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Investment opportunities, uncertainty, and renewables in European electricity markets☆

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ABSTRACT

We investigate investment decisions in electricity generation technologies under uncertainty. The econometric analysis is based on a vast dataset of electricity generation capacities of virtually all European power plants, which we combine with disaggregated measures of investment opportunities and uncertainty. Our approach allows for a disaggregated analysis at the asset level (i.e. different electricity generation technologies) of the firm. Across technologies, we find investment to follow market incentives despite sunk and irreversible capital, confirming the implications of the Tobin's q-model. Asset-specific uncertainty hinders investment in conventional technologies, especially in peak-load assets, while industry uncertainty even triggers investment. Given that renewable power replaces peak-load generation technologies and that investment incentives decrease over time, our results indicate that there may be under-investment in the long run.

1. Introduction

Investments in electricity generation capacity are irreversible, sunk, and generally take considerable time to build. Moreover, in the last decade European electricity markets have been characterized by a transition towards decarbonization with significant government intervention. Electricity prices have decreased significantly and the system has become more volatile as a result (Sinn, 2017). During times of high renewables production, residual demand for conventional generation technologies drops, decreasing their capacity utilization and profitability. This may withhold large-scale investments, and may eventually create a 'missing money problem' for investment in conventional technologies (Joskow, 2007). Conventional technologies, however, are still needed as a backup for intermittent renewables and other low-carbon technologies to ensure supply security. Understanding the main determinants of electricity generation-capacity investment bears thus importance beyond academia, since electricity is one of the keys to the success of the energy transition to a decarbonized system as a response to climate change.

In this article, we empirically investigate the determinants of physical investment decisions with regard to different electricity generation technologies in Europe. For this purpose, we focus on an investment equation based on the neoclassical investment theory, and extend it for *industry* as well as *firm-asset*[1] specific uncertainty. This issue has not been investigated thus far. We estimate electricity

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[1] We refer to different electricity generation technologies as assets.

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utilities' likelihood of investing in particular electricity generation technologies by means of a logistic model. In additional regressions, we also acknowledge the *potential endogeneity* of both asset-specific uncertainty as well as investment opportunities with the investment decision and apply a *control function approach* (i.e. residual inclusion) with exogenous instruments. Moreover, we run regressions, where we additionally control for the deployment of intermittent renewable power, which may add further uncertainty to the system, as well as a measure for the system reliability (i.e. the capacity reserve during peak load, called “reserve margin”), since over-capacity may hinder investment. Also, we acknowledge that the investment decision may follow inherently different driving forces than the disinvestment decision, which would potentially bias the estimates of an ordered multinomial logit model, in which all three outcomes, investment, no investment, and disinvestment are included. Thus, we show that our results stay consistent once we truncate disinvestment and solely focus on investment versus no investment observations.

Our paper stands out by its rich and unique panel data at the firm-asset level of 437 major electricity-generating utilities located in 13 European countries for the period 2006–2014.[2] This disaggregation level goes beyond other empirical investment papers. We calculate a disaggregate measure of uncertainty specifically for each firm's electricity generation technologies. Likewise, we calculate a measure of investment opportunities in the spirit of Tobin's q for firms' particular assets. In contrast to other measures of q based on stock market data, as widely applied in the literature, we create a measure of q based on fundamental values, which are not subject to bubbles, fads, and expectations.

One important empirical finding is that our measure of Tobin's q is indeed able to stimulate investment, which supports the notion of the q-model. This finding holds at the firm level and for conventional generation technologies (i.e. base and peak load plants, and gas plants in particular). Our finding is academically important, since it indicates that the relative failure of the q-model to explain investment empirically may be due to measurement error of q. For example, Dixit and Pindyck (1994, p. 419) state that “constructed quantities that in theory should have strong explanatory power – such as Tobin's q (…) – in practice do not.” So far, Tobin's q has been measured either at the wrong granularity level (e.g. at the firm level and not at the firm-asset level) and/or using stock market data that may deviate from fundamental values and may also contain other factors, such as speculations, unrelated to investment opportunities. We circumvent both problems by measuring q based on fundamental values from a standard electricity market supply side model at the respective granularity level. That is, using data on all power plants in Europe, we calculate marginal costs by generation technology for each firm, assess the electricity produced by each generation technology of the firm, and combine these with data on wholesale electricity prices. This allows us calculating a firm's cash flows from producing electricity for each generation technology. With standard assumptions on future cash flow profiles, life-spans of the respective generation technology, and discount factors as well as on the replacement costs of the generation capacities in place, we calculate a *fundamental q value* by generation technology, firm, country, and year.[3] Our results are also important from an economic policy perspective, since they imply that electricity wholesale markets are able to incentivize investment in generation capacity despite the presence of irreversibility, long time-to-build lags, and sunk capital. We observe a dramatic decline of average q's in recent years in electricity generation in Europe, which is most pronounced for gas.[4] Thus, our findings on the importance of q for investment together with its dramatic decline document a substantial reduction in investment activity.

We also calculate proxies for uncertainty at fine disaggregation levels. We use the stochastic part of a cash-flow function and calculate *disaggregate* uncertainty as the conditional variance of these unforeseeable components. In addition, we measure *aggregate* uncertainty as the variance of the wholesale electricity spot price that hits *all* firms in a market. Our measures of aggregate and disaggregate uncertainty find significant but opposing effects on investment activity in electricity generation capacity. Disaggregate uncertainty curtails the likelihood to invest, as found at the firm level and in particular for peak-load plants. This result is consistent with Dixit and Pindyck (1994) stating that there is a value associated with waiting, so that irreversible investments will be delayed with uncertainty. Industry-specific uncertainty, on the contrary, supports investment at the firm level, especially in base-load generation technologies (e.g. run-of-river hydro, nuclear, and coal-fired power plants), which is consistent with Bar-Ilan and Strange (1996), assuming that if aggregate uncertainty augments the value of being active in the future, it accelerates investment when lags force a firm to decide in advance whether to be active in the future or not. Electricity generation with its long time-to-build lags clearly fits this picture.

The literature argues that with well-functioning markets, price signals ensure optimal investment, even with extreme price spikes during low capacity (Roques et al., 2005), whereas distortions from government intervention create a threat of underinvestment in peak-load technologies in Europe (Jamasb and Pollitt, 2005; von der Fehr et al., 2005) and the USA (Joskow, 2007). Bar-Ilan and Strange (1996) and Leautier (2016) emphasize the peculiarities of investment in electricity generation, such as “boom-bust” cycles, lumpiness (long time-to-build), irreversibility, and sunkness. There is a general dissatisfaction with empirical papers that try to explain investment according to the q-model, as they hardly find large positive effects (see e.g. the survey by Chirinko, 1993). Reasons include the difficult measurement of fundamental investment opportunities at a proper level of disaggregation (e.g. at the firm-asset level) (Leahy and Whited, 1996; Schwert, 2002), and that the q-model does not perform well when irreversibility is in place (Scaramozzino, 1997). We add to this literature by empirically showing that an appropriately measured q is an important determinant of investment even in an industry characterized by sunk investments.

The empirical and theoretical literature is inconclusive about the effects of uncertainty on investment. A preponderance of arguments and findings point to a negative effect of uncertainty on investment, whereas the convexity of the marginal product of capital (Abel, 1983) and the existence of opportunity costs of delaying investments (Bar-Ilan and Strange, 1996) may explain a positive relationship. The need for distinguishing between disaggregate investment opportunities and different types of uncertainty (e.g. aggregate versus firm-level or even technology-level uncertainty) is emphasized (Carruth et al., 2000; Hubbard, 1994). While many studies focus on aggregate uncertainty (e.g. Campa and Goldberg, 1995; Eisfeldt and Rampini, 2006; Ferderer, 1993; Gilchrist and Himmelberg, 1995; Goldberg, 1993; Pindyck, 1988), few investigate disaggregated uncertainty

[2] Our dataset covers around 95% of total generation capacity of these countries.

[3] For example, we divide the (discounted) financial value of a firm's particular generation asset by an appropriate measure of replacement costs (namely the purchase price of the technology times its capacity) to avoid typical criticism of using replacement costs based on balance sheet data, such as that a firm operating in a high inflation environment the cost of replacement will be higher relative to a low inflation environment.

[4] While base-load technologies observe q's between one and two in the beginning of the sample period, they fall below one in 2014. Peak-load technologies, such as gas plants, witness q's between 4 and 6 in the starting years, but see a dramatic decline in the following years.

at the firm level (e.g. Bulan, 2005; Ghosal and Loungani, 1996, 2000; Guiso and Parigi, 1999; Leahy and Whited, 1996; Minton and Schrand, 1999); no study has yet investigated the investment-uncertainty nexus at an even further disaggregation level (e.g. at the asset-level) as we do. With respect to investment in electricity generation, many studies investigate regulatory uncertainty (Cambini and Rondi, 2010; Mulder, 2008; Roques et al., 2005) but do not provide a more general picture of uncertainty. We add to the investment and irreversibility literature in that we empirically show that different types of uncertainty bring about diverse effects.

2. Investment theory and empirical model

The neoclassical "working house" model of the determinants of investment is the Tobin's q model (Tobin, 1969). Under the q-model, the firm invests whenever the expected value of the shadow price of capital (the marginal benefit of investment) is larger than the purchase price of new capital (relative to the price of output), i.e. whenever marginal Tobin's q is larger than one. Adjustment costs to the new optimal capital stock mitigate the reaction to any given discrepancy in a given period. For our empirical purposes, we put average Tobin's q, defined as the ratio of a firm's financial value (V) to the replacement cost of its existing capital stock ($p_I \cdot K$), where K is the capital stock and p_I is the purchase price of new capital (relative to the price of output), in the investment equation:

$$q_{avg} = \frac{V}{p_I K} \tag{1}$$

Thus, the q-model of investment implies that whenever q_{avg} is larger than unity, the firm should invest. The problem with the "naive" q-model of investment is that it makes two assumptions, which are unlikely to hold in our case of electricity generation investment. First, it assumes that capital can be sold easily to other users (i.e. that capital is reversible), and second that each investment opportunity is a once and for all opportunity. Yet, in our setting of electricity generation, investments are irreversible, sunk, lumpy and are characterized by a long time-to-build. Thus, we need to account for these characteristics and augment the standard neoclassical investment model.

