Do Intermittent Renewables Threaten the Electricity Supply Security?

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October 9, 2018

Abstract: Around the globe, intermittent renewable energies in the form of wind and solar power are on the rise. This study tests if renewable energies replace conventional electricity generation technologies. We estimate a dynamic investment model for 14 European economies for the period 2002–2016 and find a non-negligible negative impact of intermittent renewables on investment in peak-load capacity (mainly gas), while base-load plants are unaffected. However, the production flexibility of thermal peak-load plants represents a particularly vital function to balance the supply intermittency of wind and solar. Thus, dispatchable conventional power plants are still necessary to back the system under scarcity events, such as unfavorable weather conditions during high electricity demand. In the long-run, the vast deployment of renewables creates a significant underinvestment gap in peak-load capacity. To prevent the risk of a blackout and to ensure a reliable supply of electricity, the need for policy intervention and a redesign of the current electricity markets seems inevitable.

Keywords: Electricity Generation, Investment, Missing Money, Intermittent Renewables, Supply Security

JEL Classification: D25, L16, L51, L94, Q42

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

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1 Introduction

Growing concerns about climate change in combination with unfavorable energy dependence and continuously increasing energy demand have induced politicians in many economies around the globe to revise incumbent energy policies. As a consequence, renewable energy sources (RES), foremost among them wind and solar power, are viewed as one of the most efficient tools to tackle these problems. In Europe, RES enjoy tremendous subsidies and have thus become essential components in the energy mix. The market share of RES has been steadily increasing over the last two decades and is expected to grow further (IEA, 2017). In 2015, RES made up 29.9% of the EU-28's total electricity production. In terms of installed electricity generation capacity, the share of wind and solar increased from a low 0.4% in 1995 to 24.3% in 2015 (EC, 2017). Despite the potential benefits of RES to abate carbon emissions through clean electricity production, adverse effects emerge. RES may undermine incentives to invest in conventional thermal power plants, which are still needed to ensure the security of electricity supply, because wind and solar plants cannot produce when the wind does not blow and the sun does not shine. Moreover, given RES's intermittent nature, gaps between electricity supply and demand have to be filled by flexible conventional technologies, such as gas-fired power plants. Underinvestment in conventional electricity generating sources may thus threaten the system reliability in the long run.

In this paper, we study how the deployment of RES replaces conventional thermal electricity plants.[1] Even if capacity from RES were abundant, their intermittency makes it necessary to back the electricity system with dispatchable conventional power plants. One reason is that wind and solar generally enjoy subsidization in the form of prioritized feed-in at guaranteed (minimum) tariffs, so that their electricity production is decoupled from demand variations. Instead, they feed in whenever the wind blows or the sun shines. What aggravates the problem is that large-scale electricity storages are not (yet) technically and economically feasible, apart from the limited scope of pump storages in mountain areas (e.g. the Alps).

At the outset, the effect of intermittent RES on investment in conventional generation capacity is not clear-cut. Some studies (e.g. Traber and Kemfert, 2011) mention that the deployment of RES clearly reduces the residual demand for thermal peak-load plants, whereas their production volatility may again increase the utilization of these plants. In a similar vein, Green and Vasilakos (2011) postulate that a large deployment of volatile wind power in the UK may require a vast amount of peak-load capacity ("plants with low capital costs", p. 2) whereas base-load plants may become obsolete. Bushnell and Novan

[1] From here on we will refer to the effect of replacing conventional technologies with RES as 'replacement effect'.

(2018) find for the Californian electricity market that the drastic expansion of solar power lead to a decrease of average wholesale prices, whereas the decrease is non-linear, so that mid-day prices decline while "shoulder hour prices" increase. The authors conclude from these findings that rather base-load plants could be affected while peak-load plants may remain in the market. Hence, it is not entirely clear whether the deployment of RES decreases investment in base- or peak-load plants.

Nonetheless, a preponderance of arguments point in the direction that RES *impede investment in conventional peak-load capacity* for several reasons.[2] One reason is that RES have a negative effect on the wholesale electricity *price level* – the so called 'Merit Order Effect'. Given that dispatchable thermal plants (foremost gas) operate at high marginal costs, a low wholesale price may undermine their profitability. In contrast, base-load power plants (e.g. run-of-river hydro, nuclear, and coal) have high fixed costs but relatively low marginal costs. For these plants, the merit order effect may not be pronounced enough to fall below their marginal costs. Another reason is that not only a lower price level, but also a shrinking peak/off-peak *price spread* resulting from more RES hinders investment in peak-load plants. The relatively high marginal costs of peak-load plants require peaking wholesale prices to be profitable. A third reason is that RES feed-in at essentially zero marginal cost, which has a decreasing effect on the capacity utilization of peak-load plants as they get pushed out of the merit order more frequently.[3] In the long run, the effect of replacing conventional peak-load technologies with RES may be strong enough to put the system viability under pressure, increasing the risk of a blackout.

Table 1 shows a stylized example of how RES push gas out of the merit order for a given electricity demand. In panel (a), the market works in the conventional fashion assuming a country without RES, but having installed base-load capacity in the form of run-of-river hydro, nuclear, lignite, and hard coal, and peak-load capacity in the form of gas and oil. In this setup, gas represents the marginal technology and determines the wholesale market price, P. In panel (b), the country installs RES capacity in the form of wind and solar plants, which have (almost) zero marginal costs. These plants shift the supply curve to the right. At given demand, now hard coal becomes the marginal technology leading to a price drop from P to P' (i.e. the merit order effect). We can see that RES first replace peak-load plants (in this case gas) with high marginal costs, whereas base-load plants remain in the merit order. However, with further deployment

[2]Section 2 provides in-depth details and reviews the relevant literature on how RES may replace conventional power plants.

[3]There may be other reasons for less investment in dispatchable thermal units. For example, a higher market risk arising from the deployment of RES may discourage investment in conventional thermal plants (see, e.g., Steggals et al., 2011). Also, Cramton and Ockenfels (2012) highlight that political and regulatory uncertainty hinders investment in conventional generation technologies.

of RES, it is well possible that base-load plants are also affected.

This paper puts forth empirical evidence regarding the renewables' replacement effect on conventional generation capacity – a well-established but surprisingly under-researched idea. We utilize data from Platts PowerVision on different types of electricity generation capacity combined with other data sources to provide an aggregate view on how the deployment of fluctuating RES affects capacity investments in conventional technologies in 14 European economies for the sample period 2002–2016.[4] Our results point to a non-negligible replacement effect on investment in peak-load plants in Europe.

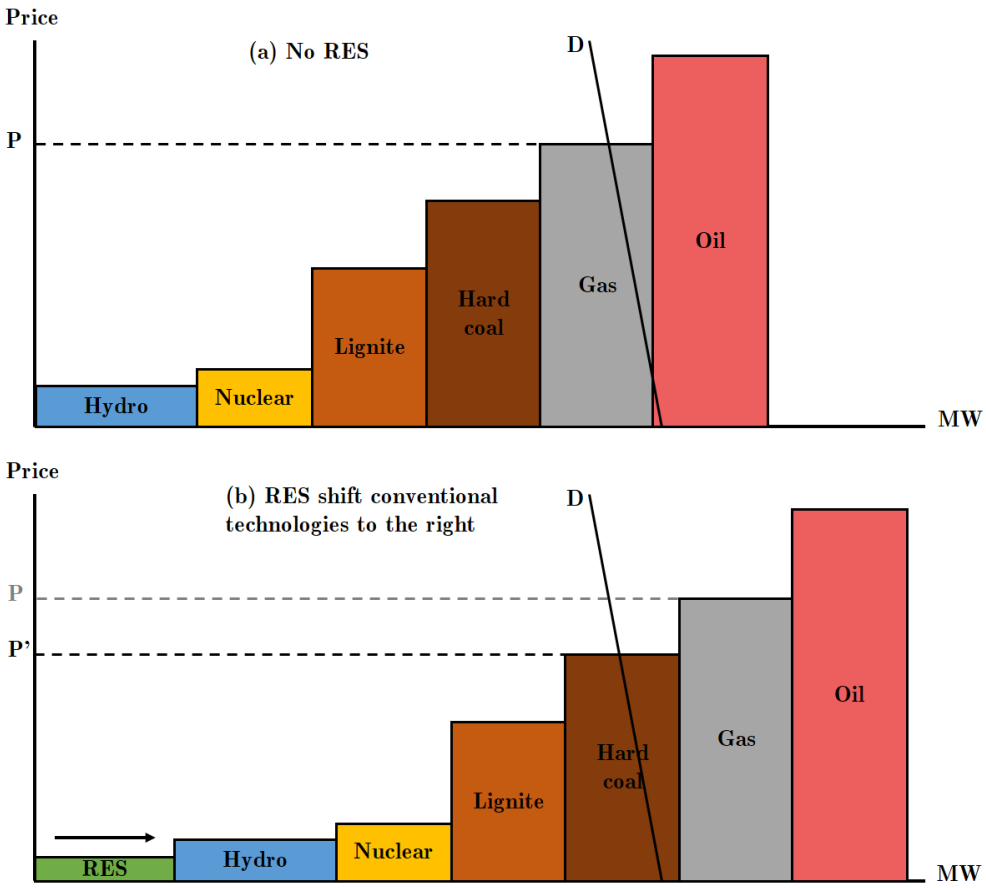
A well-known issue in the application of dynamic panel estimations is that simple OLS with fixed effects may yield biased coefficient estimates. As our investment model requires the inclusion of a lagged dependent variable, we apply various estimators (i.e. LSDVC, difference GMM, and system GMM) to account for this kind of bias and arrive at robust estimates. In contrast to peak-load investment, our results indicate that base-load investment is unaffected by intermittent RES. Moreover, we disentangle the effects of wind and solar power and reach the conclusion that our finding of a negative reaction among investments in peak-load capacity due to increased RES is mainly driven by *wind* feed-in, whereas the relatively modest solar feed-in during our sample period did not manifest in a statistically significant effect. Our results are also robust to alternative estimators and model specifications.

