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The recent transformation of European electricity markets with increasing generation from intermittent renewables brings about many challenges. Among them, decaying wholesale prices, partly due to support schemes for renewables, may send insufficient investment signals for other generation technologies. We investigate the investment decision in a structural equation based on the Tobin's q-model, which we extend by both industry- and firm-technology-specific uncertainty. We utilize rich and novel data at the disaggregated generation technology level of European electricity generating firms for the period 2006–2014. Our results show that investment in any generation technology follows market incentives despite sunk and irreversible capital, confirming the implications of the *q*-model. Moreover, while firm-technology-specific uncertainty decreases firms' investment activity, especially in coal and gas, aggregate uncertainty triggers firms' investment. Our results raise concerns about system reliability in the long run since conventional technologies (e.g. gas) still serve as a flexible system back-up.

Keywords: Tobin's q, Uncertainty, Investment, Electricity

JEL codes: L22, L25, L51, Q48

1. Introduction

The European electricity markets are confronted with a vast transformation away from nationally organized markets with vertically integrated regional monopoly utilities towards internationally integrated and liberalized markets. Moreover, many European countries (with Germany paving the way) have been introducing subsidized and prioritized feed-in for intermittent renewables (and other low-carbon technologies) with the aim of decarbonizing electricity generation.[1] In the current transition phase, day-ahead spot prices have been deteriorating significantly, partly as a result of the increasing share of wind and solar in total production.[2]

This bears important implications for investment in electricity generation capacity. First, artificially low prices through subsidizations of renewables may send wrong investment signals, and thus make investments in generation capacity less profitable. Second, the increased intermittency of renewables supports uncertainty in the market. This in turn may decrease large-scale investments, which are sunk. Third, the increased feed-in of renewables largely replaces conventional peak technologies (e.g. gas, oil) with relatively high marginal costs. This is called the "Merit Order Effect" (Woo et al., 2016). Consequently, residual demand for conventional generation technologies drops during times of high renewables production, decreasing their capacity utilization (i.e. number of hours running). These effects may eventually create a *missing money problem* for investment in conventional fuel types – which are needed as a backup system for intermittent renewables and other low-carbon technologies, ensuring supply security during and after the transition phase of decarbonisation in Europe.

In this paper we empirically investigate the determinants of physical investment decisions with regard to different generation technologies in Europe. Investment in electricity generation capacity is characterized by long periods of no investment with sporadic bursts of investment activity, mainly due to irreversibility and sunk costs (e.g. Nilsen and Schiantarelli, 2003). Thus, we estimate a multinomial logistic regression, where the dependent variable has three possible values, namely disinvestment, zero investment, and investment. We focus on a structural investment equation based on the neoclassical investment theory. In this regard, we derive a measure for *variable profits* from various generation technologies following the argumentation of Tobin's *q*. We calculate

[1] In 2014, all EU Member States have had some form of renewables support scheme (see Klessmann, 2014).
[2] Besides other influential factors, e.g. decreasing fuel and carbon prices, weak demand due to the economic crisis; cf. European Commission (2015), Milstein and Tishler (2011).

yearly variable profits from a fundamental market model as the aggregate over hourly differences between the realized spot price and a technology's marginal costs times estimated output.

Moreover, our rich data allows for the distinction between firm- (and even firm-technology-) specific uncertainty and aggregate industry-specific uncertainty, which may have opposing effects on investment decisions (Hubbard, 1994). We measure (the inverse of) *firm-specific uncertainty* as the number of hours a firm's respective generation technologies are running per year. In other words, we have information about a *firm's current plant utilization*, which may be a good predictor about future plant utilization. The lower the expected utilization rate the higher a firm's uncertainty. On the other hand, we measure *industry-specific uncertainty* as the *variance in wholesale spot prices*, which affects *all* firms in the industry.

Our results show that expected profits stimulate investment across all generation technologies. Contrary to many finance studies,[3] this finding supports the notion of the *q*-model. We argue that profits from different generation technologies, our proxy for *q*, indeed capture fundamental values, whereas stock market data may also include speculations, bubbles, and/or fads. This result also indicates that electricity wholesale markets are indeed able to incentivize investment despite the presence of irreversibility, long time-to-build lags, and sunk capital.

Our measures of firm-technology-, firm-, and industry-specific uncertainty find significant effects on investment activity, too. Firm-technology- and firm-specific uncertainty (i.e. decreasing expected capacity utilization) curtails the likelihood to invest and in particular for coal and gas plants. This result is consistent with Dixit and Pindyck (1994) stating that there is a value associated with waiting so *investments will decrease with uncertainty*. It raises concern about system reliability. Increasing production from prioritized and subsidized renewables decreases spot prices and the capacity utilization rates of conventional e.g. coal and gas plants. Consequently, these technologies get pushed out of the market, despite their important function as flexible back-up for the system. In the long-run, under-investment in conventional technologies may put the electricity supply security under pressure.

Aggregate industry uncertainty, on the contrary, increases investment in renewables and base load technologies. Regarding long investment lags in base load technologies (e.g. run of river and nuclear plants) and the option to abandon, not only the option value of waiting increases but the

[3] See, for example, Chirinko's (1993) survey.

opportunity cost of waiting also increases 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, we find evidence for the pattern "positive effects of aggregate uncertainty but negative effects of firm-specific (or plant-specific) uncertainty on investment." In addition, we find a substitution effect between firms' investment activities and aggregate renewables penetration, which is especially pronounced for peak load plants. This implies that countries' support schemes for renewables (partly) replace peak load capacity.

2. Relevant Literature

In this section, we discuss the most relevant literature on the determinants of investment with emphasis on the effect of uncertainty in general and in electricity generation. In this regard, we mainly focus on empirical studies, while section 3 provides an overview about the theory of investment.

Standard economic theory suggests that in an efficient market supply and demand meet to send optimal price signals ensuring optimal investment. If capacity is low, peak demand results in high shortage prices that in turn trigger investment (Roques et al., 2005). Government support schemes are one reason (besides, e.g. market power) why spot prices in electricity markets may be distorted. In the long run, downwardly distorted spot prices may create a missing money problem (Cramton and Stoft, 2006; Joskow, 2007) causing *underinvestment in peak load technologies*.

Policymakers in Europe (cf. Newbery, 2005; Jamasb and Pollitt, 2005; Von der Fehr et al., 2005) and the USA (Joskow, 2007) are concerned about the security of electricity supply and adequate investment incentives. There are special characteristics to investment in electricity generation capacity. As noted by Léautier (2016) many capital-intensive industries, like electricity, experience phases of over- and underinvestment ("boom bust" cycles). Bar-Ilan and Strange (1996) assume that there will be *lumpy* capacity additions due to economies of scale. Additionally, long times-to-build and irreversible sunk investments are special features that have to be considered when investing in electricity generation.

The neoclassical investment literature, and especially the Tobin's (1969) *q-model*, strongly focuses on the *expected profitability of actual investments* (see the detailed summary of the investment theory in section 3). Empirical investment studies generally calculate a measure for *q* based on stock price information from *firms listed at the stock market*. Such studies are generally not able to find corroborative evidence for a large positive effect of *q* on investment (see e.g. the survey by Chirinko, 1993). Likely explanations are that stock prices also capture bubbles and/or fads, and/or do not reflect the specific granular assets under scrutiny. Thus, they may not only reflect fundamentals and they may be low signal to noise ratio statistics (see e.g. Leahy and Whited, 1996 and Schwert, 2002). In contrast, we are able to calculate a proxy for q, namely variable profits at the firm and even firm generation technology level, from a fundamental market model (that constructs firms' supply (merit order) curves). These are likely to provide more accurate measures for investment incentives.[4] Our measure also applies for non-listed firms, is tailored to the assets under consideration, and is based on market fundamentals.

In that respect focusing on one industry has additional advantages. One is that a potential bias stemming from heterogeneity between different industries can be avoided as argued in Carruth et al. (2000). Scaramozzino (1997) finds that the *q* model does not perform well for firms where the irreversibility constraint is binding while it does for other firms. Therefore an advantage is that our measure for *q* is more likely to be accurately measured since the degree of irreversibility is the same for all firms investing in the same technology type.

