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Essays in Empirical Energy Economics

Author:
Philip C. Schnaars
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First supervisor: Prof. Dr. Grischa Perino
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Authors: Grischa Perino and Philip Schnaars

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Abstract

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by Philip C. Schnaars

This thesis investigates three relevant issues that are associated with transitioning a fossil-fuel based energy system towards a renewable structure. To this end, extensive data on the German electricity system and the interactions with its neighboring countries is gathered. The first paper deals with the substitution effect of unilateral renewable electricity and resulting long-term abatement under the overarching reformed emission trading scheme EU ETS. While onshore and offshore wind replace more emissions in the short term than solar power, the market stability reserve allows for a fraction of these short term replacements to result in long-term abatement, depending on the year of abatement effort. The second paper is related to this first topic and deals with the trading of renewable electricity, one step in time before the described actual emission reductions occur and its response to an increase in the weather forecast risk. The results imply that changes in forecast risk do not change market outcomes, suggesting that renewable firms do not incorporate such information into their decisions. Another consequence of expanding renewable capacity, often spatially distant from load centers, is more frequent grid congestion in zonal electricity markets. With reliable forecasts and high sensitivity on the grid, plant operators can engage in arbitrage between the day-ahead and the redispatch market if prices are sufficiently different between the two markets. A detailed analysis in the third paper reveals that a cluster of power plants in Germany engages in such arbitrage behavior, thus increasing the level and costs of congestion. This dissertation underlines the importance of designing a coherent and holistic policy environment to increase market efficiency and thereby reduce the costs of decarbonization.

UNIVERSITÄT HAMBURG

Zusammenfassung

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Essays in Empirical Energy Economics

by Philip C. Schnaars

Diese Thesis untersucht drei zentrale Aspekte der Umstellung eines fossilen Energiesystems zu einem System, das auf Erneuerbaren Energien beruht. Umfassende Daten über den deutschen Strommarkt und dessen Nachbarmärkten bilden die Basis dieser Analyse. Das erste Papier prüft den Substitutionseffekt von einseitiger Erneuerbare Energie und die daraus resultierende langfristige Emissionsvermeidung unter dem umfassenden reformierten Emissionshandelssystem EU ETS. Die kurzfristige Emissionsverschiebung von Strom aus Onshore- und Offshore-Windanlagen ist größer als die von Solarenergie. Die Marktstabilitätsreserve ermöglicht es, dass, abhängig vom Vermeidungsjahr, ein Teil dieser kurzfristigen Emissionsreduktion auch langfristig vermieden werden. Das zweite Papier bezieht sich auf die erste Fragestellung und untersucht das Handelsverhalten von Erzeugern Erneuerbarer Energien unter dem Eindruck von Risiken in der Wettervorhersage, bevor die beschriebenen Emissionsveränderungen passieren. Die erzielten Ergebnisse belegen keinen systematischen Zusammenhang zwischen der angebotenen Menge an Erneuerbarer Energie und dem Vorhersagerisiko. Dies deutet darauf hin, dass die Firmen diese Informationen bei Ihrer Angebotsentscheidung nicht berücksichtigen. Eine weitere Konsequenz des Ausbaus von Erneuerbarer Erzeugungskapazität, häufig örtlich entfernt von den Konsumenten, ist eine Zunahme von Netzengpässen in zonalen Elektrizitätsmärkten. Mit belastbaren Vorhersagen und einer hohen Netzsensitivität können Kraftwerksbetreiber zwischen dem Day-Ahead und dem Redispatchmarkt arbitrieren, sofern eine Preisdifferenz zwischen den beiden Märkten besteht. Eine detaillierte Analyse im dritten Papier deutet darauf hin, dass ein Cluster von Kraftwerken solch Arbitrage vollzieht und damit das Niveau und die Kosten von Netzengpässen erhöht. Diese Dissertation unterstreicht die Bedeutung eines kohärenten und gesamtheitlichen Regulierungsrahmens, um die Markteffizienz zu erhöhen und die Kosten der Dekarbonisierung zu senken.

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List of Abbreviations

ADF	**A**ugmented **D**ickey-**F**uller test
AT	**A**ustria
BIC	**B**ayesian **I**nformation **C**riterion
CAISO	**Ca**lifornia **I**ndependent **S**ystem **O**perator
CH	**C**umby-**H**uizinga test for autocorrelation
CZ	**Cz**ech Republic
BMWi	**B**undes**m**inisterium für **W**irtschaft und Energie
	(Federal Ministry for Economic Affairs and Energy)
CCGT	**C**ombined **c**ycle **g**as **t**urbine
CH	Switzerland
CO$_2$	**C**arbon Di**o**xide
COSMO-DE-EPS	**Co**nsortium for **S**mall-scale **Mo**delling **E**nsemble **P**rediction **S**ystem
DAG	**D**irected **A**cyclic **G**raph
DEHSt	**D**eutsche **E**missions**h**andels**st**elle (German Emissions Trading Authority)
DFGLS	**D**ickey-**F**uller **G**eneralized **L**east **S**quares test
DGP	**D**ata **G**enerating **P**rocess
DK	**D**enmar**k**
EEX	**E**uropean **E**nergy E**x**change
EnBW	**En**ergie **B**aden-**W**ürttemberg
EPH	**E**nergetický a **P**růmyslový **H**olding
e.g.	**e**xempli **g**ratia (for example)
EU	**E**uropean **U**nion
EUA	**Eu**ropean Emission **A**llowance
EU ETS	**E**uropean **U**nion Emission **T**rading **S**cheme
ENTSO-E	**E**uropean **N**etwork of **T**ransmission **S**ystem **O**perators for Electricity
EPEX Spot	European **P**ower Exchange
EUR	**Eu**r**o**
FR	**F**rance
GW	**G**iga**w**att
GWh	**G**iga**w**att**h**our
i.e.	**i**d **e**st (that is)
IEA	**I**nternational **E**nergy **A**gency
IRENA	**I**nternational **R**enewable **En**ergy **A**gency
kg	**K**ilo**g**ramm
kJ/m^2	**k**ilo**J**oule per squaremeter
km	**k**ilo**m**eter
kt	**k**ilo**t**on
LEAG	**L**ausitz **E**nergy **AG**
m/s	**m**eters per **s**econd
MSR	**M**arket **S**tability **R**eserve

MW	**M**ega**w**att
MWh	**M**ega**w**att**h**our
NL	**N**ether**l**ands
OCGT	**O**pen **c**ycle **g**as **t**urbine
Ofgem	**Of**fice of **G**as and **E**lectricity **M**arkets
OLS	**O**rdinary **L**east **S**quares
PJM	**P**ennsylvania-New **J**ersey-**M**aryland Interconnection
PL	**P**o**l**and
PP	**P**hillips - **P**erron unit root test
t	**t**on
USD	**U**nited **S**tates **D**ollar
UTC	Coordinated Universal Time

Für die Familie.

1 Introduction

Mitigating the impacts of global climate change and local pollution on the environment, economies and societies worldwide requires an international transition from a fossil-fuel based energy system towards energy provision that is primarily based on renewable sources. While the share of renewable sources in the electricity sector has become more significant in recent years, other sectors like transport and heating are lagging behind in reducing emissions. In these sectors, options for decarbonization tend to be more expensive than in the electricity sector (IRENA, 2020). The coupling and integration of these sectors via technologies like renewable hydrogen or heat pumps provides a viable option for decarbonization. This development will increase the worldwide consumption of electricity, with estimates ranging up to 300 percent compared to today's level (IRENA, 2021). The additional electricity demand from (indirect) electrification of transport (Emonts et al., 2019; Sterchele et al., 2020), heating (Bloess et al., 2018) and industry (Napp et al., 2014) has to be covered primarily by carbon-neutral technologies like nuclear power plants and intermittent renewable technologies such as wind turbines and solar panels in order to meet international climate targets. This vast expansion in the size of electricity markets highlights the need for extensive research about this development.

This dissertation is about the transition away from a fossil-fuel based electricity system towards an electricity market with a significant share of intermittent renewable capacity. This transition involves, among others, three major aspects. First, the development of overall system-wide emissions depends on a set of complementing and overlapping policies. The research presented in chapter 2 takes interactions of the German renewable subsidy scheme and the European Union Emission Trading Scheme (EU ETS) as an example of overlapping policies and estimates the overall marginal long-term emission abatement of subsidized renewable electricity in Germany. Second, the price risk increases with renewable intermittency, which in turn impacts the trading of electricity. Chapter 3 develops predictions for the bidding behavior of subsidized renewable firms under the presence of individual and aggregate risk in the relevant weather forecasts, which arises from the inherent renewable intermittency. These predictions are tested empirically. Third, inefficient market outcomes due to grid congestion and hence costly redispatch measures are more frequently observed. This is a result of the prevalent zonal market design and an increasing spatial mismatch between supply and demand from spatial clustering of renewable generation capacity. The study in chapter 4 derives the preconditions and incentives for German conventional firms to engage in arbitrage between the day-ahead and the redispatch market, thereby increasing the level of congestion and social cost. This is assessed empirically, where the mentioned weather forecasts provide an essential part of the analysis. Every chapter uses extensive real-world data from Germany, a declared front-runner in climate protection, to test causal hypotheses.

Policy makers have a variety of instruments available to foster the transition towards renewable-based electricity supply. These broadly fall into the categories of market-based instruments, such as a cap-and-trade scheme for emissions (Schmalensee and Stavins, 2017; Narassimhan et al., 2018), financial incentives, for example a tax on CO_2 (Haites, 2018) or subsidies for renewable electricity (Hitaj and Löschel, 2019), direct investment like funding of research on less emission-intensive technologies (Acemoglu et al., 2016) and quotas and standards, such as emission standards on cars (Official Journal of the European Union, 2019; Reynaert, 2021), improving energy efficiency of appliances (Jarke-Neuert and Perino, 2020) or the ban of certain technologies (Perino and Pioch, 2017). Explicitly pricing carbon emissions is considered to be the first-best policy in achieving an efficient market outcome by internalizing external effects (Stiglitz et al., 2017).

In the case of the European Union, as one of the most climate-ambitious jurisdictions worldwide, the different legislative entities rarely implement and target a certain sector with

only one policy instrument, but often apply a mix of multiple policies. Reasons include differences in preferences for climate protection among member states (Marchiori et al., 2017), national renewable targets set at the supranational level in addition to the union-wide EU ETS to grant long-term stability to businesses by explicitly favoring certain technologies (Delbeke et al., 2015), stakeholders' perception that complementary efforts are required to increase the effectiveness of a single intervention, such as subsidies for investment and innovation or measures targeting distributional aspects (Baranzini et al., 2017), the need to regulate sectors for which a carbon price was not implemented while interactions between the different sectors exist (Drummond and Ekins, 2017) and directly addressing non-carbon related issues such as local air pollution (Bollen and Brink, 2014; Zwickl et al., 2021). Such a policy mix can be more cost-effective in reaching certain climate goals by overcoming path-dependencies, policy failure and political resistance (Lehmann and Gawel, 2013; Dimanchev and Knittel, 2020). It can also drive up abatement costs by for example not directly targeting environmental externalities or distorting the calibration of preexisting instruments, hence for instance reducing the allowance price under a cap-and-trade scheme (Böhringer et al., 2008; Marcantonini and Ellerman, 2015; Gugler et al., 2021). This ambiguity arising from the complexity of policy-interactions highlights the need for extensive research on complementing policies.

In its recently proposed climate policy package "Fit for 55", the European Commission takes an integrated and holistic perspective by aligning different policy instruments, such as reducing the emission cap in the EU ETS while increasing targets for energy efficiency and renewable energy as well as dealing with related distributional issues (European Commission, 2021).

Combining different policy measures increases the likelihood of overlapping policies, where multiple policy instruments targeted at the same source of pollutants are implemented at different governmental levels (Coria et al., 2021; Perino et al., 2020). Chapter 2 of this dissertation focuses on the interaction of the EU ETS, implementing a price on carbon in the European power sector, and a reduction in short-term demand for those allowances from additional German renewable electricity, largely induced by national subsidies, with respect to long-term abatement of emissions.

This first paper has the title *"The real substitution of effect of renewable electricity: An empirical analysis for Germany"* and uses comprehensive data on electricity generation of power plants located in Germany in order to infer the reduction in emissions from those plants induced by a marginal increase in generation from onshore and offshore wind parks as well as solar panels. Emissions of a power plant are non-linearly related to its generation, which is negatively, and again non-linearly, connected to renewable infeed via the merit-order effect (Ketterer, 2014). Using an estimation method that allows for these nonlinearities, the research reveals that, mainly as a result from a heterogeneous intradaily generation pattern, wind electricity tends to reduce short-term domestic emissions on a larger scale than solar electricity sources, supporting previous results (Abrell et al., 2019; Gugler et al., 2021). Negative leakage effects via additional exports are found to be substantial, causing emission reductions in Germany's neighboring countries.

As opposed to a textbook cap-and-trade system where a full waterbed effect prevails in response to additional unilateral efforts, these estimated aggregate short-term emission reductions can result in long-term emission abatement via the allowance cancellation mechanism of the Market Stability Reserve. Depending on the year of abatement and aggregate emission allowance market outcomes, a fraction of unilateral mitigation efforts will lead to permanent emission savings. The research described in chapter 2 of the dissertation provides an empirical application to the phenomena outlined by, for example, Perino et al. (2020) and Bruninx et al. (2019) and highlights the need for appropriate calibration of complementing policy instruments.

The aforementioned dispatch decisions of conventional generators and thus their emissions are to a large extent determined on various stages of a central wholesale electricity market, where an increase in renewable supply tends to decrease the market price (merit-order effect). Other consequences of renewable capacity expansion include higher price volatility from the intermittent nature of major renewable capacity leading to a more frequent occurrence of negative electricity prices (Nicolosi, 2010), a decreasing market value of renewable capacity by suppressing the average market price (López Prol et al., 2020; Bernath et al., 2021), altering investment incentives for conventional capacity by changing the expected revenue stream from selling electricity (Gugler et al., 2020) and higher risk in the expected final demand for conventional generation due to non-perfect forecastability of renewable production (Kulakov and Ziel, 2021). It is this risk that is inherent to renewable forecasts that is the subject of chapter 3.

The relevance of this risk for market outcomes depends on the prevalent subsidy scheme. In many electricity markets, renewable generation is supported by the policy-maker in order to reap associated climate and environmental benefits (see chapter 2 and discussion above). The subsidies are designed to allow plant operators the recovery of their levelized cost of electricity, mainly investment and operating cost, which tend to be higher than for (existing) conventional capacity. The exact choice of the subsidy scheme determines the effectiveness in reaching a desired renewable capacity, total support costs and overall market efficiency (Winkler et al., 2016). While capacity-based subsidy schemes allow for complete market integration of renewables in the sense of full competition based on marginal costs, price-based schemes are more prevalent, for example in Germany, Japan or Netherlands and have some distorting effects on market competition.

In the European Union, a wide-spread transition from feed-in tariffs to premium-based schemes has been observed, to a large part due to concerns about conflicts with state aid regulation (Banet, 2020), with the aim to reduce total public costs for renewable support and to enhance market- and systemintegration by exposing the producers to signals of scarcity. Most relevant to chapter 3 of this thesis are the supply decisions of renewable generators on the previously described market stages, which depend on the employed subsidy scheme (Dressler, 2016; Winkler et al., 2016). A subsidy scheme that makes firms' profits independent of the market price, such as a feed-in tariff, tends to hinder market integration, in particular when implemented together with a priority dispatch rule, which is in place for example in Germany (Fabra et al., 2014). In the case of Germany, subsidy schemes are altered towards a sliding premium, paying a premium depending on average market prices, to incentivize firms to base their output on market conditions, while sticking to the priority dispatch rule.

The second paper, titled *"Renewable risk and its impacts on market prices: The case of Germany"*, joins adjusted subsidy schemes and increasing importance of renewable forecast risk by empirically analyzing the market behavior of renewable firms in Germany in response to an increase in their individual forecast and hence output risk.

I argue that firms should, depending on their individual and aggregate renewable output risk, respond by reducing their day-ahead commitment in order to hedge against undesired intraday market outcomes. The empirical analysis, including a detailed measure for the renewable forecast risk, suggests that firms do not respond to changes in their day-ahead output risk. This result is based on analyzing multiple aggregate market outcomes.

The work builds on research predicting firm behavior with a significant share of renewable generation capacity (Acemoglu et al., 2017; Kakhbod et al., 2021), strengthening previous results about the relevance of forecast risk on prices (Kulakov and Ziel, 2021; Kiesel and Paraschiv, 2017). It extends the existing knowledge about price formation in current electricity markets by showing that firms do not consider their individual and aggregate output risk as relevant information when placing their bids at the German day-market. This result

should guide the design of future subsidy schemes to achieve the pronounced goals of full market integration.

Other than firms operating renewable capacity, a company marketing conventional capacity is more likely to base its bidding behavior on expectations about subsequent market outcomes. Reasons include the dispatchability of the technology, full market competition without subsidies and more market experience. At the day-ahead market stage, firms might, in order to increase profits, consider expectations about outcomes at later market stages, namely the a) intraday market, mainly used for balancing forecast errors before actual delivery as discussed above, b) the redispatch stage, where grid operators adjust power plant output before actual delivery to avoid damage to the electricity grid as a result from local bottlenecks (Wang et al., 2003) and c) the imbalance market, designed to maintain a grid-safe frequency by counterbalancing deviations from the last market equilibrium before delivery[1] (Mazzi and Pinson, 2017).

While arbitrage-related behavior between the intraday and the imbalance market (Just and Weber, 2015) as well as interactions between the redispatch stage and the imbalance market have been observed (Chaves-Ávila et al., 2014), chapter 4 investigates power plants behavior at the interplay between the day-ahead market and the redispatch stage, which arises from a discrepancy between the dispatch decisions and the grid infrastructure.

At the day-ahead market stage, the equilibrium price and hence quantity supplied and demanded are determined solely on the respective relative willingness to sell or buy. The location of supply or demand within this zonal market is not considered for market clearing. A geographical mismatch between supply and demand, often as a result from a local increase in renewable capacity (Hubert and Spiridonova, 2021), can lead to bottlenecks in the electricity grid. In that case, the responsible grid operators procure capacity from power plants on either side of the bottleneck, allowing them to spatially shift generation and hence resolve the congestion[2]. This need to redispatch power plants indicates an inefficient market outcome and increases social costs. In the case of Germany, the additional expenses of the grid operators are levied onto consumers via increased grid fees.

This geographical component of the redispatch process introduces additional heterogeneity among power plants, as the initial equilibrium resulting from earlier market stages does not incorporate this information. During the redispatch stage, the zonal market becomes fragmented with at least two smaller markets for every bottleneck, where market participation depends on the power plant's location relative to the bottleneck. In each of these submarkets, profit opportunities can deviate from the zonal market, depending on relative prices. By exploiting these profit opportunities, generators will increase their day-ahead sales in order to increase the magnitude of their individual redispatch mandate, thereby altering the market outcome and increasing the level of congestion and welfare loss. Such arbitrage can occur in a market-based redispatch system, where prices are determined via a market process (Hirth and Schlecht, 2020) or in cost-based redispatch, where remuneration is determined bilaterally between the grid operator and the respective power plant.

The third paper *"Arbitrage in cost-based redispatch: Evidence from Germany"* assesses the presence of described arbitrage behavior in cost-based redispatch as it is conducted in Germany. Extensive data suggests that arbitrage is not a widespread phenonomenon, but a cluster of power plants sharing a similar location engages in arbitrage between the day-ahead and the redispatch market. This arbitrage, albeit it appears to be relatively small, reduces market efficiency.

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[1]These deviations can, for example, arise from renewable forecast errors that remain after the intraday market, sudden changes in electricity demand or the failure of a power plant.

[2]This description is limited to adjusting generation, as this is the prevailing approach in practice. It is possible to also include the demand side in this process.

This result contributes to the discussion about the most efficient solution to grid congestion. In zonal electricity markets, congestion can frequently arise. With the aim of designing the redispatch process more efficiently by including additional sources of flexibility and increasing competition, the European Union pushes towards market-based procurement of the required redispatch capacity (EU, 2019).

The results in chapter 4 underline fears of arbitrage behavior in such a system by showing that many prerequisites, like reliable congestion forecasts and high sensitivity on the relevant bottleneck, are met by significantly many firms under the current regulation. While splitting the zonal market into many small pricing zones via the introduction of nodal pricing provides a long-term efficient solution to grid congestion and eliminates arbitrage in the short run, the associated transition costs are significant and likely played a role in the decision to stick with zonal pricing in the European Union (Antonopoulos et al., 2020), while solutions to easing associated distributional concerns based on free allocation of transmission rights are being proposed (e.g. Kunz et al., 2016)).

The three papers in this dissertation contribute to the understanding of modern electricity systems with sizable shares of intermittent renewable capacity and the behavior of economic agents in the relevant markets. The results can inform policy makers by evaluating the consequences of already implemented policies on aggregate market outcomes in chapters 2 and 3. Chapter 4 draws its motivation from a discussed policy-reform and provides relevant arguments to this consultation. The studies show that policy makers must pay attention to designing an appropriate regulatory environment for the desired energy transition, may it be by allowing for unilateral emission reductions under a multilateral cap-and-trade scheme via supplementary policies like permanent cancellations of emission allowance auction volume or by minimizing welfare losses via congestion-resolving mechanisms that limit the ability for market participants to arbitrage.

The research in this thesis alone does not address all issues that arise during the development towards a more sustainable energy system. Further research is needed on the increasing temporal divergence between supply and demand that is touched upon in chapter 2. This discrepancy requires regulatory instruments that allow for a short-term price signal that represents the marginal costs for electricity both for households, where rates are currently predominantly fixed for up to multiple years, and above described storage- and sector-coupling technologies that balance supply and demand over time, thereby reducing abatement costs. Chapter 3 mentions price-distorting effects of subsidy schemes, which are likely required for reaching significant sector-coupling capacities (van Nuffel et al., 2018), which will in turn alter short-term behavior of incumbents and investment incentives for potential new entrants. It is necessary to accompany this development with thorough and holistic research with the aim of reaching full market-integration of these technologies. Market designs are currently being developed and tested, allow for market-based redispatch in a zonal setting whilst limiting arbitrage by estimating the true flexibility potential of market participants, for example in Germany (Klempp et al., 2020; Brunekreeft et al., 2020), thus addressing some concerns expressed in chapter 4.

This thesis uses a mix of classical econometrics and modern machine learning methods to answer questions and assess hypotheses. It therefore provides examples of how these relatively new methods can be successfully integrated into applied economic research.

Unlike convention in many empirical economic papers and journals, this dissertation does not use asterisks to denote statistical significance of estimated coefficients. These asterisks indicate the size of the estimated p-value, associated with a test of the null hypothesis of a parameter, generally testing the absence of an effect. If the p-value of the null hypothesis is below a cutoff set ex ante, commonly five percent, the null hypothesis is rejected and the estimated coefficient is considered to be statistically significant.

There are a few problems with this approach. First, the cutoff is arbitrary[3]. A certain hypothesis associated with a p-value just under the cutoff is not entirely different from a hypothesis where the estimated p-values lies just above the threshold. Considering the first estimate as statistically significant and the second estimate as statistically insignificant suggests a substantial difference between the two hypotheses. A small change in the model specification or the sample size alone can change the conclusion (e.g. Wasserstein and Lazar (2016)). Together with publication bias, where journals tend to favor papers with results considered as statistically significant (Ioannidis, 2005; Andrews and Kasy, 2019), this can create an incentive for researchers to tune their model assumptions in order to allow for statistically significant results (Rosenthal, 1979). As a result, pre-analysis plans are gaining traction in economics where all steps of the data analysis are described before the actual analysis (Olken, 2015).

Second, following from the first point, not rejecting the null hypothesis does not necessarily imply the absence of an effect or the truth of the alternative hypothesis.

Third, there are many potentially relevant hypotheses about the size of the estimated parameter that can be tested. Using asterisks focuses on the common null hypothesis of no statistical effect. Fourth, labeling a statistically significant result with asterisks can lead readers to believe in the economic significance of the estimated model parameter, irrespective of the magnitude.

Albeit many problems with such a hard cutoff for statistical significance exist and some argue for abandoning statistical significance altogether (McShane et al., 2019), in many research settings a binary decision about the presence of an effect is desired. For example, all research presented in this dissertation relies on drawing conclusions about the size of the estimated parameters. Furthermore, many econometric tests about the nature of the data at hand guide the modeling decision based on the rejection of a null hypothesis (see also Krueger and Heck (2019)).

Proposed solutions include drawing inference based on estimation graphics allowing for the display of complete statistical information (Ho et al., 2019), adjusting the threshold and significance level from five percent to a lower value in order to decrease the number of false positives (Benjamin et al., 2018) and using the Bayes factor for testing the relative plausibility of the considered hypotheses (Lavine and Schervish, 1999), which directly addresses the problem second point mentioned above. The American Economic Association does not accept papers with asterisks in its leading outlet American Economic Review and just requires reporting of the associated standard errors. By not using these stars, the researcher does not present the estimates with some kind of subjective judgment.

Parameter estimates in this paper are presented together with an associated confidence interval. The confidence interval is a function of the parameter size, the associated standard error and a cutoff, which is here increased to one percent to admit the relatively large sample sizes. It contains the true effect size in the population if many different studies were conducted on many different samples. This approach directly addresses the size of the estimated effect and the underlying uncertainty arising from the estimation, hence displaying more information than a single p-value. At the same time, it allows the researcher to draw dichotomous conclusions about the presence of an effect. This approach provides no panacea to all the issues mentioned above, but provides many improvements while remaining related to convention.

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[3]The seminal work on statistical tests by Fisher (1925) considers the still prevailing five percent as "convenient".

2 The real substitution effect of renewable electricity: An empirical analysis for Germany

Author: Philip Schnaars

Abstract: Renewable electricity is the backbone for a net-zero carbon society. This paper estimates the national and international emissions effect of German renewable electricity in the years 2017 to 2019 using a Random Forest algorithm, finding negative but heterogeneous effects on emissions demand. A fraction of the estimated emission reductions translate into allowance cancellations in the EU ETS and thereby reduce overall long-term emissions.

2.1 Introduction

The electricity sector in the European Union is one of the main contributors to the union's greenhouse gas emissions. Currently, there are two policy levels targeted at decarbonizing the electricity sector. First, the supranational EU ETS, which covers power plants and industrial sites, requires regulated entities to surrender an allowance for every ton of CO_2 they emit into the atmosphere. Second, as preferences for tackling climate change appear to be heterogeneous across the European Union (Marchiori et al., 2017; Ćetković and Buzogány, 2019), some member states have implemented their own, additional policies, such as setting energy efficiency targets or subsidizing the generation of renewable electricity with the goal of achieving a climate-neutral electricity sector.

Germany has implemented a subsidy scheme for renewable electricity in 2000, with multiple modifications over the years. This has contributed to renewables providing just over 50 percent of German electricity demand in the year 2020 (Fraunhofer, 2021), up from six percent in the year 2000 (BMWi, 2021). At the same time, about 17 percent of European emissions in the electricity sector were emitted from power plants located in Germany (DEHSt, 2020), making it a particularly interesting case to study.

The two policy layers overlap and there are interaction effects. Before the EU ETS was reformed in 2018 by implementing the Market Stability Reserve (MSR), unilateral policies such as renewable subsidies only shifted cumulative emissions in time and space but did not reduce them, because the supply of allowances was fixed. The MSR alters this picture by permanently deleting allowances depending on the amount of unused allowances in circulation (Perino, 2018). Unilateral policies can now reduce total emissions - but at least in principle, they can also increase them (Perino et al., 2020; Gerlagh et al., 2021).

In light of these issues, this paper answers the question of how effective renewable electricity in Germany is in abating greenhouse gas emissions in the EU. To that end, I construct a rich dataset of hourly plant-level emissions and cross-border trade. I estimate the amount of offset emissions in response to higher renewable production using a novel estimation technique based on Machine Learning algorithms. Together with a detailed analysis on emission leakage via cross-border flows, this gives deep insights into the mechanics of the German electricity system, including the climate impact of grid congestion. I merge these results with recent insights about the behavior of the MSR to estimate the long-term abatement effect of German renewable electricity.

Onshore and offshore wind are more effective in reducing emissions than electricity from solar panels. Redispatch measures have only a slight impact on this magnitude. Negative leakage effects (Baylis et al., 2014) within the EU are substantial, reinforcing the reduction in emissions demand. This result is in line with internal carbon leakage for demand side policies[4] from Perino et al. (2020). The estimates range up to 91 percent for solar, meaning a domestic emission reduction is almost mirrored by Germany's neighboring countries. A fraction of these emission cuts translate to long-term abatement under the EU ETS as a result of additional allowance cancellations. This portion approaches one with increasing duration of MSR storage for electricity produced before 2018, but decreases for later abatement.

It is well established in previous literature that the emission impacts of renewable electricity differs between conventional technologies[5]. Generally, wind is more effective than solar in reducing emissions. I extend the literature by studying onshore and offshore wind

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[4]Perino et al. (2020) consider renewable subsidies to be a demand side policy, as it decreases the demand for carbon-intensive electricity.

[5]Prominent studies include Ireland (Di Cosmo and Malaguzzi Valeri, 2017; Dorsey-Palmateer, 2019), Texas (Kaffine et al., 2013; Novan, 2015; Cullen, 2013) as well as Spain, Germany (Abrell et al., 2019) and the UK (Gugler et al., 2021).

separately. These two technologies are heterogeneous in terms of intermittency and generation peak within the day. Both technologies tend to reduce emissions by less than the system-average in all considered settings. The technical efficiency of power plants is found to be negatively affected by renewable supply as a result of increased cycling (Kaffine et al., 2013). I construct a detailed plant-specific emission series that adjusts the often used average emission rate when the turbine is running at part load.