Our study extends the relatively limited literature that investigates intermittent renewables' detrimental investment effects. The rising uncertainty about sufficient profit margins to justify investments in conventional power plants has become an influential parameter in investors' decision-making processes and has since gained attention as the 'missing money problem' in the literature (Joskow, 2008). Drawing inferences from a computational market model, Winkler et al. (2016) argue that the penetration of RES decreases average wholesale electricity prices, which evokes concerns about the returns on infrastructure investments. Moiseeva et al. (2017) point out the need for flexible conventional power plants that are capable of balancing gaps between electricity supply and demand resulting from fluctuating RES and deviations from production forecasts because of unpredictable weather conditions. A lack of sufficient dispatchable generation capacity (independent from weather conditions) may cause significant price spikes when variable electricity generation departs from forecasted levels and may trigger problems in terms of system reliability and energy supply.[5] Based on a computational energy market model for Germany, Traber and Kemfert (2011) find that increasing market penetration of renewables (especially wind) reduces residual demand for conventional plants, which leads to

[4] The actual regression samples are limited to 2004–2016 due to lags and first differences in the employed variables.

[5] Wozabal et al. (2016) find a non-linear effect of intermittent RES on the price volatility. While small to moderate shares of RES dampen the price variance, the effect increases with large shares of RES.

Figure 1: Merit order (a) without and (b) with RES and the resulting wholesale price



The figure shows a stylized merit order (supply) curve (a) without and (b) with intermittent RES (i.e. solar and wind) for a given demand, D. In (a) gas is the marginal technology, which determines the wholesale price P. In (b) the RES shift the conventional technologies to the right, so that now hard coal becomes the marginal technology at a lower price P'.

crowding out effects. Additionally, the authors find a negative impact of wind penetration on investment incentives in peak plants (especially gas) and conclude that this result is mainly driven by the lower utilization of peak-load plants.

Praktiknjo and Erdmann (2016) raise concerns about the long-term viability of the electricity system in Germany, as they claim that the merit-order effect of renewables has brought about electricity prices to fall below even the most efficient combined-cycle gas turbines, so that investments in those "ideal backup units" (p. 91) have been canceled. Indeed, many other studies (e.g. Clo et al., 2015; De Vos, 2015; Gelabert et al., 2011; Gil et al., 2012; Hirth, 2013; Ketterer, 2014; Welisch et al., 2016; Würzburg et al., 2013), find corroborative empirical evidence for the negative effect of RES on wholesale prices in various countries. Although many drivers, such as the vast deployment of RES, may be held responsible for the lack of investment incentives, some authors (Hogan, 2017; Praktiknjo and Erdmann, 2016) mention that over-capacity – a typical feature of electricity markets – may also be blamed. Hence, we fill a gap in the literature as (i) we econometrically investigate how intermittent RES impact investment in conventional back-up generation capacity, whereas the few other studies that do so rely on computational models; (ii) while many studies show that wholesale prices are distorted through the deployment of RES, we model the direct link between RES and investment; (iii) we explicitly control for excess capacity in the electricity system and show that otherwise the negative effect of RES on investment in peak-load technologies would be overstated.

The findings in our paper that the vast deployment of volatile RES curtails investment in conventional generation technologies imply consequences for resource adequacy. This raises the need for action, as the potential threat of underinvestment in conventional peak-load technologies calls into question the current state of electricity market designs. For countries such as Germany that have been tremendously subsidizing wind and solar technologies, our results predict a severe investment gap in gas-fired plants, which will result in missing dispatchable electricity generation capacity in the long run. Other countries, such as Poland, that still have to achieve the transition from a largely coal-fired electricity system to a low-carbon intensive production, in order to meet the EU renewables targets set for 2020 and 2030, may also have to deal with the threat of underinvestment in electricity backup capacity in the coming years. We emphasize that the integration of intermittent RES while at the same time maintaining adequate security of power supply may not be feasible without political intervention. Policy-makers may either incentivize investment in conventional generation capacity, for example by establishing capacity markets or other capacity payment mechanisms, or try to reduce the adverse effects of renewables subsidies in an energy-only market, which may come at the cost of undesirably high greenhouse gas (GHG) emissions. Our results are also informative for countries outside of Europe with a massive deployment of wind and solar

generation sources in their electricity markets, such as China, USA, Japan, or India.[6]

2 Background

The International Energy Agency (IEA, 2012) already warned about a potential investment gap in European electricity markets in 2012, as it identified maintaining the long-term supply security of electricity during the current phase of decarbonization in Europe as one of the main challenges. Not only in Europe, but also globally, wind and solar power are on the rise, because these technologies have been determined by policy-makers as the most powerful tools to tackle global warming (below we show that advanced economies heavily invest in wind and solar power). In contrast, other emission-free technologies face major drawbacks. Nuclear power does not produce greenhouse gas emissions, yet has become politically undesirable in many European economies, not least since the Fukushima Daiichi nuclear incident in March 2011 (Grossi et al., 2017). Other renewable energy sources have proven inefficient as they have not yet achieved technological maturity (e.g. biofuels) or are limited in their availability (e.g. geothermal).

The global deployment of installed wind generation capacity has multiplied almost thirty-fold from 17,684 MW in 2000 to 539,256 MW in 2017 (EurObserv'ER, 2018). Outside Europe, the countries with the highest installed wind turbine capacities are China (124,710 MW), USA (67,870 MW), India (23,762 MW), and Canada (10,204 MW), whereas leading European countries are Germany (42,367 MW), Spain (22,987 MW), the United Kingdom (13,313 MW), and France (9,819 MW).[7] At a global level, solar PV also enjoys a massive capacity build-up from an initial 1,288 MW in 2000 to 404,500 MW in 2017, with China, India, USA, and Japan having the highest forecasted capacity additions between 2018 and 2022 outside Europe, while Spain, Germany, and France have the highest in Europe (SolarPower Europe, 2018).

Although confirmed as a success when it comes to the build-up of renewable capacity (Dijkgraaf et al., 2018; Jenner et al., 2013; Mints, 2012; Moosavian et al., 2013), these developments raise concerns among academics and institutions, as the vast deployment of intermittent wind and solar generation technologies brings about adverse effects that put pressure on the electricity system. The commitment to sustainable energy production has resulted in higher volatility in energy markets (Hirth, 2013). This is best shown by the development of electricity prices, where negative power prices in the wholesale electricity market have become a fairly common phenomenon in times of excess energy supply (De Vos, 2015). Moreover, the increasing penetration of renewables has further caused

[6] These countries have the highest investment rates in renewable power in 2015 (Bloomberg, 2018).

[7] 2015 values; data according to the World Wind Energy Association (WWEA), `https://wwindea.org/blog/2015/09/09/hyr2015/`, accessed on August 2, 2018.

average electricity prices to decrease, which has evoked concerns about the returns on infrastructure investments (Winkler et al., 2016).[8] The rising uncertainty about sufficient profit margins to justify investments in conventional power plants has become an influential parameter in the decision making process of investors and has since gained attention as the 'missing money problem' in the literature (Joskow, 2008). *The Economist*[9] has also investigated the problem of underinvestment due to intermittent RES and expresses the problem clearly: "an electricity industry that does not produce reliable revenues is not one that people will invest in."

