Renewable energy and its impact on thermal generation[⋆]

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Abstract

Electricity production from renewable sources generally displaces thermal generation, which leads to lower CO_2 emissions in the power sector. However, the intermittent nature of many renewable technologies in combination with less residual demand leads to greater inefficiencies in the operation of existing fossil power plants. This inefficiency translates into a higher rate of emissions relative to output. In this paper we focus on Italian power installations between 2005 and 2014. Using panel econometrics, we show that a 10% increase in photovoltaics and wind infeed has reduced yearly CO_2 emissions of the average thermal installation by about 2% while the average plants emissions relative to its output have increased by about 0.3%.

Keywords: Emission factors, load-cycling, inefficiency

1. Introduction

In the past decade, there has been considerable growth in the production of electricity from renewable energy sources, in particular from solar photovoltaic (PV) and wind. For the most part, this growth has been supported by dedicated environmental and energy policies, which have impacted many power markets around the world.

Electricity production from renewable sources affects power systems in various ways. The determining factor of all those changes is that renewables have an almost zero marginal cost of production and therefore displace conventional

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generators with a positive marginal cost. This displacement of thermal production generally translates into lower average spot market prices (see, e.g., Green & Vasilakos, 2010; Woo et al., 2011; Würzburg et al., 2013; Paraschiv et al., 2014; Clò et al., 2015) and also impacts spot price variance (see, e.g., Wozabal et al., 2016).[2] From an environmental perspective, electricity generation from renewable sources generally leads to fewer emissions in the power sector as they tend to replace fossil fuel generation (see, e.g., Berghmans et al., 2014, for the case of European thermal plants). This first-order effect of renewables on emissions is one of the main justifications to support the deployment of renewables in the power sector, which is the largest emitter in terms of global CO_2 emissions.[3]

In this paper, we study the effect of intermittent renewables, i.e., power generation from PV and wind, on the emission factors of conventional generators. Emission factors are defined as emissions relative to output. The power generation profile of intermittent renewables fluctuates and is partially unpredictable which may lead to an increase of the emission factor due to two main reasons. First, it results in increased load-cycling activity of thermal units since electricity demand has to match supply instantaneously. This is especially relevant if storage technologies, interconnection, or demand side flexibility are absent, and the only option to match demand and supply is to intensively ramp thermal units up and down.[4] Second, the reduced demand for conventional generation increases the probability that thermal units work at a capacity factor lower than that designed for maximum efficiency. Those factors partially offset the reduction of CO_2 emissions due to the reduction in the use of fossil fuels and it increases the abatement cost in the power sector. The goal of this paper is to study empirically the impact of PV and wind on the emission factors of thermal generation, in particular of coal and gas power plants.

There exists a considerable amount of literature on the impact of renewables on the power system and, in particular, on CO_2 emissions reduction. One strand of literature takes an engineering approach and estimates the impact of wind and solar by using power sector modeling (examples are Weigt et al. (2013) for Germany, Denny & O'Malley (2006) for Ireland, Delarue et al. (2009) for Belgium, Holttinen & Tuhkanen (2004) for the Nordic countries). In general, these works predict the impact of future large shares of solar and wind energy production and thus take an ex-ante approach. A second strand of literature uses econometric techniques to analyze empirical data on production and emissions. These works take an ex-post approach as they estimate how solar and

[2]The effect on final consumer prices, which very often includes the cost of renewable subsidies, is unclear. Cludius et al. (2014) point to the re-distributional effects between different consumer groups in Germany: industrial consumers benefit from lower average spot market prices while households and small and medium size enterprises carry most of the cost of subsidizing renewables.

[3]According to IEA Statistics (2014) electricity and heat generation accounted for 42% of global CO_2 emissions in 2012.

[4]Graff Zivin et al. (2014); Carson & Novan (2013) explore the impact of demand-side interventions on marginal emissions. From a market perspective, such interventions flatten the daily load profile by replacing a portion of peak period electricity generation with increased off-peak production. Since in many cases the latter is dirtier than the former, total market CO_2 emissions may increase. However, the load-cycling activity of a single thermal plant may be reduced given that the load is less volatile and therefore its emissions relative to output decrease.

wind energy have already impacted the power system. In the case of Texas, Novan (2015) and Kaffine et al. (2013) studied the effect of renewables in market environments and evaluated the effect of wind generation on emissions by using aggregated system-wide emissions data. Cullen (2013) answered the same question but using disaggregated data on CO_2 emissions based on average plant emission rates. They all find that, on average, a MWh[5] of electricity generated by wind offsets between 0.5 and 0.7 tons of CO_2 emissions in Texas. For Europe, Berghmans et al. (2014), using panel-data econometric analysis of power plants in the EU, find that CO_2 reduction in the electricity sector was mostly due to the development of renewable energy production.

The literature points out that the exact effect of renewables on emissions is highly heterogeneous in various dimensions: (i) spatial, i.e., across markets depending on the generation mix and therefore on the marginal plants affected; (ii) temporal, i.e., their effect differs across time or levels of electricity demand (see, e.g., Novan, 2015; Graff Zivin et al., 2014; Cullen, 2013; Fell & Linn, 2013; Kaffine et al., 2013; Siler-Evans et al., 2012); and (iii) within markets depending on the installed capacity (see, e.g., Novan, 2015). In fact, the larger the amount of installed capacity, the more it affects plants at the bottom of the merit order stack, which tend to be the dirtiest and least flexible ones, i.e., coal plants.

Regarding the impact of renewables on emission factors, Katzenstein & Apt (2009) were among the first to explicitly take into account the increase of load-cycling as a consequence of increased penetration from PV and wind. They measure this effect from an engineering standpoint for two gas generators only. They use production and emission data to compare the actual emission offsets from PV and wind with those implied when using average emission factors. Consequently, they find that through renewable penetration, CO_2 emissions may be 20% higher than expected if the power fluctuations caused no additional emissions. A limit of this study is that the findings lack a system perspective where the externalities of renewable generation may be shared among many power installations (Cullen, 2013). Troy et al. (2010) studied the impact of high wind penetration on base-load cycling in Ireland using a scheduling model of the power sector. They found that wind penetration affects the cycling operations of the base-load units: when installed wind capacity goes from 0% to 42%, the annual start-ups for a typical coal unit increase by 32%, and those of a combined cycle gas turbine (CCGT) unit increase by 340%. Van den Bergh & Delarue (2015) studied the impact of large penetration of wind and solar on the cycling of conventional power plants using a dispatch model applied to the German power system. When penetration from renewables is low, flexibility is provided by starting up and shutting down of high dynamic CCGT power plants. With the increase of generation from renewables, flexibility comes more from the ramping of low dynamic steam power plants and less from the start-up/shut-down of CCGT power plants. Characteristic of these works is the engineering approach based on dispatch models.

