.3521)	(2.7187)
Stock of RE knowledge, log	0.7906	1.8316	−0.1530	0.8299	1.0408
	(3.4382)	(3.8056)	(1.8900)	(2.7745)	(0.7198)
Observations	494	494	494	494	494
R-squared	0.4760	0.4350	0.3332	0.3710	0.0939
Number of countries	24	24	24	24	24

of MF capacity is more important for more variable RE sources, whose peak supply is less aligned with times of peak demand (i.e. wind) than for RE sources with stronger supply in peaks hours (i.e. sun). Finally, if we limit the dependent to biomass, the coefficient associated with MF is statically insignificant, and one order of magnitude smaller than that presented in Models 1 and 2.

Table 6 presents robustness aimed at lowering concerns regarding the endogeneity of our main explanatory variables ($Cap\_pc_{it}^{MF}$ and $Cap\_pc_{it}^{TF}$). Model 1 studies the determinants of MF diffusion. This exercise allows us to show to what extent the decisions regarding MF 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 MF investments, and on the further assumption that the drivers of MF investments are different from the ones of RE investments. Indeed, model 1 in Table 6 shows that RE capacity has no effect on MF investments. Similarly, environmental policies have no effect on the change in MF capacity. This highlights the fact that to date investors in MF 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 MF investment, where the latter are key support technologies for the former, but not vice versa.

Model 2 in Table 6 further addresses the concern that the results presented so far do not fully resolve all the endogeneity concerns regarding the estimated effect of MF capacity, as discussed in Section 4, by fitting a dynamic model using the difference-GMM estimator proposed by Arellano and Bond (1991), where the two variables of interest $ShareCap_{\mathrm{it-1}}^{\mathrm{MF}}$ and $ShareCap_{\mathrm{it-1}}^{\mathrm{TF}}$ are instrumented with their lagged values. The important result here is that the coefficient associated with our variable of interest $ShareCap_{\mathrm{it-1}}^{\mathrm{MF}}$ is roughly half the size of those presented in Table 3. While this indicates that not addressing the issues of persistency of RE investment leads to an overestimation of the role of MF 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. Indeed, the system GMM results indicate that the combined effect of the lagged terms in RE capacity is 0.86.[19] Notice that 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.[20]

7. Conclusions and policy implications

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 modern fossil technologies. We contribute to the literature with one key result. We show that countries where MF capacity was available were more likely, ceteris paribus, to invest in renewable energy generation. This effect is sizeable, as moving from the first to the third quartile of the distribution of modern fossil technologies is associated with an increase in renewable energy capacity of roughly 6–14 kW per thousand people, on average and ceteris paribus. This result holds in a series of robustness checks, including different definitions of RE capacity and system GMM estimator. Our paper thus calls attention to the fact that renewables and modern fossil technologies appear as highly complementary and that they have been jointly installed to meet the goals of cutting emissions and ensuring a stable supply. To date MF technologies enabled RE

[19] Actually, the sum of the coefficients associated with the two lagged terms of RE capacity is close to − 0.14. However, our dependent variable is the change in RE capacity, thus should add 1 to the sum of the coefficients of the lagged RE capacity variables.

[20] Rodman (2009) shows that the Hansen test is not reliable when N is small as in our case. In our case, given that N is particularly small (26 countries), the p-value associated with the Hansen's test is implausibly good. We try also to obtain a reliable Hansen test using a simplified equation, where we replace year effects with a linear and a quadratic time trend. These results are available upon resquest and confirm our findings.

Table 6
Empirical results, Additional share variables.

Model	(1) Investments in MF1	(2) Investments in REN GMM
MF1 Capacity		0.0102*
		(0.0057)
TF1 Capacity	-0.0724	-0.0623*
	(0.0812)	(0.0319)
REN Capacity, t-1	0.0105	0.1278
	(0.0970)	(0.0784)
REN Capacity, t-2		-0.2637***
		(0.0723)
Feed-in-Tariffs	3.5094	1.3981
	(3.6418)	(1.6168)
Certificates	-10.9817	-0.0855
	(10.5826)	(2.0243)
Limits	-6.8523	-1.9046
	(8.3406)	(1.8756)
Taxes	0.7661	4.1509*
	(5.2193)	(2.1068)
PMR - Entry	3.0938	-1.1092
	(5.2572)	(1.0209)
Growth in Electricity Consumption	220.4517	14.3473
	(169.9077)	(15.8178)
GDP per capita, log	44.0008	-68.6253*
	(34.3528)	(35.6677)
Share of Nuclear	0.0845	-0.4942
	(1.1389)	(0.3536)
Share of Hydro	-0.7341	0.5009
	(0.4581)	(0.3528)
Share of Fossil Imports in GDP	-121.7635	44.2424
	(152.6968)	(33.4010)
Share of fossil rents in GDP	-42.4678	-4.0384
	(48.3986)	(12.7332)
Stock of RE knowledge, log	-0.4300	3.0780
	(5.4794)	(6.1409)
Stock of fossil knowledge, log	2.1754	
	(7.4824)	
Number of countries	24	24
Observations	494	442
R-squared	0.0688	
Hansen J		0.00
Hansen crit. prob.		1
AR2		1.62
AR2 crit. prob.		0.11