The problem of missing money for required investments in conventional power plants will be further aggravated by the decreasing spread between peak and off-peak prices, caused by higher renewable penetration rates in the energy mix. This latter effect is rooted primarily in the high correlation between peak energy demand and the maximum possible amount of energy which can be supplied by renewables during daytime (solar PV) or season (wind). Plants that rely heavily on large arbitrage payments become unprofitable and impede investment decisions by investors. Hirth (2013) emphasizes that electricity generation technologies with high marginal costs (e.g. oil, gas) are most prone to disinvestments due to the development of intermittent RES. This is underlined by Praktiknjo and Erdmann (2016), who claim that falling wholesale electricity prices in Germany due to the merit order effect of renewables have made even the most efficient combined-cycle gas turbines unprofitable as the wholesale price has fallen below their marginal costs. Moreover, government support schemes for intermittent RES decouple their investment incentives from market-based mechanisms, while the market prices become more and more distorted, which in turn hinders investment in conventional fossil technologies. In this regard, Traber and Kemfert (2011) raise the concern that the integration of intermittent RES may endanger system reliability, for which a political solution is desirable. Other authors, too, already claim that political intervention in the electricity markets may be inevitable in order to address the problems arising with further deployment of renewables (e.g. Hildmann et al., 2015; Cludius et al., 2014; Steggals et al., 2011; Traber and Kemfert, 2011)

Hence, the integration of intermittent RES, which depend heavily on weather conditions, brings about several market distortions that may impede investment in 'dispatchable' thermal power plants – plants that are able to adjust output in response to changing economic conditions and market incentives. The literature highlights decreasing wholesale prices as a response to more RES as one form of distorted investment

[8] A small thought-experiment may underline this development: in an electricity system that is entirely driven by zero-marginal-cost-renewables the wholesale price would drop to zero, rendering any investment unprofitable.

[9] The Economist, February 25, 2017, "A World Turned Upside Down", `https://www.economist.com/briefing/2017/02/25/a-world-turned-upside-down`, accessed on 10.09.2018.

signals. Furthermore, a depression in the peak/off-peak price spread reduces the times for which peak-load plants are in the merit order, given their relatively high marginal costs. The problem becomes particularly pronounced when the wind blows during times of low electricity demand, which yields even negative prices at the power exchange, so that conventional plants lose money. Moreover, a lower utilization rate of thermal plants makes further investments unprofitable. In a system where the real-time balance between supply and demand is a prerequisite for the system stability, large shares of intermittent renewable energy production pose considerable challenges for grid operators.

However, the deployment of RES may not be the sole reason for decreasing investment activity in peak-load generation assets. Depressed investment activity may also be the result of an initial state of over-capacity, which is an inevitable feature of even healthy electricity markets. Since electricity cannot be stored in large amounts, supply has to meet demand at all times. Therefore, enough capacity reserve must be available in the system to meet peak demand (Joskow and Tirole, 2007) or to offset supply disruptions (Genc and Thille, 2011). During times of "normal" demand, over-capacity is thus a typical phenomenon. Indeed, Hogan (2017) even raises the possibility that over-capacity is the sole reason for missing investment incentives: "Most, if not all, of the financial distress currently plaguing many European and North American generation markets can easily be traced to overcapacity [...]. Sometimes claims of 'missing money' are just rent-seeking in disguise." Similarly, Praktiknjo and Erdmann (2016) construe the decline in investment in electricity generation capacity as a typical market reaction due to missing investment incentives, also pointing to over-capacity as a driving force. From this perspective, it is particularly relevant to control for excess capacity in an econometric investment regression.

To countervail the risk of a blackout in the long-run by securing adequate investment in conventional electricity generation technologies, the need for policy intervention and/or a revision of the current market design is emphasized in the literature. Cramton and Ockenfels (2012) propose capacity markets as a potential solution to the threefold problem of missing investment in times of increasing electricity demand, aging power plants that may retire, and investments becoming more risky due to political uncertainty and increasing volatility of wholesale prices as a consequence of erratic growth of intermittent RES. Capacity markets seek to guarantee resource adequacy by ensuring payment for holding enough capacity reserves together with the recall option to retrieve the capacity (e.g. at the spot price plus a strike price). A theoretical underpinning of the need for capacity markets is provided by Creti and Fabra (2007). Taking subsidized RES into consideration, Brown (2018) finds in a theoretical model that without capacity payment mechanisms underinvestment in electricity generation capacity occurs, and that capacity auctions are a way to alleviate the problem (although in that model optimal capacity

installations cannot be encompassed).

However, as European electricity markets are strongly interconnected (Gugler et al., 2018), there are concerns about unilateral policies, such as the implementation of national capacity markets. Instead, cross-border capacity markets based on market incentives are desired (Erbach, 2017). Other policy measures that may ensure a reliable electricity provision are, for example, fostering research in energy storage in order to mitigate and better adjust the volatility of RES supply to the demand, or to make final demand more price elastic (e.g. through smart metering) so that it better reacts to wholesale price spikes during scarcity events. Praktiknjo and Erdmann (2016) propose a demand-side approach that grants a monthly monetary premium to representatives of the demand side (e.g. industrial customers, retailers, balancing responsible parties) depending on their share of intermittent RES in their sales portfolio. According to the authors, such a "pull mechanism" on the demand side gives "market forces the opportunity to find innovative and flexible solutions that are likely to be precisely tailored to accommodate larger shares of renewables" (Praktiknjo and Erdmann, 2016, p. 102).

In any case, the subsidization of intermittent RES in European electricity markets creates a distortion of market forces that leads to insufficient investment signals for conventional back-up capacity through inadequate wholesale prices. Against this backdrop, this paper adds to the debate about the potential threat of intermittent renewables on the supply security by empirically investigating the impact of renewables on conventional generation capacity in terms of direction and magnitude.

3 Empirical Strategy

This empirical section aims at estimating the impact of RES on investment in conventional electricity generation capacity. First and foremost we are interested in the effect of the production share of wind and solar in total electricity production. A higher feed-in from intermittent RES may bring about significant effects on investment activity, as it is essentially electricity production (and its interplay with demand) that determines the electricity price and consequently the utilization rates of conventional plants.

Our main hypothesis for empirical examination is that RES have a negative effect on investment in peak-load generation capacity, such as oil and gas plants, because these technologies make up the steep part of the merit-order curve and are therefore most likely influenced by shifts of the supply curve due to changes in the supply from RES. However, we expect the investment activity in base-load capacity to react insensitively to changes in RES. The reason is that base-load technologies, such as hydro, nuclear, and some forms of coal, are located in the flat part of the supply curve, which may not be severely influenced by supply shifts induced by RES.

We follow the related literature that estimates investment in electricity markets (e.g. Gugler et al., 2013, 2016; Cambini and Rondi, 2010) and consider the following dynamic investment model:

$$I_{i,t} = \alpha I_{i,t-1} + \beta RES_{i,t} + X'_{i,t}\gamma + X'_t\delta + \zeta T + \upsilon_i + \epsilon_{i,t}, \tag{1}$$

where i and t denote the country and year, respectively. The dependent variable $I_{i,t}$ denotes either the investment rate of peak-load or base-load capacity. We include a lagged dependent variable $I_{i,t-1}$ to account for the possibility that investment in one year may be systematically followed by capacity additions in the next year. Our main coefficient of interest is β, which measures the effect of the production share of intermittent renewables (RES). $X_{i,t}$ is a set of control variables that vary across countries and time, whereas X_t contains control variables that are variant over time but not between countries. The time trend T (T=1 in 2004, ... T=13 in 2016) controls for changes in the dependent variables that are unobserved (and thus not captured by the right-hand-side variables) but constant across countries (e.g. technological progress). In a robustness specification we include year fixed effects instead of the time trend, which however forces us to drop X_t from the regression due to perfect multi-collinearity. The country fixed effects υ_i take up unobserved country heterogeneity that is time-invariant, while the error term $\epsilon_{i,t}$ captures random shocks. All regressions include heteroskedasticity robust standard errors that are clustered at the country level to account for serial correlation.

Because we apply a fixed effects model, which demeans all variables (i.e. for each variable the within-country means are subtracted from the actual values), identification is solely based on the within-country variation.[10] Hence, it is important that our variables have sufficient variation over time within their groups (i.e. per country). Thus, Table A1 decomposes the standard deviations of all relevant variables within and between groups. It is clear from this table that all variables employed in the analysis indeed exhibit significant within-country variation.

In our standard application of equation (1) we run OLS with fixed effects (OLS-FE). However, the inclusion of a lagged dependent variable may yield biased estimates under OLS and render the fixed-effects estimator inefficient (see, e.g., Nickell, 1981; Arellano and Bond, 1991).[11] We therefore apply the LSDVC estimator for unbalanced panels (Bruno, 2005a) that builds on previous work by Bun and Kiviet (2003), Kiviet (1995), and Kiviet (1999). The LSDVC estimator is designed for panels where N is small (Bruno, 2005b). In

[10] For example, Wooldridge (2002, p. 296) mentions that the fixed-effects estimator "is also called the within estimator because it uses the time variation within each cross section."