Abrell et al. (2019) compare relatively isolated Spain and highly interconnected Germany to highlight the relevance of inter-zonal electricity trade on domestic emission reductions. A high capacity for trade allows for sizable leakage. I use detailed data on international electricity trade that allows for specific calculation of reduced emissions in neighboring countries and thereby leakage effects.

A complementary carbon price under the EU ETS and its effectiveness in reducing emissions is empirically investigated for the EU ETS by Gugler et al. (2021) and for Texas by Cullen and Mansur (2017). Aside from endogeneity issues, the aspect of overlapping policy and its impact on long-term emission abatement is overlooked[6] in this strand of literature. I offer a new angle by analyzing the interplay between these two policy levels.

2.2 The dataset

In order to analyze the issues mentioned above, I construct a dataset that consists of 38 lignite, 56 coal and 41 gas generation units, each with a capacity of at least 100 MW. This data is made available from ENTSO-E (2020). Observations are recorded on an hourly basis for the years 2017, 2018 and 2019. Graf and Marcantonini (2017) motivate using panel data to be able to control for unit outages and maintenance. I merge data on scheduled maintenance and technical outages from the same data source. Furthermore, ENTSO-E (2020) provides information of duration and total amount of redispatch work done at the plant level.

Control variables include hourly load and renewable infeed in Germany and the neighboring countries. These and data on commercial flows on the interconnectors with the neighboring countries are also provided by ENTSO-E (2020). Prices for European Emission Allowances (*eua*) and coal and gas prices are obtained from Quandl (2020). The input prices for coal and gas plants are captured as a ratio in *gas_coal*. Changes in the ratio of the fuel input prices shift the relative marginal costs and subsequently the ordering of power plants on the supply curve. This can have a larger effect on emissions than renewable generation (Fell et al., 2021).

In order to calculate the emissions from output in each given hour for each generation unit, I use fuel emission factors for each generation type from the federal environmental agency (Umweltbundesamt, 2020). The technical efficiency factor is observed for some units. For the remaining units, the technical efficiency is estimated based on those observed efficiency factors, using the year of construction. These factors are then adjusted with a part-load penalty factor, estimated by Valentino et al. (2012) to account for increasing marginal emissions with decreasing turbine utilization. This procedure results in computed emissions that closely match the verified annual amounts under the EU ETS. See tables A.4, A.5 and A.6 in the appendix for a detailed comparison and appendix A.2 for a description of the procedure and table 2.1 for the summary statistics of the dataset.

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[6]One notable exception is Novan (2017) who studies the correlation between pollutants regulated by a cap and trade system and the emissions of pollutants that are not capped. In this paper, I focus on greenhouse gases and do not consider local pollutants.

Variable name	Variable description	Mean	Min	Max	SD	Count
emissionslig	Emissions from Lignite units tCO2	488572.70	0.00	1298326	310509	826064
emissionscoal	Emissions from Coal units tCO2	128546.90	0.00	777254	185826.80	1119432
emissionsgas	Emissions from Gas units tCO2	36353.73	0.00	338945.60	61030.65	1027667
rdlig	Redispatch work on Lignite units MWh	124.97	0.00	6370.00	390.03	867813
rdcoal	Redispatch work on Coal units MWh	7.29	0.00	4281.00	72.62	1123037
rdgas	Redispatch work on Gas units MWh	4.08	0.00	1843.00	43.24	1040587
onshore	Onshore wind generation MWh	10451.22	159.22	40389.41	8256.96	26152
offshore	Offshore wind generation MWh	2310.43	0.03	6825.23	1551.30	26152
solar	Solar generation MWh	4530.02	0.00	30028.46	6942.15	26152
eua	Price for EUA in EUR/tCO2	15.52	4.32	29.78	8.33	26152
gas_coal	Gas to coal price ratio	0.23	0.17	0.76	0.04	26152
load	Load in Germany MWh	56576.77	25248.87	79062.73	10063.19	26152
loadAT	Load in Austria MWh	7232.65	4176.40	10802.90	1397.32	26152
loadCH	Load in Switzerland MWh	6709.29	3722.44	10911.51	927.31	26152
loadCZ	Load in Czech Republic MWh	7576.18	4471.29	11142.18	1281.65	26137
loadDK	Load in Denmark MWh	3790.21	1692.95	8088.42	736.18	26152
loadFR	Load in France MWh	53882.38	30630.00	94492	11878.40	26103
loadNL	Load in Netherlands MWh	12623.15	6635.46	18983.50	2276.86	26152
loadPL	Load in Poland MWh	19350.03	11399.64	26297.15	3155.95	26151
loadSE	Load in Sweden MWh	15699.65	0.00	26618	3430.25	26150
flowATDE	Net imports from Austria MWh	-2914.65	-9478.19	4792.71	1911.53	26152
flowCZDE	Net imports from Czech Republic MWh	102.68	-2516.10	3155.00	878.13	26152
flowPLDE	Net imports from Poland MWh	-83.57	-1469.60	1688.00	368.09	26152
flowSEDE	Net imports from Sweden MWh	133.29	-614.80	1000.00	309.61	26122
flowDKDE	Net imports from Denmark MWh	22.58	-2300.00	2135.00	1261.63	26152
flowNLDE	Net imports from Netherlands MWh	-1068.04	-5934.80	5933.10	1197.15	26128
flowFRDE	Net imports from France MWh	-927.12	-9304.85	6325.00	2256.36	26152
flowCHDE	Net imports from Switzerland MWh	-459.27	-3160.53	4118.71	1270.39	26128
renewablesAT	Renewable generation Austria MWh	4342.69	1549.97	8065.40	1168.09	26152
renewablesCZ	Renewable generation Czech Republic MWh	674.32	233.03	2616.65	394.60	26137
renewablesPL	Renewable generation Poland MWh	1947.16	190.11	5765.05	1222.04	26152
renewablesSE	Renewable generation Sweden MWh	2019.43	86.00	7315.00	1224.41	26151
renewablesDK	Renewable generation Denmark MWh	2242.24	139.94	14606.27	1254.87	26149
renewablesNL	Renewable generation Netherlands MWh	1259.92	0.00	5485.79	1001.06	24296
renewablesFR	Renewable generation France MWh	9384.53	2800.00	22219.00	3093.24	26138
renewablesCH	Renewable generation Switzerland MWh	209.96	21.38	1103.22	126.65	26129

Note: The first column indicates the names of the variables that are used throughout this study. A detailed description is given in the second column. SD refers to the standard deviation.

TABLE 2.1: Summary statistics

Before testing for unit roots in a panel context, it is necessary to check for cross-sectional dependence in the data (Hurlin and Mignon, 2007). The dependence between units violates the iid-assumption of the error term, which can invalidate inference. Cross-sectional dependence means that the correlation between unit i at time t and unit j at time t is nonzero. The test is conducted by summing the correlation coefficients of the different units into one test statistic. As expected, the generation of one power plant depends on the production of other plants, i.e. the cross-sections depend on each other.

I therefore use a Fisher-type second generation panel unit root test that takes the cross-sectional dependence into account. This test is based on work done by Pesaran (2007) and the corresponding Im-Pesaran-Shin unit root tests. It can be expected that the different panel units (in this case the power plants) can not be described by the same model, i.e. that the autoregressive parameters are the same. For example, coal power plants have different output dynamics than plants running on fossil gas. This test accordingly calculates separate Augmented Dickey-Fuller based statistics for every panel unit and combines them into one statistic. This approach also allows for the panel being unbalanced. The null hypothesis is that the series are non-stationary. This test is only applied to the variable *emissions*, since this is the only variable varying over panel units. All the explanatory variables can be considered as time series and I therefore apply the usual time series unit root and stationarity tests.

All series except for *eua*, *gas* and *coal* are not integrated of order one. I decide to include the price for *eua*, *gas* and *coal* in levels despite their unit root behavior, since the prices are only available on a daily basis and therefore do not vary on an hourly basis. Differencing these series would lose valuable information. Full results of these tests can be seen in table A.7.

The sample only includes a subset of installed generation capacity. Table 2.2 compares the installed capacity covered by the sample and the figures provided by Bundesnetzagentur (2019b).

Technology	Sample capacity	Installed capacity	Percent covered
Lignite	19.9	21.1	94.3
Coal	20.3	24.0	86.0
Gas	12.9	15.6	83.0

Note: This table compares the generation capacity covered in this sample to the overall installed capacity that is connected to the public electricity grid, as reported by Bundesnetzagentur (2019b).

TABLE 2.2: Comparison of sample and installed capacity

It becomes clear that the sample covers the lion's share of the power plants, making it possible to draw out-of-sample conclusions. It is possible that units outside the sample react differently to an increase in renewable production. First, there can be spatial heterogeneity, making generalization impossible. However, the in-sample generation units are spatially heterogeneous as well, especially those burning fossil gas. Second, smaller units might not participate in the electricity market as frequently or at all. If they do take part, the price signal is the same, independent of the size, so they should react in a similar manner (Graf and Marcantonini, 2017). If the in-sample results are adjusted to represent the elasticity of the whole power system, the bias should be small.

2.3 Domestic emissions

I first estimate the amount of emissions from lignite, coal and gas units that is offset when generation from renewable sources in Germany is marginally increased. Figure 2.1 shows how unit-level emissions, a nonlinear function of output, are determined. A generation unit adjusts its emissions based on marginal costs (*gas_coal, eua*), demand (*load*) and the amount of renewables (*onshore, offshore, solar*) fed into the grid in each respective hour. In addition, renewables can cause the electricity grid to be congested. To resolve this and to prevent grid failure, the grid operators requests generators to increase or decrease their production, depending on their location (*redispatch*).
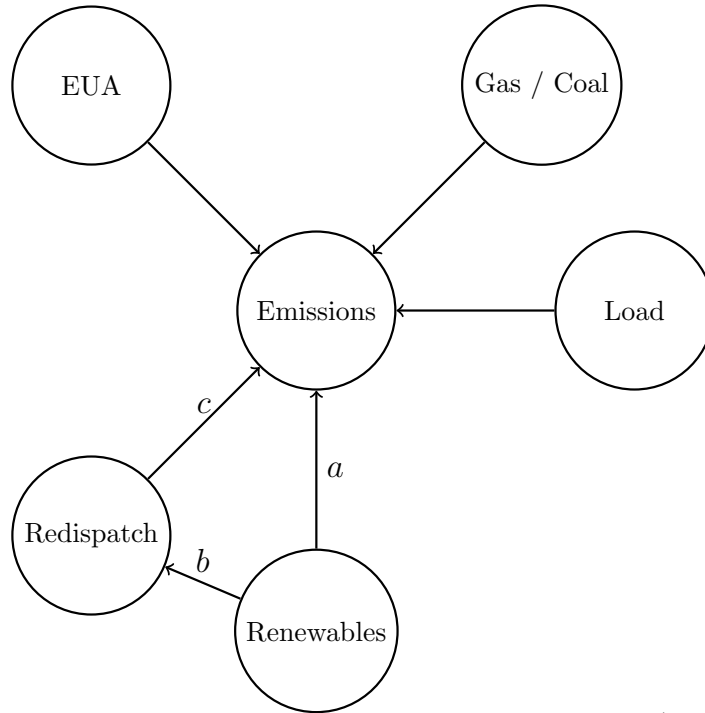
Note: A node represents a variable while directed arrows represent an explanatory path from one variable to another that can be estimated by statistical methods. The letters *a*, *b* and *c* are path labels. Emissions are determined by the demand for electricity (*load*), the marginal costs (*gas_coal*, *eua*) and the infeed of renewables (*onshore*, *offshore*, *solar*). Generation and therefore emissions can be regulated by the grid operator via *redispatch*.

FIGURE 2.1: Determinants of generation unit emissions

Figure 2.1 represents a Directed Acyclic Graph (DAG). Such a graph consists of nodes which indicate model variables and paths, represented by arrows, that show the relationships between the variables. In the absence of paths, or series of paths, that start and end in the same variable (acyclic), causal effects can be identified (Pearl, 2013).

Renewables therefore have a direct path as well as an indirect path on emissions. A statistical model of emissions on renewables will therefore return the total effect of renewables, the sum of the direct and indirect effect (Pearl, 2017). The existing literature described above has exclusively estimated the total effect. The indirect effect is given by the product of the path coefficients *b* and *c* from figure 2.1. The direct effect of renewables on emissions, irrespective of redispatch, is given by *a*. Table 2.3 shows the total effect given by

$$\gamma = a + b \cdot c \tag{2.1}$$

where redispatch is not included as a covariate. The direct effect *a* can be estimated directly by including *rd* as an explanatory variable in the model (VanderWeele, 2015). The potentially mediating effects of redispatch are then given by

$$b \cdot c = \gamma - a \tag{2.2}$$

The total effect can therefore be decomposed using sequential identification in order to

quantify both the direct and indirect effect. As shown by VanderWeele (2013), this decomposition holds for nonlinear relationships as well. It is likely that, for example, emissions relate nonlinearly to renewable generation, as previous research has demonstrated (Gugler et al., 2021).

2.3.1 Total effect of renewables on emissions

I first estimate the total effect, i.e. not isolating the effect of renewable-induced redispatch measures on emissions. As mentioned previously, the relationship between renewables and emissions is likely to be nonlinear. This poses a challenge when specifying a parametric model. Other papers in this strand of literature have dealt with the specification issue in various ways. Among others Cullen (2013), Di Cosmo and Malaguzzi Valeri (2017) and Abrell et al. (2019), Novan (2017) use lagged conventional generation variables, polynomials as well as interaction terms among the explanatory variables in order to account for dynamic constraints and expectations of conventional electricity producers. Fell et al. (2021) and Gugler et al. (2021) use a Heckman selection model and distinguish between the extensive and the intensive marginal impacts of renewables on emissions (i.e. shutting down completely versus reducing output). The goal is to increase the predictive power of the model.

To learn a good predictive model from the data, I use the nonparametric Random Forest algorithm (Breiman, 2001). This procedure was found to have strong predictive power in various applications. The algorithm estimates the regression function using a pool of covariates X_t (Athey et al., 2019). A Random Forest consists of multiple Regression Trees. A Regression Tree works along the following lines. First, the sample is randomly split into subsamples. Within these subsamples, the regression function is estimated as the average outcome. The splits are made sequentially and based on a single explanatory variable from X_t at a time. The goal is to minimize the average squared error in the subsamples, i.e. to group more similar observations together.

When a new set of observations is considered, one can work his way down the tree based on the particular values of the covariates, until a terminal leaf is reached. The average outcome in that leaf is the predicted value of the dependent variable, given the values of the predictors. The more similar the observations in the particular leaf, the higher the prediction accuracy. As Regression Trees have a tendency to overfit[7] the data, Random Forests average multiple Regression Trees that are fitted using a bootstrapped sample and only consider a random subset of covariates for splitting at each node.

In this particular analysis, each Random Forest consists of 1000 Regression Trees in order to smooth the estimated function across the covariate distribution. I fit a Random Forest for each generation unit i in the sample in order to allow for a heterogeneous response to the explanatory variables. To estimate the causal effect of a 1 MWh renewable increase, I apply the *do*-operator from Pearl (2013). I construct a "treated" sample X^T that is identical to the observed sample X^C except for the value of the respective renewable infeed, which is increased by 1 MWh in every hour observed. Apart from the three renewable sources *onshore*, *offshore* and *solar*, explanatory variables include *eua*, *gas_coal*, *load* as well as a variable capturing maintenance and outages. In addition, dummy variables for the hour of the day and month of the year are included to model seasonality.

The causal effect $\hat{\tau}_i$ of a marginal increase in renewable generation is then defined as the difference between the predicted emissions $\hat{y}_{it}^C$ using the observed sample and the predicted emissions with a higher renewable infeed $\hat{y}_{it}^T$. The subscript t indicates time and subscript

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[7]If a model perfectly replicates the sample data, it not necessarily generalizes well to the population data. Predictions based on this model can fail by generating unnecessary variance (Hastie et al., 2009). Overfitting can be assessed via the out-of-sample prediction accuracy. If the out-of-sample predictive power is high, the model generalizes well. This typically increases with the number of trees in the forest.

i the power plant. This procedure is sometimes called Single Tree algorithm[8] (Athey and Imbens, 2015) or S-learner (Kuenzel, 2019). I split the data into two parts of equal size, where one part is used for building the model and treatment effects are computed on the second subset, also termed honest estimation (Wager and Athey, 2018). This procedure ensures that the structure of the forest is exogenous to the data.

$$\hat{y}_{it}^C = f_i(\boldsymbol{X}_t^C) \tag{2.3}$$

$$\hat{y}_{it}^T = f_i(\boldsymbol{X}_t^T) \tag{2.4}$$

$$\hat{\tau}_i = \hat{y}_i^1 - \hat{y}_i^0 \tag{2.5}$$

As the predictive model f_i does not capture the statistical noise inherent in the data, using this to solely predict the outcome under treatment $\hat{y}_{it}^T$ (eq. 2.4) could bias the results, as the estimated treatment effect $\hat{\tau}_i$ could then contain an error. To avoid this, I also predict the "untreated" outcome y^0 (eq. 2.3), i.e. the emissions as predicted by the observed covariates. The predictive error will then cancel out in equation (2.5). For the estimated treatment effect to be consistent, the overlap assumption needs to be satisfied. This assumption requires that the distribution of the samples $\boldsymbol{X}_t^C$ and $\boldsymbol{X}_t^T$ overlap. Figure A.2 shows the distributions of the three renewable series in both treatment and control sample. There is only a very small fraction of $\boldsymbol{X}_t^T$ that is not originally observed in $\boldsymbol{X}_t^C$, the distributions of the variables are visually indistinguishable. The impact on the results is assumed to be negligible.

Table 2.3 shows the treatment effect per technology in response to a 1 MWh increase of renewable infeed. This is obtained by summing up the statistically significant $\hat{\tau}_i$ over all generation units of the same technology. Confidence intervals for the plant-level estimates are constructed using the percentile interval method[9] (Efron and Tibshirani, 1998). This is a nonparametric approach that does not assume an underlying normal distribution, as the constructed bootstrapped distribution of the marginal effect is used. As a result, the computed confidence interval need not be symmetric. I use 95 percent confidence intervals to assess the statistical significance of the estimates, presented in appendix A.3.

Technology	Onshore	Offshore	Solar
Lignite	-77.75	-151.34	-13.85
Coal	-131.90	-305.44	-26.44
Gas	-25.57	-72.35	-8.46

Note: Figures represent kg CO_2 reduction in emissions from all plants of a respective fuel type in response to an additional unit of respective renewable electricity.

TABLE 2.3: Emission response to renewables in the sample

Generally, wind offsets more emissions than solar, confirming the existing literature. I find that offshore wind is superior to onshore wind in reducing emissions from all three considered conventional technologies. Output from offshore wind parks exhibits relatively

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[8]They use a single tree where I use an ensemble of trees, i.e. a forest.
[9]For each bootstrapped sample, the parameter of interest is computed. These estimates are then ordered to form a distribution. The desired percentiles represent the bounds of the interval.

low intermittency, Due to their relative position in the merit order, coal units decreases emissions more than those burning lignite. As solar has a clear, recurring infeed-pattern, peaking around midday, one would expect gas plants to reduce their emissions more severely than coal units, as gas plants tend to be at the margin during this time of day. Gas plants are less carbon-intensive than coal-fired plants, which explains part of this result.

Solar shows a relatively strong emission reduction effect for coal plants. This can be explained by the recent increase in the price for emissions allowances that started in 2018, midway through the sample, from about 10 Euro to around 25 Euro per ton of CO_2. This surge, in combination with lower gas prices, induced a change in the merit order, also known as fuel-switching (Agora, 2020). The marginal costs of coal plants can be above those for gas plants, as carbon costs increase more for coal plants. With primarily coal plants covering peak demand, solar will principally offset emissions from those.

Overall, the emission reductions are below the average emissions of 1,137 kg/MWh for lignite, 835 kg/MWh for coal and 399 kg/MWh for gas (Umweltbundesamt, 2020). This qualitative result is found in all empirical settings. For a comparison to the literature, refer to table A.8.

2.3.2 The importance of redispatch

Grid congestion, often induced by renewable infeed, happens frequently in the German grid, especially at the transmission level. To resolve these issues and maintain grid stability, conventional power plants are required to either increase or decrease their production, depending on their location. If that is not sufficient, the infeed of renewable electricity, especially onshore and offshore wind, is curtailed. In 2018, conventional generators were paid 472 Mio. Euro to redispatch 15,529 GWh. Renewable producers spilled 5,403 GWh, which equals 2.4 percent of total production and received compensation of 634 Mio. Euro (Bundesnetzagentur, 2019a).

Overall, during 50 percent of the sample hours there was at least one redispatch measure ordered. These figures show that this is a very relevant issue, potentially mediating how much emissions renewables can offset. Due to technical and spatial pecularities, lignite plants were almost exclusively required to reduce their generation, while gas nearly only increased electricity infeed. The picture for coal plants is less clear-cut, where increases and decreases are nearly balanced on the yearly aggregate (Bundesnetzagentur, 2019a).

Redispatch is also well present among the sample units. 34 lignite units, 27 coal units and 20 gas units were mandated to change production at least once over the sample period. For these units, I will estimate how much the renewable offsetting is affected by this by effect decomposition. Redispatch can either increase the offsetting effect if the unit is asked to reduce output or vice versa. The path coefficient *a* is again estimated via Random Forest, where the hyperparameters and sample split ratio are as above.

Technology	Onshore	Offshore	Solar
Lignite	-63.10	-151.98	-13.55
Coal	-116.77	-292.17	-23.64
Gas	-24.94	-71.08	-6.16

Note: Figures represent kg CO_2 reduction in emissions from all plants of a respective fuel type in response to an additional unit of respective renewable electricity, adjusted for redispatch.

TABLE 2.4: Emission response to renewables adjusted for redispatch

Table 2.4 shows the estimated direct effect of renewables on emissions, indicated by *a* in figure 2.1. There are only slight differences between the total and the direct effect of renewables on emissions. This suggests that redispatch does not have a large impact on the emission savings. However, as grid congestion also frequently requires renewable curtailment, the potential for emission reductions is limited by bottlenecks in the grid.

2.4   International spillover effects

Renewable electricity, due to the short-run marginal cost being close to zero, has been shown to suppress the wholesale electricity price (Ketterer, 2014). This makes exporting electricity to neighboring countries more profitable or decreases the imports from neighboring countries. Lower net imports to Germany will decrease the amount of conventional production in the respective neighboring country. German renewable electricity can offset emissions in other countries as well.

I measure the net trade flows from all of Germany's neighbors, apart from Belgium[10]. Generally, the electricity flow is determined by the price ratio, which of course is endogenous. Exogenous explanatory variables are demand in Germany and the respective country as well as electricity production from renewable sources. Furthermore, the marginal costs of conventional sources are driven by the price for emission allowances and fuel. This is again depicted in a DAG (figure 2.2), where the index *i* ranges over the set of countries. The non-indexed variables *load* and *renewables* refer to Germany. The price for emission allowances and the gas to coal price ratio is assumed to be homogeneous across Europe.

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[10]There did not exist a transmission grid level interconnection between the German and the Belgium grid over the sample period.
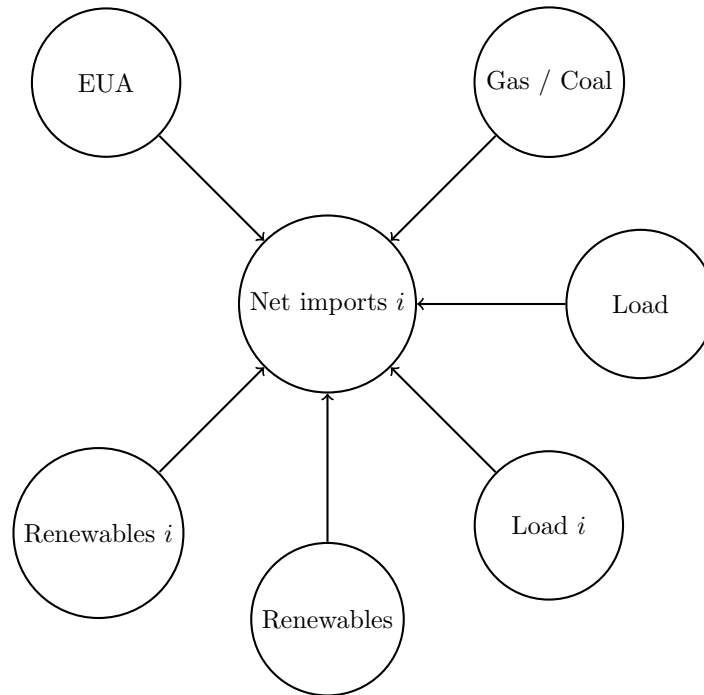
Note: A node represents a variable while directed arrows represent an explanatory path from one variable to another that can be estimated by statistical methods. Compared to the DAG in figure 4.3 potentially mediating effect of redispatch is not displayed for ease of presentation. Electricity flow is determined by the price ratio between two countries. The exogenous drivers of this are the renewable amount and demand for electricity, both in Germany and the respective trading country, indexed by i.

FIGURE 2.2: Causal determinants of net imports

As the relationship can be very heterogeneous across countries, due to e.g. interconnector capacity, and is potentially nonlinear among the explanatory variables, I again exploit the flexibility of the Random Forest algorithm. Estimation of the treatment effect is analogous to before, using the *do*-operator. I fit a predictive model for the net flow for every country. As flows are measured in MWh, I multiply this with the respective average emission factor. I use marginal emission factors obtained from the European Environment Agency for 2016 and the Swiss Bundesamt für Umwelt for 2014 (European Environment Agency, 2018; Bundesamt für Umwelt, 2014). By estimating country-specific export effects and emission factors I can precisely calculate the offset emissions in neighboring countries. Table 2.5 shows the results.

| | **Electricity (MWh)** | | | | **Emissions (kg CO$_2$)** | | |
	Onshore	Offshore	Solar	kgCO$_2$/MWh	Onshore	Offshore	Solar
AT	-0.163 [-0.203 , -0.124]	-0.162 [-0.200 , -0.124]	-0.102 [-0.161 , -0.066]	85.1	-13.87	-13.79	-8.68
CZ	-0.082 [-0.102 , -0.065]	-0.057 [-0.090 , -0.031]	-0.026 [-0.038 , -0.013]	512.7	-42.04	-29.22	-13.33
PL	-0.013 [-0.019 , -0.006]	-0.024 [-0.034 , -0.015]	-0.014 [-0.019 , -0.010]	773.3	-10.05	-18.56	-10.83
DK	-0.107 [-0.125 , -0.089]	-0.104 [-0.140 , -0.072]	-0.066 [-0.080 , -0.053]	166.1	-17.77	-17.27	-10.96
NL	-0.034 [-0.055 , -0.015]	0.030 [-0.024 , 0.084]	0.012 [0.000 , 0.026]	505.2	-17.18	0	0
FR	-0.081 [-0.110 , -0.052]	-0.203 [-0.267 , -0.146]	-0.010 [-0.038 , 0.018]	58.5	-4.74	-11.88	0
CH	-0.048 [-0.072 , -0.027]	-0.079 [-0.106 , -0.055]	-0.021 [-0.038 , -0.005]	29.8	-1.43	-2.35	-0.63

Note: 95 percent confidence intervals using the percentile-method derived from 1000 bootstrap replications in brackets. Emission factors are taken from European Environment Agency (2018) and the Swiss Bundesamt für Umwelt (2014).

TABLE 2.5: International emission reductions

The estimates suggest that on average 46 percent of renewable electricity is exported. The extent depends the renewable technology and on installed cross-border transmission capacity, which is highly heterogeneous across countries. These transmission lines are regularly congested as a result of loop and transit flows, limiting available trading capacity (BMWi, 2020).

2.5 Abated emissions

Up to this point in the analysis, I have estimated the short-term offsetting effect of renewable electricity. However, since the electricity sector in Europe is regulated under the EU ETS, a short-term emission reduction does not necessarily translate into a long-term emission saving. Perino et al. (2020) demonstrate that this long-term climate benefit depends on carbon leakage within the EU ETS and the waterbed effect.

The rate of internal carbon leakage is defined[11] as $L_i = -\Delta e_{-i}/\Delta e_i$ and can be calculated as using information from tables 2.3 and 2.5[12]. With Δe_{-it} the change in emissions in all neighboring countries and Δe_{it} unilateral emission reductions in Germany, the internal leakage rate is estimated to be -51 percent. For every ton of CO$_2$ offset in Germany due to onshore wind, 510 kg of CO$_2$ are abated in its neighboring countries. Offshore wind triggers an additional 18 percent emission reduction abroad, while a marginal increase in solar electricity has an international impact 91 percent of the domestic reduction. This partly explains the relatively low domestic emission reductions. Compared to Abrell et al. (2019), who report

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[11]Note that the definition in Perino et al. (2020) features information about the timing of the impact of the policy. As I only consider past emission reductions, I abstract from long-term internal carbon leakage.

[12]I assume for simplification that there is no leakage between sectors in the EU ETS (see Jarke and Perino (2017)). Recalling the relatively low price-elasticity of electricity demand (Knaut and Paulus, 2016) and available sector-coupling capacity like electric cars with a share of 0.7 percent in the German market 2018 (Kraftfahrt-bundesamt, 2020), this assumption should not change the results in a significant manner.

an aggregate of -78 percent[13], this is a relatively low value[14]. Two factors are at play explaining this difference. First, I use more specific emission factors, avoiding overestimation of abroad emission reductions. Second, recent shifts in allowance prices are responsible for a fuel-switching effect towards coal plants being the marginal technology more frequently, implying that domestic emission reductions increase compared to international emission reductions.