In this paper, we study the effect of PV and wind on the emission factors using empirical data for the Italian power system. We apply panel data econometrics to the market data from 2005 to 2014. This is an interesting period to

[5]MWh is a unit of energy equivalent to 1 megawatt (MW) of power expended for one hour. 1,000 MW equals 1 gigawatt (GW) and 1,000 GW equals 1 terawatt (TW).

analyze as Italy has experienced an impressive growth in wind and solar energy. Combining hourly electricity production data for 93 thermal installations with their annual CO_2 emissions, we are able to analyze the effect of additional renewable infeed on annual emission factors. To the best of our knowledge, we are the first to study the emission efficiency of thermal generation with measured emissions on installation level in a market environment over a ten year period.

Our contribution to the literature is twofold. Firstly, with respect to the specific literature on the impact of renewables on emission factors, we are able to quantify the inefficiencies caused by renewables over ten years using empirical data for a large set of fossil fuel-fired power installations. Secondly, with respect to the more general econometric literature on the impact of renewables on CO_2 emissions, we can use data on measured emissions over time for each power installation, while previous papers only combined generation data with average plant emission factors, or estimated the impact of renewables on total market emissions. By using installation level panel data over the course of ten years, we can evaluate the effect on different plant types and analyze the role of investment in more modern plants. Moreover, Italy's power sector is a system dominated by fossil fuels that has faced a high penetration from PV and wind over the past few years. Such transformations are currently observed in many other power systems around the world, which make our results globally relevant.

Our results suggest that additional penetration from wind and PV increase the emission factor. Hence, there is an increase in emissions relative to output for the average installation. The results are significant and stable across several model specifications. Furthermore, we find that additional intermittent renewables lessen the expected reduction of emissions by about 11% for the average installation. This number is lower than in Katzenstein & Apt (2009) and highlights the importance of a system perspective where the burden of intermittency may be shared among many power installations. We find a less pronounced effect for plants which have been retrofitted.

We organize the remainder of the paper as follows. In Section 2, we describe our empirical strategy to identify the effect of renewables on emission factors. Thereafter, in Section 3, we detail the data gathering and matching process. Furthermore, we briefly describe the Italian electricity market as well as the European Emissions Trading System (EU ETS). In Section 4, we present our results, quantify the increased inefficiency, and provide several robustness checks. We conclude the paper in Section 5.

2. Empirical strategy

In this paper, we apply several specifications of panel data models to pin down the effect of additional renewables in the system on emissions of thermal plants. Due to the low marginal cost of production of many renewables, it is obvious that more costly thermal generation will be offset if there is an increase in the amount of renewables in the system. This is known as the first-order effect of renewables on thermal production and henceforth on CO_2 emission reduction. However, the intermittent nature of many renewable power production sources as, e.g., wind or PV, may require thermal plants to adjust their production more frequently than in a system where only demand is variable. Furthermore, increased renewable generation in general would likely push some thermal generation off the margin and running at a lower capacity factor may impact the thermal plant's emissions intensity. Thus, the second-order effect of renewables on emissions is the increased inefficiency of thermal plants induced by renewables. A major contribution of this paper is to quantify the magnitude of the second-order effect. Therefore, we analyze the effect of additional intermittent renewable production on the emission factors of thermal plants, i.e., their emissions relative to output. Emission factors for each thermal installation i and each year t are defined as

$$\phi_{i,t} = \frac{E_{i,t}}{Q_{i,t}},$$

whereas $E_{i,t}$ denotes the annual CO_2 emissions and $Q_{i,t}$ the annual production.

We explain those emission factors by two types of variables: system-specific variables and installation-specific variables. The amount of renewable generation in the market and the residual demand left to all thermal installations in the system belong to the former category. These factors vary over time, but not over installation, while the installation variables vary over both dimensions, as, e.g., the commissioning year of the installation or its input cost structure.

We consider the annual residual demand RD_t, defined as the demand left to all thermal installations operating in the system, as a system-specific variable. Formally, we define it as

$$RD_t = (D_t - H_t - I_t) - R_t = D'_t - R_t,$$

whereas D_t denotes the annual electricity demand, R_t the amount of intermittent renewables in a year, H_t the annual net generation from hydro power,[6] and I_t the net imports, i.e., the imports minus exports. In this paper, we are mostly interested in the effect of an increase in R_t, hence we use only R_t and D'_t as explanatory variables. To enhance readability, we refer to D'_t as residual demand in the remainder of the paper although it describes only the demand minus hydro production and net imports.

Besides fixed effects for every installation, we also include other installation-specific effects $X_{i,t} = (Y_{i,t}, F_{i,t})$ as control variables in our regressions. These are the commissioning year $Y_{i,t}$ and the input cost structure of an installation $F_{i,t}$. The latter is the cost of the energy input which includes the cost of the fossil fuel and the CO_2 cost.[7] The inclusion of input cost structure is motivated by the fact that plants with higher input cost structure are less competitive and therefore less dispatched in a market framework. To account for inter-installation

[6] We added electricity consumption for pumped hydro storage to the electricity generation from hydro plants. Hydro production from pumping amounted to only 1,711 GWh in 2014. Assuming an efficiency factor of 0.75, electricity consumption for pumped hydro storage represents only 0.8% of the total demand or 6.1% of PV and wind generation. Hence, we do not explicitly consider the effect of hydro storage.

[7] Prices paid for coal, gas, and oil by the power plants are often determined in long-term contracts which are not publicly available. For our analysis, we used the estimations made by REF-E which come from the analysis of the European historical spot prices and on information on the Italian power sector that REF-E regularly collects. For the CO_2 price, we used the prompt-future of the European Union Allowances as this is one of the most liquid market of the EU ETS allowances. Data were retrieved from Point Carbon and ICE. Fuel type specific average carbon conversion factors are taken from Graf & Wozabal (2013). These are 0.32 for coal, 0.18 for gas, and 0.25 for oil and represent tons of $C0_2$ per MWh.

variance, we put the unit-capacity weighted averages of the variables $Y_{i,t}$ and $F_{i,t}$. For example, if an installation consists of a 400 MW capacity gas generation unit and an 800 MW coal generation unit, its gas capacity share is equal to 1/3 and its coal share is equal to 2/3. We decided to use capacity weights instead of generation weights because the latter would suffer from endogeneity bias. Installation-specific effects show variation within installation in 27 out of 89 cases.