2.1. Irreversibility, uncertainty and investment

Dixit and Pindyck (1994) state that there is a value associated with delaying investments so *investments will decrease with uncertainty*. This is particularly relevant if investment decisions entail sunk costs (e.g. because investment is irreversible) and therefore future returns are uncertain. By investing, the firm forgoes the option of delaying the investment, which is clearly costly. Incorporating uncertainty in the q-model, the firm invests only if q_{avg} exceeds unity by a certain margin: This applies if the discounted future revenue from an additional unit of capital exceeds the purchase price by at least the lost option value to delay.[5] This would imply that the coefficient on q is biased towards zero reflecting both a range of inaction by the firm if the option value to wait exceeds the necessary margin and the true effect of q.[6]

To test whether there is a direct effect of (some forms of) uncertainty on investment we add uncertainty measures to the q-equation (see Eq. (2)).[7] The coefficient may be negative if an increase in uncertainty raises the benefit of waiting but not its opportunity costs in the presence of irreversible and sunk costs. There may, however, exist a countervailing effect of uncertainty if there are "time-to-build" lags, i.e. if there is an interval of time between the decision to invest and the receipt of the project's first revenues (see Bar-Ilan and Strange, 1996). The intuition is as follows. With investment lags and the option to abandon, the opportunity cost of waiting also increases with uncertainty. If uncertainty raises the value of being active during a future period, it accelerates investment when lags force a firm to decide in advance whether to be active or not in the future. Thus, increased uncertainty may also mean that there may be high demand and/or a high price in the future, and a non-investing firm may not benefit from these peaks if the project has a long time-to-build.[8]

2.2. Forms of uncertainty

"Uncertainty" comes in a variety of ways, however. One useful distinction is between aggregate (macro- or industry-level) uncertainty and disaggregated uncertainty specific to the firm or even specific to certain asset classes of the firm.[9] *Disaggregated uncertainty* can be analyzed in the spirit of Dixit and Pindyck (1994): if the firm delays investment, it can reduce exposure to an adverse shock and preserves the option to invest. Thus, an increase in firm-specific (or firm-generation-technology-specific) uncertainty should unambiguously undermine investment incentives, for the reason that the option value to wait increases for those specific firm-assets. However, the analysis may differ with respect to industry-wide uncertainty. If aggregate uncertainty increases for given firm- or firm-asset-specific uncertainty, this effect is equal for all firms in the industry and firms may invest more, since there is a larger value of

5 Hubbard (1994) elaborates on the determinants of the size of this wedge. First, as uncertainty about future returns rises, the wedge also rises (because the option value to wait increases). Second, an increase in the discount rate increases the wedge (because if the future is valued less, the present value of the project paying off in the future declines). Third, an increase in the trend value of growth increases the wedge (because the project is more valuable if realized in the future).

6 Abel and Eberly (1997) show that the option values are increasing in the time-invariant level of uncertainty suggesting that the responsiveness of q to investment should decrease with the level of uncertainty. Bloom et al. (2007) describe the effects of uncertainty such that both fewer units or types of capital will invest (the extensive margin) and each unit or type that does invest will invest less (the intensive margin). Moreover, the option to wait and do nothing is more valuable for firms that face a higher level of (demand) uncertainty. Bloom et al. (2007) test this proposition by including an interaction term between uncertainty and demand growth in their investment equation. They find not only that as uncertainty rises, firms cut investment rates but also that they respond less to investment opportunities. When we include such an interaction term in the regressions below, we find corroborating evidence to Bloom et al. (2007), i.e. the sensitivity of investment to investment opportunities declines with (firm-level) uncertainty.

7 Abel and Eberly (1994) show theoretically that investment depends only on marginal q and the capital stock, so that uncertainty affects investment only through marginal q. Indeed, Leahy and Whited (1996) find that uncertainty mainly enters through Tobin's q because for an inclusion of q the uncertainty measure becomes insignificant. We find a separate direct channel of influence of uncertainty on investment.

8 Tishler et al. (2008) provide another rationale for a possible positive effect of uncertainty (in their case measured by demand volatility) on investment particularly relevant for electricity generation. On the one hand, an increase in demand volatility increases the percentage of time during which capacity is idle reducing optimal capacity; on the other hand, it increases the maximum value of the price, which in turn increases optimal capacity. The first effect dominates when volatility is small (there is not much to gain from higher price spikes), the second effect dominates when volatility is high (there is a lot to gain from an increase in price spikes). Hence, with increased uncertainty, investment in electricity-generating capacity may increase the benefit from high price spikes. Still another rationale is due to Kulatilaka and Perotti (1998), who explain that greater uncertainty will lead to higher investments if there is scope for strategic competition, which offers room to acquire options to grow. Finally, a positive effect of uncertainty on investment may be due to a general convexity of the profit function.

9 Hubbard (1994, p. 1818) asserts that this distinction "must" be made!

being active in a future period and/or there are more gains from an increase in price spikes.

2.3. Investment model

Before arriving at the main specification of our investment equation, two important aspects of the data generating process in electricity generation investment have to be discussed. First, investments in electricity generation are lumpy, i.e. they come in bursts. This implies that periods of zero investment are followed by a large increase in capacity when a new generation plant is connected to the grid. Of course, the "zeros problem" becomes aggravated for smaller companies operating only a few plants and/or when we estimate the investment equation at a finer aggregation level (i.e. generation-technology level). As many zero values may introduce biases (Nilsen and Schiantarelli, 2003), we employ an ordered logit model where the dependent variable is coded as zero for disinvestment, one for no investment, and two for investment. Compared to other empirical literatures (e.g. EC, 2015; Kim et al., 2012) that estimate tobit models and, thus, have to truncate or recode disinvestments, our ordered logit model allows for the inclusion of disinvestment. Our main specification therefore reads:

$$\begin{aligned}\Pr[I_{f,g,c,y} = i] = \Pr[c_{i-1} < \beta_1 I_{f,g,c,y-1} + \beta_2 \log(q_{f,g,c,y}) + \beta_3 \log(CVarCF_{f,g,c,y}) \\ + \beta_4 \log(VarP_{c,y}) + \beta_5 T + \upsilon_c + \epsilon_{f,g,c,y} \le c_i] \qquad (2)\end{aligned}$$

Ordered logit models estimate an underlying score as a linear function of the independent variables and a set of cut points ($c_1, \ldots, c_{k-1}$), where k is the number of potential outcomes (i.e. three in our case: disinvestment, no investment, investment). The probability of observing outcome i corresponds to the probability that the estimated linear function, plus random error, is within the range of the cut points estimated for the outcome. c_0 is taken as $-\infty$, and c_k is taken as $+\infty$. The error term ϵ is assumed to be logistically distributed.

The subscripts f, g, c, y denote the firm, generation technology, country, and year, respectively. The dependent variable I denotes the investment category. We control for the fact that investment in one year is systematically followed by investment in the next year by including a lagged dependent variable. q represents Tobin's q at the respective granularity level. $CVarCF$ measures disaggregated uncertainty as the Conditional Variance of the stochastic components (residuals) of the hourly Cash Flows at the respective granularity level (see below and Appendix A for the exact definitions).[10] Thus, Tobin's q and disaggregated uncertainty are measured either at the firm-country level or the firm-generation-technology-country level depending on the estimated equation. $VarP$ is aggregate uncertainty measured as the wholesale spot-price variance. The time trend T is relevant because it captures unobserved changes across time. Among these effect may be policies, which hit all countries in our sample, such as the Large Plant Combustion Directive introduced by the European Commission forcing large thermal power plants (>50 MW) to comply with specific emissions standards or phase out their production (Directive 2001/80/EC). The time trend may also account for a general sentiment against nuclear power or technological progress.

Table 1
Generation technologies.

Technology level	Description	Included technologies
RES	Intermittent renewables	Solar & wind
BASE	Base load technologies	Hydro, nuclear, other renewables (geothermal, biomass, biogas, waste), various forms of coal
PEAK	Peak load technologies	Various forms of gas (GAS) & oil

The country fixed effects, υ_c, capture unobserved but time-invariant heterogeneity across countries. The error term ϵ captures random shocks.[11]

3. Data

3.1. Variables

To estimate the investment equation, we utilize data from various sources to construct a rich and unique panel dataset at the generation-technology level of electricity-generating firms from 13 European countries (i.e. Austria, Denmark, Finland, France, Germany, Hungary, Italy, Norway, Portugal, Slovakia, Spain, Sweden, Switzerland) over the annual period 2006–2014. However, as the regressions use first differences to calculate investment from capacity stocks and a lagged dependent variable, the estimation sample covers 2008–2014. PLATTS PowerVision provides data on European firms' *installed capacities by generation technology*. We combine these data with measures on firms' *investment opportunities* (q) and *disaggregated uncertainty* (i.e. measures for firm- or firm-technology-specific uncertainty), which we derive from a fundamental market model that constructs firms' merit order curves (i.e. supply curves) according to the marginal costs of their installed generation technologies.[12] Additionally, we employ *hourly* data from day-ahead spot markets to obtain the average yearly price variance, as a measure for *industry-specific uncertainty*.

Our data on installed generation capacities also include firms that do not have electricity generation as their core business (e.g. a steal producing firm with its own electricity generation plant). Hence, we drop all firms with total generation capacity of less than 50 MW over the entire sample period to ensure that our sample firms' investment decisions are mainly driven by determinants related to electricity.[13] Also, we exclude pump storage capacity because it represents a storage rather than a generation technology and may thus follow different investment incentives. Our sample includes 437 electricity-generating firms, which cover around 95% of total generation capacity in the 13 countries in 2014. At the firm level, we observe whether a firm invests or disinvests irrespective of which particular technology. Moreover, we dig into a deeper disaggregation level where we distinguish between types of generation technologies (i.e. intermittent renewables, base load, peak load, and gas) within firms, as presented in Table 1. A still finer disaggregation level renders econometric estimation inconsistent as investment/disinvestment observations for some asset classes fall below a meaningful number of observations.

[10] We cannot rule out that vertically integrated firms having both retailing and generation may be better able to hedge against uncertainty. If this were the case, we would overestimate firm-specific uncertainty for integrated firms compared to stand-alone firms, and therefore overestimate the negative effects of firm-specific uncertainty on investment for integrated firms. Unfortunately, we have no data to rule out this concern.

[11] As already mentioned in footnote 6, we also expanded the model by an interaction term of q with firm-specific uncertainty ($\log(q) \times \log(CVarCF)$) and got corroborating evidence to Bloom et al. (2007).

[12] As detailed in Appendix A, we differentiate between 73 types of generation units (combinations of turbine types, fuel types, and construction years) in the underlying data, which are then aggregated for our analysis.

[13] The results stay robust when increasing the threshold to 500 MW.

Table 2
Dependent variable: ordered investment categories.