[11] Nickell (1981) shows that not only might the coefficient of the lagged dependent variable be biased (due to a correlation of the lagged dependent variable and the contemporaneous error term), but if the other regressors are correlated with the path-dependent variable, the dynamic panel bias might spread on their coefficients as well.

our case, the number of countries is relatively small (N=14), whereas the sample spans a relatively long period of T=13 years (2004–2016). Other estimators, such as the Anderson-Hsiao estimator (Anderson and Hsiao, 1982), difference GMM (Arellano and Bond, 1991), or system GMM (Arellano and Bover, 1995), are designed for panel datasets with large N but small T. Judson and Owen (1999) suggest that the bias-adjusted LSDVC estimator is a suitable choice if T is relatively large (in their case $T = 20$), although GMM (and the Anderson-Hsiao estimator) seem to perform well, too. Bruno (2005b) carries out Monte Carlo simulations for samples of $N = 10, T = 40$ and $N = 20, T = 20$ and concludes that the bias-corrected LSDVC outperforms GMM estimators. Hence, besides OLS-FE, we run equation (1) by LSDVC to account for potential bias arising from the path-dependency of the investment variable. Given the above discussion, we believe that this is the most appropriate estimator for our analysis.[12] However, for the sake of completeness, we also apply GMM.

4 Data

For the purpose of estimating the investment model, as presented in equation (1), we utilize panel data on installed electricity generation capacities from Platts PowerVision, which we combine with data from various sources, such as the International Energy Agency, the OECD, the BP Statistical Review of World Energy, the World Bank, and the Fraunhofer Institute. Our estimation sample includes 14 European countries (Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain, Sweden, Switzerland, United Kingdom) for the period 2002–2016. However, as the investment rate uses the change from year t to year t-1 (relative to t), we lose one sample year. Moreover, the inclusion of a lagged dependent variable takes out another year. Hence, the regression sample pans over 2004–2016.

We obtained data on electricity generation capacity for various generation technologies (distinguished by their primary fuel and turbine type) from Platts PowerVision, a major independent data and information provider for energy and commodity markets. The data are structured for the individual plant level and distinguish between different plant types. For this analysis, we have aggregated the capacity data to the country level at an annual frequency. Moreover, we place the individual generation types into the following technology classes: peak-load generation capacity consists of all types of gas and oil plants (although oil plants amount to a negligible share); base-load capacity consists of hydro-

[12] Since LSDVC requires stationarity of individual time series when estimated with level data, we perform an Im-Pesaran-Shin panel unit-root test, which automatically chooses the lag length based on the Bayesian information criterion (BIC). The H_0 of a panel-unit root is rejected at the 1% level. Similarly, Fisher-type panel unit-root tests based on the Adjusted Dickey-Fuller approach with both zero and one lag reject the H_0 of a panel unit-root.

electric, nuclear, waste, geothermal, and coal plants;[13] intermittent renewable capacity consists of installed wind and solar capacities; capacity from other technologies encompasses pump storage plants and undefined capacity. We then use these data to create measures of base-load and peak load investment rates as $I_{g,c,t} = (K_{g,i,t} - K_{g,i,t-1})/K_{g,i,t-1}$, where g denotes the technology (peak or base), i represents the country, and t is the year.

Data on electricity production from different technologies were retrieved from the International Energy Association (IEA) Database on Energy Statistics. These data are structured at the country-year level and allow for creating a measure of wind and solar production as a percentage of total production ($\text{RES}_{\text{GenShare}}$). In additional regressions, we also disentangle (the percentage shares of) wind ($\text{WIND}_{\text{GenShare}}$) from solar ($\text{SOLAR}_{\text{GenShare}}$) to asses their impacts separately.

In the regressions, we control for over-capacity in the system, which we assume to have a negative influence on the decision to invest in peak-load generation capacity. Since the storage of large amounts of electricity is technically and economically not feasible (for the time being), there must be enough excess capacity in the system to be able to meet the highest peak demand.[14] Thus, the various European electricity markets are characterized by significant over-capacities. Our data allow for creating a measure of over-capacity, which we define as the difference between the maximum possible output under full capacity utilization during each hour per year and the actual annual electricity output as a percentage of the maximum possible output: $OverCap = (K_{total} * 365 * 24 - G_{total})/(K_{total} * 365 * 24) * 100$.[15] We include our measure of over-capacity lagged by one year in our regressions to avoid a potential simultaneity bias as the dependent variable (investment in peak-load capacity) and the over-capacity variable are both derived from capacity. Indeed, over-capacity turns out to be crucial in our regressions as without this variable the effect of intermittent RES on peak-load capacity investment will be significantly overestimated by around 25 percentage points (i.e. coefficients range from -0.77 with OLS-FE to -0.73 with LSDVC, while the other coefficients stay robust; see Appendix Table A5).

[13] Hydroelectric, waste and geothermal power have not been included as renewable energy sources due their non-intermittent nature. In our context, these generation sources are better viewed as base-load technologies.

[14] With the increasing promotion of international electricity market integration (Gugler et al., 2018), the need for national overcapacity becomes less pressing.

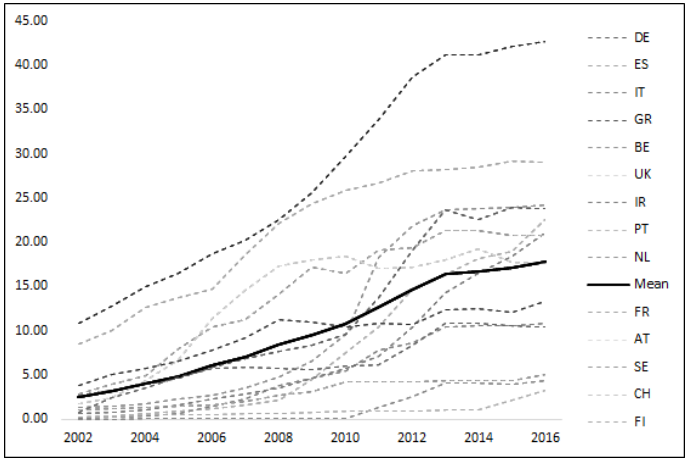
[15] Another suitable measure would be the electricity generation capacity relative to the peak load, called the "reserve margin" (Joskow, 2007). Unfortunately, we lack *hourly* load data for our sample of 14 countries over the long time period 2002–2016 necessary for determining the peak demand (i.e. the maximum load per year). Nevertheless, our measure of over-capacity may still be useful to test whether or not over-capacity has a negative effect on investment in peak-load plants.

Table 1: Sample statistics

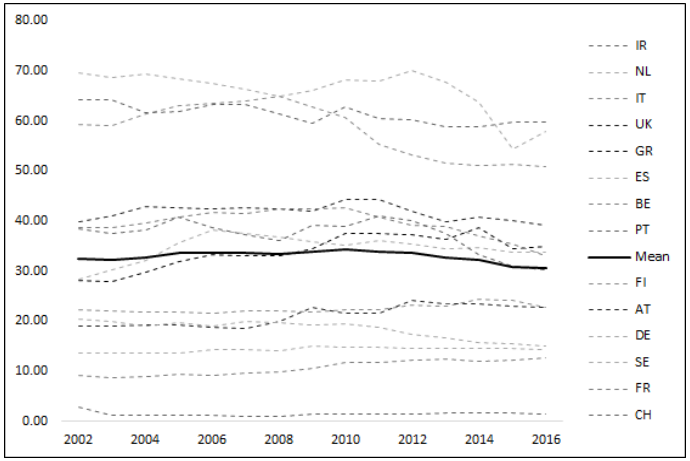
Variable	Description	Mean	Std. Dev.	Min.	Max.
K_{total}	Total capacity (MW)	50,383	45,932	5,982	172,863
K_{base}	Base-load capacity (MW)	24,684	25,313	1,474	90,504
K_{peak}	Peak-load capacity (MW)	15,232	15,746	201	59,840
K_{res}	Wind & solar capacity (MW)	7,851	14,158	9	73,351
K_{other}	Other capacity (MW)	2,616	2,558	0	8,464
I_{peak}	$(K_{peak,t}-K_{peak,t-1})/K_{peak,t-1}\cdot 100$ (%)	2.51	6.89	-18.05	28.13
I_{base}	$(K_{base,t}-K_{base,t-1})/K_{base,t-1}\cdot 100$ (%)	-0.04	4.91	-19.47	47.40
$RES_{CapShare}$	$K_{res}/K_{total}\cdot 100$ (%)	11.25	9.73	0.05	42.72
G_{total}	Total generation (GWh)	203,488	192,463	25,569	648,394
G_{res}	Wind & solar generation (GWh)	13,788	21,435	24	117,932
G_{wind}	Wind generation (GWh)	10,800	15,560	6	79,206
G_{solar}	Solar generation (GWh)	2,989	7,029	0	38,726
$RES_{GenShare}$	$G_{res}/G_{total}\cdot 100$ (%)	6.70	6.64	0.04	24.18
$WIND_{GenShare}$	$G_{wind}/G_{total}\cdot 100$ (%)	5.60	5.73	0.01	23.25
$SOLAR_{GenShare}$	$G_{solar}/G_{total}\cdot 100$ (%)	1.10	1.99	0.00	8.11
OverCap	Share of overcapacity (%)	53.67	9.07	35.82	71.57
GDPpc	Real GDP per caita (1000 $)	38.796	7.366	23.313	63.192
P_{gas}	Gas spot price ($/mBtu)	5.03	2.13	2.46	8.85
P_{eex}	EEX electr. spot price (€/MWh)	41.58	10.75	26.26	66.77

Note: The sample statistics are provided for the 182 country-year observations during the period 2004–2016 as employed in the main regression.