Similar to Bushnell & Wolfram (2005), we use fixed effects models and a log-log specification in our main specification. There are several reasons why we prefer a log-log specification to a linear one. First, on the unit level the relation between output and thermal efficiency is concave (see, e.g., Van den Bergh & Delarue, 2015). Second, the log-log specification outperforms the linear specification in terms of fit. Third, in a later step we relate the estimated inefficiency to the emission reduction of the average plant. Since electricity generation is measured in MWh and CO_2 emissions in tons, a log-log specification allows us to compare the two in terms of percentage increase. We do not consider any dynamic effects since we operate with annual data. We estimate the following regression

$$\ln(\phi_{i,t}) = \beta_1 \ln(D_t') + \beta_2 \ln(R_t) + \beta_3 \ln X_{i,t} + \epsilon_{i,t}, \tag{1}$$

whereas the error term $\epsilon_{i,t}$ in (1) can be broken down into

$$\epsilon_{i,t} = \mu_i + \nu_{i,t},$$

where μ_i denotes the unobservable installation-specific fixed effect and $\nu_{i,t}$ the independent and identically distributed remainder error term, i.e., $\nu_{i,t} \sim \mathrm{IID}(0, \sigma^2_{\nu_{i,t}})$. In our case the installation specific effects capture variables as technology, efficiency, and the like. Explanatory variables are assumed to be independent of $\nu_{i,t}, \forall i, t$.

We are mostly concerned about the size and the statistical significance of β_2 the coefficient of $\ln(R_t)$ in (1). Its interpretation is that a 1% increase in renewables increases the average installations' emission factor by β_2 percent. If it were zero, the second order effect of renewables on thermal plants emissions will be absent, or put differently, more intermittent renewables will not increase the inefficiency of the average plant.

We argue that all our explanatory variables are exogenous. Annual electricity consumption mostly depends on macroeconomic factors; net imports depend on market conditions in neighboring countries relative to the own country; and the production from hydroelectric plants depends on weather. The exact amount of renewable penetration also depends on weather conditions while the amount of installed renewable capacity mostly depends on subsidies which are politically decided.

3. Data and descriptive statistics

Italy is the geographical focus of this study for two reasons. First, because of the considerable increase of generation from wind and PV in the last few years, and second, because of the excellent data availability for this market. Both factors qualify Italy for an excellent study case.

In order to identify the increased inefficiency of thermal installations caused by additional renewables in the system, we combine data-sets from five different sources: (i) accepted electricity market offers and bids at generation unit level published by the Italian electricity market operator (GME),[8] (ii) verified total emissions at installation level provided by the European Transaction Log (EUTL)[9], (iii) data on renewable production and electricity consumption from the Italian transmission system operator (TERNA),[10] (iv) additional data on Italian power generators obtained from an Italian consulting company (REF-E),[11] and (v) data on imports and exports provided by the European Network of Transmission System Operators for Electricity (ENTSO-E).[12] Our data spans from 2005 to 2014.

3.1. Italian electricity market

The Italian electricity spot market is organized in a sequential manner, with a day-ahead market, five intra-day markets, and ancillary service markets. The day-ahead market is the most important one in terms of volume transactions. It started operation in 2004, but active demand bids entered the market in 2005. In the day-ahead market, generators and suppliers submit their supply and demand bids for each of the 24 hours of the next day. The day-ahead market price is determined in a single price, closed bid auction for every hour of the following day (see, e.g., Bigerna & Bollino, 2014, for a more detailed description of the market). In the presence of congestion in the electricity grid, the market is split into up to six different market zones (see Figure 1) with different prices. However, according to Bigerna et al. (2015, 2016); Sapio (2015) this is mainly an issue between Sicily and the mainland.

After the clearing of the day-ahead market, participants have the chance to rebalance their bids on the intra-day markets. In the last instance – in and near real time – the transmission system operator TERNA acts as a counterpart to ensure that demand equals supply. Those interventions are necessary to guarantee system security and they are organized in the ancillary service markets.[13]

In order to derive the total production schedules of the generators, we add the net positions of the intra-day markets and ancillary service markets to the day-ahead market offers. The market bids also include bilateral trades hence it is possible to derive a very detailed production profile. This is confirmed when comparing the aggregated manually derived production to the total net production reported by TERNA over the years 2005 to 2014, which is around 95%. Hence, we conclude that the derived production serves as a valid proxy for actual production.

Figure 2 shows the Italian power production mix and its transition. Most production stems from thermal generation, whereas most of which comes from

[8] We include accepted offers on the day-ahead spot market, as well as accepted net offers on intra-day and ancillary service markets.

[9] See http://ec.europa.eu/environment/ets.

[10] See http://www.terna.it.

[11] See http://www.ref-e.com.

[12] See https://www.entsoe.eu.

[13] For further details on the sequence of clearing, we refer to https://www.mercatoelettrico.org/En/Mercati/MercatoElettrico/MPE.aspx.

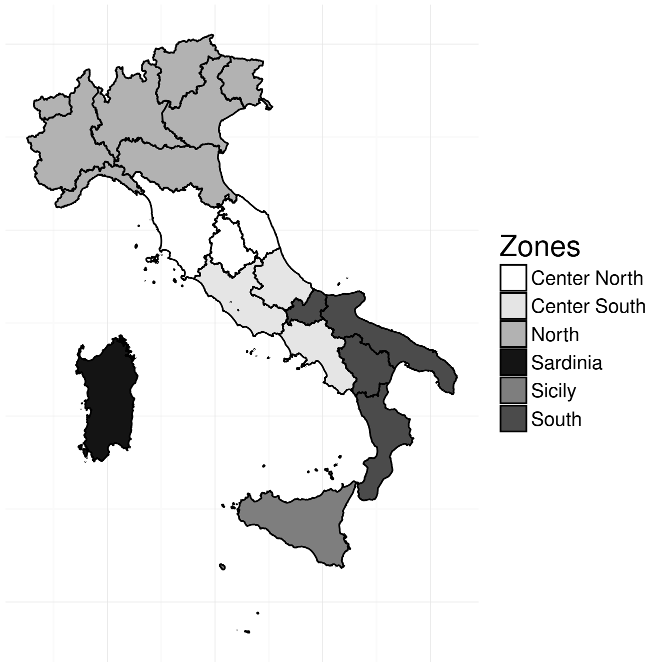


Figure 1: Italian market zones in 2014.

gas turbines. While thermal production shares have been around 80% between 2005 and 2008, they have decreased drastically thereafter due to a demand shock (economic crisis) and the large deployment of wind and PV. This huge increase in production from renewables in few years is the result of the Italian renewable energy policies which gave generous incentives for renewable production and supported large investment in wind and solar capacity. These policies have been implemented also to comply with the European Union (EU) binding targets for 2020. For Italy, that is 18% of final energy consumption from renewables by 2020. Italy has implemented different types of support scheme: for wind, the most important has been "Certificati Verdi," a green certificate system, while for solar "Conto Energia," a feed-in premium tariff (see, e.g., Marcantonini & Valero, 2017). As a result of the massive expansion of renewables, thermal plants accounted for only 61% of Italy's total electricity production in 2014.