	FIRM	RES	BASE	PEAK	GAS
Disinvestment (0)	138	4	110	51	41
	(5.1%)	(0.4%)	(5.3%)	(3.6%)	(3.0%)
No investment (1)	1973	713	1665	1203	1189
	(73.5%)	(78.5%)	(79.6%)	(85.7%)	(86.5%)
Investment (2)	572	191	317	149	145
	(21.3%)	(21.0%)	(15.2%)	(10.6%)	(10.5%)
Total obs.	2683	908	2092	1403	1375

Notes: The table shows the number of observations and their percentage shares in total observations (%) regarding the multinomial categories of the dependent variable at the firm and technology level.

3.1.1. Dependent variable

In electricity generation, capacity investments are associated with high sunk costs and thus come in bursts. Hence, the measure of physical investments per firm (and per generation technology) contains many zero values. For this reason, we employ ordered investment categories (0 = disinvestment, 1 = no investment, 2 = investment) as our dependent variable in order to avoid estimation bias towards zero. Table 2 gives an overview about the dependent variable at different aggregation levels. In 21.3% of firm-year observations firms invest in additional capacity, in 5.1% firms disinvest, and for the predominant part of 73.5% no investment takes place.

3.1.2. Investment opportunities (q)

As already mentioned, there are predominantly two problems with the measurement of Tobin's q in the literature. First, it has been measured at a too crude granularity level that does not reflect the actual investment decision (e.g. at the firm level and not at the firm-asset level). Second, the literature is confined to using stock market data that may however deviate from fundamental values and may also contain other factors e.g. market power rents unrelated to investment opportunities. We circumvent both problems by measuring a fundamental q value from a standard electricity market supply side model at the respective granularity level.[14] We use data on all power plants in Europe to calculate marginal costs by generation technology for each firm, assess the electricity produced by each generation technology of the firm, and combine these with data on *hourly* wholesale electricity prices to calculate cash flows (which we eventually aggregate to the annual frequency) from producing electricity for each generation technology and firm. Standard assumptions on future cash flow profiles, life-spans of the respective generation technology, and discount factors as well as on the replacement costs of the generation capacities in place allow us to calculate a *fundamental q value by generation technology*, *firm*, *country and year*.

Applying Eq. (1), our measure of q relates to the value of the generation assets, $\bar{V}$, which we define as the present discounted value of the cash flow stream earned from these assets, relative to their replacement costs, calculated as the purchase price (PP) of the technology times capacity (Cap):

$$q_{f,c,g,y} = \frac{\bar{V}_{f,c,g,y}}{PP_g \cdot Cap_{f,c,g,y}} \tag{3}$$

where the subscript f denotes the firm located in country c; g indicates the generation technology (RES, PEAK, BASE, or GAS), and y stands for the year. We use data on the purchase price of 10 different generation technologies from IEA (2010, 2015).[15]

The value of the generation assets, $\bar{V}$, is generated by cash flows (CF) from selling electricity, the (assumed constant) discount rate (r, which we set at 5%),[16] the (assumed constant) expected inflation rate (i, which we set at 1.7% according to the average rate during our sample period), and the average life-span of a particular technology (n_g):[17]

$$\bar{V}_{f,c,g,y} = \frac{CF_{f,c,g,y}}{r-i} \cdot \left(1 - \frac{(1+i)^{n_g}}{(1+r)^{n_g}}\right) \tag{4}$$

Since our cash flow measure applies daily spot prices to *total* available capacity as the output of the firm, there is no systematic bias in our measure of q as long as spot prices represent the opportunity costs for all of the generating assets of the firms. Indeed, day-ahead spot markets are by far the largest and thus the most relevant markets for wholesale electricity. Even if wholesalers used other channels (e.g. OTC markets, long-term contracts, intra-day or reserve markets), the day-ahead spot market still represents the *opportunity market*.[18] We assume that a firm will decide to produce and sell electricity with its total available capacity at the day-ahead market, as long as the wholesale price exceeds the marginal costs of its generation assets. From this perspective, even if a firm decided to sell some electricity at another market (e.g. the balancing market), in our model the firm obtains its revenue from the spot market. This implies that we treat capacities sold at other markets as if they operated at wholesale markets. Under the assumption that the spot market represents the opportunity market, the bias in our model will be small. Thus, prices (and derived statistics) determined in the day-ahead spot market represent good measures for opportunity costs and benefits for all of the generating assets of the firm.

Fig. 1 depicts a stylized electricity generating firm's supply curve (i.e. marginal costs; mc) and the actual spot price (exogenously determined at the wholesale power exchange; p) in a given hour. We assume that firms generate cash flows from their various types of installed generation capacities if the spot price exceeds their associated marginal costs. If a technology's marginal costs exceed the spot price, we assume that this technology is not running and thus accrues a cash flow of zero for that hour. For intermittent renewables (wind and solar), we also take granted subsidies (s) into account. However, incorporating subsidies into the calculation is a difficult task because of heterogeneous renewables support schemes (e.g. feed-in tariffs, feed-in-premiums, green certificates, investment grants) are in place in different countries and changing support schemes over time. Since we do not have country specific data on subsidy payments for specific generation technologies over time, we take the average RES subsidy payments per MWh (s) at the country-year level, as reported in the annual reports on RES support schemes by the Council of European Energy Regulators (CEER, 2013, 2015), and add these to the spot price (p). That is, s approximates for the cash flows of owners of RES capacities.[19] Thus, we calculate cash flows (CF) in each hour (h) and

[14] This is a state-of-the-art approach in energy economics to infer about marginal costs (see also Burger et al., 2012, chapter 7). We provide a detailed description of our fundamental model in Appendix A (including various data sources, construction of variables, and intuition).

[15] There are other data sources for purchase prices than IEA, e.g. IRENA (2012) or MIT (2009), which however give very similar results.

[16] A discount rate of 5% is approximately what other studies use (IEA, 2010, 2015). When we use different discount rates such as 10% the main results hold up.

[17] We calculated life-spans from PLATTS data as the difference between a plant's online date and retirement date. We distinguish between 73 generation unit types, which we then aggregate to our asset classes (RES, BASE, PEAK, GAS). Our results are robust to life-spans published by IEA (2010, p. 43) and IEA (2015, p. 30).

[18] Puller (2007), for example, also takes day-ahead energy prices as the reference prices. Ortner and Totschnig (2019) evaluate the relevance of European balancing markets and reach the conclusion that their associated revenues and traded volumes are of minor importance relative to day-ahead markets.

[19] This is of course not a perfect measure but just an approximation. Note, however, that the potential measurement error only affects RES but not other technologies.

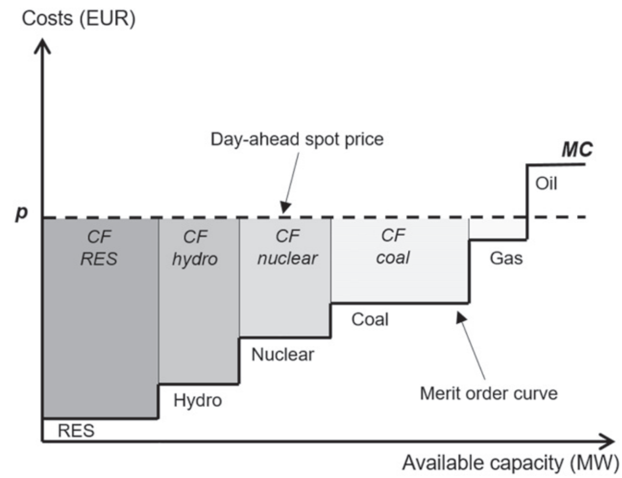

Fig. 1. A stylized firm's cash flows by generation technology. Note: The figure shows a stylized electricity generating firm's marginal cost curve (MC, i.e. merit order curve) in a given hour. The spot price p, which is exogenously determined at the power exchange, determines the firm's cash flows (CF) from its individual generation assets (intermittent RES, hydro, nuclear, coal, gas).

then aggregate over the total number of hours per year (8760 in a normal year and 8784 in a leap year):

$$CF_{f,c,g,y} = \sum_h \begin{cases} (p_{c,h,y} + c_{c,y} - mc_{g,h,y}) \cdot avCap_{f,c,g,h,y} & \text{if } p_{c,h,y} > mc_{g,h,y} \\ 0 & \text{if } p_{c,h,y} \le mc_{g,h,y} \end{cases} \tag{5}$$

We calculate cash flows as the yearly sum of hourly differences between the actual spot price (p) (observed in the country (c) of the firm's location) and the marginal cost (mc) of the firm's generation technology (g) times the available capacity ($avCap$) if the price exceeds marginal costs. Cash flows are assumed to be zero during hours of marginal costs exceeding prices.

Firms' *marginal costs* are calculated for 73 generation unit types (which are combinations of turbine types (tt), fuel types (ft), and construction years (cy)). For this purpose, we take fuel prices (FP), the carbon dioxide (CO_2) price ($CO2P$), emission factors ($CO2E$), and efficiency factors (EF) into consideration (for more details see Appendix A):

$$mc_{tt,ft,cy,h,y} = [FP_{ft,h,y} + (CO2P_{ft,h,y} \times CO2E_{ft})]/EF_{tt,ft,cy} \tag{6}$$

Eventually, we aggregate over turbine types (tt), fuel types (ft), and construction years (cy) to arrive at marginal costs ($mc_{g,h,y}$) for our types of generation technologies (g) in any given hour (h) in a year (y). Appendix B provides an illustration of how we calculate q for one particular firm in our sample (i.e. the German utility E.ON).

3.1.3. Measures of uncertainty

The most common measure of uncertainty is to use stock market data, such as the variance or standard deviation of daily stock returns (see e.g. Bloom et al., 2007; Leahy and Whited, 1996). The disadvantage of using stock returns is that they may be quite noisy reflecting not only changes in fundamentals but also bubbles, fads, and the influence of noise traders. Moreover, measures from accounting data, such as the volatility of realized cash flows require long horizons and may fail to capture uncertainty about future profitability.

We develop a measure of *disaggregated uncertainty* from our above presented calculations of cash flows. We follow Ghosal and Loungani (2000) who assume that firms forecast future profits by the deterministic part of a profit function (that includes two autoregressive terms and a time trend), whereas the unsystematic component measures profit uncertainty.[20] The authors then develop a measure of uncertainty as the volatility of the residuals. Accordingly, we estimate cash flows using Eq. (5) for each firm (f) in country (c) for each generation technology (g) at the hourly frequency (h) as a function of two autoregressive terms, a time trend (T), and firm-fixed effects (γ_f) as well as generation-technology-fixed effects (γ_g):

$$CF_{f,c,g,h} = \alpha_1 CF_{f,c,g,h-1} + \alpha_2 CF_{f,c,g,h-2} + \beta_1 T + \gamma_f + \gamma_g + \epsilon_{f,c,g,h}. \tag{7}$$

We then take the hourly residuals representing the unsystematic components and build the yearly conditional variance to create a measure of *firm-technology-country-specific uncertainty* ($CVarCF_{f,c,g,y}$). $CVarCF$ captures uncertainty (and not risk) as it measures the stochastic part that a firm is not able to predict. At the firm level, the uncertainty measure is weighted by its technologies' available capacities.