Empirical literature on the influence of uncertainty on investment at an aggregate level includes Pindyck (1988), Ferderer (1996), Eisfeldt and Rampini (2006) and Gilchrist et al. (2010). The employed levels of aggregation and measures of uncertainty differ greatly. As measures for uncertainty macroeconomic variables such as inflation rates, exchange rates, GDP, interest rates, real wages and energy prices as well as stock market return volatility are employed. Volatility is described in different ways including ARCH- and GARCH-estimations of conditional variances or by using standard deviations when assessing realized fluctuations. To account for the forward-looking nature of investments some empirical studies such as Bachmann et al. (2010) and Ferderer (1993) employ business surveys and the term structure of interest rates, respectively. This strand of literature concludes that aggregate capital investments are negatively affected by uncertainty.

Focusing on more disaggregated industry- and firm-level data, conclusions on the sign of the uncertainty- capital investment relationship are not as clear cut as with the analyses at the aggregate level. While the relationship still seems to be negative, the inclusion of controls such as Tobin's *q*

[4] See also Bond et al. (2004).

weakens the results implying that the relationship is not robust or at least weak. The literature on a more disaggregated level can be classified due to their different measures of uncertainty. Literature employing input and output prices includes Huizinga (1993) and Ghosal and Loungani (1996), while Goldberg (1993) and Campa and Goldberg (1995) employ exchange rate volatility. Minton and Schrand (1999) and Ghosal and Lougani (2000) use measures of firm performance. Extensive literature including Leahy and Whited (1996), Bulan (2005) and Bloom, Bond and van Reenen (2007) employ stock returns as their measure for uncertainty. Leahy and Whited (1996) argue that uncertainty mainly enters through Tobin's q since for an inclusion of q the uncertainty measure becomes insignificant.

Bo (2002) uses a state space model to distinguish idiosyncratic from aggregate demand uncertainty. Like we do, he finds that idiosyncratic uncertainty is more important than industry-wide uncertainty and that the former source of uncertainty negatively affects investment spending. Caballero and Pindyck (1996) on the other hand argue that industry-wide uncertainty is more important than firm-specific uncertainty for industry equilibrium investment. Yet, their finding may be driven by strong assumptions including homogeneous firms, a production technology with constant returns to scale and perfect competition. Stein and Stone (2012) measure uncertainty using the volatility of oil prices and equity options which represent the expected stock price volatility on capital investment and R&D spending, among others, and find that while R&D spending increases, capital spending decreases with uncertainty. Goel and Ram (2001) on the other hand find a negative effect of uncertainty on R&D investments and attribute this to the high degree of irreversibility of such spending. Some uncertainty measures lack statistical significance and have a positive coefficient. They point out that more disaggregated data to control for firm- and technology-specific uncertainties would be helpful to gain a better understanding of the underlying processes.

Empirical literature concerning uncertainty in electricity markets mainly focuses on the impact of regulatory uncertainty on investments in energy generating capacity. Ishii and Yan (2004) explain the sensitivity of infrastructure investments to institutional stability by stating that regulatory restructuring can create substantial uncertainty increasing the option value which leads to a delay in investments. The importance of stable regulatory policies with limited possibilities of the state to engage in a hold-up of investments is outlined by Roques et al. (2005), Mulder (2008), Cambini and Rondi (2010), and Eyraud et al. (2011). Milstein and Tishler (2011) argue that higher renewable generation capacity results in more supply uncertainty and may increase price volatility if support schemes are not designed properly but do not comment on the impact on investments. Baker and Adu-Bonnah (2008) examine how uncertainty affects optimal investment in R&D programs in the energy sector. According to different scenarios of the effect of R&D on reductions of abatement costs or emissions-to-output ratios and damages they conclude that uncertainty can have a positive effect on R&D investments depending on the technology type and the probability of a catastrophe to occur. The argument for investments being higher in riskier R&D is that alternative energy will benefit most if improvements are large which is why riskier R&D might pay off.

3. Investment Theory and Empirical Model

Under the neoclassical theory of investment, a firm invests to the point where its marginal returns on investment equal its cost of capital. Thus, the firm invests only, if the expected value of the shadow price of capital exceeds the purchase price of this additional unit. If I denotes investment, K the capital stock, α quadratic adjustment costs, $E(\lambda)$ the expected value of the shadow price of capital (the marginal benefit of investment) and p_I the purchase price of new capital (relative to the price of output), and u an error term (and ignoring firm or time subscripts), we get:

$$\frac{I}{K} = \frac{1}{\alpha}(E(\lambda) - p_I) + \mu. \tag{1}$$

Thus whenever there is a discrepancy between $E(\lambda)$ and p_I, the firm has an incentive to change its capital stock. The larger the adjustment costs (α) are, the smaller is the reaction in a given period to any given discrepancy.

The q-version of the model (Tobin, 1969), uses information from financial markets to relate $E(\lambda)$ to observables. Average (Tobin's) q is defined as the ratio of the financial value of the firm (V) to the replacement cost of its existing capital stock ($p_I K$): $q_{avg} = \mathrm{V}/(p_I K)$. As shown by Abel (1980), Lucas and Prescott (1971) and Mussa (1977), there is a relation between marginal q, which is defined as the ratio of the discounted future revenues from an additional unit of capital to its purchase price ($q_{mrg} = E(\lambda)/p_I$), and investment. The arguments for putting Tobin's q in an investment equation rest on the assumptions of perfect competition, constant-returns-to-scale and that firms are price takers, which imply that the marginal and average returns on capital are equal, and equal a firm's cost of capital (see Hayashi, 1982). Under these conditions, $V = E(\lambda)K$. From the above, the q investment model follows as:

$$\frac{I}{K} = \frac{1}{\alpha}q + \mu, \tag{2}$$

with $q = (q_{avg} - 1)p_I = V/K - p_I$. Thus, the q-model of investment implies that whenever q_{avg} is larger than unity, the firm should invest, and whenever q_{avg} is smaller than unity, the firm should disinvest.

Reinserting for q_{avg} and multiplying by K, we get:

$$I = \frac{1}{\alpha}V - \frac{1}{\alpha}p_I K + \mu K. \tag{3}$$

which comes closest to our empirically estimated equation (as presented below). 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 (no sunk investments), and second that each investment opportunity is a once and for all opportunity. Yet, in our setting of electricity generation, investments are irreversible (sunk) and lumpy (long time to build). Thus we need to account for these characteristics and augment the standard neoclassical investment model.

Uncertainty and Investment

Dixit and Pindyck (1994) state that there is a value associated with waiting 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 foregoes the option of delaying the investment, which is clearly costly. Hence, the firm investing today has to be "compensated" somehow. Incorporating uncertainty in the q-model (see Equation (2)), 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 at least by the lost option value to delay.[5]

[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).

Empirically this would imply that uncertainty affects investment mainly via the marginal product of capital, which in the context of a multi-period model becomes marginal *q*.[6] In terms of equation (2), 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 marginal *q*.[7] This would give implausibly high adjustment cost estimates, however. Moreover, one would expect sporadic bursts of investment or disinvestment, consistent with typical plant level evidence (e.g. Doms and Dunne, 1998, and Nilson and Schiantarelli, 2003). Additionally, Abel and Eberly (1997) show that the option values are increasing in the time-invariant level of uncertainty suggesting that the responsiveness of marginal *q* to investment should decrease with the level of uncertainty.[8]

Thus, the *q*-model in equation (2) cannot capture all real world fundamental determinants of investment. To test whether there is a *direct effect of uncertainty on investment* we add uncertainty in the *q*-equation. 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).[9] 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. To put it differently, 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".

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[6] For example, Abel and Eberly (1994) show that investment depends only on marginal q and the capital stock, so that uncertainty affects investment only through marginal q. For an empirical comparison of average and marginal *q*, see Gugler et al. (2004).

[7] Bloom et al. (2007) describe the effects of uncertainty such that both less 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.

[8] 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.

[9] Since "time-to-build"-lags are common in electricity generation, foremost for base-load technologies with low marginal costs and high fixed costs (e.g. nuclear or run of river plants), we take this possibility seriously in our context.

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.[10] 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.

Forms and Measurement of Uncertainty

"Uncertainty" comes in a variety of ways, however. One useful distinction is between aggregate (or industry-level) uncertainty and uncertainty specific to the firm or even specific to certain asset classes of the firm.[11] *Firm-specific uncertainty* can be analysed as above: if the firm delays investment, it can reduce exposure to an adverse shock and preserves the option to invest. However, the analysis may differ with respect to *industry-wide uncertainty*. One may argue that the possible positive effects of uncertainty on investment ("value of being active" and "gain from an increase in price spikes") are more likely with aggregate uncertainty in electricity generation. The "value of being active" is very similar across firms at least for specific generation types, as time-to-build-lags are similar for a given generation type. Likewise, the "gain from an increase in price spikes" is similar across firms, since wholesale electricity prices are the same for all firms in a spot market and marginal costs are similar.