3.2. EU ETS

The European Union Emissions Trading System (EU ETS) is the largest cap-and-trade program in the world. The system was introduced in 2005 and is the main pillar of the EU climate policy. The EU ETS includes 31 countries (the 28 EU member states plus Norway, Iceland, and Liechtenstein) and more than 15,000 installations from the major industrial sectors. Specifically for the power sector, it includes all generating installations with a net heat excess of 20 MW. The definition of an installation in the EU ETS does not correspond

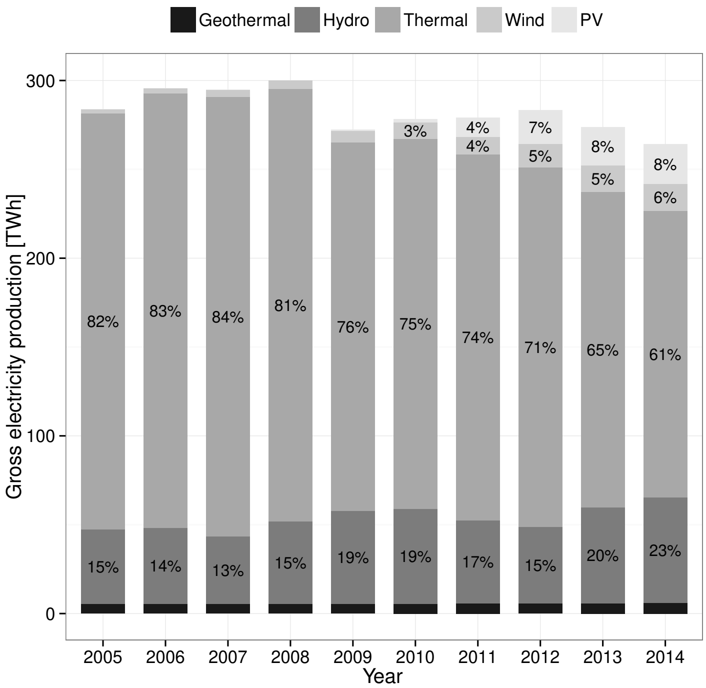


Figure 2: Italian yearly gross electricity production mix. Source: TERNA.

to the definition of a generation unit in the power market and, in general, one installation in the EU ETS may include different generation units. Each installation must monitor their emissions and report them to the competent national authority. Each national authority verifies the information and reports it to the European Commission that stores it in a central registry called the European Union Transaction Log (EUTL), which is publicly available.

3.3. Data matching

We are able to derive hourly production schedules for each generating unit participating in the Italian electricity market. Data on CO_2 emissions from the EU ETS, however, is available only in annual resolutions and at installation level. A power installation defined by the EU ETS usually comprises more than one generation unit. Using the REF-E generator database, which includes technical information on most Italian power plants, we are able to match the spot market production data with the EU ETS emission data, and identify annual generation for almost all Italian EU ETS power installations.[14] We managed to match 98 EU ETS installations, which represent 76% of the Italian gross

[14]The European Commission (EC) provides data on emissions at installation level including the 4 digit NACE code for the years 2005 until 2012, see `https://ec.europa.eu/clima/policies/ets/allowances/leakage_en#tab-0-2`. NACE Rev. 2 code 35.11 stands for "Production of electricity." We used this list as a starting point to match the data and manually applied the remainder.

thermal generation (excluding auto-production and geothermal production)[15] between the years 2005 and 2014.

According to the EIA, the average US CO_2 emission factors for natural gas plants were around 0.55 tons per MWh in 2013 and for bituminous coal around 0.94.[16] To avoid biased results and to hedge against data mismatch, we exclude installations with annual emission factors larger than two in one of the ten years of observations. Disproportionately high emission factors are often in plants that are in operation only for a few hours in a year. In the most extreme case, the emissions produced by switching on a unit whose spot market offer is accepted only for one single hour in a year exceeds the emissions produced by generating electricity for this particular hour.

By restricting the emission factor, our remaining sample still covers 93 Italian EU ETS power generation installations, which represent 73% of Italy's total net thermal production between 2005 and 2014. In comparison to the total of 98 matched installations, we still cover 96% of the emissions. The 93 installations contain 222 generation units, so on average an installation consists of about two generating units. Furthermore, we excluded installation/year observations for new installations from our samples. A new installation may have to perform some test-runs which show up on the CO_2 balance but not in market production. A zonal comparison of the sample corrections reveals that the Center North and Center South zones are more affected than all others. For the econometric analysis, we exclude installations which include units running on a special regime called CIP-6. A unit qualified as CIP-6 does not participate in the power market but receives subsidies for its production. We eventually end up with 89 installations.