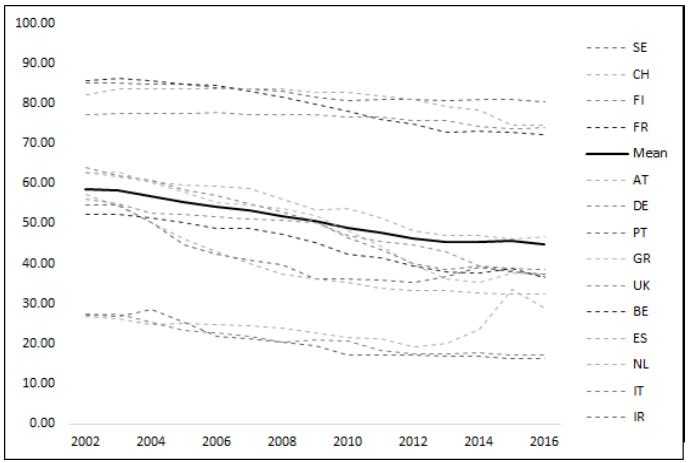
Figure 2: Capacity and generation shares



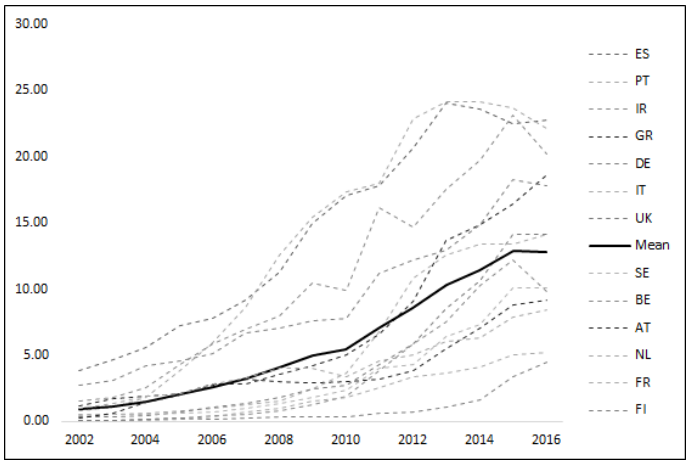
(a) Share of RES capacity (%)



(c) Share of peak-load capacity (%)



(b) Share of base-load capacity (%)



(d) Share of RES feed-in (%)

Note: The countries in the legend are sorted according to 2016 values in descending order.

We include the real GDP per capita (expenditure approach) in our regressions to account for country specific business cycles and changes in aggregate demand. The variable is denominated in US dollars at constant prices (base year is 2010) and was retrieved from the OECD database on national accounts. Moreover, we aim at controlling for input prices, since these are likely to affect investment behavior. An increase in fuel prices may hamper investment in thermal power plants. As input prices are not available for individual countries, we apply international spot price data that vary over time but not across countries. *Spot* prices are applied for two reasons: (i) they represent the opportunity cost to futures prices, and (ii) peak-load plants may buy at the spot market for short-term production decisions, whereas futures prices may be more suitable to capture long-term base-load production decisions. We use the commodity price of gas, namely the annual mean Henry Hub natural gas spot price (in US Dollars per mBtu[16]), as obtained from the BP Statistical Review of World Energy 2017.

Moreover, we include the wholesale price of electricity, which we expect to have a positive influence on investment decisions because a higher wholesale price makes electricity production more profitable. Unfortunately, individual spot price data from the countries' power exchanges are not available for a time period as long as our sample (2002–2016).[17] For this reason, we apply the (volume weighted) annual mean EPEX day-ahead spot price for the German-Austrian price zone as a proxy for the price of wholesale electricity for all countries in our sample.[18] The data are provided by the Fraunhofer Institute for Solar Energy Systems (ISE).

Table 1 provides sample statistics for all variables employed in this analysis, as well as the underlying capacity and generation data to create the investment rates and renewable shares. Table A1 in the Appendix gives correlations of the main variables and indicates that multi-collinearity is not an issue.

Figures 2a–2c show the developments of the capacity shares of RES, base-load and peak-load technologies, respectively, as percentages of total installed capacity. Figure 2a depicts a substantial build-up of solar and wind generation capacity over the sample period, from a low 2.50% in 2002 to 17.80% in 2016. Germany is paving the way with a dramatic increase in installed wind and solar capacity from 10.85% in 2002 to 42.72% in 2016. Unlike Germany, Finland, Switzerland, Sweden, and Austria have invested significantly below average in wind and solar power, most likely because of their endowment with a vast amount of hydro-power, so that for these countries the 2020 climate targets are already achieved.

Figure 2b shows that essentially all but one country (the Netherlands) face a constantly

[16] Million British thermal units

[17] Many power exchanges were only established during the late 2000s or early 2010s.

[18] Gugler et al. (2018) show that all individual European day-ahead electricity spot price series are highly correlated.

decreasing base-load capacity share. On average, base-load generation capacity fell from 58.70% in 2002 to 44.93% in 2016. Moreover, Figure 2c indicates, on average, a fairly stable development of peak-load capacity, with a slight increase from 32.44% in 2002 to 34.45% in 2010, followed by a slight decrease to 30.65% in 2016. Yet, the variation across countries is greater compared to the base-load capacity shares. At fist sight, one may draw the conclusion that peak-load capacity hardly reacts to the massive deployment of intermittent renewables, whereas base-load capacity decreases due to increasing RES. This univariate analysis, however, seems to be misleading, as we will show in Section 5, when we present estimates based on multi-variate regressions. In other words, once we control for a set of confounding factors in the regressions, we find that peak-load investment indeed reacts negatively to intermittent renewables. By contrast, base-load's reaction turns out to be statistically insignificant.

Finally, Figure 2d presents the development of RES *feed-in* as a share of total generation. On average, the production of electricity from wind and solar technologies has been increasing steadily from 0.91% in 2002 to 12.81% in 2016, coinciding with the capacity build-up presented in Figure 2a. However, comparing the two figures gives a hint about the actual capacity utilization rates of RES. While Germany has by far the highest share of wind and solar generation capacity installed in Europe, Spain, Portugal, Ireland, and Greece outperform Germany in terms of RES generation shares, most likely due to more favorable climate and weather conditions.

5 Results

5.1 Main Results

In this section, we present regression estimates of the impact of the share of wind and solar production on investment activity in peak-load electricity generation capacity by estimating the dynamic investment model, as presented in equation (1). Table 2 presents the regression estimates from three estimators, namely OLS-FE, LSDVC, and GMM-Diff. Specification 1 applies OLS-FE, as the baseline regression. In Specification 2, we include year fixed effects instead of the time trend as well as the spot price of gas and the wholesale price of electricity, which are invariant across countries. The idea is that year fixed effects control for any unobserved shocks that are common to all economies in our sample but are variant over time (e.g. technological progress, changes in installation costs of electricity generation technologies, etc.). As mentioned in Section 3, OLS-FE does not address potential bias from the lagged dependent variable. Thus, in specification 3 we perform LSDVC – our preferred estimator – which controls for bias from path-dependency. Finally, to check for robustness, specification 4 presents estimates from one-step difference

GMM, which uses internal instruments (lags of the exogenous control variables and further lags of $I_{peak,t-1}$) to account for dynamic panel bias.[19] Wherever possible (i.e. OLS-FE, GMM), we apply heteroskedasticity robust standard errors clustered at the country level. However, for the LSDVC estimator clustering standard errors is not feasible, which is why we present normal standard errors (based on 1000 bootstrap replications).[20]

We can see that the coefficient estimate of the main variable of interest, $Res_{GenShare}$, stays robust and statistically significant across specifications in a narrow range of -0.471 to -0.524. The interpretation is that an increase in the share of intermittent RES by 10 percentage points reduces the rate of investment into peak-load capacity by 4.85 percentage points (c.f. specification 3). In economic terms, this estimated elasticity is non-negligible and may pose a threat to the electricity supply security, given the relatively strong negative reaction of peak-load investment to RES feed-in.

If we expect a similar development of the renewables generation share for the near future as has been observed over the last 5 sample years in the magnitude of an additional 4.25 percentage points (i.e. from 8.56% in 2012 to 12.81% in 2016), investment activity in peak-load plants would be expected to fall by 2.06 percentage points (= 4.25 percentage points × 0.485). Evaluated at the last sample year's investment rate in peak-load generation capacity of -2.47%,[21] we predict a significantly negative investment rate of -4.53% in the near future. Given the strong positive trend in RES feed-in well above the sample average in some European countries, one may expect in such cases that the fall in peak-load investment will be even more pronounced. The potentially dramatic long-term consequences of a negative investment rate of -4.53% per annum may be best illustrated by its exponential behavior, which implies that within only five years peak-load capacity is expected to decrease by about 20% ($(1-(1-0.0453)^5) = 20.69\%$).