In any case, one of the major additions of this paper to other related literatures is that we distinguish between firm-specific (or even firm-technology-specific) uncertainty and (aggregate) industry-wide uncertainty and include proxies for both in an investment equation. Measuring uncertainty is inherently difficult. Reasonably high-quality price data is often not available on a sufficiently *disaggregated* basis, and technology shocks are largely *unobservable*. Moreover, uncertainty concerns not what actually happens but what might occur, and data on *expectations* are notoriously poor.

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[10] Another rationale is due to Kulatilaka and Perotti (1998). They explain that greater uncertainty will lead to higher investments if there is room for strategic competition which offers room to acquire options to grow.

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

The most common measure of uncertainty is thus to use stock market data, such as the variance or standard deviation of daily stock returns (see e.g. Leahy and Whited (1996) or Bloom et al. (2007)) and/or measures of realized cash flow volatility from accounting data.[12] The disadvantage of using stock returns is that asset returns may be quite noisy, reflecting not only changes in fundamentals, but also bubbles, fads, and the influence of noise traders. Accounting data requires long horizons and fails to capture uncertainty about future profits. Moreover, these sorts of measures capture – if at all – all risky aspects of the firm, not only uncertainty concerning specific types of investment, and they may be jointly determined with the firm's investment decisions. As outlined next, we apply measures of uncertainty which, as we argue, do not suffer from these shortcomings.

In order to assess how an increase in uncertainty will influence investments in generating capacities and the incentives to invest, we employ the number of hours running for each generating type (*NOHR*) as a firm- (or even firm-generation type-) specific uncertainty measure, as well as the variance of wholesale electricity prices (*VarP*) as an industry-wide measure of uncertainty. The number of hours running of a generation type is a measure of capacity utilization, which (inversely) determines the riskiness of a firm's investment decision in electricity generation (see also Tishler et al., 2008).

Thus, (i) $NOHR$ is a firm- or even firm-technology-specific measure of uncertainty depending on which level of *aggregation* we take.[13] If e.g. gas generation drops out of the merit order curve, since its marginal costs are higher than the wholesale price for a large part of the year, the uncertainty surrounding the gas assets of the firm is large. If a large part of firm generation assets drop out of the merit order, firm uncertainty goes up. (ii) $NOHR$ captures supply side *technology shocks*. If e.g. renewable feed-in shifts marginal generation technologies (e.g. gas, coal, or oil) out of the market, we capture that via a decreased $NOHR$ for these marginal technologies. As a consequence, these assets get more risky to hold. *NOHR* may also capture demand side shocks. If demand for electricity is low (high), prices are likely to be low (high), and NOHR is likely to be low (high). (iii) $NOHR$ is an *ex ante* measure of uncertainty, since it utilizes wholesale prices, which are determined according to supply and demand on electricity exchanges incorporating also

[12] There is a large literature in the finance and management literature as how to measure "business risk", see e.g. Fama and French (2002).

[13] As we show below, our regressions are either at the firm level or at a more disaggregated level, where we investigate different types of generation technologies.

expectations about future conditions. Since prices closely follow a random walk, current prices are good predictors for future prices.[14] This implies that firms can very well predict future $NOHR$ values from their current $NOHR$ levels disaggregated by generation type. For example, firms know that it is risky to invest in gas, since their current $NOHR$ (i.e. capacity utilization) is very low. Moreover, wholesale electricity prices do not suffer from the shortcomings of stock returns, like bubbles, fads, and the influence of noise traders. (iv) Finally, since our $NOHR$ measure utilizes measures for output prices and marginal costs and not accounting data, it can be seen as a *structural measure of uncertainty*.

The variance of wholesale electricity prices ($VarP$) is a good ex ante measure of industry-wide uncertainty, since the good electricity is homogenous (at least what the physical characteristics are concerned), very well defined, and equal for all the companies.

Summarizing, the pattern "positive effects of aggregate uncertainty but negative effects of firm-specific (or plant-specific) uncertainty on investment" would fit well with theory. If aggregate uncertainty increases *for given firm-specific uncertainty*, a firm may invest more, since there is a larger value of being active in a future period and/or there are more gains from an increase in price spikes. In contrast, *for given aggregate uncertainty* an increase in firm-specific uncertainty should unambiguously undermine investment incentives, since the option value to wait increases for that specific firm. Concretely in our case, increased firm specific uncertainty implies that the firm cannot be sure that it will be in the merit order for a lot of hours a year and will therefore better postpone investment.

Investment Model

Before arriving at the main specification of our structural investment equation, two important aspects of the data generating process in electricity generation investment have to be discussed. First, investments or disinvestments 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 or by a large decrease in capacity when a generation plant is closed down or sold to another firm. Of course, this problem is more prevalent for smaller companies operating only a few plants and/or when we estimate the investment equation at a finer level of aggregation, e.g. at the "3-type-level" (renewables, base and peak capacity) or at the "6-

[14] Augmented Dickey Fuller tests cannot reject the null hypothesis of a unit root for the hourly spot price series.

types-level" (wind and solar, run of river, other renewables, nuclear, coal, gas). This proves to be cumbersome in econometric regressions (Nilsen and Schiantarelli, 2003). Therefore an ordered logit model is employed where investment is coded as zero for disinvestment, one for no investment, and two for investment. Compared to other empirical literatures (e.g. European Commission, 2015; Ishii and Yan, 2004; Kim et al. 2012) that estimated tobit models and, thus, have to truncate or recode disinvestments, our multinomial ordered logit model allows for including disinvestment. Our main specification therefore reads:

$$I_{f,g,c,y} = \alpha + \beta I_{f,g,c,y-1} + \gamma \log\left(\pi_{f,g,c,y}\right) + \delta NOHR_{f,g,c,y} + \zeta VarP_{c,y} + \nu_c + \varepsilon_{f,g,c,y}, \qquad (4)$$

where f, g, c, y denote the firm, generation technology, country, and year, respectively. I are the investment categories. 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. π are variable profits, $NOHR$ the number of hours running, $VarP$ the wholesale spot-price variance, and ε the error term. The fixed effects, ν_c, capture unobserved and time-invariant heterogeneity across countries.[15]

We run the regressions for different aggregation levels. The highest aggregation level is at the firm-country-year level, for which we aggregate over all types of generation. Thus, the subscript g drops from the equation. At the disaggregated level, we distinguish either between three generation technologies (“3 types”), i.e. renewables, base, and peak load capacities, or between six generation technologies (“6 types”), i.e. renewables (wind, solar), run of river, other renewables (i.e. waste, wood), nuclear, coal, and gas.

Summarizing, our investment equation (i) is estimated by ordered logit to tackle the "zeros" problem following from the lumpy nature of electricity generation investment; (ii) incorporates a lagged dependent variable to capture adjustment costs in electricity generation investments; (iii) employs a novel proxy for the value of the specific invested capital and therefore for investment opportunities in that specific fuel type of generation; (iv) employs both novel proxies for firm- or fuel type-specific uncertainty and for aggregate industry-specific uncertainty.

[15] We also expanded the model by an interaction term of variable profits with firm-specific uncertainty ($\log(vCF) \times NOHR_{f,g,c,y}$ and get corroborating evidence to Bloom et al., 2007.

4. Data

To empirically estimate the investment equation, we utilize data from various sources to construct a rich and unique panel dataset of electricity generating firms from 14 European countries[16] over the annual period 2006–2014.[17] PLATTS PowerVision provides data on European firms' *installed capacities by generation technology*. We combine these data with measures on firms' *variable profits* (i.e. a proxy for future expected profitability) and *capacity utilization* (i.e. a proxy for the inverse of 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.[18] Additionally, we employ hourly data from day-ahead spot markets to obtain the average yearly *price variance*, as a measure for industry-specific uncertainty.

Dependent Variable

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 owing 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.[19] Also, we exclude pump storage capacity since 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 these 14 countries in 2014.[20] At the most granular level, we distinguish between six types of generation technologies within firms.[21] To get a more general picture from our regressions, we also aggregate these data to a three-types-level and to the firm level, as presented in Table 1.

[16] Austria, Denmark, Finland, France, Germany, Hungary, Italy, Norway, Portugal, Slovakia, Spain, Sweden, Switzerland, United Kingdom.

[17] Since the regressions include first differences and a lagged dependent variable, the estimation sample covers 2008–2014.