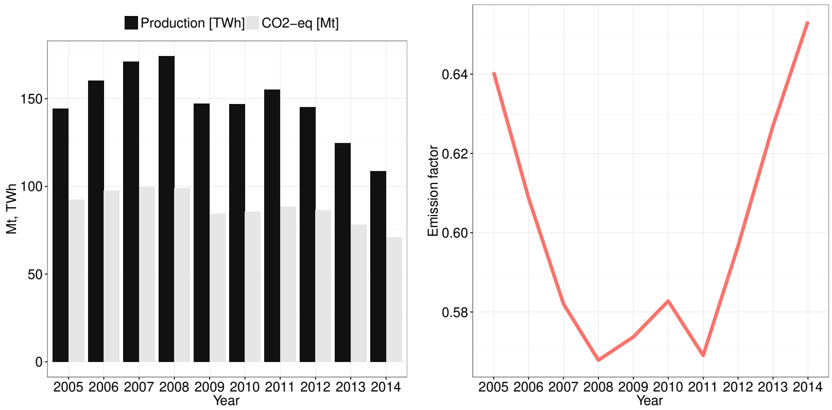
3.4. Descriptive statistics

Figure 3, Panel a, shows aggregated yearly production and emissions of the installations in our sample. The production pattern is similar to that of all Italian thermal plants as depicted in Figure 2. Emissions are coupled with production – the higher production the higher the emissions. However, the emissions relative to output vary considerably over time, as can be seen in Figure 3 (b). While the average emission factor decreased between 2005 to 2008, it has increased thereafter and quite impressively after 2011 – the time when intermittent renewables started playing an even more important role in the power mix. The average effect may be also driven by changing fuel prices which have an influence on the dispatch. For example if coal gets cheaper, electricity generation from coal will increase and hence the average emission factor will increase as well, since coal is dirtier than gas. However, as shown in Figure A.5, when we split the sample into installations either running on coal or gas, we find an increase in the average emission factors for both technologies after 2011.

In Table 1, we show the descriptive statistics of variables used in our regressions. The age is calculated as 2014 – the maximum year of our sample –

[15] Data provided by TERNA.

[16] EIA reports pounds of CO_2 per kWh for bituminous coal equal to 2.07 and for natural gas equal to 1.21. Data are calculated using the average heat rates for US steam-electric generators in 2013. See `http://www.eia.gov/tools/faqs/faq.cfm?id=74&t=11`.



(a) (b)

Figure 3: Panel (a): Aggregated production/emissions of the thermal plants in our sample. Panel (b): Aggregated emissions relative to aggregated production.

Variable	Abbr.	Mean	SD	Min	Max	Unit
Production	Q	1,919,617	2,351,159	71	16,700,000	MWh
Emissions	E	1,146,594	1,854,985	65	15,300,000	tCO_2
Emission factor	ϕ	0.65	0.28	0.36	1.69	Ratio
Renewables	R	15,959,000	14,481,743	2,347,000	37,484,000	MWh
Residual demand	D'	221,161,648	17,035,207	189,956,525	242,104,675	MWh
Age	Y	20.27	14.10	2	60	Year
Input cost structure	F	38.33	11.40	11.97	77.60	EUR/MWh

Table 1: Descriptive statistics.

minus the capacity weighted commissioning year of each installation. We also use capacity weights to calculate the installation's input cost structure.

4. Results

4.1. Baseline regression

In order to estimate the average effect of additional electricity generation by intermittent renewables sources on thermal plants' emission factors, we run several specifications of the regression model stated in (1). We always use robust standard errors clustered by installation in order to allow for heteroskedasticity and correlation over time for a given installation.

4.1.1. All installations

We report the regression results including all installations in column 1 of Table 2. An increase of 1% intermittent renewables in the system leads to a 0.03% higher emission factor on average. The residual demand left for thermal installations as well as the installation's input cost structure negatively affect the emission factor although both coefficients are not statistically significant. The absolute value of β_1 – the coefficient of $\ln(D')$ – is larger than that of renewables, which can be explained by the different levels of the two variables.

	(all)	(base)	(peak)	(old)	(zonal)
Residual demand	-0.065	-0.021	0.077	-0.131	
	(0.108)	(0.151)	(0.201)	(0.136)	
Renewables	0.028^{***}	0.023^{**}	0.049^{*}	0.037^{**}	
	(0.007)	(0.008)	(0.021)	(0.011)	
Age	0.208^{**}	0.150^{*}	0.161	0.149	0.195^{**}
	(0.065)	(0.067)	(0.115)	(0.101)	(0.064)
Input cost structure	-0.030	-0.063	-0.032	0.018	-0.023
	(0.031)	(0.050)	(0.064)	(0.024)	(0.032)
Residual demand (zone)					-0.071
					(0.083)
Renewables (zone)					0.012^{**}
					(0.004)
Installation fixed-effects	Yes	Yes	Yes	Yes	Yes
R^2 within/between	0.17/0.54	0.15/0.56	0.13/0.18	0.21/0.47	0.15/0.52
Observations	721	508	213	337	721
Installations	89	65	27	37	89

Notes: All variables in natural log form. Robust standard errors clustered by installation reported in parentheses. Asterisks indicate statistical significance at 5% (*), 1% (**), and 0.1% (***) levels.

Table 2: The effect of renewables on emission factors.

A percentage increase of D' has a higher impact on thermal installations than an equivalent decrease in R, since current production of wind and PV is only about one-tenth of the maximum residual demand.[17]

The age of the plant has a positive effect on the emission factor, i.e., a one-year increase in the hypothetical capacity weighted age in 2014 leads to an increase in the emission factor by about 0.2%.

The R^2, and thereby the fraction of explained variation, is 17% between installation and 54% within installations. The values are reasonable and and therefore the possibility of wrongly estimated coefficients due to omitted variables is limited.

4.1.2. Examining installation heterogeneity

The fixed effects model captures firm heterogeneity by including an indicator variable for every installation. Thus, the intercept is allowed to change for every installation. The installation's slopes, however, are homogenous which means that the respective coefficients reflect only the average effect of, e.g., additional renewable infeed. Such a model does not fully account for the peculiarities of power systems. Cheap renewables first displace expensive peak-load generation and their emissions. Given that installed renewable capacity is low to moderate, base-load plants are affected only in situations of low demand and high renew-

[17] The correlation between $\ln(D')$ and $\ln(R')$ is equal to -0.7. Removing $\ln(D')$ from the regressions affects the magnitude of β_2 only slightly and has no effect on its statistical significance.

able production. In terms of flexibility peak-load plants outperform base-load plants. Hence, adjusting the load of a peak-load generation unit is much more efficient in terms of cost and emissions. Consequently, there are two contrary effects at work: peak-load installations are more frequently affected but the impact on emission factors is smaller compared to base-load installations which are affected less frequently but the impact is higher.

To account for the difference in slope heterogeneity, our first strategy is to split the sample into base-load and peak-load installations. We classify as base-load installations the installations consisting of coal generating units, co-generation units, or combined cycle units. The remaining installations we define as peak-load installations. As a second strategy, we run a random coefficient model whose results are presented in Section 4.3.

Column 2 in Table 2 reports the results including only base-load installations. It turns out that the coefficient of renewables is lower compared to the baseline regression (column 1). When reducing the sample to peak-load installations only, we observe a larger effect. Hence, we find evidence that, at current levels of intermittent renewables in the system, the peak-load installations' emission factors are affected more (column 3) than those of base-load installations.