On June 26, 2018 the EU Parliament revised its initial renewables target for 2030 from 27% to 32% renewables in the *gross final consumption* of its Member States. Regarding the *electricity sector*, Banja and Jegard (2017, p. 2) state that "in 2030 the EU needs to meet 54% of its gross electricity generation needs using renewable technologies" and "to reach the 2030 target the EU will need to increase its current renewable electricity installed capacity by 90%." Assuming that a large proportion of these RES capacity add-ons will be met by wind and solar power – the scope for further hydro plants is largely

[19] Roodman (2009) warns that in panels with many years, the number of instruments in GMM applications tends to explode, which may cause the estimator to deviate from the asymptotic ideal, and that the Hansen J-statistic may produce "implausibly good p-values of 1.000" (p. 98). Hence, we restrict the instruments to one lag. Indeed, the p-value of the Hansen J-statistic turns out statistically insignificant (i.e. the H_0 of valid instruments cannot be rejected) at 0.784, which is still far from unity.

[20] We use the user-written Stata command `xtlsdvc`, which does not have a built-in option for clustering standard errors.

[21] The investment rate in peak-load electricity generation capacity over the most recent sample years is as follows: 2014 = -2.52%, 2015 = -2.08%, 2016 = -2.47%.

Table 2: Effect of RES generation share on investment in peak-load capacity

	(1) OLS-FE I_{peak}	(2) OLS-FE I_{peak}	(3) LSDVC(AB) I_{peak}	(4) GMM-Diff(1 lag) I_{peak}
$I_{peak,t-1}$	-0.0475	-0.0817**	-0.0040	-0.0007
	(0.0343)	(0.0348)	(0.0560)	(0.0389)
$RES_{GenShare}$	-0.5186**	-0.5237*	-0.4845**	-0.4716***
	(0.1844)	(0.2463)	(0.2197)	(0.1746)
$OverCap_{t-1}$	-0.3781**	-0.3487**	-0.3684**	-0.4083***
	(0.1361)	(0.1449)	(0.1631)	(0.1334)
GDPpc	0.0876	0.3026	0.0817	-0.0368
	(0.2823)	(0.2512)	(0.2429)	(0.3360)
P_{gas}	-1.4161***		-1.4037***	-1.1971***
	(0.4057)		(0.4237)	(0.4282)
P_{eex}	0.1156**		0.1085**	0.0970**
	(0.0420)		(0.0497)	(0.0441)
T	-0.1396		-0.1745	-0.0422
	(0.2137)		(0.3340)	(0.2229)
Country FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	No
Obs.	182	182	182	168
R^2	0.294	0.347	NA	NA

Notes: $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$. OLS-FE & GMM: Robust standard errors clustered at the country level in parentheses. LSDVC: standard errors in parentheses. Specification (2): LSDVC uses the Arellano–Bond (AB) consistent estimator to initialize bias correction; standard errors are based on 1000 parametric bootstrap iterations with bias correction up to O(1/T). Specification (3): One-step difference GMM is applied. The estimation is in first differences and thus corresponds to the inclusion of country fixed effects. A limit of 1 lag and an orthogonality condition is imposed to keep the number of instruments low. Hansen J-stat. p-value = 0.784. Arellano-Bond test for AR(1): p-val. = 0.004 & AR(2): p-val. = 0.650.

exhausted; biomass and biogas have still not reached technological maturity and only make up a negligible fraction of the energy mix – we expect further massive deployment of intermittent RES in Europe.

Our econometric finding is consistent with Traber and Kemfert (2011), who show in a computational model that an increase in RES production (in their case only wind but not solar) leads to lower incentives to invest in thermal and especially gas-fired power plants. Once flexible thermal generation capacity becomes sufficiently scarce, the balancing of fluctuations in the electricity supply or demand becomes particularly difficult. Furthermore, the supply of electricity becomes even more volatile and unpredictable with an increasing deployment of intermittent RES. Without countervailing measures (see a

discussion in Section 6) the significantly negative response of investment in peak-load capacity to RES deployment may pose a threat on the electricity supply security in the long run.

The estimates are surprisingly robust across specifications: LSDVC and GMM-Diff, which we apply to correct for potential bias from the inclusion of a lagged dependent variable on the parameter estimates of the other variables, are particularly alike. OLS with fixed effects delivers similar results to the bias-corrected LSDVC estimator and difference GMM. However, we find that OLE-FE produces slightly more pronounced estimates of the variable of interest, $\text{RES}_{\text{GenShare}}$, which may indicate modest bias. Nonetheless, the parameter estimates are statistically not different from each other, so statistically we cannot confirm dynamic panel bias in our regressions.[22] This may be explained by the fact that the coefficient of the lagged dependent variable is close to zero and statistically insignificant (so path dependency and the bias that comes with it are negligible) but also that the bias is likely to vanish in panels covering a relatively large number of years (Arellano, 2003, p. 86). LSDVC is based on the Arellano-Bond (AB) estimator to initialize bias correction. To provide evidence that the results are not subject to this choice, specifications 1 and 2 of Table A4 in the Appendix gives the estimates of LSDVC based on the Anderson-Hsiao (AH) method as well as on the Blundell-Bond (BB) method.

Regarding GMM, we apply the one-step difference GMM estimator, for which we restrict the instrumentalization of the lagged dependent variable to one lag (see also footnote 19) to avoid issues created by too many instruments. The p-value of 0.784 of the Hansen J-statistic suggests that the instruments are valid (i.e. the H_0 of valid instruments cannot be rejected). To provide robustness, specification 3 of Table A4 in the Appendix presents GMM-Diff estimates where we relax the restriction to 2 lags. Although the GMM results are fully robust, yet the p-value of the Hansen J-statistic becomes 1.00, which may indicate too many instruments (Roodman, 2009).

We now turn to the estimates of the control variables by looking at the LSDVC regression output. Over-capacity is negative and statistically significant suggesting that a higher share of excess capacity in the system is associated with less investment in peak-load generation capacity. An increase in the over-capacity by 10 percentage points leads to a drop in the peak-load investment rate by 3.68 percentage points. Indeed, it turns out that it is crucial to control for excess capacity because otherwise we would overestimate the effect of $\text{RES}_{\text{GenShare}}$. Appendix Table A5 yields an estimated coefficient of $\text{RES}_{\text{GenShare}}$ of -0.732 by omitting OverCap.

[22] We evaluate the difference between the estimated coefficients of $\text{RES}_{\text{GenShare}}$ from specifications 1 ($\hat{\beta}_1$) and 3 ($\hat{\beta}_3$) based on a z-value: $z = (\hat{\beta}_1 - \hat{\beta}_3)/\sqrt{SE(\hat{\beta}_1)^2 - SE(\hat{\beta}_3)^2} = (-0.5186 + 0.4845)/\sqrt{0.1844^2 + 0.2197^2} = -0.0002$. The critical value for the 90% significance value is -1.96, so we cannot reject the H_0 of equal coefficients.

In line with expectations we find statistically significant effects of the price of gas and the wholesale price of electricity on the investment rate in peak-load electricity generation capacity. A higher factor price of natural gas (P_{gas}) attenuates the profitability of investments and thus hampers investment activity. In contrast, a higher wholesale price of electricity (P_{eex}) triggers investment for the opposite reason (see also Gross et al., 2010). The effect of GDP per capita is positive – a higher level of income is associated with deeper investment activity in peak-load capacity – but turns out to be statistically insignificant. The time trend, which captures unobserved effects, such as technological change, is also statistically insignificant.

As discussed earlier, the significantly negative impact of electricity production from intermittent RES on investment in *peak*-load plants confirms our initial suspicion. However, we expect the impact on investment in *base*-load technologies to be less pronounced, for the reason that not only the merit-order effect (i.e. the reduction of the electricity price due to an increase in the RES production), but also a lower capacity utilization rate, and a decrease in the peak/off-peak price spread from higher RES feed-in all unfold in the steep part of the supply curve, where peak-load plants are located. Indeed, the effect of RES on investment in base-load technologies is negative but statistically insignificant, as the regression estimates of specifications 1 and 2 of Table A3 in the Appendix show.[23]

Since in this study, we group hydro, nuclear, geothermal, waste, and coal generation sources in the base-load category, one may suspect that *coal* in particular exhibits some peak-load characteristics, as it is located at the beginning of the steep part of the merit-order curve. However, specifications 3 and 4 of Table A3 still yield statistically insignificant coefficient estimates for the RES generation share when specifically investigating its impact on investment in coal-fired plants. Our finding that peak-load rather than base-load capacity is vulnerable to the deployment of intermittent renewables is also emphasized by Graf and Marcantonini (2017) who find that emission factors of peak-load (but not of base-load) plants react to the intermittency of RES feed-in through an increasing ramping activity.[24]

5.2 Distinction between wind and solar

So far, we have been interested in the overall effect of intermittent RES on investment in peak-load electricity generation capacity. We now disentangle the individual effects of wind and solar generation by replacing RES in equation (1) with the generation shares

[23] The regressions for the investment rate in base-load capacity include the spot price of gas for the sake of comparability with the regressions on peak-load investment, whereas the spot price of coal may be more adequate. When we include the spot price of coal instead, the results stay robust.