For a long-term climate benefit, additional renewable electricity has to translate into lower allowance supply. Under the EU ETS, a power plant has to surrender one emission allowance for every ton of CO_2 that it emits into the atmosphere. The overall amount of emissions is capped and this cap is decreasing over time. Reducing emissions unilaterally does not directly change the total amount of allowances in circulation and allows other participants to emit more. This is called the waterbed effect.

The MSR came into effect on January 2019, lowering this waterbed effect. The MSR adjusts the short and long-run supply of allowances based on the number of allowances firms transfer to future years (Perino, 2018). An immediate reduction in demand for allowances as a result of renewable production will increase the number of allowances that are banked for future use and hence the amount of allowances placed in the MSR. This leads to cancellation of allowances.

This reform is retroactive due to banking from earlier phases. Emission reduction efforts prior to this reform will contribute to the amount of allowances stored in the MSR (Perino, 2018). This includes 2017, the first year of the sample. An additional ton of CO_2 abated will result in less-than-one marginal reduction in long-term emissions. The magnitude of this long-term reduction depends on for how many years the MSR will remain active after the year of abatement.

In the following I estimate the overall marginal emission abatement effect of increasing the German renewable supply, where the emission reduction effect is the sum of the domestic effect from section 2.3 and the international spillovers from section 2.4.

The duration of storage depends on market outcomes, more specifically past and future emissions, which are determined by the expectations about future abatement costs. The higher abatement costs in the future relative to today's costs, the longer will the MSR take in allowances (Bruninx et al., 2019). Estimates in the relevant literature for the year the MSR stops storing additional allowances range from 2022 (Perino and Pioch, 2017), over 2039 (Gerlagh et al., 2021) to the more extreme case 2052 (Bruninx et al., 2019). I chose 2018 as the representative year of abatement in my sample. The discussion shows that there is a wide range of estimates and uncertainty about market outcomes is high.

The interaction of the renewable induced reduction in emissions demand with the MSR can lead to unintended effects, i.e. increase the total number of allowances and hence emissions, if the demand reduction is anticipated and sufficiently far into the future (Bruninx et al., 2019; Rosendahl, 2019; Gerlagh et al., 2021; Perino et al., 2020). This assessment considers the effect of policies announced before the introduction of the MSR, allowing me to ignore these effects. When transferring the findings to the impact of future changes in renewable support schemes, both anticipation effects and a reduction in the remaining active period of the MSR needs to be taken into account. Figure 2.3 shows the long-term abatement effects of one additional MWh of renewable electricity in Germany, estimated in sections 2.3

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[13]This is calculated based on their table 5 as follows. The domestic emission reductions per renewable technology wind and solar are compared to the international emission reductions under two different assumptions. The average of those four figures yields -78 percent. This highlights the importance of using country-specific emission factors.

[14]Note that a comparison is possible here as the dataset in the study of Abrell et al. (2019) is also restricted to generation from power plants larger 100 MW.

and 2.4. Hatched areas represent international emission abatement, while blank bars refer to domestic reductions.
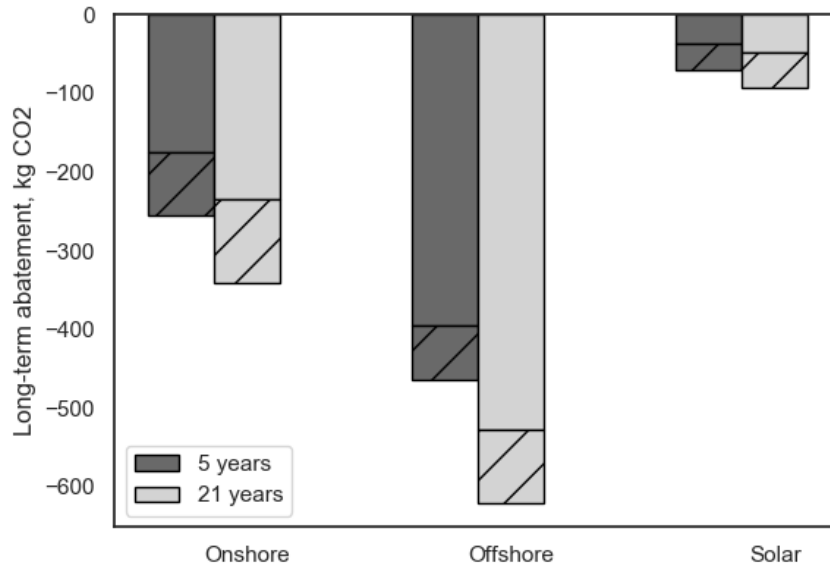
Note: Blank bars indicate long-term domestic emission reductions, hatched parts report estimated emission reductions in neighboring countries in response to one additional renewable MWh. The colors indicate how long the MSR is expected to take in allowances from the year 2018, the middle sample year.

FIGURE 2.3: Long-term abatement effects of renewable electricity

The MSR weakens itself over time. Unilateral emission reductions closer to the date when the MSR stops reducing allowance supply are less effective in reducing long-term emissions. This is due to the fact that there is less time for the MSR to take in allowances after the reduction effort has taken place.

Overall, the effectiveness of German renewables to decrease long-term cumulative emissions depends on uncertain market outcomes. The longer the unilaterally unused allowances are not used by other EU ETS participants, the more of the effort results in long-term abatement.

2.6 Conclusion

I estimate the short-term greenhouse gas emission replacement effect of renewable electricity in Germany using a rich dataset on fossil power plants. Both onshore and offshore wind reduce pollutants more than electricity from solar panels, confirming previous findings. This can be explained by timing of infeed and different export opportunities. These additional exports lead to substantial negative leakage effects, reducing emissions in neighboring countries. These emission reductions are comparatively lower when the respective country exhibits a lower emission intensity than Germany.

These short-term emission reductions lead to long-term abatement under the EU ETS via reduced demand for emission allowances. The MSR subsequently deletes a fraction of these additional unused allowances. This fraction is increasing the longer the number of unused allowances is above the upper MSR threshold. The calculated fraction is specific to

the sample period. Future effective marginal abatement will be lower, being zero once the MSR stops taking in allowances. If announcement effects Rosendahl (2019) are considered, anticipated renewable capacity expansion could even lead to increased emissions.

This discussion shows that policy makers have to be aware of interactions between different policies if they want to design effective instruments for the long-term abatement of emissions. This research highlights, using Germany as an example, what parameters are most important in determining the long-term effectiveness.

A Appendix to chapter 2

A.1 Sample plants

Name	ID	Capacity	Heat	Inactive since
Frimmersdorf P	BNA0313	289	0	01.10.2017
Frimmersdorf Q	BNA0314	291	0	01.10.2017
HKW Klingenberg 1-3	BNA0081	164	1	-
KW Boxberg Block N	BNA0122	500	1	-
KW Boxberg Block P	BNA0123	500	1	-
KW Boxberg Block Q	BNA0124	840	1	-
KW Boxberg Block R	BNA1404	630	0	-
KW Jänschwalde Block A	BNA0785	500	1	-
KW Jänschwalde Block B	BNA0786	500	1	-
KW Jänschwalde Block C	BNA0787	500	1	-
KW Jänschwalde Block D	BNA0788	500	1	-
KW Jänschwalde Block E	BNA0789	500	1	01.10.2019
KW Jänschwalde Block F	BNA0790	498	1	01.10.2018
KW Lippendorf Block R	BNA0115	891	1	-
KW Lippendorf Block S	BNA0116	891	1	-
KW Schwarze Pumpe Block A	BNA0914	755	0	-
KW Schwarze Pumpe Block B	BNA0915	755	0	-
Neurath A	BNA0696	294	0	-
Neurath B	BNA0697	294	0	-
Neurath C	BNA0698	294	0	-
Neurath D	BNA0699	604	0	-
Neurath E	BNA0700	606	0	-
Neurath F	BNA1401a	1060	0	-
Neurath G	BNA1401b	1060	0	-
Niederaußem C	BNA0712	296	0	-
Niederaußem D	BNA0705	301	0	-
Niederaußem E	BNA0713	302	0	01.10.2018
Niederaußem F	BNA0706	300	0	01.10.2018
Niederaußem G	BNA0708	629	0	-
Niederaußem H	BNA0707	639	0	-
Niederaußem K (BoA 1)	BNA0709	924	0	-
Schkopau A	BNA0878	450	0	-
Schkopau B	BNA0879	450	0	-
Weisweiler E	BNA1025	322	0	-
Weisweiler F	BNA1026	322	0	-
Weisweiler G	BNA1027	663	0	-
Weisweiler H	BNA1028	656	0	-

Note: The dummy indicator for Heat is equal to one if the plant is delivering heat to their local grid and zero otherwise.

TABLE A.1: Lignite plants in sample

Name	ID	Capacity	Heat	Inactive since
DEFARGE____1_____	BNA0147	350	0	-
DEWHV_____1_____	BNA1674	726	0	-
DEZOLLI___1_____	BNA1093	472	1	-
ELVERLINGSEN_4	BNA1037	325	0	22.02.2018
Ensdorf 1	BNA0253	106	0	26.01.2017
Ensdorf 3	BNA0252	283	1	21.12.2017
Gersteinwerk K2	BNA1046a	614	0	31.03.2019
GK-WEST_1	BNA0990	320	0	04.02.2017
GK-WEST_2	BNA0989	320	0	19.02.2017
HERNE_3	BNA0449	280	1	10.05.2017
HERNE_4	BNA0450	460	1	-
Heyden	BNA0793	875	0	-
HKW Altbach/Deizisau Block 1	BNA0020	433	1	05.07.2017
HKW Altbach/Deizisau Block 2	BNA0019	336	1	-
HKW Heilbronn Block 7	BNA0434	778	1	-
HKW Moorburg Block A	BNA1673	800	0	-
HKW Moorburg Block B	BNA1558	800	0	-
HKW Reuter Block C	BNA0082	124	1	-
HKW Reuter West Block D	BNA0086	282	1	-
HKW Reuter West Block E	BNA0087	282	1	-
HKW Tiefstack Block 2	BNA0402	189	1	-
HKW Wedel Block 1	BNA0404	134	1	-
HKW Wedel Block 2	BNA0403	116	1	-
HKW West Block 1	BNA1076a	138.5	1	-
HKW West Block 2	BNA1076b	138.5	1	-
Ibbenbüren B	BNA0493	791	1	-
Kiel	BNA0526	323	1	31.3.2019
Kraftwerk Rostock	BNA0849	514	1	-
Kraftwerk Voerde Block A	BNA0991	695	0	31.03.2017
Kraftwerk Voerde Block B	BNA0992	695	0	31.03.2017
KW Hafen Block 6	BNA0146	300	1	
KW Hastedt Block 15	BNA0144	119	1	
KW Lünen Block 1	BNA1508	746	0	-
LUENEN_6	BNA0618	149	1	-
LUENEN_7	BNA0619	324	1	-
Nord 2 T20	BNA0969b	333	1	-
RDK 7	BNA0518a	505	1	-
RDK 8	BNA0518b	842	1	-
Scholven B Scholven	BNA0332	345	0	-
Scholven C Scholven	BNA0331	345	0	-
Staudinger 5	BNA0377	510	1	-
VOELKLINGEN_HKV	BNA0999	211	1	-
VOELKLINGEN_MKV	BNA0998	179	1	-
WALSUM_10	BNA0216b	725	0	-
WALSUM_9	BNA0216a	370	1	-
Westfalen E	BNA0413c	780	0	-
Wilhelmshaven	BNA1061	757	0	-

Note: The dummy indicator for Heat is equal to one if the plant is delivering heat to their local grid and zero otherwise.

TABLE A.2: Coal plants in sample

Name	ID	Capacity	Heat	Inactive since
Lausward Block F	BNA1817	595	1	-
Block GT 11	BNA0614b	206	1	-
Block GT 12	BNA0614b	206	1	-
Block GT1	BNA0615	178	1	-
Block GT2	BNA0615	167	1	-
Emsland B	BNA0604	475	1	-
Emsland C	BNA0605	475	1	-
Emsland D	BNA0606	870	1	-
Franken I Block 1	BNA0744	383	0	-
Franken I Block 2 + GT	BNA0745	440	0	-
Gersteinwerk F	BNA1044	410	0	-
Gersteinwerk G	BNA1040	402	0	-
Gersteinwerk K1	BNA1046b	112	0	-
GKB Mittelsbueren GuD	BNA1820	450	0	-
GTHKW Nossener Bruecke	BNA0207	260	1	-
GuD Dormagen	BNA0199	586	1	-
GuD-Anlage-HKW-Merkenich	BNA0546	110	1	-
HERDECKE_H6	BNA0442	424	1	-
HKW Lichterfelde Block 1	BNA0075	144	1	-
HKW Lichterfelde Block 3	BNA0076	144	1	-
HKW Nord GuD Nord	BNA0588	167	1	-
HKW Tiefstack GuD	BNA0400	127	1	-
Huntorf GT	BNA0239	321	0	-
KMW_KW2	BNA0627	335	1	-
KMW_KW3	BNA0626	450	1	-
Knapsack 1	BNA0548a	784	0	-
Knapsack 2	BNA0548b	426	0	-
KW Hamm-Uentrop Block 10	BNA0410	425	0	-
KW Hamm-Uentrop Block 20	BNA0411	425	0	-
KW Mittelsbueren Block 4	BNA0142	176	0	-
NIEHL-3	BNA1818	453	1	-
NIEHL-II-DT	BNA0545	147	1	-
NIEHL-II-GT	BNA0545	266	1	-
RDK 4	BNA0514	353	0	06.04.2017
Sued GuD1 GT2	BNA0683c	108	1	-
Sued GuD1 GT3	BNA0683b	108	1	-
Sued GuD2 DT60	BNA0684c	128	1	-
Sued GuD2 GT61	BNA0684a	136	1	-
Sued GuD2 GT62	BNA0684b	136	1	-
Weisweiler VGT - BI. G	BNA1023	200	0	-
Weisweiler VGT - BI. H	BNA1024	200	0	-

Note: The dummy indicator for Heat is equal to one if the plant is delivering heat to their local grid and zero otherwise.

TABLE A.3: Gas plants in sample

A.2 Calculation of emissions

In order to correctly calculate the hourly emissions of a power generation unit based on the electricity output, it is necessary to know the unit-specific technical efficiency. This information is generally not publicly available. Taking a similar approach as Hintermann (2016), I estimate the technical efficiency for each plant, using individual efficiencies that were available. The following equations show the estimated relationship between the technical efficiency η and the year of construction t for each technology.

Lignite:

$$\eta = 31.431 + 0.2112 \cdot (t - 1960) \tag{A.1}$$

Coal:

$$\eta = 33.591 + 0.224 \cdot (t - 1960) \tag{A.2}$$

Gas:

$$\eta = 39.553 + 0.3277 \cdot (t - 1960) \tag{A.3}$$

The estimated "rate of technical progress" per year is virtually the same for lignite (equation A.1) and coal (equation A.2) and slightly higher for gas plants. The fitted values of these three equations are similar to those technical efficiencies that I actually observe.

Valentino et al. (2012) calculates part-load penalties for gas[15] and coal plants to adjust the marginal emission rate. Figure A.1 shows these depending on the percentage of capacity in use (usagerate)[16]. I adjust the data accordingly. When coal plants are only starting up, the emissions from producing one MWh of electricity are about twice as high as when the plant is running at full capacity.
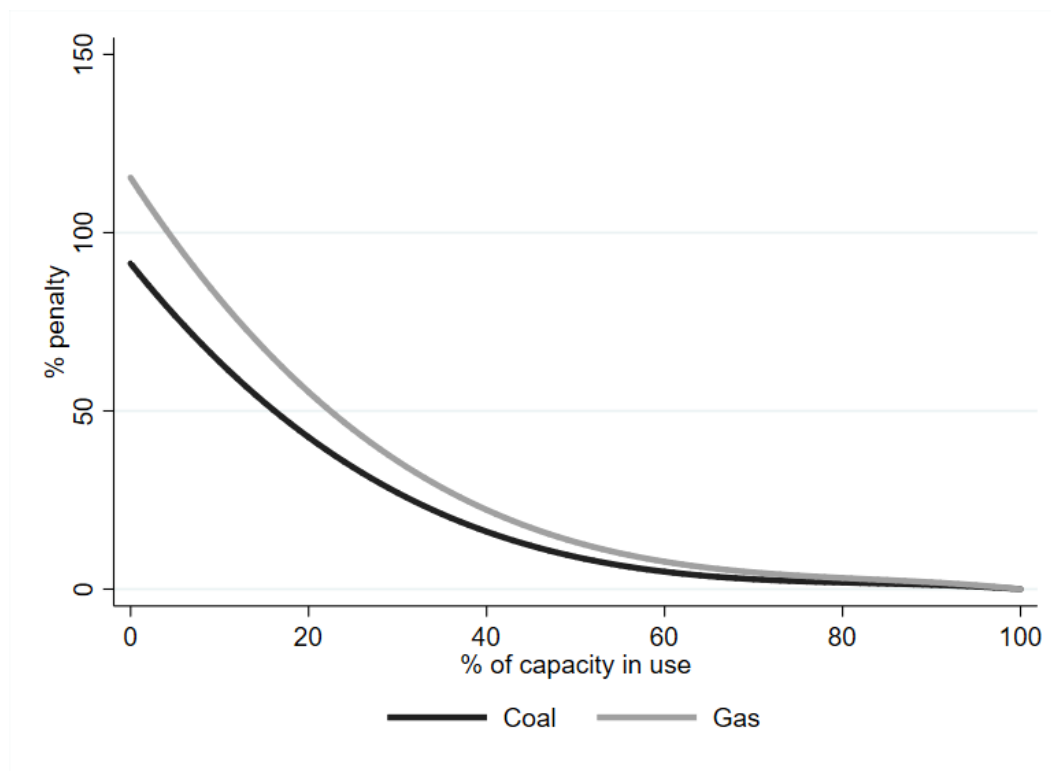
Note: This figure shows the additional emissions that arise as a result of a turbine running at part load.

FIGURE A.1: Part load penalties

Due to the regression approach above, the estimated emissions will not match exactly the verified emissions on the plant level. The constructed emissions will be above the reported emissions for some plants and below for others. The verified emissions, as part of the EU ETS, are published by DEHSt (2020) on an annual level. Tables A.4, A.5 and A.6 show

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[15]As there are both OCGT and CCGT plants in the sample, I use average emission factors and part-load penalties for these two technologies. CCGT plants have a higher technical efficiency.

[16]The values are adjusted during times when maintenance is undertaken. This data is taken from ENTSO-E (2020).

these values as well as the constructed emissions in the sample. The tables only show the results for those power plants where the generation units in the sample make up the overall power plant as defined in the EU ETS. There can be a difference if a power plant consists of one block with a capacity larger than 100 MW and one block with a capacity below 100 MW. Since the same calculation is applied to all units in the sample, it seems reasonable to assume that the constructed emissions for the units not in these tables also closely match the actual emissions.
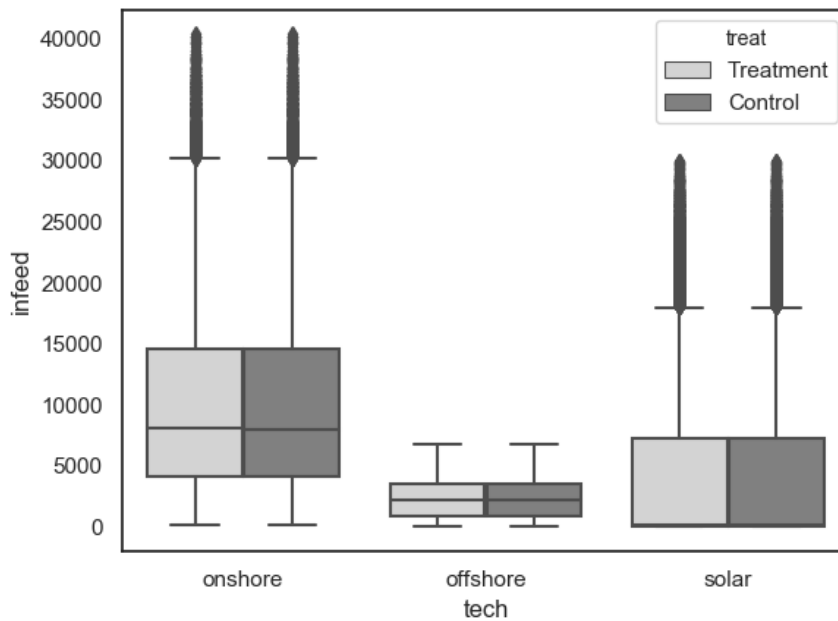
Note: The distribution of the observed infeed of onshore wind, offshore wind and solar (dark gray) is compared to the treated values where every observation is increased by one unit (light gray) using a boxplot.

FIGURE A.2: Distributions of treated variables

Power plant	Generation unit	Verified emissions 2017-2019	Sample emissions 2017-2019	Deviation
Jänschwalde	KW Jänschwalde Block A			
	KW Jänschwalde Block B			
	KW Jänschwalde Block C			
	KW Jänschwalde Block D	64.048	63.674	0.58%
	KW Jänschwalde Block E			
	KW Jänschwalde Block F			
	Neurath A			
	Neurath B			
	Neurath C			
Neurath	Neurath D	84.654	84.851	-0.23%
	Neurath E			
	Neurath F			
	Neurath G			
	Niederaußem C			
	Niederaußem D			
	Niederaußem E			
Niederaußem	Niederaußem F	71.527	74.274	-3.84%
	Niederaußem G			
	Niederaußem H			
	Niederaußem K (BoA 1)			
Boxberg Werk III	KW Boxberg Block N	24.952	25.019	-0.27%
	KW Boxberg Block P			
Schwarze Pumpe	KW Schwarze Pumpe Block A	34.239	34.190	0.14%
	KW Schwarze Pumpe Block B			
Schkopau	Schkopau A	15.334	15.315	0.12%
	Schkopau B			
Frimmersdorf	Frimmersdorf P	3.582	3.582	0.00%
	Frimmersdorf Q			

TABLE A.4: Verified and estimated emissions of lignite power plants

Note: Verified emissions in million tons CO_2 from DEHSt (2020) are compared to estimated emissions in the sample. Verified data is available on a power plant level, generation units from the sample are aggregated accordingly. The data is given as a sum over the three years in the sample. The deviation from the verified to the estimated amount is given in percent.

Power plant	Generation unit	Verified emissions 2017-2019	Sample emissions 2017-2019	Deviation
Rostock	Kraftwerk Rostock	5.909	5.918	-0.15%
Zolling	DEZOLLI___1	3.670	3.668	0.06%
Herne	HERNE_3	2.976	3.938	-32.35%
	HERNE_4			
Heyden	Heyden	4.367	4.369	-0.03%
Heilbronn	HKW Heilbronn Block 7	6.446	6.370	1.17%
Reuter West	HKW Reuter West Block D	6.200	6.169	0.49%
	HKW Reuter West Block E			
Wedel	HKW Wedel Block 1	3.417	3.340	2.28%
	HKW Wedel Block 2			
Ibbenbüren	Ibbenbüren B	6.290	6.278	0.19%
Lünen Trianel	KW Lünen Block 1	8.546	8.542	0.04%
Lünen	LUENEN_6	2.041	2.044	-0.18%
	LUENEN_7			
Scholven	Scholven B	12.644	12.432	1.68%
	Scholven C			
Walsum	WALSUM_9	9.533	9.512	0.22%
	WALSUM_10			
Bexbach	BEXBACH_A_GESAMT	0.626	0.625	0.18%
Bergkamen	BERGKAMEN_A	3.930	3.693	6.03%
Moorburg	HKW Moorburg Block A	17.146	17.149	-0.02%
	HKW Moorburg Block B			
Farge	DEFARGE___1	2.979	2.972	0.25%
Ensdorf Block 1	Ensdorf 1	0.047	0.047	0.00%
Ensdorf Block 3	Ensdorf 3	1.043	1.043	0.00%

Note: Verified emissions in million tons CO_2 from DEHSt (2020) are compared to estimated emissions in the sample. Verified data is available on a power plant level, generation units from the sample are aggregated accordingly. The data is given as a sum over the three years in the sample. The deviation from the verified to the estimated amount is given in percent.

TABLE A.5: Verified and estimated emissions of coal power plants

Power plant	Generation unit	Verified emissions 2017–2019	Sample emissions 2017–2019	Deviation
Mainz Wiesbaden	KMW_KW2	1.798	1.783	0.81%
	KMW_KW3			
Huntorf	Huntorf GT	0.022	0.022	0.98%
Nossener Brücke Dresden	GTHKW Nossener Bruecke	2.192	2.205	-0.59%
Herdecke	HERDECKE_H6	0.749	0.763	-1.80%
Hamm-Uentrop	KW Hamm–Uentrop Block 10	1.406	1.418	-0.87%
	KW Hamm–Uentrop Block 20			
	NIEHL-3			
Niehl	NIEHL-II-DT	4.532	4.568	-0.80%
	NIEHL-II-GT			
Franken I	Franken I Block 1	0.441	0.438	0.61%
	Franken I Block 2 + GT			
	Emsland B			
Emsland	Emsland C	4.812	4.810	0.04%
	Emsland D			

TABLE A.6: Emissions Gas

Note: Verified emissions in million tons CO_2 from DEHSt (2020) are compared to estimated emissions in the sample. Verified data is available on a power plant level, generation units from the sample are aggregated accordingly. The data is given as a sum over the three years in the sample. The deviation from the verified to the estimated amount is given in percent.

Variable	ADF	DFGLS	Lags
onhsore	-14.586	-14.405	19
offshore	-23.841	-21.412	2
solar	-7.703	-6.008	28
eua	-0.970	-2.413	1
coal	-0.012	-0.704	1
gas	-3.731	-3.776	1
load	-11.286	-4.408	19
flowATDE	-14.298	-13.612	26
flowCZDE	-14.37	-10.096	26
flowPLDE	-12.873	-7.783	26
flowSEDE	-16.221	-14.305	29
flowDKDE	-18.926	-18.368	28
flowNLDE	-14.525	-15.118	27
flowFRDE	-11.665	-9.738	27
flowCHDE	-10.173	-11.098	26
loadAT	-16.215	-13.149	30
loadCH	-9.295	-9.449	37
loadCZ	-11.526	-8.466	38
loadDK	-15.188	-8.617	38
loadFR	-7.020	-5.442	38
loadNL	-11.022	.	58
loadPL	-20.723	-11.196	30
loadSE	-6.996	-6.586	27
renewablesAT	-11.143	-7.430	19
renewablesCZ	-11.532	-8.101	28
renewablesPL	-20.81	-18.369	3
renewablesSE	-15.505	-12.484	16
renewablesDK	-16.816	-14.228	17
renewablesNL	-28.288	-28.083	3
renewablesFR	-8.289	-6.298	20
renewablesCH	-4.632	-4.985	20
	Fisher-type test		Lags
Emissions lignite	2518.848		5
Emissions coal	3029.753		5
Emissions gas	2785.947		5

Note: This table reports results of the Augmented Dickey-Fuller (ADF) and Dickey-Fuller Generalized Least Squares (DFGLS) test. The optimal lag for the tests were chosen via the BIC. The Dickey-Fuller tests include a drift term. Critical values at the 1% (5%) level are -3.96 (-3.41) for the ADF and -3.48 (-2.386) for the DFGLS test.

TABLE A.7: Stationarity tests

Technology	Total	Lignite	Coal	Gas
This study				
Onshore	236	78	132	26
Offshore	529	152	305	72
Solar	49	14	26	9
Average emissions per MWh lignite: 1,137				
Average emissions per MWh coal: 835				
Average emissions per MWh gas: 399				
Kaffine et al. (2013): Texas				
Wind	523	–	–	–
Cullen (2013): Texas				
Wind Static	562	–	184	378
Wind Dynamic	430	–	6	423
Average emission intensity: 667				
Novan (2015): Texas				
Wind	628	–	–	–
Di Cosmo and Malaguzzi Valeri (2017): Ireland				
Wind 1st quartile	500	–	178	125
Wind 2nd quartile	472	–	162	160
Wind 3rd quartile	474	–	160	168
Wind 4th quartile	440	–	154	177
Average emission intensity: 480				
O'Mahoney et al. (2017): Ireland				
Wind	208 – 322	–	–	–
Average emission intensity: 480				
Abrell et al. (2019): Germany & Spain				
Germany Wind	176	51	105	20
Germany Solar	234	50	152	32
Spain Wind	250	–	153	98
Spain Solar	169	–	74	95

Note: The figures are given as a reduction of CO_2 equivalent in kg per MWh. The difference between Wind Static and Wind Dynamic in Cullen (2013) is the inclusion of lagged components of the model. Average emissions for Germany are taken from Umweltbundesamt (2020).