4.1.3. The role of investment

Another source of heterogeneity are installations that have built up new capacity in comparison to installations which have not done so. In order to identify the role of investment in newer generating units, we look at installations which have not increased their capacity weighted commissioning year during that time or which have a capacity weighted commissioning year lower than 2005. New capacity build-up is generally more efficient and, possibly, the response to a changed market environment, while for older installations the opposite holds true. The results – stated in column 4 of Table 2 – show that the effect of additional renewables on emission factors is larger compared to the scenario where we include all installations. Hence, relative emissions from installations that have not invested in newer generation capacity show a larger response to increased penetration from renewables.

Figure 4 shows the installed capacity of the installations in our sample. There have been considerable investments in gas generation units from 2005 to 2012. Oil units almost completely disappeared. The capacity of coal has remained quite constant over the period analyzed, it had a non negligible increase only from 2009 to 2010.

The massive investment in gas generation units possibly led to the drop in the overall emission factor in 2008 and 2011, as can be seen in Figure 3(b).[18]

4.1.4. Market splitting

In case of physical congestion, Italy's electricity market can be divided into six different market zones. In order to account for possible market splitting, we replace cross-country residual demand and generation from intermittent renewable sources by their zonal values. We denote the former by zD' and the latter

[18]According to TERNA, the amount of combined cycle gas capacity has roughly doubled between 2004 and 2014, see "Impianti di generazione" under `http://www.terna.it/it-it/sistemaelettrico/statisticheeprevisioni/datistatistici.aspx`.

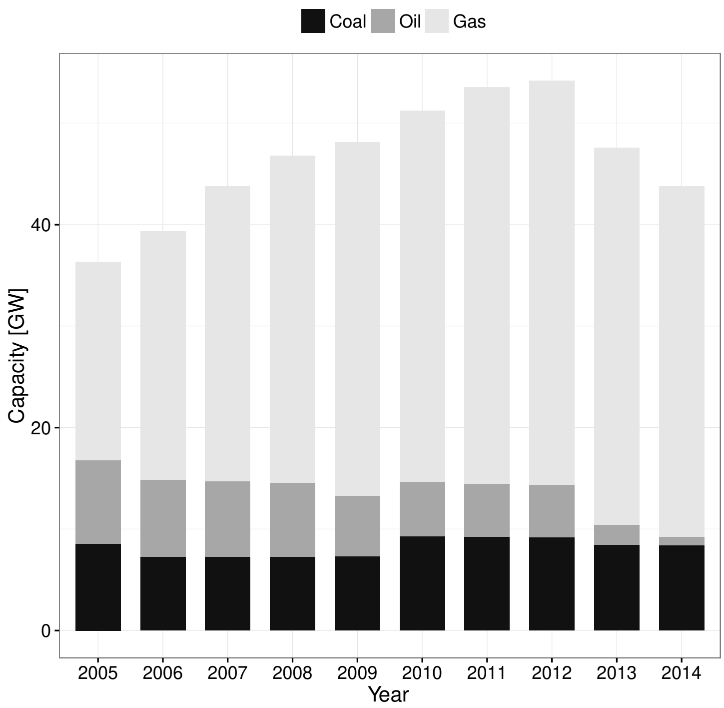


Figure 4: Installed capacity.

by zR. The positive effect of additional renewable generation on the emission factor is still statistically significant albeit its level is slightly lower compared to the other regressions (see column 5 in Table 2). Another advantage of using data differentiated by zones, is that we now have variation of renewables and residual demand over time and zone and not solely over time which highlights the causal effect of renewables on emission factors. However, according to Bigerna et al. (2015, 2016); Sapio (2015) inter-market congestion is mainly an issue between Sicily, and the mainland. Hence, in the remainder of the paper we mainly concentrate on the other cases.

4.2. Magnitude of the effect

An important issue is the magnitude of the increased inefficiency caused by renewables. More precisely, the share of the increased inefficiency in comparison to the offset emissions. Therefore, we estimate also the first-order effect of renewables on the emissions, i.e., $\ln(E_{i,t})$. As explanatory variables, we add capacity to the set of explanatory variables specified in (1).[19] Table 3 shows the estimates for the five versions as we had it before with the emission factors.

The coefficients of $\ln(R)$ are negative and statistically significant in all specifications. Their values range between -0.19 and -0.67, i.e., a one percent increase in intermittent renewables leads to a reduction of emissions between

[19]To be precise we use the natural log of capacity. Omitting this variable leads only to a slight change in the level of the coefficients of interest.

	(all)	(base)	(peak)	(old)	(zonal)
Residual demand	3.898***	2.953***	1.145	3.069**	
	(0.738)	(0.664)	(1.809)	(1.101)	
Renewables	−0.226**	−0.186**	−0.671**	−0.319**	
	(0.068)	(0.063)	(0.211)	(0.103)	
Age	0.075	−0.132	3.386	4.881*	0.344
	(0.226)	(0.334)	(2.169)	(2.006)	(0.213)
Input cost structure	−1.083***	−0.495*	−0.163	−0.789*	−0.937***
	(0.254)	(0.200)	(0.677)	(0.364)	(0.247)
Capacity	1.418***	0.621	1.584***	1.821***	1.592***
	(0.322)	(0.337)	(0.331)	(0.451)	(0.396)
Residual demand (zone)					2.428***
					(0.624)
Renewables (zone)					−0.112**
					(0.034)
Installation fixed-effects	Yes	Yes	Yes	Yes	Yes
R^2 within/between	0.49/0.57	0.40/0.65	0.62/0.28	0.43/0.19	0.42/0.38
Observations	721	508	213	337	721
Installations	89	65	27	37	89

Notes: All variables in natural log form. Robust standard errors clustered by installation reported in parentheses. Asterisks indicate statistical significance at 5% (*), 1% (**), and 0.1% (***) levels.

Table 3: The effect of renewables on verified emissions.

0.19 and 0.67 percent. The coefficient of residual demand is positive although not statistically significant in the sample restricted to peak-load installations. The R^2 are reasonable in all specifications.