Standard errors in parentheses
** $p < 0.05$
*** $p < 0.01$
* $p < 0.1$

diffusion by providing reliable and dispatchable back-up capacity to hedge against variability of supply.

Overall, our contribution suggests that the importance of the complementarity of RE and MF generation technologies has so far largely been overlooked in the policy debate and in much of the economic analysis focusing on the diffusion of RE generation. This suggests that the costs of integrating RE generation in the energy system may be underestimated. Specifically, our results give rise to three key policy implications.

First, a policy debate centered on the juxtaposition of RE and fossil technologies is missing the important complementarity role that MF technologies play with respect to handling the variability of RE generation. Indeed, while not paying the external cost of pollution, MF technologies provide an unremunerated positive externality of long-term flexible capacity for back-up. In light of this, 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 becomes an important, thorny policy issue which will need to be addressed and discussed.

Second, the relationship and the complementarity between MF and RE technologies imply that the system costs associated with the latter are high, and will likely increase with an increase in RE penetration. In this respect, our analysis complements recent attempts to systematically assess the grid-level system costs for different technologies and points indeed to the high indirect costs of renewables. We draw 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. Therefore, pricing both back-up services and greenhouse gas emissions appears as a key priority of a sound energy policy (see also Gowrisankaran et al., 2016). Pricing back-up services poses an additional challenge to the regulator in liberalized energy markets. Indeed, either private utilities will need to be subsidized to maintain the appropriate level of back-up capacity, or higher costs should be passed directly on the bills of final consumers as part of the contribution paid to support renewable energy generation.

Third, our results call attention to the need to develop alternative technologies which can substitute MF capacity in handling variable energy generation. Overstating the ability to substitute fossil generation with renewable energy generation may lead to a poor support of alternative enabling technologies. On the contrary, public support to improve large scale storage options is crucial. While storage technologies for non-stationary sources (transport) have seen significant decreases in costs in the last decade, storage for stationary sources is still not cost-competitive. In light of this, it is of paramount importance to support research, development and demonstration in this technological area. This would allow us to decouple RE penetration from lock-in in (modern) fossil technologies. However, note that the large uncertainty regarding expectations about future storage technology costs for large scale applications indicates that progress in this specific technological area may be rather slow and less then linear.

Overall, we conclude a policy and academic debate centered on the juxtaposition of renewable (clean) and fossil (dirty) technologies misses the important aspect linked with handling variable generation, 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. Conversely, our analysis suggests the need for a systemic perspective and the coordination of different types of investments (in storage technologies, RE and MF) 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 MF capacity. This will further lower any concerns linked with the possible endogeneity of the share of MF capacity.