TABLE A.8: Total amount of offset emissions

A.3 Unit-level estimates

Generation unit	onshore	offshore	solar
KW Jänschwalde Block E	-1.605	0.212	-0.134
	[-2.838 , -0.434]	[-2.867 , 3.605]	[-1.094 , 0.879]
Neurath F	-2.719	-5.267	-1.404
	[-5.964 , 0.172]	[-13.295 , 2.247]	[-4.160 , 1.243]
KW Boxberg Block R	-2.615	-3.339	-0.644
	[-4.453 , -0.898]	[7.923 , 0.692]	[-1.995 , 0.597]
KW Jänschwalde Block C	-2.842	-5.569	-0.880
	[-4.134 , -1.554]	[-8.944 , -2.222]	[-2.434 , 0.471]
KW Jänschwalde Block D	-1.965	-0.656	1.032
	[-4.157 , -0.204]	[-3.884 , 2.423]	[-0.095 , 2.269]
KW Jänschwalde Block F	-1.825	-7.487	0.187
	[-3.638 , -0.249]	[-12.561 , -2.521]	[-1.427 , 1.625]
Neurath G	-3.099	-14.160	0.413
	[-5.776 , -0.608]	[-21.246 , -7.600]	[-2.686 , 3.101]
Frimmersdorf P	-0.498	7.419	-1.271
	[-2.360 , 1.359]	[-0.345 , 17.918]	[-3.222 , 0.380]
KW Jänschwalde Block B	-3.025	-1.396	-0.042
	[-4.086 , -2.083]	[-4.276 , 1.422]	[-1.000 , 0.919]
Niederaußem G	-3.025	-3.088	2.592
	[-5.995 , -0.253]	[-10.471 , 4.213]	[-1.806 , 8.129]
Neurath E	-4.499	-10.891	-0.283
	[-6.719 , -2.336]	[-16.593 , -5.403]	[-3.149 , 2.506]
Niederaußem H	-3.479	-9.594	-1.233
	[-6.036 , -0.968]	[-17.912 , -1.112]	[-3.396 , 0.802]
Niederaußem E	-1.500	-1.638	-1.843
	[-3.068 , 0.191]	[-4.728 , 1.531]	[-3.311 , -0.335]
KW Jänschwalde Block A	-3.906	-1.853	0.616
	[-5.124 , -2.695]	[-4.709 , 1.064]	[-0.482 , 1.719]
KW Lippendorf Block S	-6.891	-14.010	-3.475
	[-9.504 , -4.190]	[-19.933 , -8.445]	[-5.753 , -1.353]
HKW Klingenberg 1-3	-0.046	-0.347	-0.021
	[-0.155 , 0.076]	[-0.680 , 0.012]	[-0.157 , 0.118]
Weisweiler E	-1.342	-5.365	-0.395
	[-2.112 , -0.509]	[-7.766 , -3.118]	[-1.655 , 0.867]

Note: The coefficients give the estimated average reduction in kg CO_2 to a one MWh increase in the respective renewable technology. 95 percent confidence intervals in brackets.

TABLE A.9: Individual treatment effect of lignite units I

Generation unit	onshore	offshore	solar
Frimmersdorf Q	-1.650	-10.677	0.417
	[-3.740 , 0.375]	[-18.926 , -4.023]	[-0.719 , 1.678]
Neurath A	-0.956	0.852	-0.206
	[-1.849 , -0.032]	[-3.714 , 6.100]	[-1.325 , 0.920]
Neurath C	-0.441	-6.011	-2.369
	[-3.033 , 4.198]	[-9.967 , -2.311]	[-4.074 , -0.581]
Neurath D	-3.442	-13.986	-1.903
	[-5.448 , -1.151]	[-19.846 , -7.745]	[-4.392 , 0.335]
Niederaußem C	-1.496	-1.837	-0.238
	[-2.347 , -0.642]	[-3.777 , 0.170]	[-1.235 , 0.773]
Niederaußem K (BoA 1)	-5.958	-8.486	-1.897
	[-9.064 , -2.991]	[-17.517 , -0.992]	[-4.396 , 0.387]
KW Schwarze Pumpe Block A	-2.444	-2.446	0.173
	[-4.131 , -0.774]	[-7.135 , 2.796]	[-1.534 , 1.682]
Neurath B	-0.100	-8.583	-0.976
	[-1.571 , 1.496]	[-11.787 , -5.322]	[-3.275 , 1.166]
KW Schwarze Pumpe Block B	-4.488	-5.453	-2.129
	[-6.637 , -2.388]	[-9.758 , -1.127]	[-4.038 , -0.381]
KW Boxberg Block Q	-3.143	-0.970	-0.211
	[-5.397 , -0.712]	[-8.102 , 5.760]	[-2.595 , 1.808]
Weisweiler H	-2.950	-7.456	0.678
	[-6.799 , 0.062]	[-12.418 , -2.844]	[-1.205 , 2.717]
Niederaußem D	-1.380	-2.662	-0.560
	[-2.352 , -0.361]	[-6.518 , 2.491]	[-2.366 , 1.014]
Weisweiler G	-4.420	-7.422	0.552
	[-7.877 , -2.000]	[-12.791 , -1.892]	[-1.653 , 2.851]
KW Boxberg Block N	-0.945	-3.371	1.622
	[-3.130 , 1.031]	[-7.015 , 0.193]	[-0.064 , 3.868]
KW Boxberg Block P	-0.718	10.646	0.083
	[-1.857 , 0.410]	[-1.575 , 20.858]	[-0.941 , 1.173]
Schkopau B	-1.691	-4.859	0.385
	[-2.927 , -0.507]	[-7.613 , -2.105]	[-0.853 , 1.602]
Schkopau A	-2.948	-5.500	-1.452
	[-4.222 , -1.678]	[-8.735 , -2.352]	[-3.535 , 0.393]
KW Lippendorf Block R	-3.664	-5.836	-1.367
	[-6.035 , -1.202]	[-10.332 , -0.930]	[-3.309 , 0.680]
Weisweiler F	-0.730	-0.297	-1.164
	[-1.499 , 0.096]	[-2.569 , 2.374]	[-2.868 , 0.026]
Niederaußem F	-1.604	1.222	-4.037
	[-3.015 , -0.164]	[-6.690 , 9.244]	[-8.931 , -0.201]

Note: The coefficients give the estimated average reduction in kg CO_2 to a one MWh increase in the respective renewable technology. 95 percent confidence intervals in brackets.

TABLE A.10: Individual treatment effect of lignite units II

Generation unit	onshore	offshore	solar
HKW Reuter West Block D	-0.120	-0.682	0.118
	[-0.578 , 0.293]	[-1.790 , 0.356]	[-0.425 , 0.623]
HKW Reuter West Block E	-0.278	-0.782	-0.618
	[-0.715 , 0.151]	[-1.780 , 0.195]	[-1.201 , -0.105]
GK-WEST_2	-2.123	-0.645	0.707
	[-4.417 , -0.039]	[-5.239 , 4.476]	[-0.871 , 2.402]
Scholven B	-0.669	-1.361	-1.047
	[-1.407 , 0.028]	[-2.846 , 0.233]	[-2.422 , 0.074]
HKW Wedel Block 2	-0.513	-0.984	-0.138
	[-0.813 , -0.178]	[-1.661 , -0.302]	[-0.722 , 0.536]
BERGKAMEN_A	-6.871	-22.735	0.488
	[-9.199 , -4.581]	[-31.585 , -15.388]	[-2.468 , 3.512]
WALSUM_10	-3.697	-15.105	0.983
	[-5.571 , -1.771]	[-19.722 , -10.179]	[-1.868 , 3.733]
Scholven C	-0.521	-1.048	-0.306
	[-1.265 , 0.190]	[-3.058 , 0.915]	[-1.639 , 0.918]
VOELKLINGEN_MKV	-1.122	-2.921	-0.357
	[-1.917 , -0.482]	[-3.978 , -2.004]	[-0.828 , 0.130]
VOELKLINGEN_HKV	-1.082	-3.247	-0.093
	[-1.502 , -0.652]	[-4.310 , -2.324]	[-0.744 , 0.561]
Wilhelmshaven	-5.508	-18.007	-3.312
	[-7.960 , -3.295]	[-23.478 , -12.500]	[-5.145 , -1.438]
LUENEN_7	-3.575	-5.257	-0.430
	[-5.680 , -1.693]	[-9.613 , -0.908]	[-1.938 , 1.070]
HKW Moorburg Block B	-9.133	-10.818	-1.286
	[-11.482 , -6.887]	[-15.989 , -5.859]	[-3.736 , 1.180]
HKW West Block 1	-0.278	1.101	-0.004
	[-0.536 , -0.039]	[-0.278 , 1.888]	[-0.524 , 0.518]
Kiel	-1.643	-6.832	-1.916
	[-2.617 , -0.674]	[-9.780 , -4.457]	[-3.185 , -0.553]
LUENEN_6	-0.383	-3.878	0.593
	[-1.196 , 0.296]	[-5.657 , -2.036]	[-0.200 , 1.326]
Westfalen E	-6.283	-15.617	-2.268
	[-8.461 , -4.199]	[-20.160 , -11.005]	[-4.459 , -0.440]
Ibbenbüren B	-6.685	-26.119	-3.944
	[-9.248 , -3.986]	[-33.751 , -19.715]	[-7.053 , -1.006]
HKW West Block 2	-0.192	-0.065	-0.250
	[-0.397 , -0.007]	[-0.652 , 0.596]	[-0.887 , 0.284]
Heyden	-9.052	-21.435	-3.026
	[-11.851 , -6.547]	[-27.845 , -15.238]	[-5.269 , -0.772]
Nord 2 T20	-0.249	-1.694	-1.252
	[-0.688 , 0.202]	[-2.755 , -0.501]	[-2.068 , -0.436]

Note: The coefficients give the estimated average reduction in kg CO_2 to a one MWh increase in the respective renewable technology. 95 percent confidence intervals in brackets.

TABLE A.11: Individual treatment effect of coal units I

Generation unit	onshore	offshore	solar
Staudinger 5	-2.916	-6.486	-1.378
	[-4.331 , -1.311]	[-9.605 , -3.362]	[-2.706 , 0.084]
WALSUM_9	-2.036	-7.773	-0.852
	[-2.860 , -1.215]	[-9.897 , -5.639]	[-2.154 , 0.461]
BEXBACH_A_GESAMT	0.491	-1.982	-0.491
	[-0.937 , 1.892]	[-6.590 , 3.008]	[-1.850 , 0.887]
DEZOLLI_1_	-4.364	-10.012	-2.037
	[-5.957 , -2.867]	[-13.428 , -6.775]	[-4.154 , 0.255]
HERNE_4	-1.170	-4.873	-1.266
	[-2.069 , -0.330]	[-7.367 , -2.459]	[-2.165 , -0.332]
HKW Wedel Block 1	-0.766	-1.477	-0.155
	[-1.153 , -0.381]	[-2.244 , -0.691]	[-0.919 , 0.564]
Kraftwerk Voerde Block B	-11.074	-4.910	-2.032
	[-18.937 , -4.181]	[-20.812 , 10.006]	[-9.325 , 6.119]
RDK 7	-2.908	-7.942	-0.300
	[-4.536 , -1.323]	[-11.201 , -4.448]	[-1.859 , 1.300]
HERNE_3	-2.407	0.529	0.908
	[-4.732 , -0.427]	[-5.585 , 7.612]	[-0.108 , 1.870]
KW Hafen Block 6	-1.186	-2.063	-1.349
	[-1.878 , -0.519]	[-3.668 , -0.369]	[-2.074 , -0.627]
Ensdorf 1	-0.111	-1.988	0.004
	[-0.283 , 0.053]	[-3.776 , -0.720]	[-0.104 , 0.114]
DEFARGE___1___	-3.718	-15.030	-0.749
	[-5.228 , -2.157]	[-18.524 , -11.773]	[-2.746 , 1.361]
Ensdorf 3	-0.600	-2.794	0.750
	[-1.132 , -0.098]	[-3.758 , -1.779]	[-0.075 , 1.703]
HKW Altbach/Deizisau Block 2	0.072	-9.900	0.307
	[-2.902 , 3.470]	[-17.056 , -2.629]	[-1.076 , 1.473]
HKW Tiefstack Block 2	-0.161	-1.072	-0.753
	[-0.439 , 0.143]	[-1.780 , -0.269]	[-1.279 , -0.255]
GK-West_1	-1.039	0.449	0.287
	[-2.635 , 0.366]	[-5.112 , 5.908]	[-1.066 , 1.875]
Kraftwerk Voerde Block A	-9.937	-19.953	-9.949
	[-17.024 , -3.312]	[-42.707 , 2.573]	[-29.728 , 2.864]
HKW Reuter Block C	-0.102	-0.779	0.005
	[-0.276 , 0.079]	[-1.441 , -0.112]	[-0.238 , 0.248]
Kraftwerk Rostock	-4.608	-11.842	-1.378
	[-6.172 , -3.108]	[-15.488 , -8.006]	[-2.942 , 0.347]
KW Lünen Block 1	-5.295	-5.776	-1.081
	[-7.015 , -3.468]	[-9.838 , -1.562]	[-3.007 , 0.885]
HKW Moorburg Block A	-8.381	-19.504	-2.855
	[-10.908 , -5.991]	[-25.920 , -13.500]	[-5.148 , -0.436]
RDK 8	-2.843	-14.536	-3.884
	[-5.070 , -0.450]	[-19.946 , -9.108]	[-6.363 , -1.474]
HKW Heilbronn Block 7	-9.035	-18.281	-0.477
	[-11.611 , -6.386]	[-24.842 , -11.798]	[-4.446 , 3.984]
ELVERLINGSEN_E4	-0.898	-8.666	-0.006
	[-1.789 , -0.101]	[-12.956 , -4.855]	[-0.782 , 0.846]

Note: The coefficients give the estimated average reduction in kg CO_2 to a one MWh increase in the respective renewable technology. 95 percent confidence intervals in brackets.

TABLE A.12: Individual treatment effect of coal units II

Generation unit	onshore	offshore	solar
KMW_KW2	-0.152	-1.599	-0.122
	[-0.417 , 0.054]	[-3.019 , -0.585]	[-0.326 , 0.088]
Sued GuD DT60	-0.096	-0.321	-0.090
	[-0.180 , -0.008]	[-0.526 , -0.124]	[0.298 , 0.140]
Weisweiler VGT - Bl. G	-0.233	-0.313	-0.066
	[-0.598 , 0.132]	[-0.922 , 0.191]	[-0.405 , 0.299]
GKB Mittelsbueren GuD	-1.109	-1.040	-0.191
	[-2.029 , -0.298]	[-2.581 , 0.496]	[-1.290 , 0.897]
Gersteinwerk F	-0.070	0.166	-0.047
	[-0.438 , 0.248]	[-0.521 , 0.724]	[-0.359 , 0.262]
HKW Nord GuD Nord	-0.613	-0.737	0.097
	[-0.877 , -0.347]	[-1.123 , -0.341]	[-0.198 , 0.421]
Weisweiler VGT - Bl. H	-0.120	-0.163	0.104
	[-0.432 , 0.217]	[-0.661 , 0.344]	[0.235 , 0.475]
Block GT2	0.052	0.007	-0.228
	[-0.138 , 0.231]	[-0.718 , 0.635]	[-0.453 , -0.016]
HKW Lichterfelde Block 1	0.076	-0.288	-0.086
	[-0.027 , 0.195]	[-0.535 , -0.043]	[-0.190 , 0.009]
Sued GuD2 GT62	-0.150	-0.514	-0.330
	[-0.291 , -0.021]	[-0.894 , -0.158]	[-0.605 , -0.076]
GuD Dormagen	-2.322	-4.553	-0.846
	[-2.974 , -1.697]	[-6.135 , -3.000]	[-1.565 , -0.141]
GuD-Anlage-HKW-Merkenich	-0.033	-0.646	0.038
	[-0.189 , 0.144]	[-0.965 , -0.336]	[-0.093 , 0.174]
RDK 4	0.038	-0.216	-0.680
	[-1.155 , 1.227]	[-2.824 , 2.260]	[-2.356 , 0.559]
Knapsack 2	-2.432	-4.825	-0.416
	[-3.201 , -1.588]	[-6.908 , -2.769]	[-1.091 , 0.223]
Emsland B	-1.415	-3.901	0.094
	[-2.094 , -0.758]	[-5.206 , -2.529]	[-0.758 , 0.971]
Emsland C	-1.389	-3.282	-0.999
	[-2.074 , -0.778]	[-4.850 , -1.847]	[-1.730 , -0.182]
Emsland D	-2.499	-8.419	-2.499
	[-3.934 , -1.176]	[-11.562 , -5.483]	[-4.105 , -1.259]
GTHKW Nossener Bruecke	-0.127	-0.686	-0.168
	[-0.252 , 0.009]	[-1.020 , -0.336]	[-0.335 , -0.008]
Gersteinwerk K1	-0.010	-3.600	0.090
	[-0.262 , 0.255]	[-5.840 , -1.741]	[-0.099 , 0.313]
Block GT1	0.002	-0.084	-0.003
	[-0.122 , 0.125]	[-0.352 , 0.181]	[-0.151 , 0.125]
KMW_KW3	-2.194	-3.150	-0.900
	[-2.843 , -1.580]	[-4.697 , -1.670]	[-1.847 , 0.008]
KW Hamm-Uentrop Block 2	-1.977	-4.791	-0.855
	[-2.694 , -1.317]	[-6.873 , -3.027]	[-1.639 , -0.015]

Note: The coefficients give the estimated average reduction in kg CO_2 to a one MWh increase in the respective renewable technology. 95 percent confidence intervals in brackets.

TABLE A.13: Individual treatment effect of gas units I

Generation unit	onshore	offshore	solar
Sued GuD1 GT2	-0.250	-1.019	0.384
	[-0.423 , -0.055]	[-1.463 , -0.578]	[-0.028 , 0.807]
Sued GuD1 GT3	-0.119	-1.440	-0.257
	[-0.272 , 0.029]	[-1.975 , -0.936]	[-0.670 , 0.221]
NIEHL-3	-0.371	-2.446	-0.038
	[-0.948 , 0.199]	[-4.084 , -1.015]	[-0.738 , 0.633]
NIEHL-II-GT	-1.401	-1.683	-0.017
	[-1.943 , -0.892]	[-2.932 , -0.411]	[-0.626 , 0.612]
Franken I Block 2 + GT	-0.090	-2.801	-0.924
	[-0.583 , 0.365]	[-4.214 , -1.491]	[-1.740 , -0.085]
Sued GuD2 GT61	-0.206	-0.255	-0.229
	[-0.346 , -0.073]	[-0.605 , 0.090]	[-0.461 , 0.002]
Gersteinwerk G	0.092	-0.566	0.362
	[-0.533 , 0.700]	[-1.292 , 0.228]	[-0.233 , 1.052]
Knapsack 1	-1.863	-5.055	-1.096
	[-3.104 , -0.651]	[-7.591 , -2.128]	[-2.510 , 0.294]
Block F	-1.359	-2.238	-0.951
	[-2.091 , -0.657]	[-3.660 , -0.791]	[-1.902 , 0.013]
Block GT 12	-0.190	-0.695	-0.256
	[-0.386 , 0.007]	[-1.128 , -0.270]	[-0.446 , -0.088]
HKW Tiefstack GuD	-0.279	-1.140	-0.282
	[-0.492 , -0.063]	[-1.585 , -0.675]	[-0.615 , 0.086]
Huntorf GT	0.035	-0.326	0.136
	[-0.189 , 0.245]	[-0.755 , 0.119]	[-0.381 , 0.648]
KW Hamm-Uentrop Block 10	-1.345	-3.948	-0.270
	[-1.977 , -0.670]	[-5.230 , -2.660]	[-0.993 , 0.422]
Franken I Block 1	-0.474	-2.056	-0.650
	[-0.887 , -0.074]	[-3.229 , -1.002]	[-1.101 , -0.212]
HERDECKE_H6	-1.428	-6.521	-0.708
	[-2.176 , -0.744]	[-8.799 , -4.412]	[-1.429 , -0.052]
Block GT 11	-0.111	-0.107	-0.041
	[-0.273 , 0.053]	[-0.508 , 0.262]	[-0.329 , 0.324]
NIEHL-II-DT	-0.772	-0.216	-0.222
	[-1.079 , -0.442]	[-0.860 , 0.429]	[-0.662 , 0.147]
HKW Klingenberg 1-3	-0.046	-0.347	-0.021
	[-0.155 , 0.076]	[-0.680 , 0.012]	[-0.157 , 0.118]

Note: The coefficients give the estimated average reduction in kg CO_2 to a one MWh increase in the respective renewable technology. 95 percent confidence intervals in brackets.

TABLE A.14: Individual treatment effect of gas units II

3 Renewable risk and its impacts on market prices: The case of Germany

Author: Philip Schnaars

Abstract: This paper develops a framework for renewable producers to withhold capacity from the day-ahead market in response to higher renewable output risk. The developed hypotheses are tested on a rich dataset from the German electricity market, with a novel measure of renewable forecast risk. The data does not support the presence of renewable withholding in Germany, based on the observed risk premium and day-ahead supply bids. This suggests that firms do not have access to this information or do not regard this as relevant.

3.1   Introduction

Do renewable firms react to risk in weather predictions? Aspects of the transition towards sustainable energy systems include, among others, the price impact of renewable production, firm behavior with now diversified portfolios and the balancing of forecast errors. The question raised in this paper relates to all of these issues but is distinct.

Firms' response to uncertain weather forecasts is relevant, as the share of intermittent renewable capacities exposed to market prices is set to increase in electricity markets around the world. The market price will be increasingly driven by renewable supply and their supply decision has a significant impact on the market outcome[17]. This will likely increase price volatility, as storage capacities are lagging behind in development.

If renewable firms face output and price risk, they should withhold capacity from the day-ahead market to avoid being short and having to cover their obligations at high prices at the next market stage, the intraday market. This additional market stage has been introduced to allow firms to hedge risks from forecasts. Withholding will increase the day-ahead price by lowering low-cost supply.

The incentives for firms in markets with a significant share of renewable capacity have been theoretically examined in multiple settings. Kakhbod et al. (2021) study a one-stage market with imperfect competition among strictly renewable firms that have private information. They show that firms have an incentive to strategically withhold renewable electricity from the market in response to higher expected supply from the other firm. Fabra and Llobet (2020) consider a similar oligopolistic market setting, where firms exercise market power by withholding capacity if their utilization rate is high. This phenomenon disappears in a competitive environment. These two papers predict that renewable firms strategically impact the price in a one-stage market.

Acemoglu et al. (2017) extend this framework to allow for firms with diverse[18] generation portfolios, engaging in a two-stage market with unknown renewable generation in the first stage. Diversified firms reduce the merit-order effect of renewables via strategic substitution to lower renewable generation, keeping the total supply unchanged. The forecast risk of renewable production is not explicitly modeled.

Bessembinder and Lemmon (2002) show in their seminal paper that the day-ahead price contains a risk premium that increases with the variability of demand, as retailers hedge themselves against being short in the intraday market by increasing their day-ahead order volume. Longstaff and Wang (2004) provide empirical evidence of this effect in the Pennsylvania-New Jersey-Maryland market[19], while Pietz (2009) does not find an empirical relationship between price skewness and the price premium in Germany.

These papers study settings where the price risk arises from volatility of demand. The underlying principle is very similar when considering a market with a significant share of renewable capacity. Renewable firms hedge against weather-induced price risk on the intraday market by reducing their day-ahead exposure. The residual demand curve shifts to the right, hence increasing the day-ahead price. Obermüller (2017) identifies a variety of weather conditions and concludes that some are associated with a higher price premium in the German day-ahead price. These particular weather conditions are tied to higher forecast errors and therefore implicitly measure intraday price risk.

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[17]This paper focuses on large scale renewable generation. Koolen et al. (2021) highlight the difference between large scale renewable generation and small-scale (prosumer) sites with respect to the risk premium.

[18]A diverse generation portfolio consists both of renewable and conventional capacity.

[19]This market serves all or parts of 13 states (Delaware, Illinois, Indiana, Kentucky, Maryland, Michigan, New Jersey, North Carolina, Ohio, Pennsylvania, Tennessee, Virginia and West Virginia) and the District of Columbia (PJM, 2020).

This paper extends the existing research by deriving a general motivation for the presence of renewable withholding and consequent risk premia that is applicable to various electricity markets. It sheds light on price formation in power markets with a significant share of renewable capacity by explicitly considering the inherent risk of weather forecasts, which impacts renewable output risk and in turn aggregate price risk. This framework is then applied to the German market with unique data on renewable forecast risk and detailed information on day-ahead bidding behavior. This data is used to assess the effects of renewable output risk on the price premium and renewable withholding.

I find that renewable firms in Germany do not consider renewable output risk as important information. A higher aggregate output risk does not increase the difference between the day-ahead and the intraday price. The main driver of this price difference are the realized forecast errors of wind and solar, which confirms previous findings (Kulakov and Ziel, 2021; Kiesel and Paraschiv, 2017; Woo et al., 2016). Further, I do not find any evidence of firms withholding renewable capacity from the day-ahead market in response to riskier forecasts. This implies that firms can balance their forecast errors at reasonable prices.

3.2 Theoretical Framework

The electricity market consists of two stages and renewable firms can decide at which stage to sell their output. At the day-ahead market, firms have to form expectations about the price at the subsequent market stage and about the amount of electricity they can generate at the time of delivery in order to maximize profits. These predictions carry a certain risk, which varies with weather conditions.

This risk resolves at the intraday stage. Forecast errors have to be balanced at this stage at the equilibrium price[20]. The intraday price will decrease compared to the day-ahead price if there is additional renewable supply and vice versa. This sell pressure can either be caused by a forecast error or by renewable plant operators withholding from the day-ahead market. It is this day-ahead withholding that might introduce a risk premium into the day-ahead price. In the following, I discuss the conditions under which day-ahead withholding is in the interest of a firm in a competitive market.

I assume that a risk-averse firm operates a single renewable site, has no market power[21] and knows its distribution of potential output and hence its expected value as well as that of all other market participants. Therefore, it has knowledge about the level of confidence with which their forecasted amount will be available. The higher the output risk, the higher the probability of a significant individual forecast error. The firm also has information on the variance of the other firms' potential output. This knowledge does not entail any information about the direction of the possible forecast errors of itself and the other firms, i.e. the distributions around the predicted output are assumed to be symmetric.

Every forecast exhibits some level of risk. In the case of weather predictions, this varies with the forecast horizon and, more importantly, overall weather conditions. For this reason, weather forecasts often comprise of multiple individual forecasts that differ by assumptions

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[20]It is possible for market participants to rely on balancing services provided by the grid operator to balance their forecast errors. However, it is generally cheaper to balance deviations actively by trading on the intraday market (see Pape, 2018).

[21]The following discussion is also valid for an oligopolistic market. The single firm can then be understood as a fringe supplier without market power, similar to the design in Ito and Reguant (2016). The price risk is introduced by the output risk of at least one of the firms with market power. The German wholesale electricity market is characterized by five companies owning diverse portfolios. These portfolios made up over 70 percent of generated electricity in 2018 (Bundesnetzagentur, 2020b). The cartel office concluded in their latest report that these companies bid their marginal costs and do not withhold capacity in a significant manner (Bundeskartellamt, 2011). These companies compete with each other.

over the weather events that will develop over the forecast horizon. These "ensemble" methods implicitly measure the degree of forecast risk via the variance of the individual forecasts, which should plausibly be available to the firms. The output risk of a single firm translates into price risk when the output risk of sufficiently many firms is positively correlated. In the following discussion, I consider four distinct, stylized cases and discuss how renewable firms behave in each of them.

Case A: High Output Risk, High Price Risk
The firm will have to balance its forecast error on the intraday market, where the expected price has a high variance. To avoid this price risk, renewable electricity will be withheld from the day-ahead market, introducing a risk premium in the day-ahead price, because the high positive correlation between the individual output risks induces firms to behave similarly.

Case B: High Output Risk, Low Price Risk
The expectation of the intraday price shows low variance. The probability that the individual forecast will be wrong is high. A firm withholds output from the day-ahead market, but this does not cause a risk premium. This single firm is too small to impact the day-ahead market price.

Case C: Low Output Risk, High Price Risk
The market participant faces a wide range of possible intraday prices. As a result, renewable production will be withheld from the day-ahead market, which contains a risk premium from other firms withholding capacity.

Case D: Low Output Risk, Low Price Risk
The firm is indifferent between selling at the day-ahead or at the intraday market. No price effect is expected.

To summarize, the day-ahead market price contains a risk premium when sufficiently many firms face individual output risk, which then aggregates into price risk (cases A and C). The risk premium is defined as the difference between the day-ahead and the intraday price, which arises from renewable withholding at the day-ahead stage and therefore before the realization of forecast errors during intraday trading. My econometric specification allows to disentangle these two effects, by separately observing both the forecast risk and the realized forecast errors.

In cases A, B and C, a (small) set of firms either experience output or price risk or a combination of both. They respond by reducing the quantity offered at the day-ahead market. When renewable firms reduce their offer, the shape of the supply curve changes, keeping everything else in the market constant.

This theoretical framework can be directly applied to the German electricity market, where firms operate price-exposed renewable capacity in a two-stage market. This capacity forms clusters depending on prevailing local weather conditions, introducing heterogeneity in the price impact of renewables.

As the market price for electricity tends not to be sufficiently high for renewable producers to recover their fixed cost, the German government pays out subsidies in one of two schemes. Under the first scheme, the feed-in-tariff, producers sell their electricity to the grid operator at a fixed price. The grid operator is then responsible for marketing that electricity at the exchange. Renewable firms subsidized under the second scheme sell their output directly at the exchange and receive a premium on top of the market price. If this sum is fixed, both schemes are identical from the perspective of firm's profits (see Dressler, 2016), inducing maximum renewable output. Ito and Reguant (2016) report that renewable firms stopped withholding electricity after remuneration was changed to a fixed price.

In this particular case, the market premium is paid on top of the monthly average exchange price, enabling firms to exploit differences between this benchmark and hourly prices. As a result[22], the importance of the market premium model has been steadily increasing since its creation in 2012, making up over 95 percent for both onshore and offshore wind electricity and about 25 percent of the total solar electricity produced in 2018 (Fraunhofer, 2019). These firms should base their output decisions on the expected market price[23] and therefore behave as outlined above.

In a setting with market power and limited entry to arbitrage, strategic firms can generate a systematic price premium by splitting the quantity asymmetrically between the two market stages and thereby withholding quantity (Ito and Reguant, 2016) or restraining from arbitraging existing price differences away completely[24] (Borenstein et al., 2008). I disregard the possibility of market power. Official investigations of the bidding behavior of electricity companies did not reveal evidence in favor of firms not bidding their marginal costs (Bundeskartellamt, 2011).