We employ the variance of wholesale electricity prices ($VarP$) as an ex ante measure of *industry-wide uncertainty* because the good "electricity" is homogenous (at least what the physical characteristics are concerned), well defined, and equal across companies. Hence, we construct the yearly variances from data on *hourly* day-ahead electricity spot prices from power exchanges of our sample firms' respective countries of location.

3.2. Descriptive statistics

Table 3 presents descriptive statistics of our main variables at the firm level and at the more disaggregated level of four generation technologies (RES, BASE, PEAK, GAS). The mean sample firm has a capacity of 1377 MW. The large standard deviation of 5477 MW indicates significant firm heterogeneity. We observe positive investment at the mean of 39.6 MW, which is reflected by a mean value of the ordinal investment variable of greater than one. This masks however important differences across time. Fig. 2 depicts investment in generation capacity and the mean spot price for 2007–2014. We observe increasing investment until 2010, followed by a decline, which eventually results in negative investment in the last sample year 2014.

The average sample firm generates cash flows from its various generation technologies of 188 mio. EUR per year (not shown in Table 3), the conditional variance, $CVarCF_{f,c,y}$, is 31.39 mio. EUR per year. The mean Tobin's q at the firm level is 1.88, with q-values of renewables and peak technologies of around 2.5, and of base technologies of 1.3. This again masks important differences across time. Fig. 3 depicts the development of the firm-level q over time and at the firm-technology levels of RES, BASE, PEAK, and GAS. While firm level q's hover around three in the beginning of the sample period until 2009/2010, starting with 2010 firm q's declined to around one at the end of the period (2014). A similar pattern but with different levels can be observed for the more disaggregated q's. While base technologies observe q's between one and two in the beginning of the sample period, the average q of base technologies falls below one in 2014. Renewables and peak technologies witness q's between 4

[20] Ghosal and Loungani (1996) follow the same procedure to estimate uncertainty from output prices.

Table 3
Sample statistics.

Variable	Description	Obs.	Mean	S.D.	Min.	Max.
FIRM						
$Cap_{f,c,y}$	Total capacity (MW)	2683	1381.17	5485.98	21.00	84,442.10
$\Delta Cap_{f,c,y}$	Investment (MW)	2683	39.74	388.35	−2563.00	9389.00
$I_{f,c,y}$	Ordered investment categories (0, 1, 2)	2683	1.16	0.49	0.00	2.00
$q_{f,c,y}$	Tobin's q	2683	1.88	1.91	4.69E-06	15.50
$CVarCF_{f,c,y}$	Cond. variance of cash flows (mio. EUR)	2683	31.39	395.77	7.18E-06	12,647.67
$VarP_{c,y}$	Spot price variance (100 EUR/MWh)	2683	387.79	499.61	22.63	4415.82
$Rnwbl_{c,y}$	Wind and solar share (%)	2683	7.61	7.84	0.14	43.26
$Resmarg_{c,y}$	Reserve margin (%)	2452	42.40	14.38	10.16	62.12
RES						
$Cap_{f,c,g,y}$	Total capacity (MW)	908	861.61	4046.35	0.00	35,431.11
$\Delta Cap_{f,c,g,y}$	Investment (MW)	908	102.64	630.44	−1.75	9389.00
$I_{f,c,g,y}$	Ordered investment categories (0, 1, 2)	908	1.21	0.42	0.00	2.00
$q_{f,c,g,y}$	Tobin's q	908	2.46	1.77	0.13	14.31
$CVarCF_{f,c,g,y}$	Cond. variance of cash flows (mio. EUR)	908	65.50	675.18	0.00	12,647.67
BASE						
$Cap_{f,c,g,y}$	Total capacity (MW)	2092	1032.56	5242.95	0.09	82,828.31
$\Delta Cap_{f,c,g,y}$	Investment (MW)	2092	−1.90	93.43	−2223.00	1258.80
$I_{f,c,g,y}$	Ordered investment categories (0, 1, 2)	2092	1.10	0.44	0.00	2.00
$q_{f,c,g,y}$	Tobin's q	2092	1.32	0.67	0.01	4.10
$CVarCF_{f,c,g,y}$	Cond. variance of cash flows (mio. EUR)	2092	5.16	22.13	3E-05	337.49
PEAK						
$Cap_{f,c,g,y}$	Total capacity (MW)	1403	541.27	1237.51	0.00	8740.19
$\Delta Cap_{f,c,g,y}$	Investment (MW)	1403	11.38	113.91	−734.82	1250.00
$I_{f,c,g,y}$	Ordered investment categories (0, 1, 2)	1403	1.07	0.37	0.00	2.00
$q_{f,c,g,y}$	Tobin's q	1403	2.50	3.17	4.69E-06	15.74
$CVarCF_{f,c,g,y}$	Cond. variance of cash flows (mio. EUR)	1403	16.37	67.18	7.18E-06	856.36
GAS						
$Cap_{f,c,g,y}$	Total capacity (MW)	1375	551.86	1247.78	0.44	8740.19
$\Delta Cap_{f,c,g,y}$	Investment (MW)	1375	11.39	114.93	−734.82	1250.00
$I_{f,c,g,y}$	Ordered investment categories (0, 1, 2)	1375	1.08	0.36	0.00	2.00
$q_{f,c,g,y}$	Tobin's q	1375	2.70	3.34	4.69E-06	15.74
$CVarCF_{f,c,g,y}$	Cond. variance of cash flows (mio. EUR)	1375	16.58	67.73	7.18E-06	856.36

Notes: "Obs." is observations, "S.D." is standard deviation, "Min." is minimum, and "Max." is maximum. FIRM represents the firm level, whereas RES, BASE, PEAK, and GAS indicate the disaggregated generation-technology levels of renewables, base load, peak-load, and gas respectively. f, g, c, y stand for firm, generation type, country, and year, respectively.

and 6 in the starting years, but see a dramatic decline in the following years.[21]

Table 4 provides correlations of the main variables employed in our regressions indicating that multi-collinearity is not an issue.

4. Results

We estimate ordered logistic regressions that use the ordinal investment decision as our dependent variable, to account for the zero values problem in our investment data. Generally, logit models estimate the probability of a certain event to happen (e.g. investment). The odds ratio therefore tells the probability to be in a higher investment category (e.g. investment) compared to falling into any of the other categories (disinvestment, no investment). Note that the odds ratio is the exponential of the estimated coefficient of the ordered logistic regression, hence, a positive (negative) coefficient yields an odds ratio greater (smaller) than one.

4.1. Main results

Table 5 presents regression odds-ratio estimates of the investment decision as presented in Eq. (2) from an ordered logit model. Firstly, we focus on the aggregate firm level (specification 1), which does not differentiate across different technologies. We look at the more disaggregated level in specifications 2–4 where we distinguish between three types of generation technologies, namely intermittent renewables (RES), base load technologies (BASE) and peak load technologies (PEAK). Since PEAK incorporates gas and oil plants, where oil has become an obsolete technology that is characterized by disinvestment, we subsequently focus solely on gas in specification 5. Each specification is estimated with heteroscedasticity-consistent standard errors clustered at the firm level.

4.1.1. Firm-country level

At the firm-country level, we see that log(q) has a positive and statistically significant influence on the decision to invest. The odds ratio tells that if q increases by 100%, the odds are 13.4% higher to invest. Contrary to many empirical studies, our findings support the notion of the q-model. Investment in the previous period increases the chances to invest in the next period by 228.1%. Thus, investments come in bursts. The estimated odds ratio of firm-specific uncertainty (log(*CVarCF*)) lies below one and is statistically significant, indicating a negative impact of disaggregate uncertainty on investment. This is corroborative empirical evidence for Dixit and Pindyck (1994), as discussed in Section 2. In contrast, industry level uncertainty (log($VarP_{c,y}$)) has a statistically significant and positive influence on

[21] Since wholesale prices continued to decline in the years 2015–2018 in Europe, average q's are likely to be below one at the time of writing in 2018 for all generation categories with the exception of renewables' q's. In Germany, the country with the most ambitious plans to transform its energy sector, the situation is even more pronounced, since already in the year 2014 all generation categories' q's are below one (except for renewables).

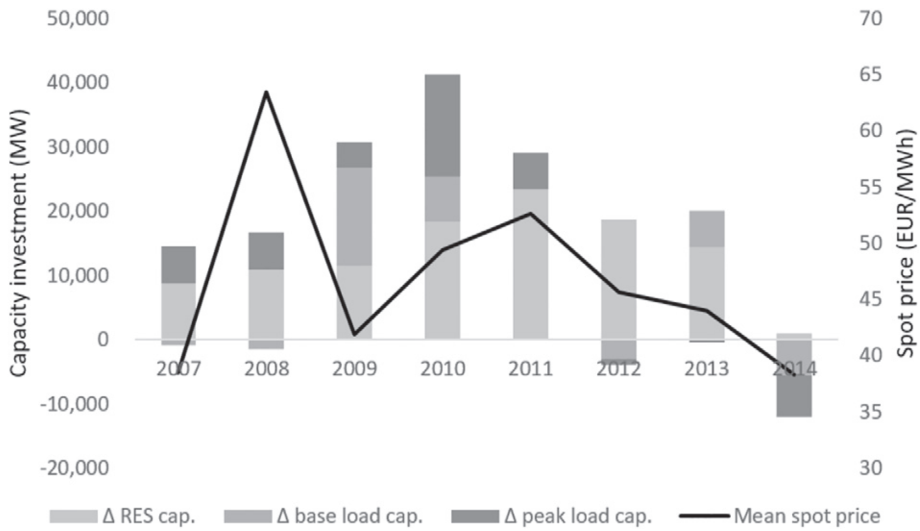

Fig. 2. Capacity investment and spot price.

investment. This indicates that if aggregate uncertainty increases for given firm-specific uncertainty, the individual firm has a higher incentive to invest. Possible explanations are that with more price uncertainty there is a higher value of being active in a future period (Bar-Ilan and Strange, 1996) and/or there are higher gains from more pronounced price spikes (Tishler et al., 2008).[22] Overall, we find the pattern "positive effects of aggregate uncertainty but negative effects of firm-specific uncertainty on investment."