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Appendix A

See Fig. A1 and A2

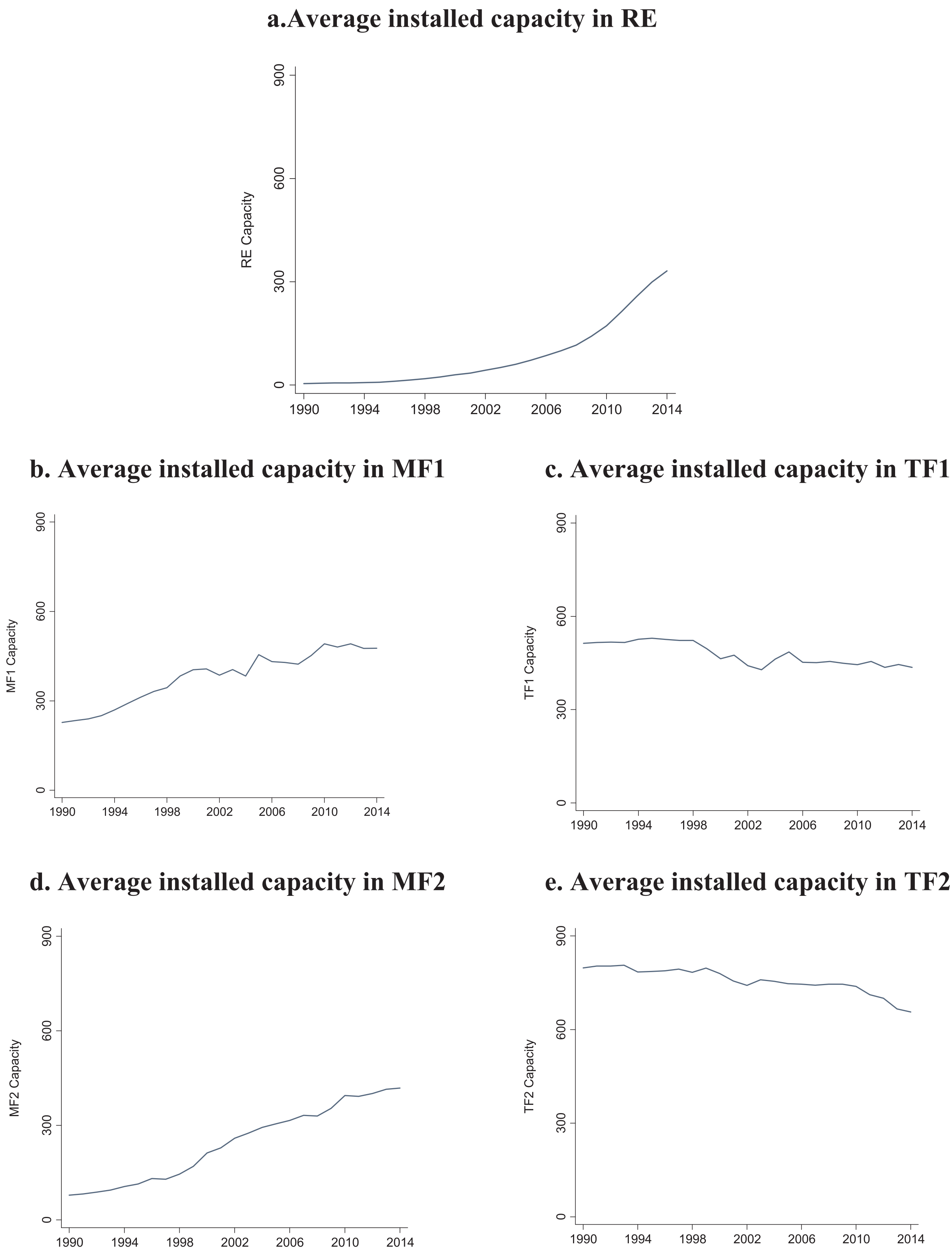

Fig. A1. Average installed capacity.