As the spatial correlation of wind speed tends to be high, one can also think about the renewable generation structure as consisting of two clusters of different sizes. One is located in the north of Germany where wind speeds tend to be higher and installed capacities are high. The other group of producers is located in the south with only small installed capacities at their disposal. The cluster in the north has an impact on the market price with its output decision and firms' individual output risk translates into price risk. The smaller cluster located in the south also faces individual output risk, but the aggregate price risk depends on the risk the bigger cluster in the north faces[25].

Case A refers to the case where both clusters face high output risk. Case B considers a situation where only the small cluster is exposed to high output risk. Case C expresses the situation where the northern cluster faces price risk while the southern cluster does not. In case D, both clusters can rely on confident predictions.

The following section introduces the data that is used to investigate the presumed behavior discussed above in the German electricity market.

3.3 The dataset

I use hourly data from the 1st of January 2015 until the 16th of May 2018. Information on the settlement prices of the day-ahead auction and the intraday transactions as well as expected and realized demand and renewable production was provided by the German power exchange operator EEX (EEX, 2020). Prices for fuels and European Emission Allowances (EUA) are taken from EEX and Quandl (Quandl, 2020). Furthermore, detailed data on day-ahead supply and demand bids were obtained by EPEX Spot (EPEX Spot, 2020).

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[22]The market premium model is mandatory for most newly-installed capacity installed after 2017 (BMWi, 2016). Firms actively opting for the market premium model highlights its additional profit opportunities compared to the feed-in tariff.

[23]The switch from a feed-in tariff towards a premium model comes with extra costs to the firms, as they are required to forecast available production. As a result, most renewable firms delegate marketing towards a third party company. These often act on behalf of multiple renewable firms (BMWi, 2018), reaching a significant size. As a result, these aggregators are more likely to engage in sophisticated operations such as measuring the inherent forecast risk than a single firm.

[24]Arbitrage behavior in a strict sense does not entail any profit risk (Dybvig and Ross, 1989). Due to the intertemporal nature of the price difference between the day-ahead and the intraday market, no complete certainty can be achieved. Throughout this paper, I use the term "arbitrage" loosely to include risky trades as well.

[25]When considering the risk of solar predictions, the relative cluster size are reversed to form a high capacity cluster towards the south-eastern part of Germany.

3.3.1   Measuring renewable output risk

Short-term weather and hence renewable production forecasts have been getting better (Gürtler and Paulsen, 2018), but a relevant portion of risk remains. This risk inherent in day-ahead weather predictions is not publicly available. Electricity companies either buy forecasts from a third party or run their own prediction models, both for their own generation as well as on the production of competitors. It is reasonable to assume that these models also provide a range of possible values, carrying the inherent risk.

To obtain a high-quality measure, I use data from the short-term ensemble prediction model COSMO-DE-EPS that was operated by the German Weather Service. This model uses information from the day before the electricity is being delivered to make predictions on the subsequent day. The weather information should therefore be very close to the data that electricity traders use. For each hour, the model predicts 20 different values. Each of those is called an ensemble member. Every ensemble member has slightly different input values, i.e. assumed weather relationships. If these ensemble members predict dissimilar values, the risk of the prediction is relatively high and vice versa. Figure 3.1 illustrates the cases of a prediction with a relatively low and a relatively high risk. This risk is calculated as the standard deviation among the 20 ensemble members.

(A) Low risk   (B) High risk
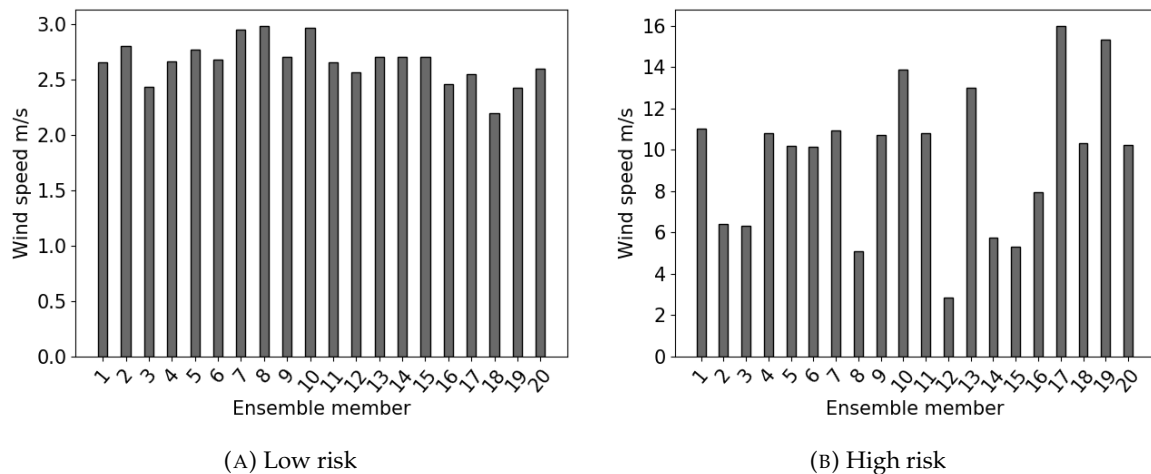
Note: Wind speed projections over 20 different ensemble member for the region for an exemplary, relatively windy region in Schleswig-Holstein (postal code-region 23). Figure (A) shows hour 4 - 5 on 30.08.2016. Figure (B) shows hour 23 - 0 on 18.01.2018.

FIGURE 3.1: Risk over time

Originally, the weather data is provided on a grid of 2.5 × 2.5 kilometers. Averages are formed along the first two digits of the postal code. This results in 95 regions, displayed in figure 3.2. The capacity-weighted[26] average represents the aggregate price risk. The figure identifies regions with a potentially higher price impact due to the relatively large installed capacity, indicated by darker colors.

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[26]Installed capacities are taken from Marktstammdatenregister (Bundesnetzagentur, 2020a).

(A) Wind   (B) Solar
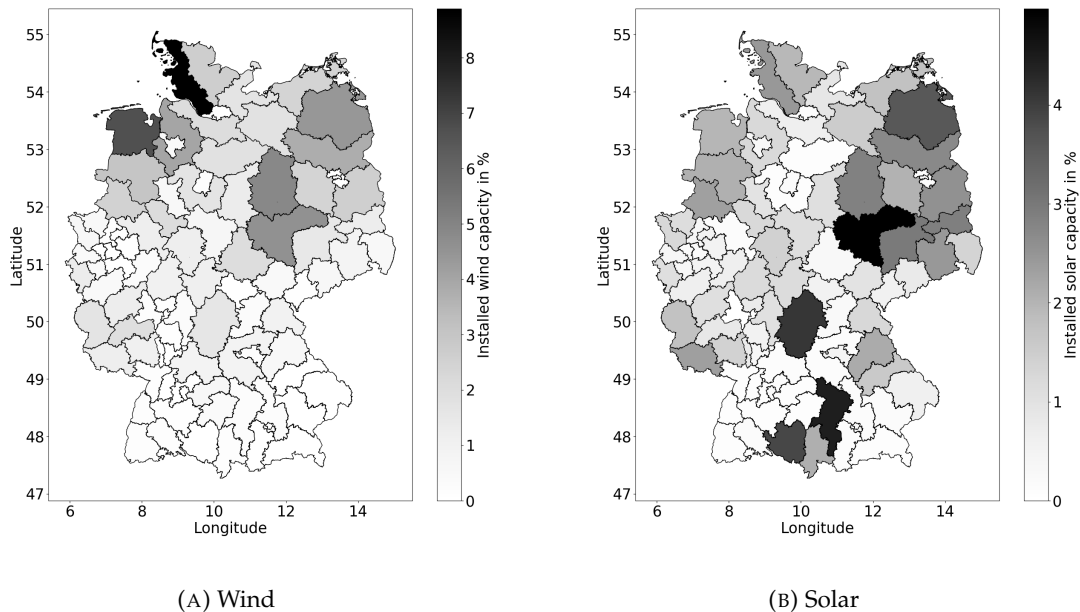
Note: Capacity shares of the of wind are displayed in figure (A) and of solar
in figure (B). Darker colors indicate a higher share.

FIGURE 3.2: Installed capacities over regions

I will use three different risk definitions in the subsequent analysis. First, the capacity-weighted average of the standard deviation over the regions for both technologies (*windstd*, *radiationstd*). Second, to relate more closely to the elaborations in section 3.2, I identify high price impact regions based on the cumulative distribution function of capacity[27]. The resulting continuous variables measure the risk of renewable output separately in high price impact and low price impact regions (*windstd_high*, *windstd_low*, *radiationstd_high*, *radiationstd_low*).

The third measure combines information about the price impact and the level of risk in a binary manner. Output risk in each of four regions from the second measure is considered to be high if it exceeds the respective 90th percentile[28] (*windstd_high_high*, *windstd_low_high*, *radiationstd_high_high*, *radiationstd_low_high*). This quantity describes the laid out theory closest.

3.3.2   Descriptive Statistics

In the presence of renewable withholding, the day-ahead price should rise over the corresponding intraday price. This difference can be considered a risk premium and measured using both observed prices[29], as in equation 3.1, which will serve as the dependent variable in the subsequent regression analysis.

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[27]Regions with an installed capacity over the 90th percentile are considered to have a high price impact. Qualitative results remain unchanged when this cutoff is altered.

[28]Qualitative results are not affected by choosing a different cutoff.

[29]The intraday market, unlike the day-ahead market, is characterized by continuous trading that settles pay-as-bid. I use the average of all transaction prices weighted by trading volume.

$$Premium = DA\_price - ID\_price \tag{3.1}$$

The identification of the effects of renewable risk on the price difference requires controlling for all other determining factors, such as the realized forecast errors of renewables and demand, as these factors tend to drive the realized intraday price away from its expectation at the day-ahead market stage. The renewable forecast errors will not have a mean of zero in the presence of withholding.

Under the null hypothesis of no renewable withholding, the companies expect the shocks to renewable availability to be random with a mean of zero. This implies that the expected intraday price equals the observed intraday price and, controlling for all relevant factors, also the day-ahead price. Among others, Haugom and Ullrich (2012) term this the rational expectation hypothesis and use the realized intraday price to measure the risk premium. The observed risk premium varies in size and magnitude over the course of the day (see figure 3.3). At night, where demand for electricity tends to be relatively low, the day-ahead price is consistently below the intraday price. As demand rises, the premium becomes positive. Bunn and Chen (2013) observe a similar pattern in the British electricity market and explain this by a switch in risk aversion from the supply to the demand side, as predicted by Benth et al. (2008). The identical phenomenon is responsible for risk premia turning negative around midday, where the residual demand for conventional production is decreasing as electricity generation from solar peaks[30]. The presence of risk premia highlights the the absence of significant arbitrage behavior in the German market.
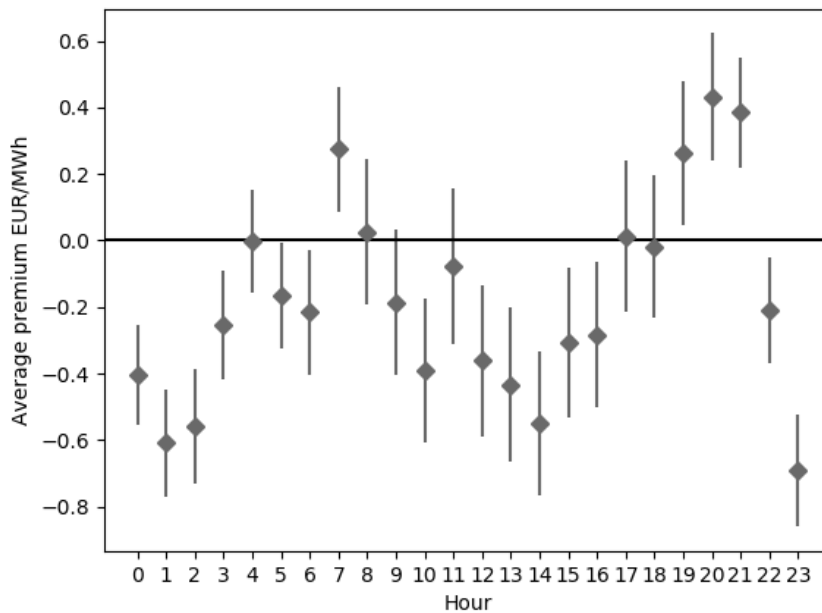
Note: Diamonds represent the mean premium for the respective hour of the day, bars the associated standard error.

FIGURE 3.3: Day-ahead premium over hours of the day

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[30]This is often called "duck curve" (CAISO, 2016).

Table 3.1 introduces the variables and their description. On average, the forecast errors for wind and solar are positive. This implies that the realized value is above the predicted amount. The opposite is true for demand. These figures are reported by the grid operators based on their own production forecasts and statistically different from zero. This could be an indication for renewable withholding if the grid operators use information provided by the firms to form their predictions.

One might be surprised by the fact that radiation can take negative values. The weather model uses the convention to denote radiation directed towards the surface with a positive sign and radiation away from the surface with a negative sign. This ensures that the intertemporal sum will always be zero. Net radiation will be negative at night, as diffuse radiation vanishes.

Variable	Description	mean	min	max	sd	count
premium	Price premium EUR/MWh	-0.181	-106	73	6.899	29185
windstd	Wind forecast risk	0.770	0	4	0.350	29185
radiationstd	Radiation forecast risk	20.276	0	200	31.371	29185
windstd_high	Wind forecast risk in high price impact cluster	0.821	0	4	0.397	29168
windstd_low	Wind forecast risk in low price impact cluster	0.698	0	3	0.304	29168
radiationstd_high	Radiation forecast risk in high price impact cluster	19.281	0	194	30.412	29174
radiationstd_low	Radiation forecast risk in low price impact cluster	21.130	0	214	32.749	29174
windstd_high_high	=1 if wind risk high in high price impact cluster	0.101	0	1	0.301	29185
windstd_low_high	=1 if wind risk high in low price impact cluster	0.101	0	1	0.301	29185
radiationstd_high_high	=1 if radiation risk high in high price impact cluster	0.100	0	1	0.300	29185
radiationstd_low_high	=1 if radiation risk high in low price impact cluster	0.100	0	1	0.300	29185
FE_wind	Forecast error wind GWh	0.101	-13	22	1.491	29185
FE_solar	Forecast error solar GWh	0.031	-11	7	0.728	29185
FE_load	Forecast error demand GWh	-0.675	-18	13	2.128	29185
windmean	Predicted wind speed m/s	5.105	0	15	2.067	29185
radiationmean	Predicted solar radiation kJ/m^2	0.118	-0	1	0.182	29185
expload	Forecasted demand GWh	55.030	29	76	9.635	29185
eua	Price EUA EUR/tCO2	6.729	4	15	2.068	29185
gas	Price Gas EUR/MWh	17.475	10	59	3.570	29185
coal	Price Coal USD/kt	69.075	43	97	16.392	29185
outcap	Fossil capacity unavailable GW	0.633	0	5	0.649	29185

Note: The column "variable" indicates the variable names that are used throughout their paper together with their description. The standard deviation is indicated by "sd".

TABLE 3.1: Summary statistics

3.4 Results

3.4.1 Risk premium

The factors that explain the risk premium are depicted in the Directed Acyclic Graph (DAG) shown in figure 3.4. The main sources of variation in this premium are the forecast errors of renewables (*RFE*) and demand (*DFE*). Important drivers of the premium are also demand for electricity (*D*) and renewables supplied (*Ren*). They control for the price level, i.e. the relevant section on the supply curve. The supply and demand curves in the day-ahead and intraday market are often considered to be different. Knaut and Paschmann (2019) confirm a difference between the hourly and the 15 minute day-ahead auction, which arises primarily due to participation constraints from the shorter supply period. I compare the hourly day-ahead and the hourly intraday price and find no statistically significant difference in the slope of the supply curve (see appendix B.3).

If renewable risk (*Risk*) affects prices as suggested above via the amount of renewables bid into the market, it should only affect the premium indirectly. The main driver of renewable generation is the weather, denoted by *W*. Additional control variables that, for example,

exogenously affect the bidding of conventional power producers, such as fuel prices, are included in the vector *X*.
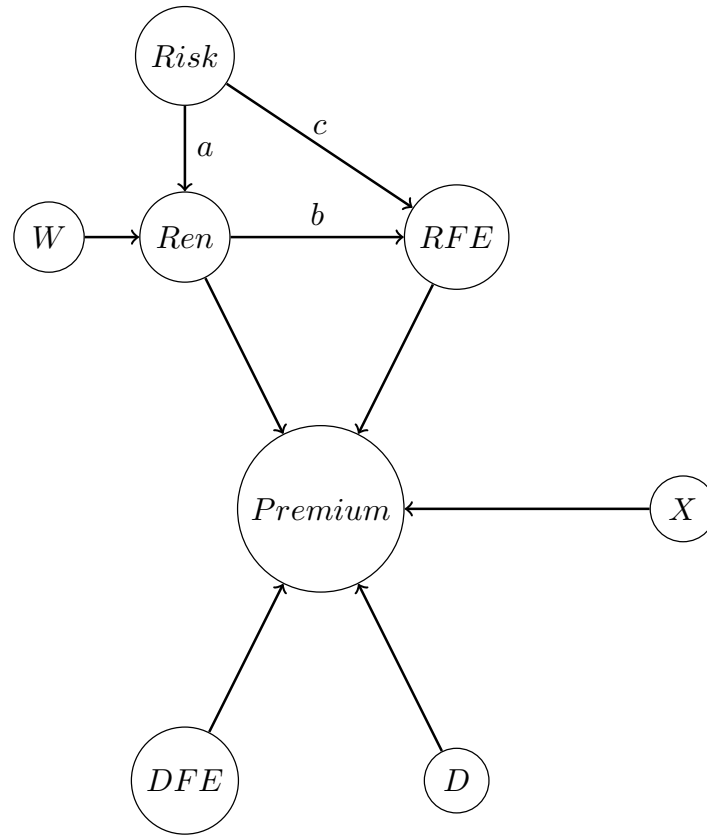
Note: Ren: Renewables, Risk: Renewable risk, W: Weather, RFE: Realized Renewable Forecast Errors, D: Demand, DFE: Realized Demand Forecast Errors, X: control variables. Path *a* is of main interest to this study.

FIGURE 3.4: DAG of price premium

Relationships between variables in a DAG can be taken as a causal relationship if there is no path, represented by arrows, that originates in one variable and ends in that same variable. The graph is then called acyclic. We can identify causal effects of any variable A on another variable Y if it is a direct cause of Y or of any variable that then causes Y (Pearl, 2009).

In the language of graph theory, the amount of renewables *Ren* represents a collider. This is defined as a node which receives edges from two other nodes (Pearl, 2009). Controlling for a collider variable in a regression will make the formerly independent variables, here *W* and *Risk*, dependent on each other. In addition, it will be impossible to examine an effect of forecast risk on the premium, if the model conditions on *Ren*. If the amount of renewables bid into the market is fixed, the effect of firms withholding renewable capacity cannot be determined. I will therefore disregard this variable in the subsequent regressions and condition on the risk *Risk* and the weather *W*. A higher forecast risk influences the size of realized forecast errors (*RFE*) and thereby indirectly the observed price difference. I block path *c* by controlling for these forecast errors in the regression model. This also achieves blocking the indirect influence of the level of expected weather conditions on the premium (path *b*). This setup allows me to identify the causal effect of renewable uncertainty on the premium, denoted by path *a*.

I estimate the following models to assess the effect of renewable forecast risk on the price difference, where X_t captures fuel prices, outage capacity, lagged dependent terms and hourly fixed effects:

$$
\begin{aligned}
premium_t \;=\; & \alpha_0 + \alpha_1 windstd_t + \alpha_2 radiationstd_t + \alpha_3 windmean_t + \alpha_4 radiationmean_t + \\
& \alpha_5 FE\_wind_t + \alpha_6 FE\_solar_t + \alpha_7 expload_t + \alpha_8 FE\_load_t + \delta_1 X_t + \epsilon_t \quad (3.2)
\end{aligned}
$$

$$
\begin{aligned}
premium_t \;=\; & \beta_0 + \beta_1 windstd\_high_t + \beta_2 windstd\_low_t + \beta_3 radiationstd\_high_t \quad (3.3) \\
& + \beta_4 radiationstd\_low_t + \beta_5 windmean_t + \beta_6 radiationmean_t + \\
& \beta_7 FE\_wind_t + \beta_8 FE\_solar_t + \beta_9 expload_t + \beta_{10} FE\_load_t + \delta_2 X_t + \eta_t
\end{aligned}
$$

$$
\begin{aligned}
premium_t \;=\; & \gamma_0 + \gamma_1 windstd\_high\_high_t + \gamma_2 windstd\_low\_high_t + \quad (3.4) \\
& \gamma_3 radiationstd\_high\_high_t + \gamma_4 radiationstd\_low\_high_t + \\
& \gamma_5 windmean_t + \gamma_6 radiationmean_t + \gamma_7 FE\_wind_t + \gamma_8 FE\_solar_t + \\
& \gamma_9 expload_t + \gamma_{10} FE\_load_t + \delta_3 X_t + u_t
\end{aligned}
$$

To confirm the presence of renewable withholding in response to higher renewable risk, the estimates of the coefficients α_1, α_2; $\beta_1, \beta_2, \beta_3, \beta_4$ and $\gamma_1, \gamma_2, \gamma_3, \gamma_4$ or a subset thereof should be positive. All variables are stationary except for *eua* and *coal*, based on unit root tests displayed in table B.1. Henceforth, these two variables will be treated in their first differences in order to achieve the same level of integration among the variables.

All variables are serially correlated over time (see table B.2). An explanatory variable x_t that is correlated over time will be correlated with the regression error term u_t if it has an influence on the serially correlated dependent variable y_t. Including lagged terms of the dependent variable will alleviate this problem if the error term becomes white noise. In this application, it is sufficient to include two lagged terms of the dependent variable as covariates to render the residuals white noise, i.e. to specify a dynamically complete model based on the first-order Cumby-Huizinga test.

	(3.2)	(3.3)	(3.4)
windstd	-0.21		
	[-0.43 , 0.01]		
radiationstd	0.00		
	[-0.00 , 0.00]		
windstd_high		0.05	
		[-0.28 , 0.37]	
windstd_low		-0.42	
		[-0.83 , -0.01]	
radiationstd_high		0.00	
		[-0.00 , 0.01]	
radiationstd_low		-0.00	
		[-0.01 , 0.00]	
windstd_high_high			-0.01
			[-0.24 , 0.22]
windstd_low_high			-0.16
			[-0.37 , 0.05]
radiationstd_high_high			-0.01
			[-0.30 , 0.28]
radiationstd_low_high			0.01
			[-0.27 , 0.28]
windmean	-0.02	-0.02	-0.02
	[-0.06 , 0.03]	[-0.07 , 0.02]	[-0.06 , 0.03]
radiationmean	-0.14	-0.19	-0.12
	[-0.91 , 0.63]	[-0.96 , 0.58]	[-0.82 , 0.58]
FE_wind	-0.42	-0.42	-0.42
	[-0.49 , -0.35]	[-0.49 , -0.35]	[-0.49 , -0.35]
FE_solar	-0.62	-0.61	-0.60
	[-0.72 , -0.51]	[-0.72 , -0.51]	[-0.70 , -0.50]
FE_load	0.07	0.07	0.07
	[0.04 , 0.10]	[0.04 , 0.10]	[0.04 , 0.10]
expload	-0.00	0.00	0.00
	[-0.01 , 0.01]	[-0.01 , 0.01]	[-0.01 , 0.01]
eua	-0.09	-0.04	-0.10
	[-2.77 , 2.58]	[-2.77 , 2.68]	[-2.76 , 2.55]
coal	-0.15	-0.21	-0.11
	[-0.69 , 0.39]	[-0.77 , 0.36]	[-0.64 , 0.42]
gas	-0.03	-0.03	-0.03
	[-0.04 , -0.01]	[-0.04 , -0.01]	[-0.04 , -0.01]
outcap	-0.15	-0.16	-0.15
	[-0.25 , -0.06]	[-0.25 , -0.07]	[-0.24 , -0.06]
l premium	0.87	0.87	0.87
	[0.82 , 0.93]	[0.81 , 0.93]	[0.82 , 0.93]
l2 premium	-0.07	-0.07	-0.07
	[-0.12 , -0.02]	[-0.12 , -0.02]	[-0.12 , -0.03]
Constant	1.03	1.10	0.83
	[0.44 , 1.63]	[0.50 , 1.70]	[0.23 , 1.42]
Observations	26,997	26,414	28,029
Cumby-Huizinga AR(1)	0.018	0.012	0.007

Note: The dependent variable is *premium*. 99 percent confidence intervals in brackets. The underlying standard errors are robust to heteroskedasticity and autocorrelation up to 14 lags. Column titles refer to the equation that is estimated. The coefficients of hourly fixed effects are not displayed. The variables *eua* and *coal* in first differences. The test-statistic of the Cumby-Huizinga test for first order autocorrelation is reported.

TABLE 3.2: Effects of risk on the price premium

The regression estimates do not support the presence of an effect of renewable forecast risk on the price premium at the 99 percent significance level, irrespective of the specification of risk.

The main drivers of the price difference are the forecast errors of both demand and the renewable technologies. The estimated coefficients and their levels of statistical significance are robust over the specifications. Forecast errors for solar have a stronger price effect than

wind forecast errors. This was also found by Obermüller (2017). This could be due to the forecast errors happening primarily at different times during the day. Solar forecast errors tend to happen at times of higher demand where the marginal power plant is different than at night. In the case of a negative forecast error the additional electricity will be provided by a power plant on a different part of the supply curve, where it might have a different slope. Unexpected changes in demand and supply explain a significant part of the price difference in electricity markets around the world (Longstaff and Wang, 2004; Furió and Meneu, 2010; Lucia and Torró, 2011).

Furthermore, the level of the price, as indicated by *expload*, does not matter for the premium. This suggests that the supply curves are sufficiently comparable between the two market stages to allow for similar prices across the observed range of demand. The estimated confidence intervals of *windspeed* and *radiation* further support this claim. It is possible that the price premium does not respond to changes in renewable risk, because market participants adjust their bidding behavior accordingly.

3.4.2 Withholding in the day-ahead bids

To further assess the presence of withholding in response to higher renewable output risk, I analyze the bids in the day-ahead auction. This data does not allow me to disentangle the bids by technology, as the bids are aggregated to form price-quantity pairs. This makes it impossible to directly assess the offered renewable quantity. I derive a data-driven solution utilizing information about the shape of the supply curve.

If renewable producers, ceteris paribus, reduce the amount they offer in the day-ahead market, the shape of the supply curve should change. I assume that operators bid their marginal costs, at least in the relevant range of the data. In particular, renewables should offer their electricity at a price close to zero. Given a certain level of demand, the point on the supply curve where the market clears should shift towards the more convex part when bid renewable volumes decrease, i.e. the second derivative of the supply function should increase. The left panel in figure 3.5 shows the observed bids on the 7th of April 2018 at 12 am. This hour was randomly chosen for illustration. Less supply from renewables will, ceteris paribus, shift the market clearing point to a higher point on the supply curve, where both the first and second derivative are higher.

(A) Supply and demand

(B) Supply with fitted spline
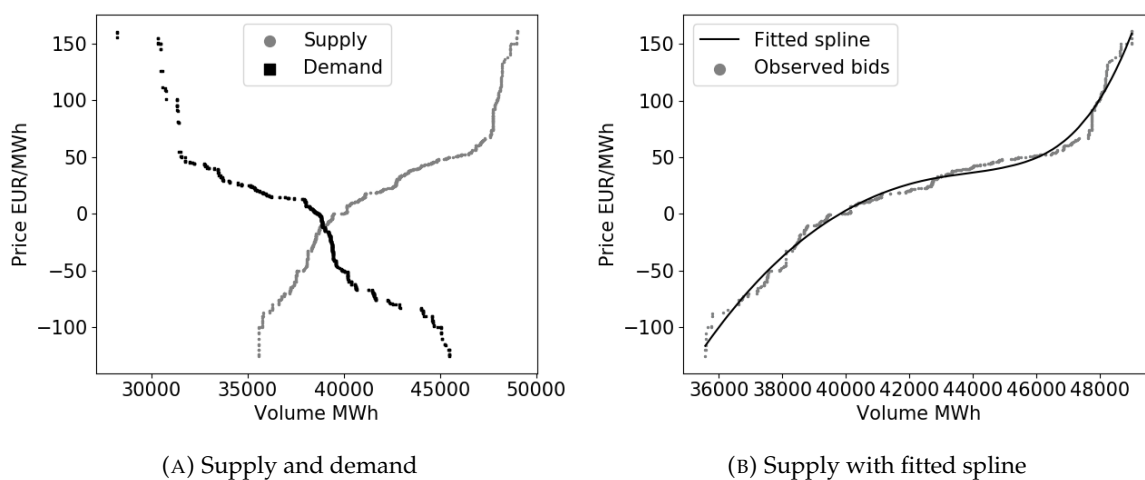
Note: The left figure (A) shows observed supply and demand bids for delivery on 07.04.2018 12am. The right figure (B) displays the supply bids and the fitted spline function.

FIGURE 3.5: Day-ahead bids and fitted spline

The bid data is restricted to the minimum and maximum day-ahead clearing price observed over the sample period[31]. The bids outside this range are not relevant for the question at hand.