[24] Ramping refers to the adjustment of thermal plants' electricity generation to balance demand and supply deviations (e.g. through unpredictable generation fluctuations of wind and solar plants), which has negative effects on their emission factors.

of wind (WIND) and solar (SOLAR):

$$I_{i,t} = \alpha I_{i,t-1} + \beta_1 WIND_{i,t} + \beta_2 SOLAR_{i,t} + X'_{i,t}\gamma + X'_t\delta + \zeta T + \upsilon_i + \epsilon_{i,t}. \qquad (2)$$

Table 3 presents the regression output of equation (2) by OLS-FE (specification 1) and LSDVC (specification 2). Both specifications yield comparable estimates. They show clearly that, while the generation share of wind has a negative and statistically significant influence on investment in peak-load power plants, the effect of solar power is rendered statistically insignificant. It seems that the overall modest generation output of solar power of 2,989 GWh and its low generation share of 1.10% on average (see Table 1) have not yet resulted in a reaction in the peak-load investment activity.

In contrast to solar power, wind power already has a significant share in the overall electricity mix of 5.6% and a feed-in of 10,800 GWh, on average. As wind power increases its share, this brings about a significant drop in peak-load investment. An increase in the wind feed-in share of 10 percentage points leads to a fall in the investment rate of peak-load plants by 5.61 percentage points. Analogously to the calculations made in Section 5.1, we can assess the impact of a further deployment of wind power for the near future assuming a similar development to the past 5 sample years. The share of wind power rose from 6.92% in 2012 to 9.85% in 2016, which corresponds to an increase of 2.93 percentage points. Given the estimated elasticity of -0.561 of WIND, we expect the investment rate in peak-load generation capacity to fall by 1.64 percentage points (= 2.93 percentage points × 0.561). Evaluated at the investment rate in peak-load generation capacity of -2.47% as of the last sample year 2016, the expected peak-load investment rate for the near future is -4.11%, driven solely by the deployment of wind energy.

These findings are comparable to Luňáčková et al. (2017) and Mulder and Scholtens (2013). Luňáčková et al. (2017) find no evidence for a merit-oder effect of solar power on the Czech wholesale electricity prices but indeed for wind and hydro power. The authors explain that the few sunshine hours per year in the Czech Republic, during which solar power shifts the merit order, are not enough to result in a (statistically) significant merit order effect. Mulder and Scholtens (2013) find that wind power in Germany has a decremental effect on the Dutch wholesale prices (given the strong interconnection between the two electricity markets), whereas no such effect is found for solar power. For Italy, a Mediterranean country with more favorable sunshine conditions, Clo et al. (2015) find that the merit order effect of solar power is only half as pronounced as of wind power. From this perspective, it is hardly surprising that our study does not find a decremental effect of solar power on investment in conventional electricity generation capacity.[25]

[25] In our sample, only four out of 14 countries can be characterized by favorable sunshine conditions (Greece, Italy, Portugal, Spain).

Table 3: Distinction between wind and solar generation shares

	(1) OLS-FE I_{peak}	(2) LSDVC(AB) I_{peak}
$I_{peak,t-1}$	-0.0464	-0.0038
	(0.0317)	(0.0551)
WIND	-0.6013***	-0.5607**
	(0.1766)	(0.2333)
SOLAR	0.0674	0.0861
	(0.3435)	(0.4321)
$OverCap_{t-1}$	-0.4638***	-0.4553***
	(0.1455)	(0.1691)
GDPpc	0.1936	0.1875
	(0.2274)	(0.2632)
P_{gas}	-1.5286***	-1.5149***
	(0.4105)	(0.4354)
P_{eex}	0.1296***	0.1225**
	(0.0430)	(0.0496)
T	-0.1867	-0.2194
	(0.2202)	(0.3330)
Country FE	Yes	Yes
Year FE	No	No
Obs.	182	182
R^2	0.302	NA

Notes: $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$. OLS-FE: Robust standard errors clustered at the country level in parentheses. LSDVC: standard errors in parentheses. LSDVC uses the Arellano–Bond (AB) consistent estimator to initialize bias correction; standard errors are based on 1000 parametric bootstrap iterations with bias correction up to O(1/T).

From a policy perspective, this is evidence that the threat of underinvestment in peak-load electricity generation capacity is most pressing with regard to wind power, whereas solar power has not yet elicited in a statistically significant reaction in the investment activity. We conclude that wind power has a non-negligible negative effect on investment in conventional peak-load plants, which may eventually result in a shortage of flexible power units that are able to meet demand and supply variations. Ironically, the vast deployment of intermittent wind power requires precisely such dispatchable backup power plants.

5.3 Alternative specification: direct unit effects

As a robustness specification, we run a similar model as in equation (1), where we estimate the impact of RES feed-in in GWh (instead of the percentage share in total generation) on the peak-load capacity in MW (instead of the percentage share in total capacity):

$$K_{peak,i,t} = \alpha K_{peak,i,t-1} + \beta G_{res,i,t} + X'_{i,t}\gamma + X'_t\delta + \zeta T + \upsilon_i + \epsilon_{i,t}, \tag{3}$$

This model, thus, allows for a more direct interpretation of the effect of interest in terms of unit changes. β tells by how many MW the peak-load capacity ($\mathrm{K_{peak}}$) changes in reaction to an increase in the generation of RES ($\mathrm{G_{res}}$) by one GWh. What is more, in an alternative specification, we replace $\mathrm{G_{res}}$ by the wind feed-in, $\mathrm{G_{wind}}$.

Table 4 presents the estimates of both the effects of RES generation as well as the effects of wind generation on peak-load capacity. Again, OLS-FE and LSDVC lead to similar results, suggesting that the dynamic panel bias is not an issue. The LSDVC estimator in specification 2 shows that an increase in the generation of renewables by one GWh reduces the peak-load generation capacity by 0.019 MW. Moreover, specification 4 shows that the effect of an increase in the wind generation by one GWh is associated with a peak-load capacity reduction of the magnitude of 0.027 MW. These effects are to be interpreted along the lines of Section 5.1. Over the last five sample years, RES generation rose by 8,306 GWh (i.e. from 18,004 GWh in 2002 to 26,310 GWh in 2016). Assuming a similar trend in the near future, peak-load capacity is expected to decline by 157.8 MW (= 8,306 GWh $\times$ 0.019), which accords to a drop of 1% of the sample mean peak-load generation capacity of 15,562 MW in 2016. Regarding wind, the last five sample years experienced an increase in the feed-in by 5,642 GWh (i.e. from 13,168 GWh in 2012 to 18,811 GWh in 2016), which leads to a predicted decline in the peak-load capacity by 152 MW (= 5,642 MW $\times$ 0.027), a similar effect as with total RES (i.e. combined wind and solar power).

Table 4: Alternative specification: direct unit effects

	(1) OLS-FE K_{peak}	(2) LSDVC(AB) K_{peak}	(3) OLS-FE K_{peak}	(4) LSDVC(AB) K_{peak}
$K_{peak,t\text{-}1}$	0.8542***	0.8976***	0.8482***	0.8928***
	(0.0233)	(0.0266)	(0.0162)	(0.0269)
G_{res}	-0.0165*	-0.0190***		
	(0.0081)	(0.0065)		
G_{wind}			-0.0225**	-0.0267***
			(0.0098)	(0.0103)
$OverCap_{t\text{-}1}$	-28.1693*	-29.5545	-32.7408**	-34.8724*
	(13.9212)	(18.4877)	(13.8664)	(18.1754)
GDPpc	-1.3597	9.6514	-2.9601	8.4805
	(26.2720)	(29.4544)	(27.8756)	(29.6959)
P_{gas}	-115.0920**	-107.4813**	-117.6943**	-110.2636**
	(51.5914)	(51.3889)	(49.5473)	(51.6168)
P_{eex}	26.3437***	24.0725***	27.2903***	25.0211***
	(6.4740)	(6.1435)	(6.5528)	(6.1705)
T	16.0498	4.9949	20.4747	10.1899
	(24.3444)	(34.2697)	(22.7917)	(34.8158)
Obs.	196	196	196	196
R^2	0.916	NA	0.9151	NA

Notes: $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$. OLS-FE: Robust standard errors clustered at the country level in parentheses. LSDVC: standard errors in parentheses. LSDVC uses the Arellano–Bond (AB) consistent estimator to initialize bias correction; standard errors are based on 1000 parametric bootstrap iterations with bias correction up to O(1/T).