[18] See the description in this section under the subheading "Variables of Interest" and the Appendix for more details.

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

[20] 2014: 95%, 2013: 95%, 2012: 93%, 2011: 95%, 2010: 96%, 2009: 95%, 2008: 92%.

[21] In the underlying data we differentiate between 73 types of generation units (combinations of turbine types, fuel types, and construction years), as we outline in the Appendix, and then aggregate to the six types level.

Table 1. Generation technologies at different aggregation levels

Firm level	3 types level	6 types level	Description
	RES	Res	Intermittent renewables (solar, wind)
		RoR	Run of river
		Nuc	Nuclear
Firm	BASE	OthRes	Other baseload renewables (geothermal, biomass, biogas, …)
		Coal	Various forms of coal
	PEAK	Gas	Various forms of gas
		(Oil)	(Various forms of oil)

Note: At the 3 types level, PEAK includes both gas and oil, while oil is excluded at the 6 types level due to a low number of observations (see Table 2).

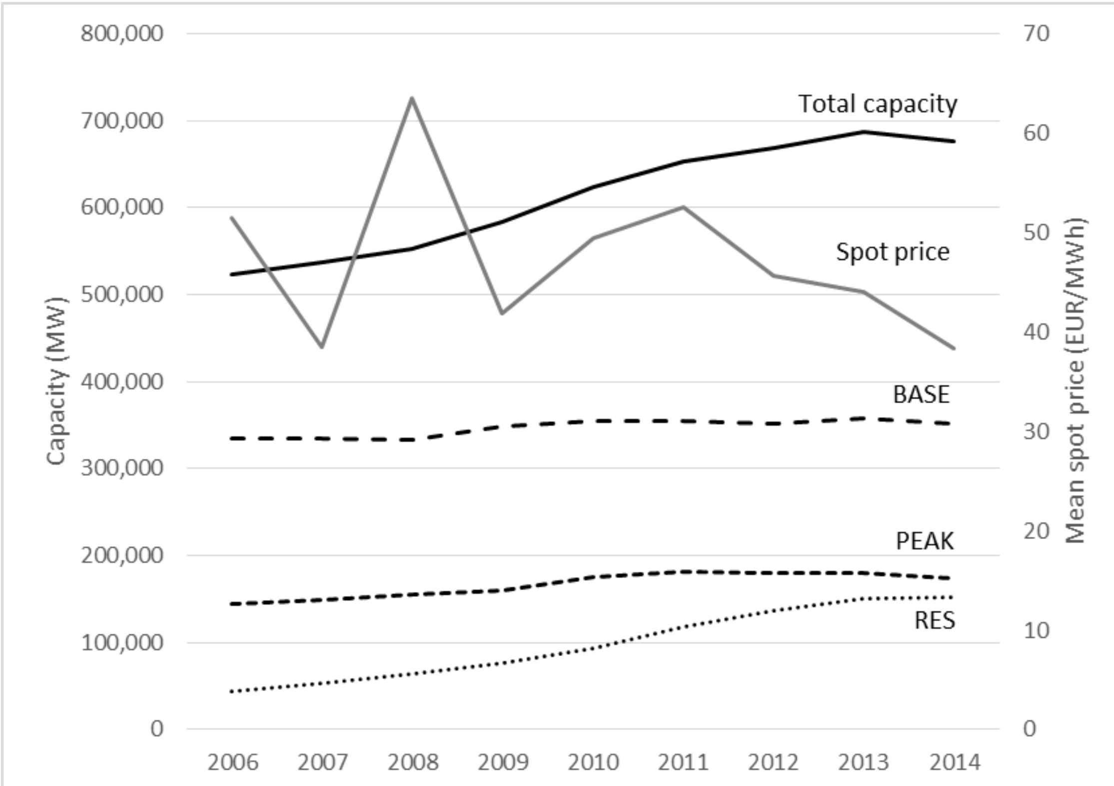
Table 1. Generation technologies at different aggregation levels

Firm level	3 types level	6 types level	Description
	RES	Res	Intermittent renewables (solar, wind)
		RoR	Run of river
		Nuc	Nuclear
Firm	BASE	OthRes	Other baseload renewables (geothermal, biomass, biogas, …)
		Coal	Various forms of coal
	PEAK	Gas	Various forms of gas
		(Oil)	Various forms of oil

Note: At the 3 types level, PEAK includes both gas and oil, while oil is excluded at the 6 types level due to a low number of observations (see Table 2).

Graph 1 provides an overview of the electricity generation capacity development and the yearly variation of the average spot price. We see a substantial increase in renewable capacity, while BASE and PEAK have been stagnant with slight disinvestments in the most recent sample years. This totals in a massive build-up in overall generation capacity from 2006 to 2013, followed by a decline in 2014. The recent drop may be partly the result of declining investment incentives as a consequence of the falling spot prices since 2011.

Graph 1. Capacity and Spot Price Developments



Note: The graph is based on data of our sample of 437 firms from 14 European countries.

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 71.8% of firm-year observations firms do not invest nor disinvest, in 22.9% they expand, and in 5.3% they reduce capacity. Base load capacity is added in 15% of firm-years and reduced in 5.6%. Renewable capacity is increased in nearly 26% of firm years.

Table 2. Dependent Variable: Multinomial Coded Investment Decision

	Disinvestment (0)		No investment (1)		Investment (2)		Total obs.
FIRM	151	5.3%	2047	71.8%	653	22.9%	2851
RES	4	0.4%	721	73.7%	253	25.9%	978
BASE	123	5.6%	1739	79.4%	329	15.0%	2191
PEAK	65	3.9%	1419	85.0%	185	11.1%	1669
Res	4	0.4%	721	73.7%	253	25.9%	978
RoR	111	5.5%	1737	85.8%	177	8.7%	2025
OthRes	4	0.5%	654	82.2%	138	17.3%	796
Nuc	14	4.9%	240	83.3%	34	11.8%	288

Coal	28	4.1%	636	92.6%	23	3.3%	687
Gas	52	3.5%	1287	86.1%	155	10.4%	1494
Oil	17	5.0%	320	93.8%	4	1.2%	341

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

Variables of Interest

We construct firms' supply curves (i.e. "merit order curves"), which represent the outputs of generation technologies sorted by their respective marginal costs, based on (the supply side of) a fundamental market model.[22] This is a state-of-the-art approach in energy economics to infer about the effects of changes in fundamentals (see also Burger et al., 2010, chapter 4).

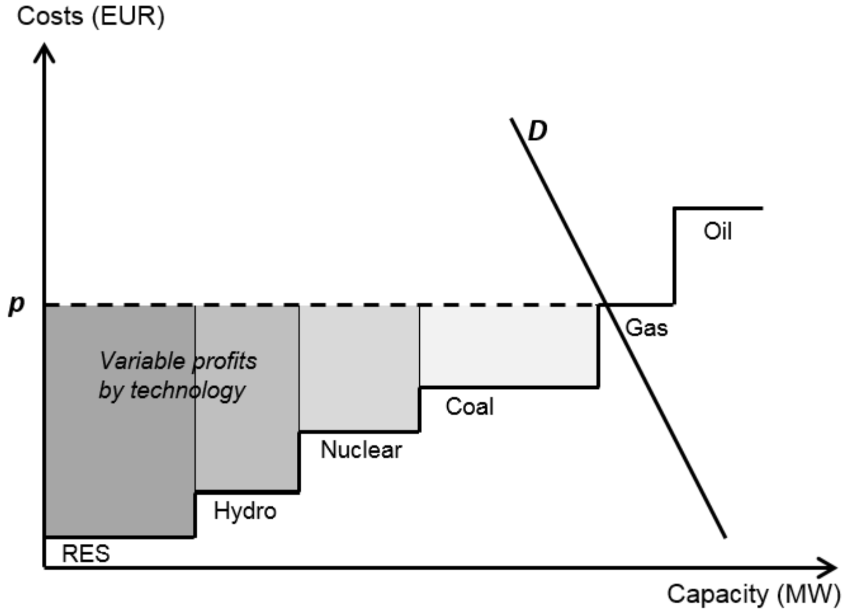
We are particularly concerned with firms' *variable profits* from different generation technologies as a measure for the profitability of investment. As shown in Graph 2, a firm will produce electricity from a specific generation technology if the marginal costs of production are below the actual spot price. Thus, the variable profits are calculated as:

$$\pi_{f,g,y} = \sum_{h=1}^{8760} (p_{c,h} - mc_{g,h}) * avCap_{f,g,h}, \text{for } p_{c,h} > mc_{c,g,h}, \tag{5}$$

where $f, c, g, h,$ denote the firm, country, generation technology, and hour, respectively. Moreover, y denotes the year, which is an aggregate over the total number of hours per year (8760 in a normal year and 8784 in a leap year). The variable profits (π) are thus calculated as 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 a firm's generation technology (g) times output, which we proxy by the available capacity ($avCap$). The marginal costs are constructed as fuel costs plus emission costs adjusted for an efficiency factor, which depends on the plant construction year; the available capacity is the installed capacity adjusted for operational limitations (e.g. scheduled maintenance and seasonal demand fluctuations). Firms generate profits from their various types of installed generation capacities if the spot price exceeds their associated marginal costs. If the spot price exceeds a technology's marginal costs, it is assumed that it is not running and thus accrues a variable profit of zero.