I fit a cubic spline to each hourly set of price-quantity supply bids, using cross-validation to avoid overfitting[32]. The right panel of figure 3.5 shows the result of the above procedure. The smoothing spline interpolation captures the information in the underlying data well without modeling the noise and provides a continuous and twice-differentiable function. For each of the fitted splines, the first and second derivatives[33] are determined. I use the curvature at the intersection with the demand curve as the dependent variable.

The identification strategy remains similar to the analysis of the price premium. At the day-ahead market, the forecast errors are not yet realized, therefore will not have a direct impact on the offered quantity. Path d will shed light on the null hypothesis.
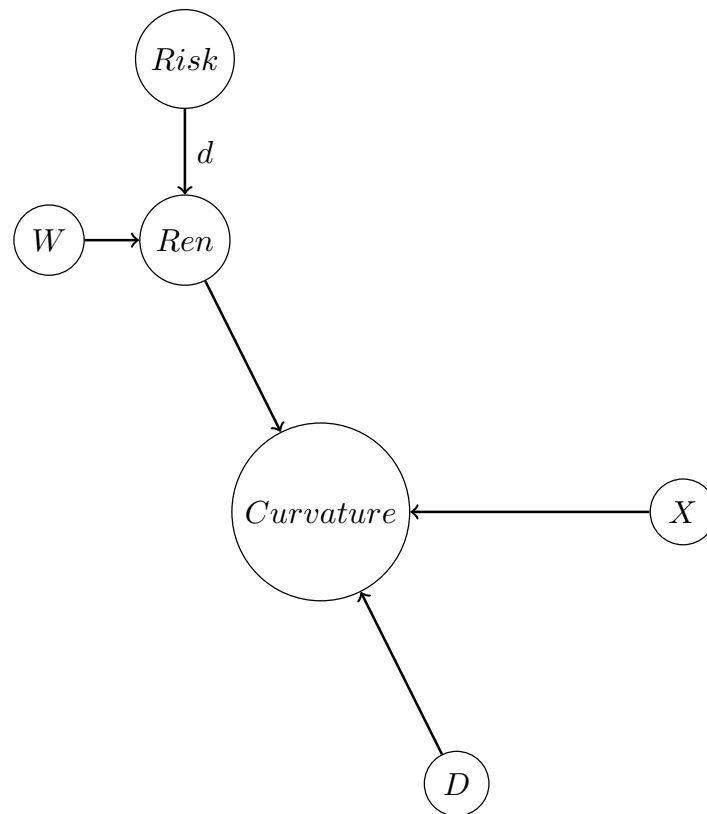
Note: Ren: Renewables, Risk: Renewable risk, W: Weather D: Demand,
X: control variables. Path d is of main interest in this analysis.

FIGURE 3.6: DAG of curvature

The following equations will be estimated by OLS to identify the effect of renewable risk on the shape of the supply curve and the offered renewable amount, where κ_1, κ_2 ; $\zeta_1, \zeta_2, \zeta_3, \zeta_4$; $\theta_1, \theta_2, \theta_3, \theta_4$ are the coefficients of interest, respectively.

---

[31]Over the sample period, the hourly day-ahead market cleared at prices between -130 EUR/MWh and 163 EUR/MWh. Bids outside of this range stem mostly from must-run conditions or at prohibitive prices.

[32]For a more detailed description of this procedure, refer to appendix B.2.

[33]The calculated values are multiplied by 10^6 to enhance readability of coefficients.

$$
\begin{aligned}
curvature_t \quad = \quad & \kappa_0 + \kappa_1 windstd_t + \kappa_2 radiationstd_t + \kappa_3 windmean_t + \kappa_4 radiationmean_t + \\
& \kappa_5 expload_t + \delta_4 \boldsymbol{X}_t + v_t
\end{aligned}
\tag{3.5}
$$

$$
\begin{aligned}
curvature_t \quad = \quad & \zeta_0 + \zeta_1 windstd\_high_t + \zeta_2 windstd\_low_t + \zeta_3 radiationstd\_high_t + \\
& \zeta_4 radiationstd\_low_t + \zeta_5 windmean_t + \zeta_6 radiationmean_t + \\
& \zeta_9 expload_t + \delta_5 \boldsymbol{X}_t + \psi_t
\end{aligned}
\tag{3.6}
$$

$$
\begin{aligned}
curvature_t \quad = \quad & \theta_0 + \theta_1 windstd\_high\_high_t + \theta_2 windstd\_low\_high_t + \\
& \theta_3 radiationstd\_high\_high_t + \theta_4 radiationstd\_low\_high_t + \\
& \theta_5 windmean_t + \theta_6 radiationmean_t + \theta_7 expload_t + \\
& \theta_8 FE\_load_t + \delta_6 \boldsymbol{X}_t + \ni_t
\end{aligned}
\tag{3.7}
$$

	(3.5)	(3.6)	(3.7)
windstd	-0.31		
	[-0.67 , 0.06]		
radiationstd	-0.00		
	[-0.01 , 0.01]		
windstd_high		-0.48	
		[-0.98 , 0.02]	
windstd_low		0.17	
		[-0.45 , 0.80]	
radiationstd_high		-0.00	
		[-0.02 , 0.01]	
radiationstd_low		0.00	
		[-0.01 , 0.02]	
windstd_high_high			-0.25
			[-0.61 , 0.10]
windstd_low_high			-0.05
			[-0.38 , 0.28]
radiationstd_high_high			-0.21
			[-0.79 , 0.37]
radiationstd_low_high			0.23
			[-0.36 , 0.82]
windmean	-0.39	-0.39	-0.39
	[-0.46 , -0.32]	[-0.46 , -0.32]	[-0.46 , -0.33]
radiationmean	-0.01	-0.01	-0.01
	[-0.01 , -0.00]	[-0.01 , -0.00]	[-0.01 , -0.00]
expload	0.00	0.00	0.00
	[0.00 , 0.00]	[0.00 , 0.00]	[0.00 , 0.00]
eua	0.88	0.76	1.05
	[-1.76 , 3.52]	[-1.96 , 3.48]	[-1.58 , 3.68]
coal	-0.08	-0.02	-0.12
	[-0.59 , 0.42]	[-0.54 , 0.49]	[-0.62 , 0.39]
gas	-0.06	-0.06	-0.06
	[-0.09 , -0.02]	[-0.09 , -0.02]	[-0.09 , -0.02]
outcap	0.00	0.00	0.00
	[-0.00 , 0.00]	[-0.00 , 0.00]	[-0.00 , 0.00]
l curvature	0.26	0.26	0.26
	[0.23 , 0.29]	[0.23 , 0.29]	[0.23 , 0.29]
l2 curvature	0.12	0.12	0.12
	[0.09 , 0.14]	[0.09 , 0.14]	[0.09 , 0.14]
Constant	-3.61	-3.58	-3.69
	[-4.62 , -2.60]	[-4.61 , -2.55]	[-4.69 , -2.69]
Observations	25,709	25,144	26,712
Cumby-Huizinga AR(1)	0.285	0.207	0.311

Note: The dependent variable is *curvature*. 99 percent confidence intervals in brackets. The underlying standard errors are robust to heteroskedasticity and autocorrelation up to 14 lags. Column titles refer to the equation that is estimated. The coefficients of hourly fixed effects are not displayed. The variables *eua* and *coal* in first differences. The test statistic of the Cumby-Huizinga test for first order autocorrelation is reported.

TABLE 3.3: Effects of risk on shape of the supply curve

The estimates presented in table 3.3 strengthen the previous results. Based on this analysis, renewable risk does not seem affect the amount of renewable electricity offered at the day-ahead market. As expected, higher wind speed and solar radiation decreases the curvature, i.e. moves the market-clearing point to the left of the curve. This is the merit-order effect. Increasing demand, as indicated by the coefficient of *expload*, moves the intersection of supply and demand curve to the right.

Overall, the empirical analysis does not reveal an effect of renewable risk on either the day-ahead price premium or the offered renewable quantity.

3.5 Discussion & Conclusion

This paper estimates the impacts of day-ahead risk in generation from renewable sources on the risk premium in the day-ahead price. Using a detailed model-based measure for this risk, the analysis shows that renewable output risk does not increase the risk premium, irrespective of the potential price impact of this risk. To review whether this implies that there is no strategic withholding in the market, detailed auction data is used. The evidence from this data does not deliver support to this hypothesis. Renewable risk does not have an effect on the shape of the supply curve. The data does not support a withholding effect.

A large share of renewable capacity is operated by firms that also own dispatchable capacity. It is possible that companies with diverse generation portfolios strategically substitute renewable quantity by conventional power, as suggested by Acemoglu et al. (2017). The total quantity offered will not change in response to renewable risk. However, this substitution within firms' portfolios should lead to a price effect, as the marginal costs of conventional power are generally larger than those of renewables. This either implies that these firms do not offer their available renewable capacity at marginal costs or there is no strategic substitution.

When firms do not consider fundamental information such as their output risk, their behavior and subsequently the market outcome can be informationally inefficient. It is possible that firms are rationally inattentive to the information about their output risk, suggesting that the costs of acquiring and using the data do not outweigh the potential benefits of an improved allocation (Gabaix, 2019). While it can be profitable to incorporate data about risk into the decisions (Maciejowska et al., 2019; Pinson et al., 2007), this information does not seem to be used on a large scale (Bessa et al., 2017).

If the firms have knowledge about their output risk, the results suggest that they can be relatively assured that they can balance their forecast errors at reasonable prices in the intraday market.

B Appendix to chapter 3

B.1 Tables

Variable	Augmented Dickey-Fuller	Phillips-Perron
premium	-20.858	-46.908
windstd	-9.458	-17.872
radiationstd	-2.868	-16.367
windmean	-12.070	-15.433
radiationmean	-0.938	-15.641
FE_wind	-14.816	-32.793
FE_solar	-19.809	-28.373
FE_load	-17.042	-26.518
expload	-17.622	-17.334
eua	2.875	1.682
gas	-6.756	-5.016
coal	-0.326	-0.313
outcap	-19.663	-36.035
curvature	-11.804	-146.118

Note: This table reports test statistics for two unit root tests. The lag length was chosen with Schwerts criterion (Schwert, 2002), resulting in 49 lags. The 1 percent critical value is -3.430 for both tests. All variables are stationary, except for *coal* and *eua*. The ADF test statistic does not correct for heteroskedasticity, while the PP accounts for the presence of changing variance. Therefore I consider *radiationmean* as stationary.

TABLE B.1: Stationarity tests

Variable	First-order autocorrelation	Variable	First-order autocorrelation
premium	0.859	FE_wind	0.985
windstd	0.969	FE_solar	0.961
radiationstd	0.960	FE_load	0.924
windstd_high	0.966	windmean	0.919
windstd_low	0.976	radiationmean	0.953
radiationstd_high	0.957	expload	0.965
radiationstd_low	0.959	eua	1.000
windstd_high_high	0.853	gas	0.998
windstd_low_high	0.874	coal	1.000
radiationstd_high_high	0.808	outcap	0.915
radiationstd_low_high	0.809	curvature	0.354

Note: This table reports first-order autocorrelation coefficients of all variables used in the analysis.

TABLE B.2: Autocorrelation

B.2 Fitting the cubic spline

This section explains the details of the procedure of fitting a cubic splice to the aggregated supply bids. An appropriate procedure to obtain a continuous function from discrete and potentially noisy data is a smoothing spline (Craven and Wahba, 1978). In this case, a cubic spline interpolation is fitted to every observed set of auction bids. The number of cubic functions fitted to the data is determined by equally placed knots, i.e. "anchor points" in the data between which a function will be fitted. The number of knots is determined by a

smoothing parameter, which is chosen using generalized cross-validation to avoid overfitting[34]. Cross-validation refers to randomly splitting the data into k folds. One fold is left validating the model, the test data, while the model is fitted using $k-1$ folds, the training data. In this case, the most common approach with $k=5$ is chosen. When the model fits perfectly to the training data, it will usually not perform well on the previously unseen test data. The model accuracy has to be decreased on the training data in order to perform better on the test data. This process is repeated for each of the k folds.

The criterion to be minimized on the test sample is

$$gcv = \frac{\frac{1}{n}||\boldsymbol{y} - \boldsymbol{X}\hat{\boldsymbol{b}}||^2}{(\frac{1}{n}\text{Tr}(\boldsymbol{I} - \boldsymbol{X}\boldsymbol{A}^{-1}\boldsymbol{X}^T))^2} \tag{B.1}$$

where $\boldsymbol{X}\hat{\boldsymbol{b}}$ are the predictions from the model fitted using the training data, $\boldsymbol{I}$ is the identity matrix and $\boldsymbol{A} = \boldsymbol{X}'\boldsymbol{X}$, the square of the matrix with the explanatory variables. In this case, $\boldsymbol{X}$ only contains one variable.

B.3 Elasticity of supply curves

This section estimates the elasticity of the supply curves, both in the day-ahead and in the intraday market, by a regression of the price on demand. The variables are transformed via natural logarithms to be able to interpret the estimated coefficient as an elasticity[35]. To be precise, the following equation is estimated, where j indicates each of the two relevant market stages.

$$\ln(price_{t,j}) = \phi_{0,j} + \phi_{1,j}\ln(demand_{t,j}) + \Phi_{t,j} \tag{B.2}$$

The trading volume on the respective market is below the aggregated demand proxied by the grid load, mainly as a result of bilateral over-the-counter trading. As the trading volume might be endogenous to the price, I use the demand as the explanatory variable. This reflects a constant relationship between demand and day-ahead trading volume. The coefficient of interest is $\phi_{1,j}$, which will give the elasticity of price to changes in demand. An estimate of 1 implies a linear supply curve. The supply curve can be considered convex if the estimated elasticity is larger than 1. Table B.3 shows the estimated elasticity for the two market stages. I use the expected residual demand, i.e. the forecasted demand (*expload*) minus expected renewable infeed (see table 3.1).

	Day-ahead	Intraday	Z-statistic DA hour - ID hour
Demand	1.229	1.119	
	[1.186 , 1.272]	[1.150 , 1.230]	1.706
Constant	-10.023	-9.599	
	[-10.499 , -10.028]	[-10.034 , -9.162]	

Note: 99 percent confidence intervals robust to heteroskedasticity in brackets.

TABLE B.3: Estimated elasticity of supply curves

---

[34]Not using a cross-validation approach in this context commonly leads to a prediction accuracy of 100 percent. The model therefore also captures the noise in the data.

[35]This looses 452 out of 29,185 observations as a result of negative prices.

The supply curve in the hourly day-ahead market seems to be convex, as expected. In addition, the weighted average prices in the hourly intraday market are considered. The estimated elasticity is different from one. The supply curve appears to be slightly convex.

The following test was suggested by Clogg et al. (1995) and can be used for comparing estimated coefficients across different regression models. The slopes of the day-ahead and the intraday supply curve do not seem to be different from each other at any common significance level[36].

$$Z = \frac{\hat{\phi}_{1,1} - \hat{\phi}_{1,2}}{\sqrt{SE^2_{\phi_{1,1}} + SE^2_{\phi_{1,2}}}} \tag{B.3}$$

---

[36]This qualitative result does not change when additionally controlling for the fossil fuel input prices in equation (B.2).

4 Arbitrage in cost-based redispatch: Evidence from Germany

Authors: Grischa Perino & Philip Schnaars

Abstract: The European Union's push towards market-based procurement of redispatch services has sparked fears of so called Inc-Dec-Gaming, i.e. the incentive to engage in arbitrage between the national wholesale market and the local redispatch market. The latter would increase both likelihood and severity of grid congestions. Such incentives might be present in the German approach of mandatory participation with reimbursement of costs if the marginal cost estimates used are not accurate. This paper develops a method to identify such behavior in cost-based redispatch. We test for the presence of Inc-Dec-Gaming at the plant level using a random forest prediction model and time series regressions using a sample of German power plants. We do find evidence of arbitrage among a small cluster of German power plants. This suggests that cost-based redispatch might not be as short run cost-effective as suggested.

4.1   Introduction

In the Clean Energy Package, the European Union (EU) set new guidelines on how member states should procure redispatch capacities (EU, 2019). As part of the new EU rules, the German regulator is bound to change the procurement of redispatch volumes from a cost-based to a market-based system. This implies that grid operators will auction off the necessary volumes based on forecasted grid constraints. The German government is aware that a change to market-based redispatch can result in higher congestion levels and hence is evaluating hybrid design options[37] (Bundesregierung, 2020). Currently, the German transmission grid operators obligate power plants to adjust their generation schedule in order to avoid overload on certain grid elements. These power plants are remunerated based on reported marginal costs of production and opportunity costs, aiming at plants being indifferent between being redispatched and independent generation.

At the day-ahead market stage, plant operators sell electricity based on market fundamentals such as expected demand and renewable supply. Under some local conditions, grid congestion requires redispatch, opening up an additional stage of the electricity market. If being forced to adjust output due to a redispatch mandate is financially attractive, incentives for increasing the volume of the redispatch mandate arise. Deliberate attempts to affect the extent of redispatch by adjustments in electricity sold in the day-ahead market is called arbitrage in what follows.[38] In the case of upward redispatch, such arbitrage would involve decreasing scheduled output in the day-ahead market in order to increase the magnitude of the redispatch mandate. This increases frequency and magnitude of congestion, grid costs and deadweight loss. For downwards redispatch firms would increase their activity in the day-ahead market in order to be curtailed more heavily in the redispatch stage. Besides the failure of the reimbursement scheme to make firms indifferent about the extent of redispatch, there are two crucial conditions for arbitrage activities to take place. First, firms need to be able to reliably forecast congestion and hence occurrence and direction of redispatch. Second, they need to be able to affect the redispatch quantity via their activity in the day-ahead market. The latter implies a high sensitivity on the relevant bottleneck, i.e. the extent to which, at the margin, a change in the firm's output translates into pressure placed on the bottleneck. We use both conditions to inform our empirical strategy.

Such arbitrage behavior is sometimes called the "Inc-Dec-Game" (Hirth and Schlecht, 2020) and is commonly only expected in market-based redispatch systems, as prices tend to be transparently different to encourage participation in the redispatch market and anticipation of the congestion is therefore less important. We argue that such arbitrage behavior can also occur in a cost-based setup, once a price difference between the two stages exists. In this system, the redispatch price is subjective and depends on individual cost estimates[39]. Once this estimate deviates from the true cost, arbitrage will be profitable for the firms.

Arbitrage can occur between any two stages of the electricity market. It has been observed between the day-ahead and redispatch stage in California, leading to an increase in the level and costs of congestion (Alaywan et al., 2004; Brunekreeft et al., 2005) and Eastern United States (Hogan, 1999). These experiences have contributed to the widespread shift

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[37]At the same time, the cost-based system is refined to reach more cost-effective solutions. For example, storage and renewable sites become part of redispatch as of October 1 2021, if they are cheaper by factor 10 (BMWi, 2019).

[38]In this paper, we use the term "arbitrage" rather loosely to include intertemporal transactions, which will always exhibit at least some residual risk.

[39]It is found that the introduction of virtual bidding, i.e. market participation of purely financial traders, leads to a decrease in price differences. This can lead to a decrease in generators' market power and higher consumer surplus, for example in Mid-Western US (Mercadal, 2018) or California (Jha and Wolak, 2015). In this paper, we do not consider the presence of such financial bidders as the costs are individual and the redispatch transaction is bilateral between the power plant and the grid operator.

towards nodal pricing in the US, where the wholesale market price reflects eventual local grid constraints via the introduction of many smaller bidding zones (Neuhoff et al., 2011). After observing intrazonal arbitrage behavior on the border between England and Scotland, the regulating entity required certain market participants to bid their marginal costs in the day-ahead market (Ofgem, 2012), thereby limiting the extent of arbitrage possible. Limited interzonal capacity can also induce arbitrage, for example between Denmark and Germany. The introduction of a countertrading mechanism led market participants to adjust bidding behavior between the two market stages to exploit price differences (Energinet, 2019). The extent of this was found to depend on the predictability of congestion. Just and Weber (2015) identify arbitrage effects between the intraday and the balancing market in Germany. Such behavior requires reliably predicting the direction of the system imbalance and the respective price. Bunn and Kermer (2021) show that such arbitrage activity tends to decrease with lower forecast quality in the Austrian market. This also holds for the Italian market (Lisi and Edoli, 2018). Arbitrage can even be profitable in expected value if the anticipated probability for a necessary redispatch event is below the common threshold of 50 percent (e.g Just and Weber, 2015)).

We develop a method that allows us to test for arbitrage behavior in cost-based redispatch. If firms can reliably predict congestion and have a high market share in the resulting redispatch market, arbitrage can be profitable. This prediction of congestion and subsequently individual redispatch mandates is the first step of our empirical strategy. We use hourly plant-level data with highly detailed regional weather forecasts and a Random Forest algorithm to estimate the expected day-ahead hourly probability of redispatch for each power plant in the sample. We find that reliability of forecasts based on the available data varies significantly between power plants. To the best of our knowledge, this paper provides the first application with this level of regional detail for Germany. To assess in a second step whether firms respond to expected redispatch by adjusting their day-ahead bidding behavior, we employ time series regression analysis. We do not find evidence for large-scale arbitrage behavior in German redispatch, albeit many plants met necessary prerequisites for this behavior. Our data supports arbitrage for small-scale arbitrage by a cluster of power plants located in the North-East .

The costs of grid congestion are manifold[40]. It increases expenses to maintain grid stability both within Germany and in its neighboring countries. These external costs are passed on to electricity consumers via a per unit increase on the grid fees that induces a deadweight loss. In addition, loop flows levy costs on neighboring countries, leading to inefficient dispatch in that area. For example, to reduce these losses, the combined German-Austrian price zone was split up, imposing a limit on the flow of electricity between these two countries (IEA, 2020), thereby internalizing a fraction of external grid costs into firms considerations. The European Commission considers placing the most important grid constraints in the German grid onto firms decisions by splitting Germany into two price zones and imposing restrictive cross-zonal transmission capacity. Expectations about the welfare benefits range from small (Fraunholz et al., 2021; Trepper et al., 2015) to considerable when assuming an optimal configuration and allowing for generation capacity relocation (Ambrosius et al., 2020). The extreme form of zonal splitting is the introduction of nodal pricing.

Another suggested remedy is to introduce a market-based redispatch system, while keeping a zonal electricity price. This would provide incentives for long-term generation investment, as local redispatch prices tend to be higher than under a cost-based system, raising congestion costs and lowering welfare in the short run. However, as a result from new capacity investments, congestion levels fall in the long run, rendering market-based

---

[40]Grid congestion can lead to higher emissions, especially when renewable electricity has to be curtailed to maintain grid stability. We do not consider those welfare impacts in this paper.

redispatch more efficient than cost-based redispatch (Vries and Hakvoort, 2002; Grimm et al., 2018). Market power can lead to inflated prices and inefficiently high congestion levels. Empirical evidence of such practice in California was found by Joskow and Kohn (2002) and Davis and Hausman (2016). It is possible that market power in latent submarkets can also arise in cost-based redispatch when only one or a few plants have high sensitivity on the congested grid element, increasing costs for grid stability. We abstain from such considerations in our analysis while we cannot rule out such market power based on our data. Our results suggests that cost-based redispatch in Germany might not be the most short run cost-effective option.

4.2 Model

Consider a power plant i that participates in mandated, cost-based redispatch. For a particular contracting period, which typically lasts for one hour, the profit-maximizing output without redispatch and any arbitrage considerations between day-ahead and redispatch market is referred to as $\bar{x}_i \in [0, x_i^{max}]$, where x_i^{max} is the plant's capacity. The profit-maximizing output is assumed to depend on market-wide fundamentals F and firm's production costs $C_i(x_i)$, i.e. not on the plant's subjective assessment of the likelihood of grid congestion μ_i. We use $\bar{x}_i$ as a reference point for our analysis of arbitrage activities.

If the grid is congested and the plant does not engage in arbitrage, it is mandated to adjust output by $r_i = \bar{r}_i$ such that realized output at the time of delivery becomes $x_i = \bar{x}_i + \bar{r}_i$. Note that $\bar{r}_i$ can be either positive or negative depending on the plant's location relative to the bottleneck in the grid. The likelihood of grid congestion and hence redispatch is assumed to be independent of plant i's output choice, i.e. we focus on arbitrage motives for "Inc-Dec-Gaming" and abstract from local market power that would allow the firm to strategically manipulate the likelihood of grid congestion.

If the plant engages in arbitrage activities between the day-ahead and the redispatch market, it increases output sold in the day-ahead market by a_i - which might be negative. As a result, the quantity reduction in case redispatch is mandated changes to $r_i = \bar{r}_i - \alpha_i a_i$ where $\alpha_i \in [0, 1]$ is the degree to which a plant is able to deliberately and unilaterally affect the quantity sold in the redispatch market, given that redispatch occurs. This mainly depends on the impact of the plant's output variation on the congested part of the grid. Note that r_i and a_i will have opposite signs. Increasing output sold in the day-ahead market will increase the mandated reduction in planned output if $\alpha_i > 0$. The responsiveness of actual output to increases in day-ahead output is hence $1 - \alpha_i$. If the plant is the only plant active in the redispatch market (or if it is a virtual plant covering all participating plants) on that side of the bottleneck, then $\alpha_i = 1$. On the other hand, if the plant is small relative to the total remaining and effective redispatch capacity on its side of the bottleneck, then $\alpha_i = 0$. Output with arbitrage at the point of delivery is therefore $x_i = \bar{x}_i + \bar{r}_i + (1 - \alpha_i)a_i$ if redispatch occurs and $x_i = \bar{x}_i + a_i$ if not.

This allows us specifying output sold in the day-ahead market

$$\hat{x}_i = x_i - r_i = \bar{x}_i(F) + a_i(\mu_i). \qquad (4.1)$$

We cannot observe $\bar{x}_i$ and a_i directly. However, given a reliable measure of the plant's subjective assessment of the likelihood of grid congestion μ_i can be constructed, that is (sufficiently) independent of market fundamentals influencing $\bar{x}_i$, arbitrage activities can be identified if they exist as only they are affected by changes in μ_i.

Market fundamentals in a zonal electricity market should be captured by the day-ahead price. It aggregates all available information on drivers of overall scarcity such as expected

renewable output and load. If, after controlling for the day-ahead price, there is still a significant impact of the estimated likelihood of receiving a redispatch mandate on plant-level day-ahead output, then this effect is mediated by arbitrage activities.

$$\hat{x}_i = f(p, \mu_i) \tag{4.2}$$

While aggregate output and market price are endogenous, this concern is much less relevant for output of an individual plant. At the plant level, the price determines output and not the other way around. Nevertheless, we test whether our findings are robust to controlling directly for market fundamentals.

To determine how a plant's arbitrage activity is affected by its ability to impact the size of its redispatch mandate (α_i) and the subjective probability of redispatch occurring in a particular contracting period (μ_i), we model its profit-maximizing response to a signal s_i about the likelihood of grid congestion.

Expected profits are

$$
\begin{aligned}
E(\pi_i|s_i) = {} & \mu_i(s_i) \left[p \cdot (\bar{x}_i + \bar{r}_i + (1 - \alpha_i)a_i) - C_i(\bar{x}_i + \bar{r}_i + (1 - \alpha_i)a_i) + f_i \cdot (\bar{r}_i - \alpha_i a_i) \right] \\
& + (1 - \mu_i(s_i)) \left[p \cdot (\bar{x}_i + a_i) - C_i(\bar{x}_i + a_i) \right]
\end{aligned} \tag{4.3}
$$

where f_i is the per-unit rate in the redispatch market. Note that typically it holds that $sign(f) = sign(r)$ as increasing output requires additional resources while reducing output tends to conserve them. In Germany, redispatch is reimbursed based on an estimate of input and opportunity costs. They are reported on a daily basis either ex ante or in some cases such as opportunity costs from forgone profits ex post as they require information on day-ahead settlement prices. The grid operator can request verification of the reported figures. Opportunity costs include foregone flexibility on the intraday markets estimated using a simple pricing equation for options based on day-ahead prices and standard deviation in the previous 30-day-period. All variable components of the reimbursement are calculated using plant and time specific, but ex ante known or highly predictable per unit rates that are a functions of the day-ahead price for electricity and input prices. The attractiveness of redispatch is therefore to a large extent independent of current market conditions.

While the aim of the reimbursement is to make plant operators indifferent about the occurrence and extent of redispatch events, if the cost approximations are systematically over- (or under-)estimating the true costs of redispatch, then firms have an incentive to engage in arbitrage between the day-ahead and the redispatch market. The latter is the case if marginal costs of plant operators are increasing in the relevant range. As at any given point in time, the per-unit rate of reimbursement is constant and given that fixed costs are reimbursed as well, profits depend on the size of the redispatch mandate.

The first-order condition of (4.3) for interior solutions (i.e. for $a_i \in \left[-\bar{x}_i, x_i^{max} - \bar{x}_i \right]$) yields

$$
\mu_i(s_i)\alpha_i \left[f_i + p - C_i'(\bar{x}_i + \bar{r}_i + (1 - \alpha_i)a_i) \right] - (1 - \mu_i(s_i)) \left[p - C_i'(\bar{x}_i + a_i) \right] = 0 \tag{4.4}
$$

For $\alpha_i = 0$ or $\mu_i = 0$ it holds that $a_i = 0$ as by definition, $p - C_i'(\bar{x}_i) = 0$. Hence, if the plant is not able to manipulate the redispatched quantity or does not expect redispatch to occur, then there will be no arbitrage activity, irrespective of how f_i is specified. If, however, $\alpha_i = \mu_i = 1$, then (4.3) becomes linear in a_i and the profit-maximizing outcome is either $a_i = -\bar{x}_i$ or $a_i = x_i^{max} - \bar{x}_i$ depending on the sign of $f_i + p - C_i'(\bar{x}_i + \bar{r}_i)$.