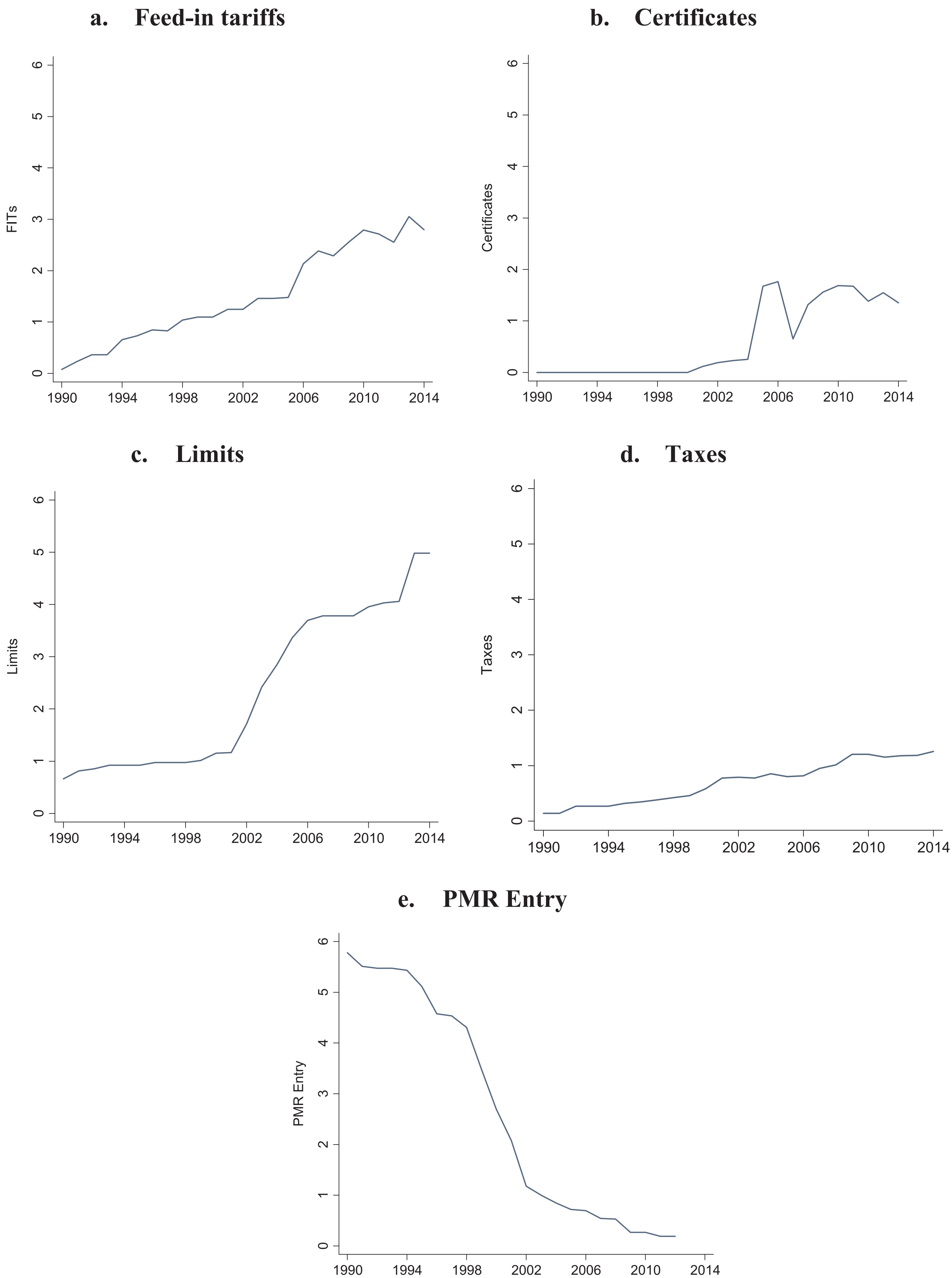

Fig. A 2. Indexes of policy stringency, averages - FITs, Certificates, Taxes, Limits, PMR.
(Authors' elaboration of data from OECD, 2015 and OECD, 2013).

See Table A1

Table A1
Additional results.

Variables	(1) Investement in renewable, in percentage terms	(2) Investement in renewable, per capita
MF1 Capacity	0.0001**	0.1887***
	(0.0000)	(0.0591)
TF1 Capacity	-0.0002**	-0.3113
	(0.0001)	(0.1888)
PMR - Entry	-0.0011**	-1.6468**
	(0.0004)	(0.6945)
Feed-in-Tariffs	0.0013**	2.2351**
	(0.0005)	(1.0524)
Certificates	0.0031**	3.6353
	(0.0012)	(2.2551)
Limits	0.0004	0.8139
	(0.0008)	(1.2906)
Taxes	-0.0019**	-1.8989
	(0.0009)	(1.7922)
Fossil fuel rents	-0.0052	-1.0269
	(0.0051)	(9.3889)
Share of Hydro	0.0002	
	(0.0002)	
Share of Nuclear	-0.0000	
	(0.0001)	
GDP per capita, log	-0.0053	-25.4140
	(0.0126)	(22.1008)
Energy Dependence	0.0009	−1.5858
	(0.0194)	(29.8423)
Growth in Electricity Consumption	-0.0015	-11.0065
	(0.0131)	(20.1636)
Stock of RE knowledge, log	0.0008	0.7830
	(0.0018)	(3.8060)
Share of Hydro, in per capita terms		-0.0346*
		(0.0173)
Share of Nuclear, in per capita terms		-0.0025
		(0.0275)
Observations	492	494
R-squared	0.4545	0.4716
Number of countries	24	24

Robust standard errors in parentheses
*** $p < 0.01$
** $p < 0.05$
* $p < 0.1$

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