[22] We provide a detailed description of our fundamental model in the Appendix (including various data sources, construction of variables, and intuition).

Graph 2. Variable Profits per Generation Technology of a Typical Firm



The variable profit indicates the actual income that is generated by the installed generating capacity and represents a good proxy for the financial value of the firm assets (or generation type assets if finer disaggregated), i.e. V in equation (3) – under the assumption that current π is a good predictor of future π.[23] The difference is that π measures period specific variable profits and V is the discounted value of all future variable profits of the asset. As argued above, variable profits are a good measure for investment incentives since electricity prices at the power exchanges closely follow a random walk[24] and the prices today are good predictors for the prices tomorrow.

We are also able to calculate the *numbers of hours running (capacity utilization)* of firms' generation technologies. We assume that generation technologies are running if the spot price in a given hour exceeds their marginal costs. Hence, $NOHR$ is increased by one hour if $p_{c,h} > mc_{c,g,h}$. At the aggregate level (e.g. firm level), the number of hours running by firm-technology type is weighted by technologies' available capacities of firms, so that $NOHR$ is normalized between 0 and the maximum of 8,784 hours per year.[25] $NOHR$ represents a measure for (the inverse of) firm-

[23] An Im-Pesaran-Shin test of $vCF_{f,c,y}$ does not reject the null-hypothesis of a panel unit-root.
[24] Augmented Dickey Fuller tests cannot reject the null hypothesis of a unit root for the hourly spot price series.
[25] The maximum hours are 8,760 in a normal year and 8,784 in a leap year.

or even *firm-technology-specific uncertainty*, depending on the aggregation level of the regressions.[26]

Industry-specific uncertainty can be proxied by the spot *price variance*. Hence, we collect data on *hourly* day-ahead electricity spot prices from the countries' respective power exchanges to construct the yearly average of hourly price variances. Day-ahead spot markets are by far the largest, and thus the most relevant markets for wholesale electricity. Even if wholesalers use other channels (e.g. OTC markets, direct contracts, intra-day or balancing markets), the *day-ahead spot market* represents the *opportunity market* (Gugler et al., 2016). Thus, prices (and derived statistics) determined in the day-ahead spot market represent good measures for opportunity costs in the whole electricity sector.

Descriptive Statistics

Table 3 presents descriptive statistics of our main variables at the firm level and the more disaggregated level of three generation technologies (RES, BASE, PEAK). The mean capacity by sample firm is 1,559 MW, with a strong heterogeneity indicated by the large variance of 5,837 MW. In our sample, investment is also positive with a mean of 33.6 MW, which is reflected by a mean value of the multinomial coded investment variable of greater than one. Mean yearly investment in BASE is, however, negative (-5.11 MW). The average sample firm generates variable profits from its various generation technologies of 188 Mio. EUR per year. Average capacity utilization is 6,250 hours per year, however, PEAK technologies run only 3,440 hours per year on average.

Table 3. Summary Statistics

Variable	Description	Obs.	Mean	S.D.	Min.	Max.
	FIRM					
$Cap_{f,c,y}$	Total capacity (MW)	2,851	1,558.72	5,837.06	0.00	91,555.10
$\Delta Cap_{f,c,y}$	Investment (MW)	2,851	33.57	395.67	-3,257.00	9,389.00
$I_{f,c,y}$	Multinomial coded investment (0, 1, 2)	2,851	1.18	0.50	0.00	2.00
$\pi_{f,c,y}$	Variable profits (Mio. EUR)	2,851	188.00	1,140.00	0.00	32,000.00
$NOHR_{f,c,y}$	Weighted number of hours running (1000 h)	2,851	6.25	2.48	0.00	8.78
$VarP_{c,y}$	Spot price variance (100 EUR/MWh)	2,851	4.00	5.13	0.32	44.16
$resmarg_{c,y}$	Reserve margin (%)	2,527	41.86	13.75	10.16	62.12
$rnwbl_{c,y}$	Wind and Solar share (%)	2,851	7.02	7.33	0.14	43.26
	RES					
$Cap_{f,c,g,y}$	Total capacity (MW)	978	806.98	3,898.31	0.00	35,431.11
$\Delta Cap_{f,c,g,y}$	Investment (MW)	978	96.50	605.13	-1.75	9,389.00
$I_{f,c,g,y}$	Multinomial coded investment (0, 1, 2)	978	1.25	0.45	0.00	2.00
$\pi_{f,c,g,y}$	Variable profits (Mio. EUR)	978	68.90	358.00	0.00	6,020.00

[26] Note that a higher $NOHR$ indicates less uncertainty.

$NOHR_{f,c,g,y}$	Weighted number of hours running (1000 h)	978	8.50	1.18	1.23	8.78
$VarP_{c,y}$	Spot price Variance 100 EUR/MWh	978	4.12	5.44	0.32	44.16
$resmarg_{c,y}$	Reserve margin (%)	855	38.94	14.55	10.16	62.12
$rnwbl_{c,y}$	Wind and Solar share (%)	978	7.01	7.78	0.14	43.26
		BASE				
$Cap_{f,c,g,y}$	Total capacity (MW)	2,191	1,118.35	5,179.76	0.09	82,828.31
$\Delta Cap_{f,c,g,y}$	Investment (MW)	2,191	-5.11	118.20	-2,641.00	1,258.80
$I_{f,c,g,y}$	Multinomial coded investment (0, 1, 2)	2,191	1.09	0.44	0.00	2.00
$\pi_{f,c,g,y}$	Variable profits (Mio. EUR)	2,191	176.00	1,230.00	0.00	31,300.00
$NOHR_{f,c,g,y}$	Weighted number of hours running (1000 h)	2,191	7.39	1.84	0.00	8.78
$VarP_{c,y}$	Spot price Variance 100 EUR/MWh	2,191	3.90	4.79	0.32	44.16
$resmarg_{c,y}$	Reserve margin (%)	1,935	41.46	14.26	10.16	62.12
$rnwbl_{c,y}$	Wind and Solar share (%)	2,191	6.16	6.80	0.14	43.26
		PEAK				
$Cap_{f,c,g,y}$	Total capacity (MW)	1,669	719.52	1,784.41	0.00	17,414.19
$\Delta Cap_{f,c,g,y}$	Investment (MW)	1,669	6.32	164.31	-2,179.00	2,000.00
$I_{f,c,g,y}$	Multinomial coded investment (0, 1, 2)	1,669	1.07	0.38	0.00	2.00
$\pi_{f,c,g,y}$	Variable profits (Mio. EUR)	1,669	49.10	184.00	0.00	3,720.00
$NOHR_{f,c,g,y}$	Weighted number of hours running (1000 h)	1,669	3.44	2.53	0.00	8.41
$VarP_{c,y}$	Spot price Variance 100 EUR/MWh	1,669	4.09	5.13	0.32	44.16
$resmarg_{c,y}$	Reserve margin (%)	1,525	43.16	13.48	10.16	62.12
$rnwbl_{c,y}$	Wind and Solar share (%)	1,669	8.12	7.34	0.14	43.26

Notes: "Obs." is observations, "S.D." is standard deviation, "Min." is minimum, and "Max." is maximum. f, c, g, y stand for firm, country, generation type, and year, respectively.