To quantify the magnitude of the second order effect, we rearrange the marginal effect of renewables on emission factors from (1) to

$$\beta_2 = \frac{\partial\left(\ln\left(\phi_{i,t}\right)\right)}{\partial \ln\left(R_t\right)} = \frac{\partial\left(\ln\left(E_{i,t}/Q_{i,t}\right)\right)}{\partial \ln\left(R_t\right)} = \frac{\partial\left(\ln\left(E_{i,t}\right) - \ln\left(Q_{i,t}\right)\right)}{\partial \ln\left(R_t\right)} = \frac{\partial \ln\left(E_{i,t}\right)}{\partial \ln\left(R_t\right)} - \frac{\partial \ln\left(Q_{i,t}\right)}{\partial \ln\left(R_t\right)}. \tag{2}$$

Furthermore, we denote the estimate of the marginal effect of renewables on the installations' emissions, i.e., $(\partial \ln(E_{i,t}))/(\partial \ln(R_t)) = \beta_2'$. Substituting β_2' in (2) yields

$$\left(\partial \ln\left(Q_{i,t}\right)\right) / \left(\partial \ln\left(R_t\right)\right) = \beta_2' - \beta_2,$$

which is the effect as if renewables had displaced all thermal capacity without causing additional inefficiencies. Hence, the percentage value of expected emissions reductions can be written as $\beta_2'/(\beta_2' - \beta_2)$. In Table 4, we show the calculations for each of the five models. Including all installations (column 1), we see that the average installation achieves around 89% of the expected reductions accounting for the additional inefficiency caused by renewables.

Our estimates are less pessimistic than that of Katzenstein & Apt (2009) who find that CO_2 emissions achieve only around 80% of the expected emissions reductions. A possible explanation for this gap is that we apply an electricity

	(all)	(base)	(peak)	(old)	(zonal)
β_2	0.028	0.023	0.049	0.037	0.012
β_2'	-0.226	-0.186	-0.671	-0.319	-0.112
$\beta_2'/(\beta_2' - \beta_2)$	89%	89%	93%	90%	90%

Table 4: Percent of expected emissions reduction.

market perspective while Katzenstein & Apt (2009) are focusing only on two types of natural gas generators. As pointed out by Cullen (2013), in an electricity market the reduction in production induced by intermittent renewables may be shared among many installations which may incur smaller changes in emission due to ramping and reduced efficiency.

4.3. Robustness checks

A test for over-identification as well as the Hausman test favor a fixed effects model over a random effects model. Furthermore, the fixed effect model, which literally allows for a different intercept of each installation seems to be more plausible. Hence, we only provide results from the fixed effects model. We use robust standard errors clustered by installation in all regressions to allow for heteroskedasticity and correlation over time for a given installation. The results of a Friedman test on the balanced panel, i.e., only taking into account installations which have been active over the whole sample period, show that the null hypothesis of cross-sectional independence cannot be rejected.

In order to account for heterogeneous slopes, we also estimate a random coefficient model. Table B.5 shows the result of regressing emissions and emission factors on renewables, demand, and the commissioning year. The average value of the renewables coefficient in the specification with the emission factor as dependent variable is slightly lower than in the fixed effects model which consequently leads to higher percentage of expected emissions reduction.[20]

We also checked whether the Large Combustion Plant Directive (2001/80/EC) had impacted our results. This is a directive that restricts flue-gas emissions from combustion plants with thermal capacity greater than 50 MW. Some plants can "opt-out" if they operate less than 20,000 hours between 2008 and 2015. This could have restricted their operating hours with possible effect on efficiency. Only few Italian plants opted out of the directive and only eight are in our final dataset (a ninth power plant was in the initial database but it was taken out because it had an emission factor larger than two).[21] Running our main regressions excluding those eight installations does not substantially change the coefficient of interest, as shown in Table B.6.

Furthermore, we show a specification in Table B.7 where we interact renewables with the age of each installation. Hence, we regress the emission factor for each installation and year on this new variable which also varies over time

[20]The standard deviations of the coefficient estimates of $\ln(R_t)$ are 0.03 in the model with $\ln(\phi_{i,t})$ as dependent variable and 0.58 in the model with $\ln(E_{i,t})$ as dependent variable.

[21]The list of the plants that opted out is available on the website of the European Environmental Agency: `http://www.eea.europa.eu/data-and-maps/data/lcp`.

and installation. In addition to installation fixed effects, we add time fixed effects in order to capture the variation in demand and the like. The coefficient of the interaction term is positive and significant in all specification except for the peak-load sample and the old vintages sample. Both samples suffer from a low number of observations since the majority of installations is qualified as base-load. The interpretation of the coefficient is difficult, since we cannot disentangle the effect of age and renewables, but the significance of the variable provides further evidence of a plausible identification strategy.

As a final robustness check, we present the results of a linear specification instead of the log-log specification in (1). Table B.8 shows the results thereof. The coefficient of renewables is statistically significant in all specification except for the peak-load sample. The coefficients of renewables is larger in all specifications than the absolute value of the residual demand coefficient. This means that the emission factor increases more when annual renewable generation rise by 1 TWh than it would decrease when annual residual demand fall by 1 TWh.

These exercises demonstrate that our derived results are robust to different methods of estimating the effect of renewables on emissions.

5. Conclusion

In this paper, we show that electricity generation from intermittent renewables has had a measurable negative effect on the efficiency of Italian thermal installations between 2005 and 2014. While the emissions of the average installation have been reduced, the emissions relative to output have increased. Our results show that intermittent renewables lessen the emission reduction by 11% for the average installation. At the current levels of PV and wind generation in the Italian power system (around 14% of annual gross electricity production in 2014), the emission factors of base-load installations are less affected than that of peak-load installations. However, when relating the emission factors to the offset emissions, both types seem to be equally affected. This may change in the future as the penetration of renewables increases, especially when PV forces base-load plants to ramp down at noon.

Our work shows that the impact of PV and wind on the efficiency of thermal installation is effectively a second order impact on emission reductions. However, it is not too small to be completely neglected either, especially in the future, when the increase in the penetration of renewables will affect much more base-load installations, which are less capable of coping with variable load-profiles.

Our results suggest two main policy implications. First, the tangible reduction of emission efficiency adds another reason for designing and supporting methods to mitigate the impact of intermittency such as the development of storage, extension of the transmission networks, and demand side management. Second, the path towards the full decarbonization of the power sector is long and we still need a large generation capacity from conventional technologies, at least in the next decade. The efficiency reduction translates into a higher generation cost for thermal power plants, in particular for base-load power plants that were designed to operate in a different environment. This may increase the impact of renewables on the so-called "missing money problem" (Hildmann et al., 2015) which is the difficulty faced by conventional generators in recovering investment costs in a liberalized market.