We therefore derive the following testable hypothesis:

Hypothesis 1 *Plant operators engage in arbitrage between the day-ahead and the redispatch market if the predicted likelihood of redispatch*

1. *affects day-ahead output ($\hat{x}_i$)*

2. *but not actual output (x_i)*

of plants with a large market share in the respective redispatch market and a high accuracy in predicting redispatch events (i.e. sensitivity in table 4.3)

We can therefore identify plants engaging in arbitrage between day-ahead and redispatch markets and for those that don't we distinguish between two reasons: a) insufficient predictability of redispatch events and b) insufficient profitability of arbitrage given that redispatch can be predicted.

4.3   The dataset

For the empirical analysis, a comprehensive dataset from various sources is constructed. It contains information on plant-level redispatch volumes (Netztransparenz, 2020), generation output, installed capacity, load forecast (ENTSO-E, 2020) and plant location. In order to gain insight into the predictability of congestion, day-ahead regionalized solar radiation and wind forecasts based on the ensemble model COSMO-DE-EPS from the German Weather Service are included (Theis et al., 2017). The latter variables are unique to our study and provide a significant level of detail. We use data from the day-ahead 3am UTC prognosis. For each hour of the following day, there exist 20 different predictions, i.e. ensembles, which are averaged. Drawing on the 2.5km × 2.5km grid resolution of the original dataset we compute regional forecasts for regions that share the first two digits[41] of their postcode. Figure 4.1 presents the regions defined by this procedure. For each of these regions, wind speed and radiation[42] forecasts represent the day-ahead information set for predicting grid congestion.

---

[41] Talks with industry representatives revealed that grid operators often use the first three digits of the postal code to combine forecasts. This would have been possible as well with our data, but given the relatively high correlation between these subregions, we do not loose much information relevant to this application.

[42] We use the sum of direct and diffuse radiation, often termed "global" radiation.
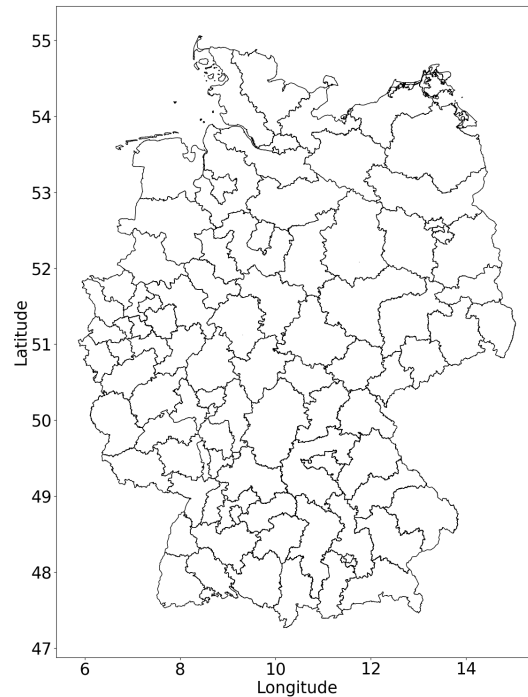
Note: Displayed regions combine all 2.5 km × 2.5 km grid cells that share the first two digits of the postcode. This results in 95 areas. For each of these regions, a day-ahead forecast for wind and radiation is available.

FIGURE 4.1: Map of regions with detailed day-ahead weather predictions

Overall, the dataset consists of hourly observations for 23 power plants for the period from January 2015 to May 2018 in Germany. This is the subset of plants that is regularly affected by redispatch measures and therefore of interest to this study. Table 4.1 reports the sample power plants. For an overview about all available plants and the selection process, consult table C.1.

The power plants Boxberg, Jänschwalde, Moorburg, Rostock, Schkopau, Schwarze Pumpe and Lippendorf are located in the north-eastern part of Germany, which is north-east of the main congested grid lines (see figure 4.2). These plants are regularly redispatched downwards as a group targeted towards the same bottleneck. The data does not allow us to precisely assign redispatch volumes to every single plant for every relevant hour in the sample. We therefore consider those plants as a virtual power plant[43] VirtualNorthEast, aggregating generation, capacity and redispatch volume. This allows us to use potentially important information, as members of this virtual power plant are frequently redispatched.

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[43]Note that we use the term "virtual" not in the prevalent sense where the included power plants are actually managed jointly by the same company. We rather consider those plants as one due to data restrictions, taking a similar perspective as the grid operator. For arbitrage it is not necessary that these plants are actually managed jointly, if they behave in a similar way.

Plant	Hours up	Hours down	Capacity	Fuel type	Postcode	ID
Emsland	577	82	1820	Gas	49808	1
Ensdorf	295	8	389	Coal	66806	2
Farge	56	1022	350	Coal	28777	3
Hamm Uentrop	642	169	850	Gas	59071	4
Heizkraftwerk Heilbronn	3733	21	778	Coal	74076	5
Herne	559	105	740	Coal	44653	6
Heyden	493	799	875	Coal	44653	7
Kiel	3	1075	323	Coal	24149	8
Knapsack	24	1037	1210	Gas	50354	9
Kraftwerk Mainz Wiesbaden	425	13	785	Gas	55120	10
Luenen	72	78	1196	Coal	44532	11
Neurath	11	1542	4212	Lignite	41517	12
Niederaußem	23	1112	3391	Lignite	50129	13
Rheinhafen-Dampfkraftwerk Karlsruhe	3321	97	1700	Coal & Gas	76189	14
Scholven	307	98	690	Coal	45896	15
Staudinger 5	2156	233	510	Coal	63538	16
VirtualNorthEast	0	12,652	11620	Lignite & Coal	–	17
Walsum	597	278	1095	Coal	47179	18
Weiher	716	0	724	Coal	66287	19
Weisweiler	0	165	2363	Lignite & Gas	52249	20
Westfalen	23	221	780	Coal	52249	21
Wilhelmshaven (Uniper)	3	958	757	Coal	26386	22
Zolling 5	2163	810	472	Coal	85406	23

Note: Hours up and hours down count the hours a power plant was redispatched in the respective direction over the sample period. Capacity gives the installed generation capacity in MW. The primary fuel type is also reported. Multiple fuel types are possible for plants that consists of multiple blocks. The location is indicated by the postcode. The plant ID refers to the number within the sample.

TABLE 4.1: Plant location and redispatch details

Figure 4.2 shows the location of the power plants in the sample in panel (A). The plants forming the virtual power plant VirtualNorthEast are marked in red. In addition, it also shows where the frequently congested lines in the German transmission grid are located in panel (B) (Bundesnetzagentur, 2018). This gives an idea of the potential local markets that might originate from a change in the regulation. The electricity commonly flows from north to south, as wind generation is clustered in the north and demand in the south. We have plants on either side of this in our sample, i.e. plants that are regularly redispatched downwards and plants that are regulary redispatched upwards. Table 4.1 strengthens this assertion. Every plant in the sample is either predominantly mandated to increase or decrease the respective output. Plant operators can be relatively sure of their mandate if they know that one of the relevant grid elements is congested. One further aspect of the table is worth mentioning. Some plants are redispatched relatively often while others are only required to do so in a few hours over the sample period, reflecting different sensitivities on congested grid elements.

(A) Location of sample power plants
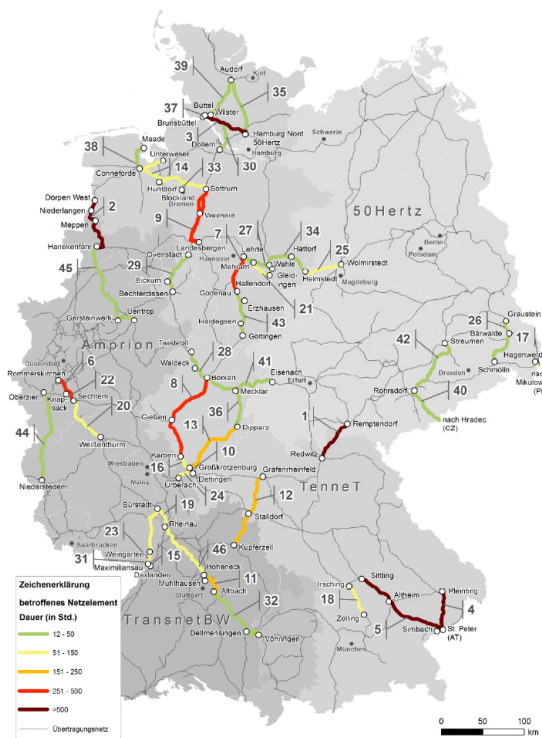
(B) Frequently congested transmission lines

Note: The red power plants in panel A are the members of the virtual power plant VirtualNorthEast. Darker colors represent more frequent congestion in panel B. It displays the situation in 2017.

FIGURE 4.2: Power plant location and congested grid elements

Identification

(A) Identification with the market price   (B) Identification with market fundamentals
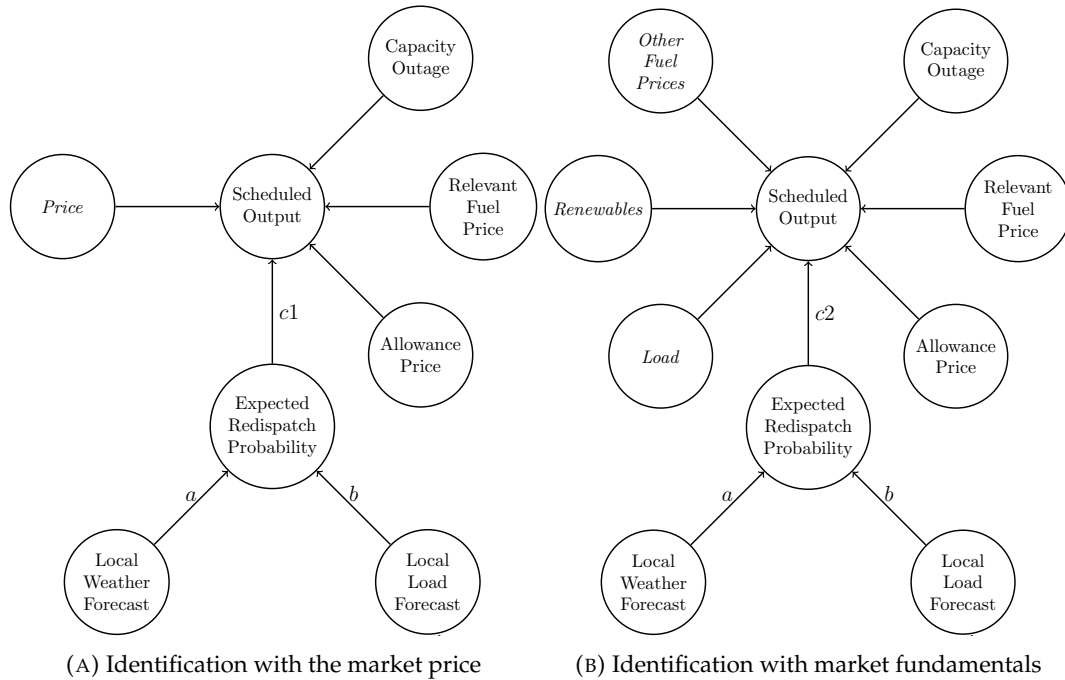
Note: A node indicates a variable while an arrow denotes a causal relation-
ship. The path coefficients $c1$ and $c2$ indicate arbitrage behavior assessed in
section 4.4.2 while a and b refer to the influence on day-ahead redispatch pre-
dictability in section 4.4.1.

FIGURE 4.3: Relationships between variables

Recall from equation (4.1) that we recover the unobserved scheduled output by the sum
of realized output and realized redispatch.

Figure 4.3 shows two Directed Acyclic Graphs denoting the relationships between the
main variables in the study. Recall that our identification strategy relies on the assump-
tion that the market price is exogenous to individual power plant's scheduled output (fig-
ure 4.3A) and we check for robustness using the market fundamentals that determine the
scheduled output directly (figure 4.3B). Scheduled power plant output, the variable to be
explained, is determined by the market price or the market fundamentals displayed in ital-
ics and individual cost components, such as the relevant fuel price or the price for emission
allowances, which determine the relative position of the plant on the merit order curve. If
capacity is unavailable for production, the output will be affected as well.

Note that our empirical analysis consists of two different steps. The perceived day-ahead
redispatch probability depends on local weather forecasts and load conditions in the rele-
vant grid area, denoted by a and b. In the first step of our analysis, we determine these rela-
tionships, which will remain unaffected by our set of control variables. In the second step,
we assess the presence and magnitude of the direct path *c1* and *c2*. This direct influence on
scheduled output is driven by the expectation of redispatch rather than its realization and
therefore captures arbitrage activities by the plant. All variables are plausibly exogenous,
conditional on controlling for the other variables.

4.4 Empirical Analysis

The empirical analysis consists of two main steps. First is the assessment of how well firms can predict their redispatch mandate and the calculation of an underlying probability. In the second step, for those power plants where the available day-ahead information is sufficient for a good prediction sensitivity, the presence of arbitrage behavior is investigated.

4.4.1 Predicting the probability

How do plant operators perceive their probability of being mandated to redispatch? We do not directly observe this private information. However, we can learn the relationship between determinants, derived from figure 4.3 and displayed in table 4.2 and the outcome from the data. To predict the probability of being redispatched given day-ahead information, we use a Random Forest Classifier with customized resampling to deal with imbalanced data (Chen et al., 2004). The Random Forest algorithm averages many[44] individual decision trees that are fit on a bootstrapped subset of the data with varying feature availability[45] to introduce randomness and therefore avoid overfitting (Probst et al., 2019). This procedure has been shown to give good approximations of the Data Generating Process (DGP) in a variety of settings (Athey et al., 2019).

Feature	Description
Day-ahead wind speed prediction	Separate feature for every region displayed in figure 4.1, in m/s
Day-ahead radiation prediction	Separate feature for every region displayed in figure 4.1, in J/m^2
Load	Zonal-wide electricity demand in MWh
Time indicators	Dummy variables for hour of the day, day of the week, year

Note: This table displays the features available to the Random Forest algorithm. There are 95 subregions and hence 95 different features containing wind speed and radiation respectively.

TABLE 4.2: Features used in Random Forest algorithm

We deem it suitable in our application for multiple reasons. First, it allows for a nonlinear approximation of the DGP which is especially valuable in this context, where interactions between the local weather conditions are likely and correlation among the variables is high. Second, the bootstrapping procedure allows for the calculation of out-of-sample predictions. This closely mimics the task that plant operators face, where they build their model only on known information and use this to make predictions. The bootstrapping procedure implies that about $\frac{2}{3}$ of the data are used for fitting a tree, while the remaining observations are left for model evaluation. Third, due to random feature selection, the performance of a Random Forest is unaffected by many potentially irrelevant predictors, making it superior to parametric approaches[46]. Fourth, the probability determining the prediction is easily accessible. Fifth, the algorithm incorporates multiclass outcomes without requiring additional user choices.

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[44]In this application, every Random Forest consists of 2000 trees.

[45]At every split, only the square root of all features, determined randomly, is considered by the algorithm.

[46]When applying OLS without regularization, including the 95 regional windspeed variables, their squares and interactions would require 9119 degrees of freedom, which exceeds the available observations in some instances. The Lasso procedure would be a viable alternative, but also suffers from a high demand for degrees of freedom.

We employ the out-of-sample prediction probability for the classes of positive, negative and no redispatch ($prob^p, prob^n, prob^0$) to construct binary variables for expected negative redispatch (expNeg) and positive redispatch (expPos), using a cutoff of 70 percent. In other words, we assume that plant operators consider one of the three cases to take effect, once its probability exceeds 70 percent. We thereby assume that plant operators need a relatively high certainty in their expectation of redispatch to conduct arbitrage.

$$expPos = \begin{cases} 1 & \text{if } prob^p > 0.7 \\ 0 & \text{if } prob^p \leq 0.7 \end{cases} \tag{4.5}$$

$$expNeg = \begin{cases} 1 & \text{if } prob^n > 0.7 \\ 0 & \text{if } prob^n \leq 0.7 \end{cases} \tag{4.6}$$

Table 4.3 reports the results of the prediction algorithm. Sensitivity refers to the true positive rate, while specificity indicates the true negative rate. It becomes clear that, based on the available information, downward redispatch is generally easier to predict than redispatch to increase generation. This is intuitive, as the pool of power plants available for redispatch is significantly smaller north of the main grid divide[47]. If plant operators use a similar prediction method, they can rely on positive redispatch predictions, as the algorithm almost never predicts a false positive.

The results of the prediction algorithm are of heterogeneous nature and suggest that the accurate prediction of redispatch requires a significant amount of information. For example, redispatch depends on very detailed modeling of the flow of electricity on the different grid levels. This was also found by Abdel-Khalek et al. (2019) in the context of European cross-border transmission capacities and by Staudt et al. (2018) when predicting redispatch on German power plants.

In this application, due to data availability, we use relatively coarse information on the load flows. We implicitly assume that the relationship between aggregate load and individual load flows, conditional on the local weather circumstances and time indicators, remains the same over the sample period. We model changes in the grid structure by including time indicators. Using information about the redispatch mandates of other plants could improve the performance of the model, as it gives insight about local load flows. We disregard this information, as it is not available to firms at the time of their day-ahead production decision. Using a model with autoregressive features was found to improve prediction performance (Staudt et al., 2018), but this information is not available at the day-ahead stage as well.

The grid structure in Northern Germany appears to be less branched than in the southwestern demand centers (Bundesnetzagentur, 2017). This supports the point of severe grid complexity limiting the prediction accuracy, as redispatch in the North can generally be more reliably predicted in our sample. Assuming perfect predictability on the side of the firms would imply that each firm runs its own load flow model with very detailed information that leads to the same conclusions as the model employed by the grid operators in terms of redispatch.

The redispatch market share[48] α_i is displayed in table 4.3 and calculated as the share of power plants redispatch volume of total volume in a certain direction, given the power plant was redispatched and was expecting this mandate (i.e. either expPos or expNeg takes the value one). The calculation relies on the assumption that in principle only two redispatch markets exist, namely one for upwards redispatch and one for downwards redispatch. Motivation for this assumption comes from the fact that electricity flows are not independent

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[47]The majority of disregarded plants is located in Southern Germany. Furthermore, the remaining sample has more plants with predominantly upwards redispatch.

[48]Note that redispatch capacities are not procured in a market process, we therefore use this term rather loosely.

and one redispatch measure in a certain direction will alter the required redispatch from another plant in the same direction, even if these two mandates are targeted towards different bottlenecks. Our calculations provide a lower bound to this market share, as power plants might have more detailed information on effective flow dependence. The degree to which this underestimates the true α_i might differ between different sections of the grid.

The virtual power plant VirtualNorthEast (17) exhibits the largest market share and a relatively strong prediction accuracy, meeting two prerequisites for arbitrage.

Plantid	Predicted redispatch upwards	Predicted redispatch downwards	Observed Redispatch upwards	Observed redispatch downwards	Sensitivity upwards	Specificity upwards	Sensitivity downwards	Specificity downwards	α_i positive	α_i negative
1	0	0	577	82	0	100	0	100	–	–
2	0	3	295	8	0	100	38	100	–	0.4
3	0	0	56	1022	0	100	0	100	–	–
4	1	11	642	169	0	100	7	100	50.1	13.7
5	4	3	3733	21	0	100	10	100	22.3	12.6
6	0	65	559	105	0	100	62	100	–	3.7
7	29	11	493	799	6	100	1	100	40.3	6.3
8	1	0	3	1075	0	100	0	100	2.7	–
9	4	0	24	1037	17	100	0	100	4.9	–
10	0	0	425	13	0	100	0	100	–	–
11	1	50	72	78	1	100	64	100	9.5	2.9
12	0	0	11	1542	0	100	0	100	–	–
13	4	0	23	1112	17	100	0	100	11.9	–
14	0	5	3321	97	0	100	5	100	–	39.1
15	0	11	307	98	0	100	10	100	–	1.7
16	2	14	2156	233	0	100	6	100	12.4	31.8
17	0	8789	0	12652	–	100	68	99	–	80.4
18	1	92	597	278	0	100	33	100	6.7	6.2
19	125	0	716	0	17	100	–	100	26.9	–
20	0	47	0	165	–	100	28	100	–	8.7
21	1	0	23	221	4	100	0	100	16.1	–
22	0	0	3	958	0	100	0	100	–	–
23	271	73	2163	810	12	100	9	100	20.8	27.9

Note: This table counts the predicted redispatch instances in both directions in columns 2 and 3, the observed instances in columns 4 and 5 and the implied sensitivity and specificity in percent. Sensitivity refers to the true positive rate, while specificity represents the true negative rate of the predictions. The plantid is defined in table 4.1. A dash (–) indicates division by zero. The α_i represent the average market share in the market for positive and negative redispatch respectively, conditional on being redispatched and expecting this mandate.

TABLE 4.3: Results of probability prediction

4.4.2 Arbitraging between day-ahead and redispatch

The prediction model shows that for some plants redispatch measures do not seem to be well predictable. This limits their ability to engage in intertemporal arbitrage, assuming this behavior is profitable. The profitability of adjusting day-ahead supply will be investigated in this subsection. To this end, we run regressions of output on the probability dummy variables and other explanatory variables, as depicted in figure 4.3.

Power plants are routinely shut down. The potential reasons are manifold, of which some are observable and some are not. The observable explanations include periods of maintenance and technical outages. Ramping constraints, which are not directly measured and can only be indirectly approximated, lead to marginally unprofitable generation and to hours where production would have been marginally profitable where no actual generation is observed. These aspects explain periods with no variation in the dependent variable, implying issues with the empirical analysis.

Correct inference based on an econometric model relies, among others, on the assumption of no serial correlation in the error term. This assumption is frequently violated and requires adjusting either the specified model, the computed standard errors or a combination thereof. Recurrent periods of zero output introduce significant autocorrelation in the error term, especially if the data is measured on a ratio scale, i.e. it has a meaningful lower bound. An empirical model never perfectly fits the data and so for those periods the error term will exhibit strong serial correlation that can hardly be modeled.

Henceforth we restrict the analysis to those observations with positive realized output. Power plants with positive arbitrage a_i will show a positive scheduled generation value in the data. Those firms could be mandated to stop the generation of electricity completely, i.e. realized output will be zero. Our constructed scheduled output $\hat{x}_i$ will be perfectly serially correlated during those periods. We loose on average 0.35 percent of the data by not considering redispatch interventions corresponding to zero realized output and hence do not expect a significant loss of information from this sample restriction[49].

Variable	Description	Mean	Min	Max	SD
output	Thermal plant output MWh	1341.901	0.010	10732.18	2023.822
expPos	=1 if probability of positive redispatch > 70%	0.042	0	1	0.199
expNeg	=1 if probability of negative redispatch > 70%	0.014	0	1	0.117
redispatch	Redispatch GWh	-0.025	-6.092	1.590	0.240
genWind	Wind generation GWh	9.315	0.135	42.612	7.591
genSolar	Solar generation GWh	3.915	0	28.665	6.043
load	Electricity demand GWh	56.969	31.455	79.063	9.945
outcap	Capacity unavailable for production MWh	30.278	0	1060	122.833
eua	Price for EUA EUR/tCO2	6.623	3.870	15.070	1.939
coal	Price for coal EUR/MWh	68.665	43.400	96.650	16.426
gas	Price for gas EUR/MWh	17.483	10.280	59.493	3.527
price	Day-ahead electricity price EUR/MWh	34.494	-130.090	163.520	14.655

Note: The variables output, redispatch and the two dummy variables expPos and expNeg take on different values for every power plant. The remaining variables are the same of each panel unit. SD refers to the standard deviation.

TABLE 4.4: Summary statistics

The serial correlation of both the dependent and independent variables has another implication for the empirical analysis. A serially correlated explanatory variable X will be correlated with the error term U from the regression of Y on X, if it has an influence on Y and the current value of Y also depends on its previous value. Including a lagged term of Y in the model is sufficient to alleviate this problem. The explanatory variables will now be correlated with the lagged term, which does not introduce a bias in the coefficient of X, the explanatory variable[50]. This strategy requires an error term that is white noise to estimate consistent effects. In other words, the model has to be dynamically complete. To reduce the serial correlation that has to be modeled, all variables are transformed to their first differences (see table C.2).

Equation (4.8) is estimated by OLS, where all variables are in their first differences. The number of lagged terms n_i, required to make the error term white noise, is plant-specific. To deal with remaining concerns about endogeneity between the plant-level scheduled output and the aggregate day-ahead price, we estimate equation (4.9), where direct measures of

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[49]Including those observations does not significantly change the estimated coefficients in the following analysis. However, the serial correlation increases the complexity of the regression models.

[50]Of course, the efficiency of the estimator is negatively affected.

market fundamentals are used as control variables. Estimates of the coefficients of interest $\beta_{1,i}, \beta_{2,i}$ are presented in panel A and for $\gamma_{1,i}, \gamma_{2,i}$ in panel B of table 4.5.

We use the day-ahead scheduled output as the dependent variable in our regression analysis.

$$
\begin{aligned}
schedoutput_{it} = {} & \beta_{0,i} + \beta_{1,i}expPos_{i,t} + \beta_{2,i}expNeg_{i,t} + \beta_{3,i}price_t + \beta_{4,i}eua_t + \qquad (4.7) \\
& \beta_{5,i}coal_t + \beta_{6,i}gas_t + \beta_{7,i}outcap_{i,t} + \sum_{j=1}^{n_i}\beta_{7+j,i}schedoutput_{i,t-j} + u_{i,t}
\end{aligned}
$$

$$
\begin{aligned}
schedoutput_{it} = {} & \gamma_{0,i} + \gamma_{1,i}expPos_{i,t} + \gamma_{2,i}expNeg_{i,t} + \qquad (4.8) \\
& \gamma_{3,i}genWind_t + \gamma_{4,i}genSolar_t + \gamma_{5,i}load_t + \gamma_{6,i}outcap_{i,t} + \\
& \gamma_{7,i}gas_t + \gamma_{8,i}eua_t + \gamma_{9,i}coal_t + \sum_{j=1}^{n_i}\gamma_{9+j,i}schedoutput_{i,t-j} + v_{i,t}
\end{aligned}
$$

In table 4.5 we report estimated parameters of those plants which we consider to have sufficient prediction performance. We base this on sensitivity and choose a value of 20 as the cutoff[51]. The results for all power plants are displayed in the appendix, while qualitative results are not altered by the remaining power plants.

	2	6	11	17	18	19	20
A: Market price							
expPos	–	–	-9.37	–	-2.85	6.45	–
	–	–	[-42.19 , 23.45]	–	[-78.06 , 72.36]	[-31.82 , 44.72]	–
expNeg	3.33	-9.67	-0.88	47.50	-3.41	–	-56.52
	[-20.61 , 27.27]	[-40.10 , 20.76]	[-56.16 , 54.40]	[11.39 , 83.61]	[-34.08 , 27.27]	–	[-138.86 , 25.83]
B: Market fundamentals							
expPos	–	–	-4.43	–	-4.10	-1.73	–
	–	–	[-132.69 , 123.82]	–	[-15.97 , 7.76]	[-36.64 , 33.18]	–
expNeg	6.78	-1.26	1.10	58.34	-0.24	–	-56.59
	[-22.15 , 35.71]	[-35.90 , 33.38]	[-44.11 , 46.31]	[22.79 , 93.90]	[-27.17 , 26.69]	–	[-139.13 , 25.94]

Note: Column titles refer to plantid from table 4.1. 99 percent confidence intervals in brackets are robust to HC3 heteroskedasticity. A dash (–) indicates that there is no sufficient variation in that variable to identify an effect. It is therefore omitted from the regression. Panel A reports selected estimates for equation (4.8) and panel B for equation (4.9). The full results for all power plants are presented in tables D.4, D.5, D.6, D.7 for equation (4.8) and in tables D.8, D.9, D.10, D.11 for equation (4.9). All variables are first-difference transformed before estimation.

TABLE 4.5: Effects of expected redispatch on scheduled output

In panel A, only the coefficient of expNeg for VirtualNorthEast (plantid 17) is statistically significant. A different set of control variables in panel B strengthens this finding. We therefore only consider VirtualNorthEast to have a statistically significant effect in this case. The presented regression results show that the first part of hypothesis 1, which is that the predicted likelihood of redispatch affects day-ahead output is met for the aggregated power plant VirtualNorthEast.

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[51]Note that we also include power plant 19 in our selection, as it shows a statistically signifant effect in the initial regression.

4.4.3   Influence on realized output

The second part of hypothesis 1 states that realized output of power plants should not change in response to a reliable prediction of redispatch. Any change in scheduled output due to arbitrage activities will, if successful, (to a large extent) be offset by the redispatch mandate. To test this empirically, we estimate the following two equations and report the results for the same subset of plants in table 4.6.

$$
\begin{aligned}
output_{it} = {} & \delta_{0,i} + \delta_{1,i}expPos_{i,t} + \delta_{2,i}expNeg_{i,t} + \delta_{3,i}price_t + \delta_{4,i}eua_t + \qquad (4.9) \\
& \delta_{5,i}coal_t + \delta_{6,i}gas_t + \delta_{7,i}outcap_{i,t} + \sum_{j=1}^{n_i}\delta_{7+j,i}output_{i,t-j} + \epsilon_{i,t}
\end{aligned}
$$

$$
\begin{aligned}
output_{it} = {} & \eta_{0,i} + \eta_{1,i}expPos_{i,t} + \eta_{2,i}expNeg_{i,t} + \qquad\qquad\qquad (4.10) \\
& \eta_{3,i}genWind_t + \eta_{4,i}genSolar_t + \eta_{5,i}load_t + \eta_{6,i}outcap_{i,t} + \\
& \eta_{7,i}gas_t + \eta_{8,i}eua_t + \eta_{9,i}coal_t + \sum_{j=1}^{n_i}\eta_{9+j,i}output_{it-j} + \ni_{i,t}
\end{aligned}
$$

The coefficients $\delta_{1,i}$, $\delta_{2,i}$ and $\eta_{1,i}$, $\eta_{2,i}$ measure the impact of arbitrage opportunities on realized output x_i, mediated by its impact on redispatch r_i. If α_i approaches one, arbitrage activities will have an increasing impact on plants' observed redispatch, as plant operators scheduled output has an increasing impact on their individual redispatch magnitude (recall $r_i = \bar{r}_i - \alpha_i a_i$). In that case we do not expect a change in x_i in response to arbitrage activities, that is, statistically insignificant estimates of $\delta_{1,i}$, $\delta_{2,i}$, $\eta_{1,i}$ and $\eta_{2,i}$ strengthen our identification strategy.