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

Table 4. Correlations of main variables at the firm level

	$I_{f,c,y}$	$\log(\pi_{f,c,y})$	$I_{f,c,y-1}$	$NOHR_{f,c,y}$	$VarP_{c,y}$
$I_{f,c,y}$	1.00				
$\log(\pi_{f,c,y})$	0.21	1.00			
$I_{f,c,y-1}$	0.19	0.23	1.00		
$NOHR_{f,c,y}$	0.14	0.47	0.11	1.00	
$VarP_{c,y}$	0.06	0.11	0.00	0.03	1.00

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

5. Results

We evaluate the determinants of firms' investment decisions in electricity generation capacity. Taking account of the zero values problem of the investment data, we employ an ordered logistic regression that uses the multinomial coded investment as our dependent variable. Generally, logit models estimate the probability of a certain event to happen (e.g. investment). The odds ratio[27] therefore tells the probability to be in a higher investment category (e.g. investment) compared to fall in any of the other categories (disinvestment, no investment).

In the following, we concentrate on the main regression results based on our main model specification presented in equation (4). Then, in section 5.2., we extend the main model by additional variables of interest to provide further empirical evidence on the drivers of investment activity in electricity generation.

5.1.Main Results

Table 5 presents regression estimates of the odds-ratios of the ordered logit model. Against the above reasoning, our investment equation includes variables for variable profits from various fuel types, firm- (firm-technology-) specific uncertainty, industry-specific uncertainty, and a lagged dependent variable. Firstly, we focus on the aggregate firm level (specifications (1)), which does not distinguish between investments in different technologies. Since investment determinants may vary with the type of generation technology, we look at a more disaggregated level subsequently (specifications (2)–(4)) and separate between three types of technologies, namely renewables (RES), base load technologies (BASE) and peak load technologies (PEAK). Each specification is estimated with country fixed effects and includes robust standard errors clustered at the firm level.

Table 5. Firm Level & 3 Types: Ordered Logit Model, Odds Ratios

	(1) FIRM	(2) RES	(3) BASE	(4) PEAK
$\log(\pi_{f,c,g,y})$	1.222***	1.549***	1.135***	1.059
	(0.041)	(0.092)	(0.033)	(0.038)
$I_{f,c,g,y-1}$	1.986***	2.666***	1.398*	1.135
	(0.249)	(0.522)	(0.277)	(0.316)
$NOHR_{f,c,g,y}$	1.045**	1.020	1.084***	1.091*
	(0.022)	(0.062)	(0.029)	(0.052)
$VarP_{c,y}$	1.015**	1.041***	1.020**	1.011
	(0.007)	(0.016)	(0.009)	(0.012)
Country FE	Yes	Yes	Yes	Yes
Total obs.	2,851	978	2,191	1,669
Investment obs.	653	253	329	185
Disinvestment obs.	151	4	123	65

*Notes: Dependent variable is investment category (0 = disinvestment, 1 = no investment, 2= investment). Robust clustered (by firm) standard errors in parentheses. ***, **, * signify statistical significance at the 99%, 95%, and 90% level, respectively.*

[27] 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.

Firm Level

At the firm level, we see that variable profits, $log(vCF)$, have a positive and statistically significant influence on the investment decision. The odds ratio tells that if variable profits increase by 100%, the odds are 22.2% higher to invest.[28] Or in other words, it is 1.222 times more likely to be in the "investment" category than to be in the combined stagnant or disinvestment category if variable profits increase by 100%. In line with the economic intuition, a firm will be more likely to invest if it accrues profits from the investment. That is, present profits are a good predictor of future profitability of investments, which positively impact total investment. This finding corroborates the q-model of investment if we interpret $log(vCF)$ in this context.[29]

The odds ratio of the lagged dependent variable is greater than one and statistically significant. This is evidence that investments in electricity generation capacity come in bursts. If investment took place in the previous period, chances are high for investment in the current period.

Concerning uncertainty, we distinguish between firm- (firm-technology-) specific uncertainty and aggregate industry-specific uncertainty. While we measure the inverse of firm-specific uncertainty by a firm's hours of production per year (the number of hours running, $NOHR$), the variance of the spot price indicates aggregate uncertainty, which hits *all* firms in the industry. The coefficient of $NOHR$ is greater than one and statistically significant. Thousand more hours of production (i.e. a unit change in $NOHR$) increase the odds to invest by 4.5%. Intuitively, if a firm's generation units are in the merit order for more hours a year, risk goes down, and the firm is more likely invest. In other words, firm-specific uncertainty (i.e. a decrease in $NOHR$) decreases the investment propensity, which empirically corroborates Dixit and Pindyck (1994).

Contrary, the positive and statistically significant coefficient on $VarP$ indicates that if aggregate uncertainty increases for given firm-specific uncertainty, the individual firm has a higher incentive to invest as there is a higher value of being active in a future period (Bar-Ilan and Strange, 1996) and/or there are more gains from more pronounced price spikes (Tishler et al., 2008). Thus, a higher price variance is associated with higher odds to invest supporting the economic intuition given by

[28] More specifically, if log(vCF) increases by one (which refers to a 100% increase in vCF) the odds to fall into the investment category are 20.9% (=1-1.209*100) higher that to fall into the stagnant or disinvest categories.

[29] Since equation (3) includes the financial value of assets which is a present value of future profits, we multiply vCF with values between 10 and 20 mimicking a reasonable range for present values. The estimates still indicate a positive effect on investment activity, yet coefficients tend to be smaller. Moreover, equation (3) includes the capital stock. Hence, the main results stay robust to the inclusion of the lagged capital stock (K_{y-2}).

Bar-Ilan and Strange (1996) and Tishler et al. (2008). In line with theory, we find empirical evidence for the pattern "positive effects of aggregate uncertainty but negative effects of firm-specific (or plant-specific) uncertainty on investment."

Three Types Level

The findings at the firm level may represent a mixture of diverse investment strategies regarding different types of generation technologies. This is why we look at a more disaggregated level of investment and focus on three generation types (specifications (2)–(4)). Indeed, we find controversial investment behaviour in some cases (e.g. substitution of peak load technologies by renewables).

Expected future profits, as measured by the actual variable profits ($\log(vCF)$), have a positive impact on the decision to invest across all generation types – although this finding is less pronounced and statistically insignificant for peak load technologies.[30] Hence, it is more likely to invest if firms expect to generate profits in the future. However, we see that renewables (odds ratio of 1.549) react much stronger to cash flow expectations compared to base (odds ratio of 1.135) or peak load technologies (odds ratio of 1.060). Renewable technologies take little time to build, which may explain their strong sensitivity to profit incentives. Interestingly, while many empirical studies in the finance literature cannot confirm the importance of q, our findings support the notion of the q-model. We argue that our data are more adequate in measuring fundamental profit incentives: We measure profits by generation type by firm, whereas studies in finance (merely) utilize data from stock prices reflecting a mixture of fundamentals and believes possibly for a diverse set of assets.

The estimates on the lagged dependent variable ($I_{f,c,g,y-1}$) are striking. There is an explosive investment in renewables over time, given the high and statistically significant odds ratio of 2.666. Investment in the previous period increases the propensity to invest in the current period. The dramatic build-up of renewable generation capacity may be explained by national policies to support the expansion of green technologies. Nevertheless, there seem to be *missing investment incentives in peak load plants*, which are generally necessary to *back the system* when wind and sunshine are absent.

[30] PEAK includes gas and oil, where the latter is a rather obsolete technology, characterized by disinvestment, which distorts the results. At a more disaggregated level, we show that future cash flow expectations have a statistically significantly positive impact on investment in *gas*, which represents the most important peak load technology.

Regarding investment in renewables, $NOHR$ becomes statistically insignificant, yet $VarP$ is significantly positive. Given that renewables generally enjoy subsidized and prioritized feed-in – renewables may generate electricity whenever possible (e.g. when wind blows or the sun shines) – it seems that firm-specific capacity utilization (the inverse of firm-specific uncertainty) is not an issue. Firms investing in renewable capacity may have a strong idea about future capacity utilization rates given their preferential feed-in, so that firm-specific uncertainty may be of minor importance. Indeed, the European Commission (2015) corroborates this notion, stating that support schemes, which are largest for renewables, have substantially limited their investors' risk exposure. Conversely, increasing spot price spikes from higher price variance ($VarP$) seem to benefit renewables and thus increase the odds to invest.[31]

For conventional base and peak load technologies, $NOHR$ is relevant, which is evidence that firm-specific uncertainty reduces the likelihood to invest. Given the replacement of conventional technologies by renewables, base load plants have decreasing capacity utilization rates (i.e. decreasing $NOHR$), which therefore decreases the odds to invest. Moreover, $VarP$ turns out positive and statistically significant, so that base load technologies can benefit from high price spikes. For peak load technologies we find basically the same yet more pronounced investment patterns regarding $NOHR$. Investment in peak load capacity reacts particularly negatively (and statistically significantly) to firm-specific uncertainty (the inverse of $NOHR$). The same reasoning applies: since peak load technologies get pushed out of the merit order by renewables, their number of hours running decreases, which in turn shrinks the odds to invest.