The main limiting factor of our study is that the emissions of European installations are currently monitored only on an annual basis. This forced us to do a yearly analysis despite having information on installation production at an hourly level. Furthermore, this did not allow us to factor in the different effects of PV and wind on installation level emissions, because of the high correlation in the yearly observations. A better data set is also needed to incorporate the effect of other causes which may affect the emission factor, e.g., the reduction of available capacity due to outages or due to the exercise of market power.

Our analysis can be further developed in several directions. In addition to trying to disentangle the effect of PV and wind on emissions, an important extension would be to evaluate how increased inefficiency affects the cost of generation, and thus the evolution of the power market. Furthermore, an in-depth analysis on the effect of renewables on re-dispatch and balancing markets can be a very interesting topic for future research.

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Appendix A. Additional figure

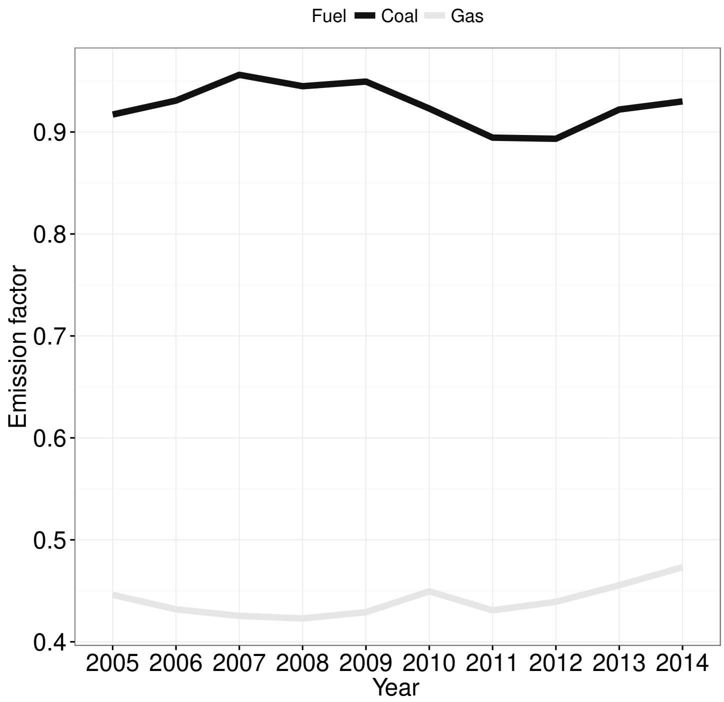

Figure A.5: Aggregated emissions relative to aggregated production by fuel type.

Appendix B. Results of alternative econometric models

Dependent variable	(all) $\ln(E)$	(all) $\ln(\phi)$
Residual demand	2.152***	−0.156
	(0.419)	(0.092)
Renewables	−0.441***	0.016*
	(0.096)	(0.008)
Age	−8.342**	1.146
	(2.799)	(0.941)
Input cost structure	−0.011	0.018
	(0.123)	(0.035)
Observations	694	694
Installations	80	80

Notes: All variables in natural log form. Bootstrapped standard errors in parentheses. Asterisks indicate statistical significance at 5% (*), 1% (**), and 0.1% (***) levels.

Table B.5: The effect of renewables on emission factors applying a random coefficient model without constant and bootstrapped standard errors.

	(all)	(base)	(peak)	(old)	(zonal)
Residual demand	−0.027	0.051	0.027	−0.110	
	(0.131)	(0.181)	(0.241)	(0.144)	
Renewables	0.031***	0.028***	0.047*	0.041***	
	(0.008)	(0.008)	(0.021)	(0.011)	
Age	0.213**	0.148*	0.234*	0.132	0.198**
	(0.067)	(0.072)	(0.104)	(0.100)	(0.066)
Input cost structure	−0.034	−0.079	−0.004	0.014	−0.024
	(0.040)	(0.064)	(0.057)	(0.022)	(0.041)
Residual demand (zone)					−0.061
					(0.105)
Renewables (zone)					0.013**
					(0.004)
Installation fixed-effects	Yes	Yes	Yes	Yes	Yes
R^2 within/between	0.17/0.55	0.16/0.60	0.14/0.23	0.23/0.50	0.16/0.53
Observations	647	463	184	317	647
Installations	81	60	24	35	81

Notes: All variables in natural log form. Robust standard errors clustered by installation reported in parentheses. Asterisks indicate statistical significance at 5% (*), 1% (**), and 0.1% (***) levels.

Table B.6: The effect of renewables on emission factors excluding installations which opted out from the European large combustion plant directive.

	(all)	(base)	(peak)	(old)
Renewables x Age	0.214**	0.167*	0.196	0.022
	(0.065)	(0.069)	(0.130)	(0.112)
Installation fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
R^2 within/between	0.18/0.53	0.16/0.48	0.19/0.20	0.24/0.20
Observations	721	508	213	337
Installations	89	65	27	37

Notes: All variables in natural log form. Robust standard errors clustered by installation reported in parentheses. Asterisks indicate statistical significance at 5% (*), 1% (**), and 0.1% (***) levels.

Table B.7: The effect of renewables interacted with age on emission factors applying a log-log specification.

	(all)	(base)	(peak)	(old)	(zonal)
Residual demand	−0.0006	−0.0002	−0.0005	−0.0008*	
	(0.0003)	(0.0004)	(0.0007)	(0.0004)	
Renewables	0.0010**	0.0009**	0.0024	0.0019*	
	(0.0003)	(0.0003)	(0.0015)	(0.0007)	
Age	0.0079**	0.0068***	0.0053	0.0039	0.0073**
	(0.0024)	(0.0019)	(0.0044)	(0.0020)	(0.0024)
Input cost structure	0.0007	−0.0005	0.0007	0.0013*	0.0006
	(0.0006)	(0.0008)	(0.0012)	(0.0007)	(0.0007)
Residual demand (zone)					−0.0008
					(0.0007)
Renewables (zone)					0.0044*
					(0.0018)
Installation fixed-effects	Yes	Yes	Yes	Yes	Yes
R^2 within/between	0.16/0.48	0.18/0.59	0.13/0.09	0.18/0.40	0.13/0.46
Observations	721	510	213	337	721
Installations	89	65	27	37	89

Notes: All variables are in levels. Robust standard errors clustered by installation reported in parentheses. Asterisks indicate statistical significance at 5% (*), 1% (**), and 0.1% (***) levels.

Table B.8: The effect of renewables on emission factors applying a linear specification. Residual demand and renewables in TWh.