6 Conclusion

In an electricity system where the real-time balance between supply and demand is a prerequisite for system stability, large shares of intermittent renewable energy production pose considerable challenges for grid operators. Many studies have warned that the current state of European electricity markets, characterized by a massive subsidization of fluctuating wind and solar power, distorts price signals for sufficient investment in conventional back-up electricity generating capacity. Along with other adverse effects of RES, this may pose a threat to resource adequacy in the long-run.

Intermittent RES create several distortions, which may deter investment in conventional power plants, such as a decreasing wholesale price (i.e. the merit order effect), lower operating hours of peak-load plants as they get pushed out of the merit order when RES feed in, and a dampened peak/off-peak price spread, which renders thermal plants with high marginal costs unprofitable. However, the very intermittency of RES creates the need for flexible backup units, such as gas-fired power plants, to support the system. Dispatchable weather-independent power plants are especially important during times of high electricity demand when there is no wind or sunshine. Underinvestment in conventional electricity generating capacity may endanger the supply security of electricity and thus increase the risk of a blackout.

Although the idea that RES distort investment incentives is well-established, sound economic studies on this subject are scarce. For this reason, we put the potentially negative effect of the deployment of intermittent RES on investment in flexible thermal power capacity to empirical scrutiny by estimating a dynamic investment model. We find a non-negligible impact, pointing to significant disinvestments in peak-load capacity in the foreseeable future. Besides other important control variables, such as factor and wholesale energy prices, we emphasize the need to control for over-capacity, as otherwise the negative effect of RES on the investment rate in peak-load capacity would be overstated. To circumvent the potential estimation bias in dynamic models (i.e. the inclusion of a lagged dependent variable) that may arise with fixed-effects OLS, we also apply the bias-corrected LSDVC estimator as well as difference GMM. Both approaches provide consistent estimates. Moreover, we subject our regression results to robustness tests by employing alternative estimators and model specifications.

While investment in peak-load capacity is significantly deterred by volatile RES, we provide evidence that base-load, and especially coal-fired generation capacity, which is located in the rather flat part of the merit order curve, is not affected by RES feed-in. Moreover, we show that most of the threat of intermittent RES on the long-run supply security stems from wind power, whereas the relatively low feed-in from solar power during our sample period 2002–2016 appears not to have caused a statistically significant

reaction.

Given the targets of the European Union to foster investment in wind and solar power at least until 2030, our results ought to raise concerns about the long-run viability of the electricity system. Assuming a similar deployment of RES as over the last five sample years, we predict a negative annual investment rate of the magnitude of -4.53% for the near future. This rate implies tremendous disinvestment in conventional thermal plant capacity of around 20% within only 5 years.

Policy-makers should be aware of the alarming threat of underinvestment. State intervention targeted at incentivizing investment in conventional back-up capacity (e.g. through capacity markets) or simply direct state aid (e.g. in the form of investment and feed-in subsidies for gas-fired plants), as well as a redesign of current European electricity markets, may be inevitable to guarantee the reliability of electricity supply. With further deployment of RES, electricity storage and transmission may become more cost effective. Both are needed to relief the system by mitigating renewables' uncertain generation volatility.

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Appendix

A Additional Tables and Figures

Table A1: Decomposition of standard deviations between and within countries

Variable	Mean	SD overall	SD between	SD within
I_{peak}	2.510	6.890	1.968	6.622
$Res_{GenShare}$	6.703	6.638	4.930	4.623
OverCap	53.666	9.069	7.290	5.712
GDPpc	38.796	7.366	7.271	2.212
P_{gas}	5.028	2.131	0.000	2.131
P_{eex}	41.581	10.755	0.000	10.755

Table A2: Correlation matrix of main variables

	(1)	(2)	(3)	(4)	(5)
(1) I_{peak}					
(2) $Res_{GenShare}$	-0.2471				
(4) OverCap	-0.0536	0.6512			
(5) GDPpc	-0.0681	-0.3077	-0.1579		
(6) P_{gas}	0.1752	-0.4708	-0.4221	-0.0150	
(7) P_{eex}	0.1825	-0.2647	-0.1751	0.0058	0.5964

Table A3: Impact of RES on investment in base-load and coal generation capacity

	(1) OLS-FE I_{base}	(2) LSDVC(AB) I_{base}	(3) OLS-FE I_{coal}	(4) LSDVC(AB) I_{coal}
$I_{base,t-1}$	-0.2051***	-0.1603**		
	(0.0491)	(0.0729)		
$I_{coal,t-1}$			-0.1023	-0.0655
			(0.0937)	(0.0720)
$RES_{GenShare}$	-0.1182	-0.1170	0.0292	0.0259
	(0.2666)	(0.1804)	(0.4499)	(0.3398)
$OverCap_{t-1}$	0.0164	0.0157	-0.2224	-0.2153
	(0.1799)	(0.1392)	(0.4499)	(0.2628)
GDPpc	-0.0102	-0.0118	-0.0086	-0.0108
	(0.0835)	(0.2067)	(0.2521)	(0.3899)
P_{gas}	-0.3261	-0.3103	-1.3012*	-1.2477*
	(0.3191)	(0.3614)	(0.6114)	(0.6787)
P_{eex}	0.0106	0.0101	0.1422	0.1406*
	(0.0488)	(0.0421)	(0.0886)	(0.0791)
T	-0.0135	-0.0054	-0.4847	-0.4597
	(0.2744)	(0.2786)	(0.4656)	(0.5234)
Country FE	Yes	Yes	Yes	Yes
Year FE	No	No	No	No
Obs.	182	182	182	182
R^2	0.040	NA	0.058	NA

Notes: $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$. OLS-FE: Robust standard errors clustered at the country level in parentheses. LSDVC: standard errors in parentheses. Specification (2): LSDVC uses the Arellano–Bond (AB) consistent estimator to initialize bias correction; standard errors are based on 1000 parametric bootstrap iterations with bias correction up to O(1/T).

Table A4: Main specification: alternative estimators

	(1) LSDVC(AH) I_{peak}	(2) LSDVC(BB) I_{peak}	(3) GMM-Diff(2 lags) I_{peak}
$I_{peak,t\text{-}1}$	0.0027	0.0037	-0.0026
	(0.0578)	(0.0574)	(0.0409)
$RES_{GenShare}$	-0.4577**	-0.4951**	-0.4727***
	(0.2286)	(0.2414)	(0.1777)
$OverCap_{t\text{-}1}$	-0.3653**	-0.3825**	-0.4065***
	(0.1710)	(0.1798)	(0.1339)
GDPpc	0.0960	0.0803	-0.0275
	(0.2548)	(0.2694)	(0.3306)
P_{gas}	-1.4066***	-1.3947***	-1.2311***
	(0.4447)	(0.4565)	(0.4127)
P_{eex}	0.1075**	0.1072**	0.0990**
	(0.0521)	(0.0536)	(0.0441)
T	-0.2075	-0.1479	-0.0584
	(0.3491)	(0.3643)	(0.2160)
Country FE	Yes	Yes	Yes
Year FE	No	No	No
Obs.	182	182	168
R^2	NA	NA	NA

Notes: $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$. GMM: Robust standard errors clustered at the country level in parentheses. LSDVC: standard errors in parentheses. LSDVC: AH uses the Anderson-Hsiao estimator, BB uses the Blundell-Bond estimator to initialize bias correction up to O(1/T); standard errors are based on 1000 parametric bootstrap iterations. GMM: One-step difference GMM is applied. The estimation is in first differences and thus corresponds to the inclusion of country fixed effects. A limit of 2 lags plus an orthogonality condition is imposed for the instrumentalization. Hansen J-stat. p-value = 1.00. Arellano-Bond test for AR(1): p-val. = 0.031 & AR(2): p-val. = 0.481.

Table A5: Main results excluding over-capacity

	(1) OLS-FE I_{peak}	(2) LSDVC(AB) I_{peak}
$I_{peak,t\text{-}1}$	-0.0595	-0.0150
	(0.0365)	(0.0558)
$RES_{GenShare}$	-0.7726***	-0.7321***
	(0.1240)	(0.1960)
$OverCap_{t\text{-}1}$	x	x
GDPpc	0.2585	0.2509
	(0.1775)	(0.2235)
P_{gas}	-1.4596***	-1.4527***
	(0.4401)	(0.4239)
P_{eex}	0.1251**	0.1182**
	(0.0462)	(0.0498)
T	-0.3934	-0.4259
	(0.2435)	(0.3007)
Obs.	182	182
R^2	0.268	

Notes: $^{***}p < 1\%$, $^{**}p < 5\%$, $^{*}p < 10\%$. OLS-FE: Robust standard errors clustered at the country level in parentheses. LSDVC: standard errors in parentheses. LSDVC uses the Arellano–Bond (AB) consistent estimator to initialize bias correction; standard errors are based on 1000 parametric bootstrap iterations with bias correction up to O(1/T).