4.1.2. Firm-generation-technology-country level

The findings at the firm level may represent a mixture of diverse investment strategies regarding different types of asset classes, which is why we look at a more disaggregated level of investment. Columns 2–4 of Table 5 investigate investment in intermittent renewables (RES), base-load technologies (BASE) and peak-load technologies (PEAK). Moreover, column 5 provides an isolated look at gas (GAS), which represents the most important peak load technology (whereas oil has become an obsolete technology).

Except for RES, log(q) has a positive and statistically significant impact on the investment decision across technologies. Thus, although base and peak technologies are characterized by sunkness and irreversibility (e.g. long average life-spans and time-to-build lags), we find that investment opportunities trigger investment.

There is an explosive investment in renewables over time, given the high and statistically significant odds ratio of 3.614 on the lagged dependent variable ($I_{f,c,g,y}$), while the estimates for BASE and PEAK are quantitatively weaker. This reflects the large build-up of renewable generation capacity in recent years.

Disaggregated uncertainty (log(CVarCF)) surrounding particular asset classes of a firm has countervailing influences on investment. At the firm level (odds ratio of statistically significant 0.938) and for conventional base- and peak-load technologies (odds ratios of 0.977 but insignificant for BASE; 0.938 and significant for PEAK), we find evidence that disaggregated cash flow uncertainty depresses the likelihood to invest. The negative effect of asset-specific uncertainty is particularly pronounced for investment in gas (odds ratio of significant 0.928). Especially for peak-load technologies, the option value of delaying investment seems to intensify with asset-specific uncertainty. On the contrary, asset-specific uncertainty has a positive effect on investment in renewables. One explanation may be in accordance with Bar-Ilan and Strange's (1996) "good news principle". It may be that delay in investment for renewables is more costly than for other types of generation because of a variety of peculiarities: (i) Renewables generally enjoy subsidized and prioritized feed-in and have marginal costs of essentially zero. Thus renewables generate cash flows whenever possible (e.g. when the wind blows or the sun shines), however they do not suffer from "merit-order-uncertainty" (i.e. they do not fall out of the merit order) as peaking technologies such as gas do. Thus, the negative influence of cash flow uncertainty may diminish.[23] (ii) As a consequence of subsidies, renewables can profit from high price spikes, while negative spikes are largely capped by a granted price. That is, renewables' profit functions may be particularly convex, and the conditional variance of cash flows – our measure for uncertainty – may capture that. (iii) Investments in solar and wind generation technologies are less sunk and take less time to build, so that the option value to wait is lower than for other technologies.

Aggregate uncertainty (log(VarP)) has a statistically significantly positive impact on investment at the firm level and for renewables and peak-load plants, while there is no statistically significant effect for peak-load (and gas-fired) power plants. The estimated odds ratio is highest for RES (1.320). Increasing spot price spikes from higher price variance seem to benefit renewables, because they can keep the rents from spot prices above guaranteed feed-in tariffs while downward spikes are generally capped, which thus increases the odds to invest. For base-load technologies, long investment lags may imply that not only the option value of waiting increases but also the opportunity cost of waiting gets higher with uncertainty (see Bar-Ilan and Strange, 1996). Assuming that aggregate uncertainty augments the value of being active in the future, it accelerates investment when lags force a firm to decide in advance whether to be active in the future or not.

Overall, our results on Tobin's q imply that conventional generation technologies significantly react to investment opportunities, as expected by the neoclassical model of investment. Our results on uncertainty are heterogeneous and explain the pattern at the firm level of a negative impact of disaggregate uncertainty and a positive

[22] Please note that we control for the expected value of the profitability of investment through the inclusion of our q measure.

[23] Indeed, the EC (2015) corroborates this notion, stating that support schemes for renewables have substantially limited investors' risk exposure.

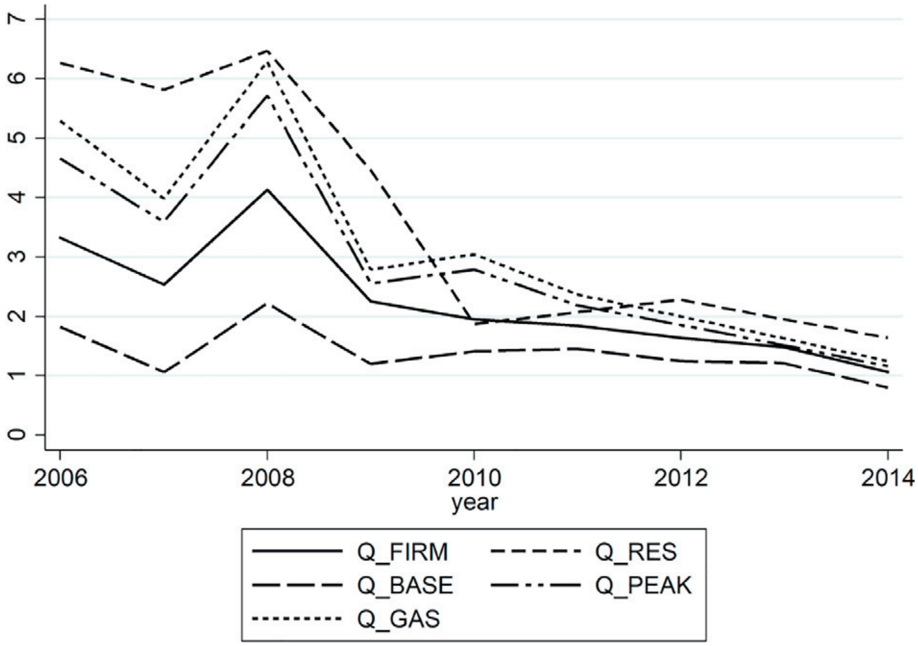

Fig. 3. Mean Tobin's q by generation technology.

effect of aggregate uncertainty. We find that investment in peak-load plants, and especially in gas-fired plants, diminishes with asset-specific uncertainty, whereas investment in renewables increases. Industry-level uncertainty triggers investment in renewables and base-load plants.

4.2. Additions and robustness

4.2.1. Additional influential factors

In order to check for additional potential influential determinants of investment activity, we also investigate the effects of the national share of intermittent renewables and of the national reserve capacity. A country's penetration of electricity from intermittent renewables (i.e. wind and solar production) as a percentage in total production ($Rnwbl_{c,y}$) may introduce some additional uncertainty – e.g. through the implied supply shocks via the generation intermittency of renewables (e.g lower planning reliability), which we did not yet control for. The data at the country-year level stem from the BP Statistical Review of World Energy 2016.

Table 6 shows that the national share of intermittent renewables indeed has a negative and statistically significant influence on investment activity, while the majority of the remaining estimates stay robust in magnitude and in statistical significance. The odds ratios of *Rnwbl* below one indicate that a higher share of intermittent production from wind and solar in total generation lowers the odds to invest in additional generation capacity at the firm level and across all types of technologies (although the effect is statistically insignificant for RES). This is evidence that there is a *substitutive relationship* between renewable penetration in the industry and investment in additional conventional generation capacity. The effect on peak load technologies (gas in particular) may be problematic, as such plants are still needed to back the system (e.g. for dispatching when renewables' production deviates from forecasts or during incidents, such as plant outages). For example, for a country like Germany, the feed-in share of intermittent renewables has three-folded (from 5.14% to 14.95%) between 2006 and 2014. Our estimated odds ratio for GAS of 0.871 implies a reduction in the propensity to invest in gas by around 39% ($= ((1 - 0.871)\cdot 3)\cdot 100$).

A country's *reserve margin*, which measures the difference between the peak generating capacity and the peak demand (Joskow, 2007), may also be important for investment decisions. We quantify the reserve margin ($Resmarg_{c,y}$) as the share of a country's excess capacity during peak demand relative to a country's total installed

Table 4
Correlations of main variables (at the firm level).

	(1)	(2)	(3)	(4)	(5)
(1) $I_{f,c,y}$	1				
(2) $I_{f,c,y-1}$	0.170	1			
(3) $\log(q_{f,c,y})$	0.082	0.048	1		
(4) $\log(CVarCF_{f,c,y})$	0.011	−0.062	0.429	1	
(5) $\log(VarP_{c,y})$	0.084	−0.023	0.383	0.549	1

Notes: The subscripts f, c, y stand for firm, country, and year, respectively.

Table 5
Main results: ordered logit model, odds ratios.

	FIRM	RES	BASE	PEAK	GAS
$\log(q_{f,c,g,y})$	1.134***	0.849	1.313**	1.098*	1.144**
	(0.044)	(0.215)	(0.143)	(0.054)	(0.066)
$I_{f,c,g,y-1}$	2.281***	3.614***	1.547**	1.290	1.707*
	(0.310)	(0.769)	(0.324)	(0.394)	(0.489)
$\log(CVarCF_{f,c,y})$	0.938*	1.183***	0.977	0.938*	0.928**
	(0.033)	(0.031)	(0.019)	(0.031)	(0.031)
$\log(VarP_{c,y})$	1.182**	1.320*	1.171*	0.996	0.925
	(0.088)	(0.187)	(0.097)	(0.120)	(0.117)
Cut point 1	−2.557	−5.114	−1.954	−4.743	−5.188
Cut point 2	1.948	3.254	2.859	1.034	0.873
Country FE	Yes	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes	Yes
Total obs.	2683	908	2092	1403	1375
Investment obs.	572	191	317	149	145
Disinvestment obs.	138	4	110	51	41

Notes: Dependent variable is investment category (0 = disinvestment, 1 = no investment, 2 = investment). Heteroscedasticity-consistent standard errors clustered by firm in parentheses.
* Signifies statistical significance at the 90% level.
** Signify statistical significance at the 95% level.
*** Signify statistical significance at the 99% level.

Table 6
Additional effect of renewables: ordered logit model, odds ratios.