Industry-specific uncertainty ($VarP$) has a statistically insignificant impact on peak load investment. What is relevant for peak load technologies is, thus, their capacity utilization ($NOHR$). The positive reaction of investment in conventional technologies to $NOHR$ combined with the fact that $NOHR$ decreases over time (renewables push them out of the merit order) provide evidence that capacity from conventional technologies may get scarce due to a lack of investment in the long run. Thus, there is evidence for a missing money problem regarding conventional plants.

Six Types Level

[31] During the sample horizon 2006–2014, in many countries renewables enjoyed minimum guaranteed feed-in tariffs. However, once spot prices were higher than the feed-in tariff, they could fully benefit from the higher prices.

We now disentangle investment into six generation technologies and present selected findings that help explain the above results in more detail. We refrain providing regression estimates for oil due to low number of observations (4 on investment, 17 on disinvestment)[32] and because it has become an obsolete technology characterized by disinvestment in Europe. Hence, peak load technologies are most prominently represented by (various types of) gas. Table 6 presents odds ratios for the investment decision. Basically all fuel types react positively to expected future profits ($\log(vCF_{i,j,c,t})$), although some odds ratios turn out statistically insignificant. Overall, the estimates confirm the implications of the q-model.

The results on $VarP$ reflect the theoretical ambiguity. In general, renewables and base load technologies react strongly and statistically significantly to changes in the spot price variance, which may be interpreted in the sense of Tishler et al. (2008) to have a value of being active and benefit from price spikes. For nuclear capacity, coal, and run of river the findings also correspond with Bar-Ilan and Strange (1996) that given the very long time to build, it may be beneficial to invest in times of higher industry-specific uncertainty in order to profit from future price spikes.

For most base load technologies (RoR, OthRes, Nuc), capacity utilization (NOHR) does not seem to matter statistically, because they are running basically all the time anyway. Again, this is also true for renewables given their prioritized feed-in. In contrast, for coal and gas NOHR plays an important role in the investment decision, as capacity utilization matters. Both generation types exhibit characteristics of marginal technologies, so it is not granted that they are in the merit order all the time.[33]

Table 6. Six Types: Ordered Logit Model, Odds Ratios

	RES		BASE			PEAK
	(5)	(6)	(7)	(8)	(9)	(10)
	Res	RoR	OthRes	Nuc	Coal	Gas
$\log(\pi_{f,c,g,y})$	1.549***	1.209***	1.227***	1.049	1.066	1.114**
	(0.092)	(0.047)	(0.058)	(0.114)	(0.132)	(0.059)
$I_{f,c,g,y-1}$	2.666***	1.336	1.441	1.777	0.899	1.415
	(0.522)	(0.452)	(0.327)	(0.920)	(0.979)	(0.396)
$NOHR_{f,c,g,y}$	1.020	0.930	0.992	0.992	1.211**	1.108*
	(0.062)	(0.057)	(0.046)	(0.194)	(0.096)	(0.060)
$VarP_{c,y}$	1.041***	1.025**	1.076***	1.086***	1.018	1.000
	(0.016)	(0.012)	(0.021)	(0.030)	(0.036)	(0.012)

[32] Neither nuclear nor coal have many observations on investment and disinvestment, for which their regression estimates should also be viewed with caution.

[33] Even some forms of coal can be pushed out of the merit order when production of renewables is high.

Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Total obs.	978	2,025	796	288	687	1,494
Investment obs.	253	177	138	34	23	155
Disinvestment obs.	4	111	7	14	28	52

*Notes: Dependent variable is investment category (0 = disinvestment, 1 = no investment, 2= investment). Robust clustered (by firm) standard errors in parentheses. ***, **, * signify statistical significance at the 99%, 95%, and 90% level, respectively.*

5.2. Additional Influential Factors

In order to check for additional potential influential factors on investment activity, we include the following measures in our regressions:

(i) A country's *wind and solar penetration* (as a percentage in total production, $rnwbl_{c,y}$) may introduce some aspects of both aggregate uncertainty – e.g. through supply shocks – and firm-specific uncertainty – e.g. their generation intermittency may distort 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.

(ii) A country's *reserve margin*, which ideally measures the difference between the peak generating capability and the peak demand (Joskow, 2007), could also measure additional aspects of uncertainty but also accelerator effects. We quantify the reserve margin ($resmarg_{c,y}$) as the share of excess capacity during peak demand relative to total installed capacity[34] and, hence, provide a measure of over-capacity in the system. The intuition is that if the reserve margin is high, enough capacity is available, which may limit investment activity. On the contrary, if the reserve capacity is scarce, investments may be valuable. To avoid a potential simultaneity bias – both the multinomial coded dependent variable and the reserve margin are (partly) derived from the capacity ($Cap_{f,c,y}$), we include the lag of the reserve margin ($resmarg_{c,y-1}$) in our regressions. We obtain the data for hourly load (to calculate peak demand) from the European Network of Transmission System Operators for Electricity (ENTSO-E).[35]

Table 7 shows the odds ratios of the coefficient estimates from the multinomial logit regressions. The inclusion of either of the two new variables indeed hardly alters the initial coefficient estimates

[34] Reserve margin (%) = [(total capacity (MW) – maximum load (MWh)) / (total capacity (MW)] * 100.

[35] Due to unavailability of load values for some countries in some years, we lose a few observations in our regressions (see Table 3).

of $\log(vCF)$ and I_{y-1}, whereas it changes the coefficients of $VarP$ and $NOHR$ – our measures for aggregate and firm-specific uncertainty, respectively.

The odds ratios of $rnwbl$ less than one indicate that a higher share of intermittent production from wind and solar in total generation (per country per year) lowers the odds to invest in additional generation capacity across all types of technologies (FIRM, RES, BASE, PEAK). This is evidence that there is a *substitutive relationship* between renewable (wind and solar) penetration in the industry and additional generation capacity, which is most prominent for PEAK. The substitution effect between subsidized renewable build-up and conventional generation technologies, in particular peak load plants, raises concerns about the security of electricity supply. Conventional peak load technologies are still needed to back the system (e.g. when renewables do not produce or for dispatching during incidents, such as plant outages). Moreover, both uncertainty terms, $VarP$ and $NOHR$, lose in significance (except for BASE) once including $rnwbl$. This is likely for the fact that intermittent renewables capture parts of the variation in our uncertainty measures.

Table 7. Ordered Logit Model, Odds Ratios

	(15) FIRM	(16) RES	(17) BASE	(18) PEAK	(19) FIRM	(20) RES	(21) BASE	(22) PEAK
$\log(\pi_{f,c,g,y})$	1.219***	1.564***	1.131***	1.067*	1.183***	1.554***	1.110***	1.043
	(0.040)	(0.090)	(0.033)	(0.038)	(0.042)	(0.096)	(0.038)	(0.037)
$I_{f,c,g,y-1}$	1.983***	2.512***	1.394*	1.083	2.122***	2.994***	1.426	1.051
	(0.247)	(0.494)	(0.276)	(0.293)	(0.296)	(0.751)	(0.336)	(0.278)
$NOHR_{f,c,g,y}$	1.024	0.920	1.072***	1.002	1.037	1.026	1.068**	1.049
	(0.022)	(0.060)	(0.028)	(0.049)	(0.025)	(0.068)	(0.035)	(0.057)
$VarP_{c,y}$	1.008	1.022	1.019**	0.996	1.008	1.026	0.988	1.024
	(0.007)	(0.017)	(0.009)	(0.015)	(0.008)	(0.022)	(0.009)	(0.017)
$rnwbl_{c,y}$	0.922***	0.892***	0.951***	0.866***				
	(0.013)	(0.025)	(0.018)	(0.019)				
$resmarg_{c,y-1}$					0.941***	0.892***	0.952***	0.926***
					(0.009)	(0.019)	(0.012)	(0.014)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	2,851	978	2,191	1,669	2,365	792	1,807	1,447

*Notes: Dependent variable is investment category (0 = disinvestment, 1 = no investment, 2= investment). Robust clustered (by firm) standard errors in parentheses. ***, **, * signify statistical significance at the 99%, 95%, and 90% level, respectively.*