	FIRM	RES	BASE	PEAK	GAS
$\log(q_{f,c,g,y})$	1.122***	0.853	1.320**	1.100*	1.145**
	(0.044)	(0.216)	(0.144)	(0.054)	(0.067)
$I_{f,c,g,y-1}$	2.214***	3.585***	1.492*	1.309	1.707*
	(0.302)	(0.775)	(0.319)	(0.399)	(0.488)
$\log(CVarCF_{f,c,y})$	0.934*	1.184***	0.974	0.937**	0.927**
	(0.033)	(0.031)	(0.019)	(0.031)	(0.031)
$\log(VarP_{c,y})$	1.276***	1.326**	1.227**	1.081	1.029
	(0.098)	(0.188)	(0.107)	(0.131)	(0.132)
$Rnwbl_{c,y}$	0.908***	0.985	0.933**	0.901***	0.871***
	(0.018)	(0.039)	(0.026)	(0.028)	(0.028)
Cut point 1	−1.473	−4.925	−1.296	−3.265	−3.236
Cut point 2	3.062	3.419	3.533	2.557	2.896
Country FE	Yes	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes	Yes
Total obs.	2683	908	2092	1403	1375

Notes: Dependent variable is investment category (0 = disinvestment, 1 = no investment, 2 = investment). Heteroscedasticity-consistent standard errors clustered by firm in parentheses.
* Signifies statistical significance at the 90% level.
** Signify statistical significance at the 95% level.
*** Signify statistical significance at the 99% level.

Table 7
Additional effect of reserve margin: ordered logit model, odds ratios.

	FIRM	RES	BASE	PEAK	GAS
$\log(q_{f,c,g,y})$	1.090**	1.114	1.343**	1.091*	1.144**
	(0.047)	(0.323)	(0.193)	(0.056)	(0.068)
$I_{f,c,g,y-1}$	2.361***	4.609***	1.525*	1.303	1.670*
	(0.352)	(1.172)	(0.378)	(0.390)	(0.482)
$\log(CVarCF_{f,c,y})$	0.951	1.158***	0.966*	0.947	0.935*
	(0.038)	(0.032)	(0.020)	(0.034)	(0.034)
$\log(VarP_{c,y})$	1.085	1.224	0.974	1.206	1.092
	(0.103)	(0.281)	(0.113)	(0.196)	(0.184)
$Resmarg_{c,y-1}$	0.957***	0.943	0.964*	0.952**	0.945**
	(0.015)	(0.039)	(0.021)	(0.022)	(0.023)
Cut point 1	−5.343	−8.214	−5.385	−5.607	−6.563
Cut point 2	−0.708	0.784	−0.374	0.092	−0.555
Country FE	Yes	Yes	Yes	Yes	Yes
Total obs.	2335	778	1778	1283	1265

Notes: Dependent variable is investment category (0 = disinvestment, 1 = no investment, 2 = investment). Heteroscedasticity-consistent standard errors clustered by firm in parentheses.
* Signifies statistical significance at the 90% level.
** Signify statistical significance at the 95% level.
*** Signify statistical significance at the 99% level.

capacity[24] and, hence, provide a measure of the margin of safety in the system. The intuition is that if the reserve margin is high, the margin of safety is high, which may limit investment activity. On the contrary, if reserve capacity is scarce, investments may be valuable. To avoid a potential simultaneity bias – both the ordered dependent variable and the reserve margin are derived from capacity – we include a one period lag of the reserve margin ($Resmarg_{c,y-1}$) in our regressions. The data for hourly load (to calculate peak demand) come from the European Network of Transmission System Operators for Electricity (ENTSO-E). Due to unavailability of load values for some countries in some years, we lose a few observations in our regressions.

The regression results, as presented in Table 7, on $Resmarg_{c,y-1}$ are intuitive. An increase (decrease) in the reserve margin lowers (increases) investment activity. This result holds at the firm level as well as for all different types of technologies (whereas the effect is statistically insignificant for RES). With the inclusion of the reserve capacity, the statistical significance of the coefficient estimates of aggregate uncertainty vanishes. Our other main results stay robust.

4.2.2. Potential endogeneity

Endogeneity may be an issue in our investment model. Investment opportunities ($\log(q)$) at the firm- or firm-technology level could be endogenous to investment. First, our measure of q incorporates capacity (see Eq. (3)), thus there may be simultaneity bias. Second, investment decisions by the firm may affect Tobin's q, so there may be reverse causality. The (logarithm of the) spot price (log(p)) is largely exogenous to firm-specific investment (assuming that firms are "small" relative to the market) and may thus serve as an appropriate instrument. Wholesale prices clearly affect Tobin's q at all levels of disaggregation, but do not directly affect investment (only via Tobin's q or uncertainty). Moreover, uncertainty may be endogenous in the investment model. While the variance in spot market prices – our measure for aggregate uncertainty – is arguably exogenous to investment at the firm or firm-asset level, there might be reverse causality with disaggregated uncertainty as investment in electricity generation capacity may change (enhance or reduce) the cash flow uncertainty surrounding a firm or its assets.

Given the lack of truly exogenous variables that determine disaggregated uncertainty, we use a one period lag ($\log(CVarCF_{f,c,g,y-1})$) as an instrument.

For discrete choice models (i.e. ordered logit in our case), potential endogeneity of continuous variables can be circumvented by a *residual inclusion approach* (see Wooldridge, 2016, Chap. 17.5.2; Terza et al., 2008). Similarly to a two-stage instrumental variables approach, we run two first-stage OLS regressions (Eqs. (8a) & (8b)) for each of our two (continuous) endogenous variables on all instruments and the remaining exogenous regressors:

$$\log(q_{f,g,c,y}) = b_{11} I_{f,g,c,y-1} + b_{12}\log(VarP_{c,y}) + c_{11}\log(P_{c,y}) + c_{12}\log(CVarCF_{f,g,c,y-1}) + T + \upsilon_c + e_{1f,g,c,y} \tag{8a}$$

$$\log(CVarCF_{f,g,c,y}) = b_{21} I_{f,g,c,y-1} + b_{22}\log(VarP_{c,y}) + c_{21}\log(P_{c,y}) + c_{22}\log(CVarCF_{f,g,c,y-1}) + T + \upsilon_c + e_{2f,g,c,y}, \tag{8b}$$

save the residuals $(\hat{e_1}, \hat{e_2})$ and include them together with the endogenous variables and the remaining regressors in the second stage ordered logit regression.

The first stages, as shown in the Appendix Tables A1 and A2, indicate that $\log(p_{c,y})$ and $\log(CVarCF_{f,c,g,y-1})$ are not weak instruments for $\log(q_{f,c,g,y})$ and $\log(CVarCF_{f,c,g,y})$ given their statistically significant correlations. The Sanderson-Windmeijer first-stage chi-squared and F statistics indicate that there are no problems with underidentification and weak identification of the endogenous regressors. The second stage results, as reported in Table 8, provide largely robust results. The magnitude of the parameters on $\log(q)$ even slightly increases relative to the main results, disaggregated uncertainty further decrements investment in PEAK and GAS, and aggregate uncertainty increases investment for RES and BASE.

4.2.3. Disregarding disinvestment

It may be the case that the decision to disinvest is inherently different from the investment decision, so that the two decisions do not follow the same drivers. In that case, our above analysis may be biased due to the inclusion of disinvestment. Hence, to check for consistency of our results, we truncate disinvestment observations and focus solely on the investment versus no investment decision.

[24] Reserve margin (%) = [(total capacity (MW) − maximum load (MWh))/(total capacity (MW)] × 100.

Table 8
Second stage of residual inclusion: ordered logit model, odds ratios.

	FIRM	RES	BASE	PEAK	GAS
$\log(q_{f,c,g,y})$	1.673***	3.345	1.151	2.003***	1.886***
	(0.260)	(4.988)	(0.259)	(0.407)	(0.408)
$I_{f,c,g,y-1}$	2.178***	4.742***	1.560**	1.224	1.674*
	(0.305)	(1.043)	(0.329)	(0.378)	(0.481)
$\log(CVarCF_{f,c,y})$	0.933	1.123***	1.035	0.767***	0.799***
	(0.048)	(0.031)	(0.028)	(0.039)	(0.037)
$\log(VarP_{c,y})$	1.189**	1.788***	1.149	1.057	0.971
	(0.103)	(0.379)	(0.106)	(0.174)	(0.185)
$\hat{e_1}$	0.691**	0.526	1.182	0.559***	0.614**
	(0.115)	(0.787)	(0.315)	(0.119)	(0.141)
$\hat{e_2}$	0.975	1.676***	0.861***	1.537***	1.525***
	(0.055)	(0.242)	(0.045)	(0.109)	(0.112)
Cut point 1	−1.684	−0.624	−1.320	−5.323	−5.197
Cut point 2	2.797	7.521	3.504	0.538	0.948
Country FE	Yes	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes	Yes
Observations	2683	908	2089	1403	1375

Notes: Dependent variable is investment category (0 = disinvestment, 1 = no investment, 2 = investment). Heteroscedasticity-consistent standard errors clustered by firm in parentheses. We account for the endogeneity of $\log(q_{f,c,g,y})$ and $\log(CVarCF_{f,c,g,y})$ by residual inclusion ($\hat{e_1}, \hat{e_1}$) based on the two first stage regressions.
* Signifies statistical significance at the 90% level.
** Signify statistical significance at the 95% level.
*** Signify statistical significance at the 99% level.

For this purpose, we estimate Eq. (2) for the case of only two outcomes ($i = 2$, i.e. 0 = no investment, 1 = investment) in a probit regression.

Table 9 shows the odds ratios of the estimated coefficients of the probit regression. Indeed, the results are largely consistent with the main results as reported in Table 5. Log(q) has a positive and significant effect on the investment decision at the firm level and for PEAK and GAS. Also, investment in the previous period enhances the likelihood of investing the following period. For the firm-asset-specific uncertainty ($CV\,arCF_{f,c,g,y}$), the odds-ratios lie below one (except for RES), suggesting that disaggregated uncertainty hinders investment, which corroborates our main results. Finally, the estimated odds ratios of aggregate uncertainty ($V\,arP_{c,y}$) are greater than one and statistically significant at the firm level and RES.

5. Conclusions

In this article, we investigate the driving forces of investment in electricity generation capacity. Our study adds to the existing literature by introducing novel features: (i) We put our empirical regressions subject to Tobin's q-model of investment, and extend it by measures for both firm- (and even firm-generation-technology-) specific uncertainty as well as industry-level uncertainty. (ii) We develop measures for investment opportunities (q) and for uncertainty based on (the supply side of) a fundamental electricity model of 437 electricity generators located in 13 European countries. The standard approach to calculate q is using stock market data, which may however also include bubbles, fads and speculative noise. Our measure of q solely mirrors fundamental values. Both measures, q and uncertainty, are measured at the firm-generation-type-country level. (iii) Our analysis not only provides evidence on the intricate relationship between uncertainty and investment at the firm level, but also shows partly countervailing effects at the more disaggregated level of investment in generation technologies (i.e. renewables, base load, peak load, and gas as a particular peak-load technology).

Table 9
Disregarding disinvestment: Probit results, odds ratios.