The regression results on $resmarg$ are intuitive. An increase (decrease) in $resmarg$ lowers (increases) investment activity. The intuition is that a high (low) reserve margin indicates over- (under-) capacity in the industry, which in turn decreases (increases) the odds to invest. This result holds at the firm level and for different types of technologies (RES, BASE, PEAK). What is more, the inclusion of $resmarg$ affects the coefficients of $NOHR$ and $VarP$, and renders them partly insignificant. A higher reserve margin leads to a higher supply security reducing price spikes, and it also reduces the probability that a given (predominantly) PEAK technology plant is in the merit order.[36]

6. Conclusions

In this paper, we investigate the driving forces of investment in electricity generation capacity to provide reasoning about the long-run electricity supply security. Our study adds to the existing literature by introducing novel features: (i) We develop structural measures for expected future profitability of investments and for uncertainty level based on a fundamental electricity model, which constructs hourly supply and demand for electricity generators from 14 European countries. (ii) We put our empirical regressions subject to Tobin's q-model of investment and extend it by measures for both firm-specific and industry-specific uncertainty. Contrary to most finance literatures, which calculate q from stock market data, our proxy for q (i.e. firms' profits from different generation technologies) better mirrors fundamental values. Indeed, our empirical results corroborate the q-model. (iii) Our data allow for the distinction between firm-specific (and even firm-technology-specific) uncertainty and aggregate industry uncertainty.

Evidently from our regressions, all firm-technologies follow market incentives. We show that positive cash flow expectations indeed drive investment. Consequently, 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.

We also find large effects of uncertainty. Increasing firm-specific uncertainty, indicated by decreasing capacity utilization ($NOHR$), is negatively associated with investment in coal, gas and

[36] Besides, we cannot rule out accelerator effects, i.e. a lower reserve margin may be associated with higher electricity demand for given capacity. The inclusion of both terms, $rnwbl$ and $resmarg$, renders the coefficients of $rnwbl$ statistically insignificant, while the coefficients of $resmarg$ stay statistically significant and robust. This intuition is that the maximum capacity (as contained in $resmarg$) is driven by renewables.

oil. This may create a severe *investment gap in the long run*, since spot prices are distorted by state intervention (e.g. subsidized renewable feed-in), so investment incentives in conventional technologies, in order to back the system, may fade. Moreover, we contend that over time, increasing generation from renewables decreases $NOHR$ for conventional technologies (i.e. the "Merit Order Effect"), in particular for peak plants, which in turn erodes respective investment incentives. Hence, market distortions supporting renewables may eventually create a *missing money problem* in electricity generation.

It is impossible to have both significant renewables support schemes and well-functioning wholesale markets with adequate investment signals at the same time. There are two ways out of the 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. On the other hand, policies may foster market dynamics and strong competitive market forces, so that markets send correct investment signals, including possibly high prices and sometimes 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. In either case, it would be of utmost importance not to ignore the fundamental threat of under-investment in one of the key industries in the economy, namely electricity.

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Appendix

Merit Order Curves

We construct hourly merit order curves (i.e. supply curves) of electricity generating firms in the style of a fundamental market model. However, we only focus on the supply side – the marginal cost curves – and take the observed spot price in any given hour into account to develop measures about firms' variable profits and capacity utilization (i.e. the number of hours running) by generation technology. This is a state-of-the-art approach in energy economics (e.g. to predict prices based on fundamentals). Hence, we follow related studies on the construction and application of merit order curves and/or fundamental market models (Borenstein and Bushnell, 1999; Burger et al., 2010, Chapter 4; Graf and Wozabal, 2013; Hirth, 2013; Schröter, 2004; Sensfuß, 2007; 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 Technical University of 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 extend at day-ahead spot markets, which are organized at power exchanges. In a power exchange, suppliers and consumers place bids (usually at 2 p.m.) 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., 2016). 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 owned technology capacity if its marginal costs of producing are below the spot price (see Graph 2). Therefore, we calculate hourly marginal costs of each firm's generation technology in order to construct *hourly merit orders*.

Data

We obtain detailed information on *installed capacity* at the generation unit level for the period 2006–2014 from Platts PowerVision. These 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 Europe irrespective of their size.

APG provided us with information on *availability factors* of power plants per turbine and fuel type. The availability of a power plant is an operational limitation determined, for example, by planned revisions (e.g. maintenances) and seasonal demand fluctuations. In accordance with Schröter (2004), we consider three periods, namely winter season, summer season and transition phase, in order to adjust our availability measure to seasonal demand fluctuations. Low electricity demand during summertime allows for higher operational flexibility. Thus most of the planned revisions take place during summer, so that our availability measure is significantly lower during this period. With respect to renewables, we utilize hourly data on wind and solar forecasts (provided by the Austrian energy trading company "e&t") to assess their availabilities. Bids at day-ahead markets generally follow wind and solar generation forecasts 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 the respective installed capacity to create a measure of *available capacity*.

APG and Energy Economics Group of TU Vienna (internal power plant database) 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 (see Graf and Wozabal, 2013; Schröter, 2004; Sensfuß et al., 2008). The variable takes up values between zero and one.

Construction of Marginal Costs, Variable Profits, and Capacity Utilization

We calculate *marginal costs* for each hour (*h*) and by 73 generation unit types (which are a combination of turbine type, fuel type, and construction year). For this purpose, we take fuel prices, the carbon dioxide (CO_2) price, emission factors, and efficiency factors into consideration. Even though data on various measures do not vary by hour (e.g. daily), we impute these values for each hour (*h*).

$$mc_{tt,ft,cy,h} = \frac{FP_{ft,h} + (CO2P_{ft,h} \times CO2E_{ft})}{EF_{tt,ft,cy}}$$

where:

mc	= Marginal cost (€/MWh)
FP	= Fuel price (€/MWh)
EF	= Efficiency factor (%)
$CO2E$	= CO_2 emission factor (tCO_2/MWh)
$CO2P$	= CO_2 spot price (€/MWh)
tt	= Turbine type
ft	= Fuel type
cy	= Construction year
h	= Hour

We distinguish between 22 plant types, which are combinations of 12 turbine types and 12 fuel types. For these plant types, we collected data on their *efficiency factors (EF)* depending on their respective *construction years*, which gives us 73 different combinations. 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. As the daily price of coal, we use ARA month future data provided by EEX. For gas, we use the daily price data provided by BAFA (the German Federal Office of Economics and Export Control). Since 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 daily price of oil we utilize Europe Brent Spot FOB provided by U.S. Energy Information Administration. Given missing uranium prices for nuclear power, like Graf and Wozabal (2013) we assume a constant (and negligible) input price of USD 9.33 per MWh (see OECD/IEA, 2010). 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* from the European Energy Exchange (EEX).

Each firm (*f*) located in country (*c*) will obtain *variable profits* (π) from its generation technologies' available capacities if the actual spot price in hour (*h*) is greater than the associated marginal costs:

$$\pi_{f,g,y} = \sum_{h=1}^{8760} \left(p_{c,h} - mc_{g,h}\right) * avCap_{f,g,h}, \text{for } p_{c,h} > mc_{c,g,h}, avCap_{f,g,h} = Cap_{f,g,h} * AF_{g,h}$$

(This equation corresponds with equation (5) in the main text body) where:

π	= Variable profits (€)
p	= Day ahead spot price (€/MWh)
mc	= Marginal cost (€/MWh)
$avCap$	= Available capacity (MW)
Cap	= Installed capacity (MW)
AF	= Availability factor (%)
f	= Firm
c	= Country
g	= Generation technology
h	= Hour
y	= Year

Our *availability factors* (AF) (i.e. a percentage score of total installed capacity) vary across 22 plant types and across three seasons of the year (i.e. summer, winter, and transition period). To obtain *available capacities* ($avCap$), we multiply generation technologies' installed capacities (Cap) with their respective availability factors. In order to get firm-year observations regarding six generation technologies, we make the following aggregations: We define six generation technologies (g), which represent aggregates over turbine type (*tt*), fuel type (*ft*), and plant construction year (*cy*) (see Table 1 for their definitions). To obtain yearly variation, we aggregate over the total number of hours (h) per year (8760 in a normal year and 8784 in a leap year).

Moreover, the merit order curves allow for constructing a measure of *capacity utilization*. An electricity generating firm will only produce with a certain generation technology in its possession as long as the technology's marginal costs are less than the spot price (otherwise it would make variable losses). Hence, we are able to measure the *number of hours running* (*NOHR*) of firms' generation technologies per year.