	FIRM	RES	BASE	PEAK	GAS
$q_{f,c,g,y}$	1.166***	0.921	1.144	1.208***	1.213***
	(0.059)	(0.124)	(0.117)	(0.059)	(0.063)
$I_{f,c,g,y-1}$	3.802***	2.282***	3.048***	1.532***	1.552***
	(0.382)	(0.341)	(0.374)	(0.228)	(0.210)
$CV\,arCF_{f,c,g,y}$	0.885***	1.110***	0.963*	0.894***	0.902***
	(0.028)	(0.023)	(0.021)	(0.018)	(0.016)
$V\,arP_{c,y}$	1.202***	1.186**	1.036	1.041	0.982
	(0.074)	(0.093)	(0.054)	(0.098)	(0.088)
Country FE	Yes	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes	Yes
Observations	2438	896	1880	1217	1215

Notes: Dependent variable is investment category (0 = no investment, 1 = investment). Disinvestment observations are regarded as missing information. Heteroscedasticity-consistent standard errors clustered by firm in parentheses.
* Signifies statistical significance at the 90% level.
** Signify statistical significance at the 95% level.
*** Signify statistical significance at the 99% level.

Our empirical findings show that investment at the firm and firm-technology level is incentivized by q indicating that fundamental investment opportunities indeed drive investment. We also find interesting patterns with regard to uncertainty. At the firm level, we find the pattern "positive effects of aggregate uncertainty but negative effects of firm-specific uncertainty on investment." Looking at firms' individual asset-classes (i.e. investment in renewables, base-load, peak-load, and gas as a particular peak-load technology), we find that disaggregate uncertainty negatively influences investment, except for renewables. Aggregate (industry-specific) uncertainty increases investment in renewables and base-load generation capacity. Additionally, we find evidence that a higher share of renewables and a higher reserve margin both lower investment activity. Also, we circumvent potential endogeneity of both investment opportunities and disaggregate uncertainty with investment decisions by applying a control function approach. Moreover, we acknowledge that investment and disinvestment decisions may follow different driving forces and show that our main results stay robust once we disregard disinvestment and solely focus on the investment versus no-investment decision.

Our paper adds to the irreversibility and investment literature. Investment responds less positively to q and more negatively to disaggregated uncertainty if assets are arguably more sunk and irreversible such as with base and peak load capacities than with other generation technologies such as renewables. Renewables face different incentives due to their shorter construction times as well as subsidized and prioritized feed-in which makes them less vulnerable to unfavorable market conditions than conventional power plants. Thus, our results support the notions of the irreversibility and investment literature of a mitigated effect of q and a negative effect of (disaggregated) uncertainty if investment is irreversible. We stress the importance of measuring investment opportunities and uncertainty at a disaggregated level.

What do our results imply for policy makers? First, the corroborative evidence for the q-model supports the notion of the allocative functioning of wholesale electricity markets, even in the presence of long-term durable and sunk investments. However, the dramatic decline of q's in recent years, which is most pronounced for gas, may significantly deter investment in conventional generation technologies. This may create an investment gap in the long run. Increasing generation from renewables may erode respective investment incentives for conventional technologies in particular gas. With disaggregate uncertainty, firms seem to delay investments in conventional peak-load technologies. Since peak load plants, such as gas, are still a vital factor in the capacity mix to relieve intermittent renewables, these developments may pose a potential threat to the supply security.

Massive renewables support schemes and well-functioning wholesale markets with adequate investment signals are at odds with each other. There are two potential ways out of this misery. On the one hand, politics may continue the support schemes for renewable electricity at the expense of allocative efficiency and security of supply. In this case, the need for capacity markets (to remunerate capacity investment) becomes more pressing. Yet, with capacity markets other distortions may occur raising the need for future research. On the other hand, policies may foster market dynamics and competitive market forces, so that markets send correct (i.e. market driven) investment signals, including high price spikes, which ensure supply security in the long run. Such “energy-only markets” should, however, avoid external (state) interventions to promote renewable electricity but promote climate policy goals by market based instruments such as an adequate price for CO_2 emissions.

Declaration of competing interest

None. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Appendix A. Merit order curves

We construct hourly merit order curves of electricity-generating firms in the style of a fundamental market model. This is a state-of-the-art approach in energy economics. Hence, we follow related studies on the construction and application of merit order curves and/or fundamental market models (Borenstein and Bushnell, 2003; Burger et al., 2012; Graf and Wozabal, 2013; Hirth, 2013; Schröter, 2004; Sensfuß et al., 2008).

For this purpose, we utilize data on installed capacities and combine these with technical information on plant characteristics and other relevant data (e.g. plant availability scores and efficiency factors; see below). The Austrian transmission system operator, Austrian Power Grid (APG), and the Energy Economics Group (EEG) of the Vienna University of Technology (TU Vienna), both having developed their own fundamental models, provided us with background knowledge, modelling support, and information.

Trading in wholesale electricity in Europe happens to a large extent at day-ahead spot markets, which are organized at power exchanges. In a power exchange, suppliers and consumers place bids for any hour of the following day. Such power exchanges are generally characterized by many suppliers and consumers and have high liquidity (Gugler et al., 2018). It is therefore reasonable to assume that electricity-generating firms place bids at their marginal costs (as under perfect competition). This assumption is necessary to determine which generation technologies are in the merit order. That is, firms will only generate electricity from their technology capacity if its marginal costs of producing are below the spot price (see Fig. 1).[25] Therefore, we calculate hourly marginal costs of each firm's generation technology in order to construct hourly merit orders.

A.1. Data

We obtain detailed information on *installed capacity* at the generation unit level for the period 2006–2014 from Platts PowerVision. This data can be attributed to the owner of the generation units (i.e. electricity generation utilities). The following information is obtained on generation unit level: plant name, construction and retire date, turbine type, fuel type, plant type, operational status, and installed capacity (in MW). In contrast to other sources like Bundesnetzagentur (2011) that publishes a list of German power plants with installed capacities larger than 20 MW, Platts PowerVision provides data for all plants in Europe irrespective of their size.

Table A1
Efficiency factors by technology and plant vintage.

Technology	Vintage	Efficiency factor
Lignite	Until 1960	0.30
Lignite	Until 1965	0.31
Lignite	Until 1970	0.32
Lignite	Until 1975	0.33
Lignite	Until 1980	0.35
Lignite	Until 1985	0.37
Lignite	Until 1990	0.39
Lignite	Until 1995	0.42
Lignite	Until 2000	0.44
Lignite	Until 2005	0.45
Lignite	Until 2014	0.47
Hard coal	Until 1955	0.30
Hard coal	Until 1960	0.31
Hard coal	Until 1965	0.32
Hard coal	Until 1970	0.33
Hard coal	Until 1975	0.34
Hard coal	Until 1980	0.36
Hard coal	Until 1985	0.38
Hard coal	Until 1990	0.40
Hard coal	Until 1995	0.43
Hard coal	Until 2000	0.45
Hard coal	Until 2014	0.48

[25] Our assumption of perfect competition is necessary to determine which plants are in the merit order (i.e. producing electricity) and which are out of merit order (i.e. not producing electricity). Indeed, we cannot rule out the possibility that firms exercise market power during some hours of the year. Under market power, the wholesale electricity price would exceed the marginal costs of the marginal plant, which is still in the merit order. In this case, inframarginal plants (those plants, which are in the merit order) would generate higher variable profits (i.e. our model underestimates their profits), while some marginal units may not produce (for which we overstate their profits). Graf and Wozabal (2013) provide evidence that day-ahead wholesale markets in Europe work well (i.e. no evidence of market power) most of the time.

Table A1 (*continued*)

Natural gas	Until 1970	0.30
Natural gas	Until 1980	0.33
Natural gas	Until 1990	0.35
Natural gas	Until 2014	0.38
Oil	Until 1980	0.33
Oil	Until 1990	0.35
Oil	Until 2014	0.38
Nuclear	All vintages	0.31
Geothermal	All vintages	0.44
Wood (pellets)	All vintages	0.44
Waste	All vintages	0.38

APG provided us with information on availability factors of conventional power plants per turbine type and fuel type. The availability of a power plant is an operational limitation determined, for example, by seasonal demand and supply variations (e.g. revisions and maintenances, availability of cooling water, weather and climate conditions, etc.). In accordance with Schröter (2004), we consider three periods, namely winter season, summer season and transition phase (spring and autumn), in order to adjust installed capacities by availability factors.

With respect to renewables, we utilize hourly data on day-ahead wind and solar forecasts (provided by the Austrian energy trading company "e&t") to assess their yearly availabilities. At day-ahead markets, bids for electricity from wind and solar generation are generally based on wind and sunshine forecasts. Biogas power plants are considered as renewable sources of electricity and receive fixed rates for their generation, and thus generate a constant power output (Graf and Wozabal, 2013). Eventually, we multiply the availability score of each generation technology with its respective installed capacity to create a measure of available capacity.

APG and the Energy Economics Group of the TU Vienna provided us with information on the efficiency factors of power plants by fuel and turbine type. The efficiency factor shows the relationship between energy input in terms of primary energy and energy output in terms of electricity. In our model, the efficiency factor of each generation unit is a function of turbine type, fuel type, and construction year. The variable takes up values between zero and one. Table A1 provides a summary about our efficiency factors applied.

A.2. Construction of marginal costs and cash flows

We calculate *marginal costs* in each hour (h) of a year (y) and for 73 "generation unit types" (which are combinations of turbine types, fuel types, and construction years).[26] For this purpose, we take fuel prices, the carbon dioxide (CO_2) price, emission factors, and efficiency factors into consideration:

$$mc_{tt,ft,cy,h,y} = [FP_{ft,h,y} + (CO2P_{ft,h,y} \times CO2E_{ft})]/EF_{tt,ft,cy}$$

(This equation corresponds with Eq. (6) in the main text body.)

where mc is marginal costs (€/MWh), FP is fuel price (€/MWh), EF is efficiency factor (%), CO2E is CO_2 emission factor (tCO_2/MWh), CO2P is CO_2 spot price (€/MWh), tt is turbine type, ft is fuel type, cy is construction year, h is hour, and y is year. Eventually, we aggregate over turbine types (tt), fuel types (ft), and construction years (cy) to arrive at marginal costs for our types of generation technologies (g; i.e. RES, BASE, PEAK, GAS, see Table 1 for their definitions) in any given hour (h) in a year (y).

We distinguish between 21 plant types, which are combinations of 12 turbine types and 12 fuel types, as shown in Table A2. For these plant types, we collected data on their *efficiency factors* (EF) depending on their respective construction years, which gives us the 73 generation unit types. The idea is that older plants are less efficient and, thus, have higher marginal costs. Moreover, we collected data on *fuel prices* (FP) depending on the 12 fuel types over time. We apply data on fuel prices, which vary across time (many of the price series vary at the daily frequency) but not across countries, because individual price series for each of the 13 sample countries were not available.

[26] Distinguishing the 21 plant types (as given in Table A2) by construction year (as given in Table A1) eventually yields 73 different "generation unit types." The idea is that at such a fine level of disaggregation, we can truly control for individual plant characteristics (i.e. turbine type, fuel type, construction year).

Table A2
Plant types.

Nr.	Turbine type	Fuel type
1	Combined cycle	Natural gas
2	Combined cycle	Fuel oil
3	Gas combustion turbine	Natural gas
4	Gas combustion turbine	Fuel oil
5	Gas combustion turbine	Refuse and waste
6	Geothermal steam turbine	Geothermal steam
7	Internal combustion	Natural gas
8	Internal combustion	Fuel oil
9	Nuclear	Uranium
10	Pump storage	Water
11	Run-of-river	Water
12	Solar	Solar
13	Steam turbine	Biomass
14	Steam turbine	Lignite
15	Steam turbine	Hard coal
16	Steam turbine	Natural gas
17	Steam turbine	Wood (pellets)
18	Steam turbine	Fuel oil
19	Steam turbine	Refuse and waste
20	Storage	Water
21	Wind	Wind

As the price of coal, we use the daily ARA month future data provided by the European Energy Exchange (EEX). We also assume that the price of lignite is 80% of the ARA coal price. For gas, we use the daily price data provided by BAFA (the German Federal Office of Economics and Export Control). As there is no spot market for lignite and consequently no price information available, in accordance with Graf and Wozabal (2013) we assume the lignite price to be 80% of the coal price. As the price of oil we utilize daily Europe Brent Spot FOB provided by the U.S. Energy Information Administration. Given missing uranium prices for nuclear power, like Graf and Wozabal (2013) we assume a constant input price of USD 9.33 per MWh (converted into €) (see IEA, 2010). We obtained a monthly varying price of refuse and waste as well as a yearly varying price of wood pellets by APG. Furthermore, we collected data on the degrees of CO_2 emissions by fuel type, which gives us the CO_2 *emission factors* (CO2E). The respective information was provided by APG. We utilize data on daily CO_2 *spot prices* (CO2P) from the European Energy Exchange (EEX). Table A3 provides a summary of our input prices.

Table A3
Input prices.

Input	Data frequency	Price (€/MWh)
CO_2	Daily	5.35
Hard coal	Daily	11.35
Lignite	Daily	9.03
Natural gas	Daily	23.95
Nuclear	Constant	8.71
Oil	Daily	40.68
Refuse and waste	Monthly	4.78
Wood (pellets)	Yearly	46.61

To get the *available capacity* (avCap) by firm (f) located in country (c) by generation technology (g) in hour (h) per year (y), we multiply generation technologies' installed capacities (Cap) with their respective *availability factors* AF: $avCAP_{f,c,g,h,y} = CAP_{f,c,g,h,y} \times AF_{g,h,y}$. The underlying data of the availability factors (i.e. percentage scores) vary across our 21 plant types and across three seasons of the year (i.e. summer, winter, and transition period). Hence, to obtain availability factors for our generation technology levels (g), as used in the investment analysis (i.e. RES, BASE, PEAK, GAS), we take averages over the 21 plant types.

We assume that each firm (f) located in country (c) will obtain cash flows (cf) from its generation technologies' available capacities if the actual spot price (p) in hour (h) is greater than the associated marginal costs (mc). To arrive at a yearly variation of cash flows, we aggregate over the total number of hours (h) per year (8760 in a normal year and 8784 in a leap year):

$$cf_{f,c,g,y} = \sum_h \begin{cases} (p_{c,h,y} + s_{c,y} - mc_{g,h,y}) \cdot avCap_{f,c,g,h,y} & \text{if } p_{c,h,y} > mc_{g,h,y} \\ 0 & \text{if } p_{c,h,y} \leq mc_{g,h,y} \end{cases}$$

(This equation corresponds with Eq. (5) in the main text body.)

Appendix B. Example of how we calculate q for E.ON

An example might clarify our approach to calculate q with respect to one particular firm in our sample: E.ON. We perform the same steps as discussed below for all 437 firms in our sample.

E.ON, the largest German electricity generator, has a total installed capacity of 17,507.10 MW in the year 2014 in Germany, which consists of renewables (19.67 MW), hydro (1284.04 MW), nuclear (5411.01 MW), coal (5364.31 MW), gas (3762.93 MW) and other types (1665.16 MW, e.g. oil, waste, etc.). Applying Eq. (5) to these assets (after calculating marginal costs using Eq. (6)) gives estimated cash flows of €4.67 mio. for renewables, €73 mio. for hydro, €1010 mio. for nuclear, €245 mio. for coal, €21.1 mio. for gas, and €11.4 mio. for other generation types; totaling €1365.17 mio. of cash flows from generation assets for E.ON for the year 2014 in Germany. Using Eq. (4), we estimate the present value of all generation assets of E.ON to be €28,030 mio. in 2014 in Germany (renewables: €77.79 mio., hydro: €1813.52 mio., nuclear: €20,271.70 mio., gas: €457.55 mio., coal: €5189.63 mio., other assets: €224.25 mio.), under the assumptions (1) that the 2014 cash flows grow annually with inflation of 1.7% and are discounted with 5% during the average life-span; and (2) of an average life-span of renewables of 25 years, of hydro assets of 54 years, of nuclear assets of 34 years, of gas assets of 39 years, of coal assets of 38 years, and of other assets of 33 years. These calculations are repeated for all years as well as all countries in which E.ON is active. This is important since E.ON's German electricity generating capacity makes up only around 35% of its total international capacity (i.e. 65% is abroad).

Turning to the q calculation of Eq. (3), we divide these present values by the estimated replacement costs of these capacities, i.e. purchase prices (renewables including wind: 1501 €/kW and solar: 2565 €/kW, hydro: 1742 €/kW, nuclear: 3030 €/kW, gas: 408 €/kW, coal: 1605 €/kW, other assets: 2261 €/kW) times the installed capacities. Our calculated q of E.ON is therefore 0.71 in 2014 for its German electricity generating assets, 2.84 for renewables, 0.81 for hydro, 1.24 for nuclear, 0.30 for gas, 0.58 for coal, and 0.08 for other assets. These values measure the investment opportunities for E.ON in Germany and for its disaggregated generating assets as of 2014.

Our example stresses the importance of calculating investment opportunities and uncertainty in this disaggregated manner using fundamental values as opposed to stock market data. For example, we see that while E.ON should not invest when looking at the firm level (and actually should disinvest in generating assets in Germany given its $q = 0.71$), particularly so for the peak technology gas ($q = 0.3$), E.ON should invest in renewables in Germany ($q = 2.84$).

Moreover, a look at the stock market q highlights the importance of using fundamental, disaggregated values. E.ON had a stock market q of around 1.4 in 2014. However, this q includes all activities of E.ON, i.e. all segments (e.g. also grids and trading activities) and international operations, and may not reflect fundamentals, which may thus give a misleading account of its investment opportunities in a given generation technology in Germany.

Appendix C. Additional tables

Table C1
First stage estimates of log(q): OLS.

	FIRM	RES	BASE	PEAK	GAS
$\log(CVarCF_{f,c,g,y-1})$	0.089***	0.001	0.016***	0.148***	0.124***
	(0.008)	(0.003)	(0.003)	(0.010)	(0.010)
$\log(p_{c,y})$	1.426***	0.425***	1.487***	1.782***	1.921***
	(0.088)	(0.086)	(0.045)	(0.195)	(0.186)
$I_{f,c,g,y-1}$	0.096***	0.005	0.016	0.142*	0.160**
	(0.027)	(0.032)	(0.016)	(0.082)	(0.081)
$\log(VarP_{c,y})$	0.160***	0.056***	0.066***	0.605***	0.687***
	(0.022)	(0.021)	(0.011)	(0.054)	(0.051)
Country FE	Yes	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes	Yes
Observations	2683	908	2089	1403	1375
R-squared	0.518	0.829	0.690	0.585	0.610
SW chi-sq. Wald stat. (p-val.)	0.00	0.00	0.00	0.00	0.00
SW F stat.	440.73	24.45	1210.14	168.90	183.93

Notes: Dependent variable is $\log(q_{f,c,g,y})$. The Sanderson-Windmeijer (SW) first-stage chi-squared and F statistics test for underidentification and weak identification of the endogenous regressors. The SW F statistics are all above the Stock-Yogo critical value of 19.93 for the 10% level.
* Signifies statistical significance at the 90% level.
** Signify statistical significance at the 95% level.
*** Signify statistical significance at the 99% level.

Table C2
First stage estimates of log(CVarCF): OLS.

	FIRM	RES	BASE	PEAK	GAS
$\log(CVarCF_{f,c,g,y-1})$	0.605***	0.956***	0.737***	0.797***	0.830***
	(0.014)	(0.009)	(0.013)	(0.015)	(0.013)
$\log(p_{c,y})$	−2.407***	−1.736***	−2.871***	−3.672***	−3.271***
	(0.159)	(0.218)	(0.185)	(0.274)	(0.236)
$I_{f,c,g,y-1}$	−0.095*	−0.182**	−0.163**	0.014	−0.007
	(0.050)	(0.081)	(0.065)	(0.115)	(0.103)
$\log(VarP_{c,y})$	1.213***	0.480***	1.129***	1.658***	1.495***
	(0.040)	(0.053)	(0.047)	(0.075)	(0.065)
Country FE	Yes	Yes	Yes	Yes	Yes
Time trend	Yes	Yes	Yes	Yes	Yes
Observations	2683	908	2089	1403	1375
R-squared	0.990	0.989	0.987	0.981	0.986
SW chi-sq. Wald stat. (p-val.)	0.00	0.00	0.00	0.00	0.00
SW F stat.	1201.21	12003.99	2932.70	293.25	398.58

Notes: Dependent variable is $\log(CVarCF_{f,c,g,y})$. The Sanderson-Windmeijer (SW) first-stage chi-squared and F statistics test for underidentification and weak identification of the endogenous regressors. The SW F statistics are all above the Stock-Yogo critical value of 19.93 for the 10% level.
* Signifies statistical significance at the 90% level.
** Signify statistical significance at the 95% level.
*** Signify statistical significance at the 99% level.

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