Estimates in table 4.6 show that the realized output does not react to changes in redispatch expectations in both specifications. This result is in line with our hypothesis. This indicates that arbitrage might occur for this specific set of power plants despite the cost-based approach that aims at making plant operators indifferent between market stages.

	2	6	11	17	18	19	20
			A: Market price				
expPos	–	–	-9.40	–	-2.78	4.60	–
	–	–	[-42.30 , 23.49]	–	[-76.61 , 71.04]	[-14.81 , 24.00]	–
expNeg	2.95	-14.41	-1.79	-14.17	0.84	–	-52.20
	[-25.40 , 31.31]	[-39.58 , 10.75]	[-57.17 , 53.58]	[-40.05 , 11.71]	[-28.25 , 29.94]	–	[-131.72 , 27.31]
			B: Market fundamentals				
expPos	–	–	-4.48	–	-4.05	-4.90	–
	–	–	[-132.60 , 123.64]	–	[-15.48 , 7.39]	[-24.26 , 14.47]	–
expNeg	6.35	-8.99	0.17	-1.45	2.93	–	-52.30
	[-26.93 , 39.63]	[-36.45 , 18.46]	[-45.19 , 45.52]	[-26.25 , 23.35]	[-23.42 , 29.28]	–	[-132.46 , 27.87]

Note: Column titles refer to plantid from table 4.1. 99 percent confidence intervals in brackets are robust to HC3 heteroskedasticity. A dash (–) indicates that there is no sufficient variation in that variable to identify an effect. It is therefore omitted from the regression. Panel A reports selected estimates for equation (4.10) and panel B for equation (4.11). The full results for all power plants are presented in tables D.12, D.13, D.14, D.15 for equation (4.10) and in tables D.16, D.17, D.18, D.19 for equation (4.11). All variables are first-difference transformed before estimation.

TABLE 4.6: Effects of expected redispatch on realized output

4.4.4 Robustness of estimated effects

The presented estimates support the presence of arbitrage behavior of our constructed power plant VirtualNorthEast. In the following, we check the robustness of our findings to different regression model specifications and the inclusion of additional control variables. In doing so, we restrict our attention to the same subset of power plants.

Correlation of regional information with $\bar{r}_i$

It is possible that the results are driven by a correlation between observed redispatch (r_i under H_1 of arbitrage and $\bar{r}_i$ under H_0 of no arbitrage) and regional information captured by the two dummy variables expNeg and expPos that is not otherwise captured in the model.

If there is positive correlation between $\bar{r}_i$ and expNeg, the coefficient should have a positive sign when having scheduled output as the dependent variable. The correlation between redispatch magnitude and expNeg is statistically different from zero for VirtualNorthEast (table C.3). In a regression analysis, this correlation does not distort the estimate from its true value if all variables are included in the regression specification, thereby controlling for all possible differences between observations with predicted redispatch and those observations where this was not the case.

However, if the model specification estimated does not fully match the true data generating process, then, as one of the redispatch prediction dummies switches on, scheduled output could change simply due to unmodeled correlation between regional variables and baseline output ($\bar{x}_i$), all else equal. If the true model is nonlinear but we specify a linear model, the estimated coefficients will not be equal to the true parameter.

We include second and third degree polynomials of genWind, genSolar and load in the regression to check for the presence of this effect. In addition, we include dummy variables for hour of the day and month within the year.

$$
\begin{aligned}
schedoutput_{it} = {} & \zeta_{0,i} + \zeta_{1,i}expPos_{it} + \zeta_{2,i}expNeg_{it} + && (4.11) \\
& \zeta_{3,i}genWind_t + \zeta_{4,i}genSolar_t + \zeta_{5,i}load_t + \zeta_{6,i}outcap_{it} + \\
& \zeta_{7,i}gas_t + \zeta_{8,i}eua_t + \zeta_{9,i}coal_t + \zeta_{10,i}genWind2_t + \\
& \zeta_{11,i}load2_t + \zeta_{12,i}genSolar2_t + \zeta_{13,i}genWind3_t + \\
& \zeta_{14,i}load3_t + \zeta_{15,i}genSolar3_t + \\
& \sum_{j=1}^{n_i} \zeta_{15+j,i}schedoutput_{it-j} + \boldsymbol{\theta D'} + \iota_{it}
\end{aligned}
$$

$$
\begin{aligned}
output_{it} = {} & \psi_{0,i} + \psi_{1,i}expPos_{it} + \psi_{2,i}expNeg_{it} + && (4.12) \\
& \psi_{3,i}genWind_t + \psi_{4,i}genSolar_t + \psi_{5,i}load_t + \psi_{6,i}outcap_{it} + \\
& \psi_{7,i}gas_t + \psi_{8,i}eua_t + \psi_{9,i}coal_t + \psi_{10,i}genWind2_t + \\
& \psi_{11,i}load2_t + \psi_{12,i}genSolar2_t + \psi_{13,i}genWind3_t + \\
& \psi_{14,i}load3_t + \psi_{15,i}genSolar3_t + \\
& \sum_{j=1}^{n_i} \psi_{15+j,i}output_{it-j} + \boldsymbol{\Psi D'} + \omega_{it}
\end{aligned}
$$

where $\boldsymbol{D'}$ represents dummy variables indicating hour of the day and month of the year. Estimates for the parameters of interest ($\zeta_{1,i}$ and $\zeta_{2,i}$) in equation (4.12) are presented in panel A of table 4.7. The estimated arbitrage effects are relatively robust to changes in the model specification. Additionally including the variables with regional day-ahead weather

information, initially used to predict the likelihood of grid congestion, does not change the qualitative results as well. Panel B of table 4.7 reports estimates of $\psi_{1,i}$ and $\psi_{2,i}$. The notable result is that the relationship between realized output and expected downward redispatch from table 4.6 is again statistically insignificant, strengthening our hypothesis. This robustness check provides further support to arbitrage at VirtualNorthEast.

	2	6	11	17	18	19	20
			A: Scheduled output				
expNeg	5.48	3.61	-0.21	53.44	0.28	–	-56.25
	[-25.60 , 36.56]	[-30.14 , 37.36]	[-45.76 , 45.33]	[17.96 , 88.91]	[-26.20 , 26.77]		[-138.48 , 25.98]
			B: Realized output				
expNeg	4.97	-4.16	-0.34	-5.71	3.42	–	-51.96
	[-30.29 , 40.23]	[-29.19 , 20.88]	[-45.81 , 45.13]	[-30.46 , 19.04]	[-22.49 , 29.33]		[-131.94 , 28.03]

Note: Column titles refer to plantid from table 4.1. 99 percent confidence intervals in brackets are robust to HC3 heteroskedasticity. A dash (–) indicates that there is no sufficient variation in that variable to identify an effect. It is therefore omitted from the regression. Panel A reports selected estimates for equation (4.12) and panel B for equation (4.13) The full results for the depicted power plants are presented in table D.20 for equation (4.12) and in table D.21 for equation (4.13). All variables are first-difference transformed before estimation.

TABLE 4.7: Effects of expected redispatch on scheduled and realized output including polynomials

Including physical cross-border flows

If the coefficients of the dummy variables expPos and expNeg pick up some variation that explains redispatch, but is not included in the regression specification via the wholesale day-ahead price or the market fundamentals, the estimates will be biased. One such candidate is the realized local load, which is not observed.

Cross-border physical flows can potentially work as proxy variables. The physical flow varies with the commercial exchange between two respective price zones, but also as a result of prevailing local load conditions on either side of the interconnector. For example, internal grid congestion in Germany leads to increased physical flows over the interconnector between Germany and Poland, unrelated to commercial exchanges (Puka and Szulecki, 2014). It seems safe to assume a relevant correlation between physical interconnector flows and local load conditions. We observe these flows on an hourly basis on the interconnectors of Germany with Austria, Czech Republic, Poland, Denmark, Netherlands, France and Switzerland and estimate the following equations for our subset of relevant power plants.

$$
\begin{aligned}
schedoutput_{it} = \; & \theta_{0,i} + \theta_{1,i}expPos_{i,t} + \theta_{2,i}expNeg_{i,t} + \\
& \theta_{3,i}price + \theta_{4,i}eua_t + \theta_{5,i}coal_t + \theta_{6,i}gas_t + \theta_{7,i}outcap_{i,t} + \theta_{8,i}flowATDE_t + \\
& \theta_{9,i}flowCZDE_t + \theta_{10,i}flowPLDE_t + \theta_{11,i}flowDKDE_t + \\
& \theta_{12,i}flowNLDE_t + \theta_{13,i}flowFRDE_t + \theta_{14,i}flowCHDE_t + \\
& \sum_{j=1}^{n_i} \beta_{14+j,i}schedoutput_{i,t-j} + \xi_{it}
\end{aligned} \tag{4.13}
$$

$$
\begin{aligned}
schedoutput_{it} = \; & \kappa_{0,i} + \kappa_{1,i}expPos_{i,t} + \kappa_{2,i}expNeg_{i,t} + \\
& \kappa_{3,i}genWind_t + \kappa_{4,i}genSolar_t + \kappa_{5,i}load_t + \kappa_{6,i}outcap_{i,t} + \\
& \kappa_{7,i}gas_t + \kappa_{8,i}eua_t + \kappa_{9,i}coal_t + \kappa_{10,i}flowATDE_t + \\
& \kappa_{11,i}flowCZDE_t + \kappa_{12,i}flowPLDE_t + \kappa_{13,i}flowDKDE_t + \\
& \kappa_{14,i}flowNLDE_t + \kappa_{15,i}flowFRDE_t + \kappa_{16,i}flowCHDE_t + \\
& \sum_{j=1}^{n_i} \kappa_{16+j,i}schedoutput_{i,t-j} + \phi_{it}
\end{aligned} \tag{4.14}
$$

The estimates of interest remain virtually unchanged when including these proxy variables in the regression specification. These results provide further support to our finding of arbitrage behavior in VirtualNorthEast.

	2	6	11	17	18	19	20
A: Market price							
expPos	–	–	–	–	4.66	5.90	–
	–	–	–	–	[-68.47 , 77.78]	[-32.25 , 44.05]	–
expNeg	2.27	-9.42	0.80	47.35	-0.66	–	-59.13
	[-21.51 , 26.05]	[-41.27 , 22.43]	[-52.77 , 54.37]	[11.29 , 83.40]	[-30.05 , 28.74]	–	[-142.07 , 23.81]
B: Market fundamentals							
expPos	–	–	–	–	1.76	4.45	–
	–	–	–	–	[-13.88 , 17.40]	[-31.80 , 40.69]	–
expNeg	6.64	-7.16	-2.59	59.74	0.47	–	-60.39
	[-26.78 , 40.07]	[-37.85 , 23.53]	[-49.06 , 43.88]	[24.33 , 95.15]	[-24.65 , 25.59]	–	[-144.58 , 23.79]

Note: Column titles refer to plantid from table 4.1. 99 percent confidence intervals in brackets are robust to HC3 heteroskedasticity. A dash (–) indicates that there is no sufficient variation in that variable to identify an effect. It is therefore omitted from the regression. Panel A reports selected estimates for equation (4.14) and panel B for equation (4.15). The full results for all power plants are presented in table D.22 for equation (4.14) and in table D.23 for equation (4.15). All variables are first-difference transformed before estimation.

TABLE 4.8: Effects of expected redispatch on scheduled and realized output including local load proxy variables

Overestimating scheduled output

The redispatch data source Netztransparenz (2020) periodically reports multiple redispatch mandates issued by the same grid operator for a certain power plant at a given hour. The bulk of these events occur at VirtualNorthEast and affects a relevant share of observations for this power plant (table 4.9).

	2	6	11	17	18	19	20
Overlapping observations	29	27	0	3338	13	16	92
Percent of redispatch observations	9.6	4.1	0	26.4	1.5	2.3	55.8

Note: Column titles refer to plantid from table 4.1. The table reports the number observations per power plant where multiple redispatch mandates are observed and its share of total redispatch instances.

TABLE 4.9: Overlapping observations per power plant

The data does not allow us to distinguish whether one mandate replaces the other as the grid operator receives new information and adjusts its redispatch accordingly or whether the actual redispatch conducted at this power plant is the sum of the two data entries. This could be the case when the grid operator adjusts its redispatch taking into account the previously issued mandate. In the analysis above, we use the sum of all reported redispatch volumes, assuming the latter procedure. However, if mandates don't supplement but replace each other, our recovered scheduled output is systematically double counting as the redispatch volume is above the true value. This could bias our regression results.

As a robustness check, we exclude all redispatch observations with multiple data entries. We again estimate equations (4.8) and (4.9) and report the results in table 4.10. We observe that the qualitative finding of arbitrage in VirtualNorthEast holds up to this robustness check, with the estimated coefficient similar in magnitude. This indicates that the previous findings are not driven by an ambiguity in the data generation process.

	2	6	11	17	18	19	20
			A: Market price				
expPos	–	–	-1.09	–	-2.83	6.42	–
	–	–	[-29.33 - 27.15]	–	[-77.57 - 71.90]	[-31.88 - 44.71]	–
expNeg	3.35	-9.57	-0.47	51.50	-3.40	–	-121.95
	[-20.75 - 27.45]	[-39.93 - 20.80]	[-55.42 - 54.49]	[13.28 - 89.73]	[-34.09 - 27.28]	–	[-299.68 - 55.78]
			B: Market fundamentals				
expPos	–	–	-0.47	–	-4.09	-1.76	–
	–	–	[-59.86 - 58.93]	–	[-15.77 - 7.59]	[-36.68 - 33.16]	–
expNeg	6.79	-5.43	0.61	61.94	-0.25	–	-120.10
	[-22.28 - 35.86]	[-36.17 - 25.31]	[-44.75 - 45.96]	[24.48 - 99.39]	[-27.18 - 26.68]	–	[-299.19 - 58.98]

Note: Column titles refer to plantid from table 4.1. 99 percent confidence intervals in brackets are robust to HC3 heteroskedasticity. A dash (–) indicates that there is no sufficient variation in that variable to identify an effect. It is therefore omitted from the regression. Panel A reports selected estimates for equation (4.8) and panel B for equation (4.9), disregarding overlapping redispatch observations. The full results for all power plants are presented in table D.4 for equation (4.8) and in table D.8 for equation (4.9). All variables are first-difference transformed before estimation.

TABLE 4.10: Effects of expected redispatch on scheduled output disregarding overlapping observations

4.4.5 Discussion

Above, we identify arbitrage behavior for a cluster of power located in close proximity. Table 4.11 reveals that most of the power plants of this virtual power plant are operated by

LEAG. The LEAG plants are rarely redispatched on their own, suggesting that grid operators perceive this as closely-tied group of power plants. A common ownership structure in addition facilitates coordinating arbitrage behavior, thus supporting our findings.

Power plant	Owner	Operator	Share individual measure	Fuel
Jänschwalde	LEAG	LEAG	4 %	Lignite
Schkopau	Uniper & Saale Energie*	Uniper	4 %	Lignite
Moorburg	Vattenfall	Vattenfall	17 %	Coal
Boxberg	LEAG	LEAG	1 %	Lignite
Rostock	EnBW & Rheinenergie	EnBW & Rheinenergie	11 %	Coal
Schwarze Pumpe	LEAG	LEAG	0.4 %	Lignite
Lippendorf	LEAG & EnBW	LEAG	6 %	Lignite

Note: The column "share individual measure" reports the share of redispatch instances that were executed by that plant individually instead of jointly by a group of plants, based on hourly data. *Note that Saale Energie and LEAG share the same parent company, Czech Republic based EPH.

TABLE 4.11: Members of VirtualNorthEast

The median redispatch volume observed at VirtualNorthEast, given that it was successfully predicted, was -2664 MWh. We estimate arbitrage effects around 50 MWh.

Additional arbitrage, while profitable, might be limited by technical constraints in cycling the power plant, which are particularly pronounced for lignite power plants that dominate VirtualNorthEast group (van den Bergh and Delarue, 2015). Note that most lignite plants within VirtualNorthEast belong to the LEAG cluster while the more flexible hard coal plants have a different ownership.

These constraints could limit the production increase that is possible between periods without predicted redispatch and arbitrage and those instances where the plant engages in arbitrage. The fact that, at least from the perspective of the grid operator, the plants in VirtualNorthEast form a cluster may suggest that the short-term flexibility of a single power plant does not suffice to resolve the bottleneck, which supports the argument that output inertia limits the extent of arbitrage activities in VirtualNorthEast. The individual arbitrage potential could also be curbed by regulation preventing the day-ahead scheduled output to exceed the nameplate capacity.

4.5 Conclusion

In this paper, we develop a method of identifying arbitrage behavior in cost-based redispatch and empirically test it among German power plants. To that end, we theoretically derive the necessary conditions for such behavior at the plant level. Reliable forecasts of a redispatch mandate and a high grid sensitivity on the bottleneck are crucial. The latter is the ability to affect the magnitude of the individual redispatch mandate with the chosen level of day-ahead scheduled output.

We find that for most plants in our sample, redispatch cannot be predicted with sufficient reliability given detailed data about local wind and radiation forecasts, while a few power plants exist where a redispatch mandate can frequently be predicted. To overcome data limitations, we compute the sensitivity for redispatch in one aggregate for upwards redispatch and one for downwards redispatch. As before, notable heterogeneity among power plants prevails.

For those power plants where the preconditions for arbitrage, reliable forecasts and high bottleneck sensitivity, are met, we do find evidence for arbitrage behavior for a cluster of

power plants located in close proximity and operated by the same company. The size of this estimated arbitrage is small compared to the median redispatch volume conducted at this cluster. The technical characteristics of the power plants involved and additional regulatory constraints might have prevented economically meaningful arbitrage levels in this case.

C Appendix to chapter 4

C.1 Tables

Plant	Redispatch observations	Plant	Redispatch observations
Boxberg	10590	Muenchen Sued GT 62	8
Emsland	659	**Neurath**	1559
Ensdorf	303	**Niederaußem**	1139
Farge	1080	Reservekraftwerk Irsching 3	402
Gersteinwerk	119	Reservekraftwerk Irsching 4	135
Hamm Uentrop	811	Reservekraftwerk Irsching 5	423
Heizkraftwerk Altbach/Deizisau	3167	Reservekraftwerk Staudinger 4	798
Heizkraftwerk Heilbronn	3834	**Rheinhafen-Dampfkraftwerk Karlsruhe**	3487
Herne	675	*Rostock*	2897
Heyden	1293	**Schkopau**	6069
Huntorf	0	**Scholven**	405
Ibbenbüren	168	*Schwarze Pumpe*	9634
Jänschwalde	11604	**Staudinger 5**	2389
Niehl	29	Voerde	191
Kiel	1088	Völklingen HKW	0
Knapsack	1068	Völklingen MKW	0
Kraftwerk Mainz Wiesbaden	488	**Walsum**	883
Lausward	0	**Weiher**	719
Lippendorf	8747	**Weisweiler**	165
		Westfalen	244
Luenen	150	**Wilhelmshaven (Uniper)**	961
Moorburg	2670	Wolfsburg West 1	3
Muenchen Sued GT 2	5	Wolfsburg West 2	3
Muenchen Sued GT 3	12	**Zolling 5**	3030

Note: The table reports all plants for which detailed information on location and output is available. The subset considered in this paper is highlighted in bold. Plants in bold and italics are aggregated to form VirtualNorthEast. Reserve power plants were not considered. The threshold was set at 200 observations, with Altbach/Deizisau, Luenen and Weisweiler being the notable exceptions. Altbach/Deizisau was transitioned to the grid reserve over the sample period, meaning it does not actively participate in the market.

TABLE C.1: Selection process of plants

Variable	Level	First difference
output	0.998	0.353
redispatch	0.960	0.003
expPos	0.645	-0.409
expNeg	0.921	-0.274
genWind	0.994	0.774
genSolar	0.952	0.873
load	0.943	0.760
outcap	0.954	-0.036
gas	0.998	-0.000
coal	1.000	-0.000
eua	1.000	-0.000

Note: First-order autocorrelation coefficients before and after taking first differences. For the variables output, redispatch, outcap, expPos and expNeg averages over all plants are displayed.

TABLE C.2: Autocorrelation coefficients

	Correlation with expNeg			Correlation with expPos		
Plantid	genWind	genSolar	load	genWind	genSolar	load
1	-0.018	0.005	-0.020	–	–	–
2	0.045	0.030	0.019	–	–	–
3	–	–	–	0.046	-0.006	-0.059
4	0.003	-0.004	0.005	–	–	–
5	-0.021	0.013	0.048	0.248	-0.025	-0.067
6	0.025	-0.008	0.025	0.078	-0.003	-0.013
7	-0.041	-0.024	0.067	–	–	–
8	0.072	0.003	0.099	0.040	0.070	-0.055
9	–	–	–	–	–	–
10	-0.010	0.027	0.008	–	–	–
11	-0.035	-0.020	0.063	-0.007	-0.008	-0.003
12	-0.008	0.001	0.012	0.012	0.010	0.008
13	–	–	–	0.047	-0.005	0.005
14	-0.010	-0.005	0.025	0.017	0.011	0.008
15	0.071	-0.016	0.012	–	–	–
16	-0.019	0.033	0.004	0.116	-0.022	-0.006
17	0.498	0.017	0.251	–	–	–
18	-0.036	-0.035	0.032	0.066	0.004	0.029
19	–	–	–	0.425	-0.050	0.028
20	-0.014	-0.017	0.041	–	–	–
21	–	–	–	-0.004	0.031	-0.029
22	–	–	–	–	–	–
23	-0.071	0.196	0.059	0.459	-0.066	0.025

Note: Correlation of the two dummy variables expNeg and expPos with the aggregate variables are displayed. A dash (–) indicates no sufficient variation to compute a meaningful figure.

TABLE C.3: Plantwise correlation among a subset of variables

D   Results for all power plants in the sample

D.1   Scheduled output as dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)
expPos	–	–	–	43.53	55.56	–
	–	–	–	[-33.56 , 120.61]	[-44.13 , 155.24]	–
expNeg	–	3.33	–	3.73	-30.91	-9.67
	–	[-20.61 , 27.27]	–	[-36.46 , 43.92]	[-135.60 , 73.79]	[-40.10 , 20.76]
price	5.63	0.94	1.34	2.93	4.32	1.37
	[4.33 , 6.94]	[0.80 , 1.08]	[1.14 , 1.55]	[2.13 , 3.72]	[3.83 , 4.82]	[1.19 , 1.55]
eua	38.73	-2.94	-0.11	-90.38	-29.04	-6.60
	[-86.74 , 164.20]	[-13.40 , 7.51]	[-34.71 , 34.49]	[-401.38 , 220.62]	[-134.46 , 76.37]	[-20.26 , 7.05]
coal	-2.63	-0.52	-3.18	4.03	2.63	-1.14
	[-23.87 , 18.62]	[-2.89 , 1.85]	[-12.44 , 6.09]	[-66.83 , 74.89]	[-37.19 , 42.45]	[-4.42 , 2.15]
gas	-7.93	-2.45	0.87	2.84	-5.94	-1.40
	[-81.94 , 66.08]	[-9.08 , 4.17]	[-5.36 , 7.10]	[-113.48 , 119.16]	[-15.79 , 3.92]	[-6.47 , 3.68]
outcap	-0.07	-0.05	-0.07	-0.27	-0.04	-0.03
	[-0.22 , 0.09]	[-0.19 , 0.08]	[-0.21 , 0.08]	[-0.76 , 0.22]	[-0.13 , 0.04]	[-0.08 , 0.03]
Constant	-10.73	-0.19	-5.58	-20.91	-3.62	-0.52
	[-15.40 , -6.07]	[-0.62 , 0.25]	[-6.59 , -4.56]	[-26.44 , -15.38]	[-5.79 , -1.45]	[-1.15 , 0.12]
Observations	5,172	19,455	14,495	3,988	14,677	19,661
CH AR(1)	1.640	1.650	1.032	2.408	0.041	0.704
Lags	40	30	1	5	1	30

Note: Column titles refer to plantid from table 4.1. 99 percent confidence intervals in brackets are robust to HC3 heteroskedasticity. A dash (–) indicates that there is no sufficient variation in that variable to identify an effect. It is therefore omitted from the regression. Reported parameters are estimates from equation (4.8). All variables are first-difference transformed before estimation. Cumby-Huizinga test does not reject the null hypothesis of no first-order serial correlation in the error term. The number of lags required to make the model dynamically complete is reported in "Lags".

TABLE D.4: Full regression results of scheduled output on price I

	(7)	(8)	(9)	(10)	(11)	(12)
expPos	-55.62	-8.29	–	–	-9.37	–
	[-162.56 , 51.32]	[-57.55 , 40.98]	–	–	[-42.19 , 23.45]	–
expNeg	12.41	–	–	–	-0.88	–
	[-82.45 , 107.26]	–	–	–	[-56.16 , 54.40]	–
price	4.42	2.01	4.71	1.61	2.85	3.31
	[3.84 , 5.00]	[1.84 , 2.17]	[3.76 , 5.66]	[1.32 , 1.90]	[2.58 , 3.12]	[2.82 , 3.80]
eua	-27.61	4.45	92.41	-23.89	11.05	-52.20
	[-86.62 , 31.40]	[-8.08 , 16.98]	[-183.26 , 368.09]	[-68.63 , 20.85]	[-16.58 , 38.68]	[-119.69 , 15.28]
coal	0.16	1.54	10.22	4.46	-2.94	-1.23
	[-15.36 , 15.68]	[-1.86 , 4.94]	[-63.04 , 83.47]	[-5.53 , 14.45]	[-9.01 , 3.13]	[-16.77 , 14.30]
gas	0.98	0.77	-22.65	6.21	-1.40	-3.22
	[-6.72 , 8.67]	[-1.96 , 3.51]	[-206.76 , 161.47]	[-11.72 , 24.15]	[-6.34 , 3.55]	[-18.21 , 11.77]
outcap	0.02	-0.02	-0.10	0.08	-0.02	-0.02
	[-0.07 , 0.12]	[-0.09 , 0.05]	[-0.30 , 0.11]	[-0.14 , 0.29]	[-0.08 , 0.04]	[-0.10 , 0.05]
Constant	-3.95	-0.45	-2.09	-4.77	-0.16	-0.14
	[-6.08 , -1.82]	[-1.08 , 0.18]	[-6.42 , 2.24]	[-6.15 , -3.39]	[-1.12 , 0.79]	[-1.87 , 1.59]
Observations	14,287	19,517	7,020	11,222	27,057	28,965
CH AR(1)	1.393	2.335	1.146	2.622	0.997	0.716
Lags	10	1	1	1	1	2

Note: Column titles refer to plantid from table 4.1. 99 percent confidence intervals in brackets are robust to HC3 heteroskedasticity. A dash (–) indicates that there is no sufficient variation in that variable to identify an effect. It is therefore omitted from the regression. Reported parameters are estimates from equation (4.8). All variables are first-difference transformed before estimation. Cumby-Huizinga test does not reject the null hypothesis of no first-order serial correlation in the error term. The number of lags required to make the model dynamically complete is reported in "Lags".

TABLE D.5: Full regression results of scheduled output on price II

	(13)	(14)	(15)	(16)	(17)	(18)
expPos	-0.22	–	–	1.85	–	-2.85
	[-120.09 , 119.65]	–	–	[-31.31 , 35.00]	–	[-78.06 , 72.36]
expNeg	–	-39.67	-32.29	-31.28	47.50	-3.41
	–	[-117.00 , 37.66]	[-87.98 , 23.39]	[-135.01 , 72.46]	[11.39 , 83.61]	[-34.08 , 27.27]
price	3.72	3.25	1.74	1.98	14.40	3.38
	[3.25 , 4.20]	[2.85 , 3.65]	[1.54 , 1.95]	[1.73 , 2.24]	[12.60 , 16.20]	[3.07 , 3.69]
eua	-21.86	-2.92	4.89	16.33	-72.54	-5.77
	[-65.88 , 22.15]	[-70.89 , 65.05]	[-11.01 , 20.80]	[-8.88 , 41.54]	[-368.24 , 223.16]	[-39.31 , 27.76]
coal	-0.71	-15.30	-0.73	-5.47	-6.72	0.92
	[-11.66 , 10.24]	[-33.81 , 3.20]	[-4.59 , 3.13]	[-14.64 , 3.71]	[-82.48 , 69.04]	[-10.82 , 12.67]
gas	-2.31	0.82	0.75	0.20	37.81	0.04
	[-10.10 , 5.49]	[-6.50 , 8.15]	[-3.01 , 4.52]	[-3.54 , 3.94]	[-10.59 , 86.20]	[-4.25 , 4.32]
outcap	-0.01	-0.00	-0.05	-0.10	0.02	0.01
	[-0.06 , 0.04]	[-0.05 , 0.05]	[-0.11 , 0.01]	[-0.28 , 0.08]	[-0.10 , 0.13]	[-0.03 , 0.05]
Constant	-0.10	-1.88	-0.10	-2.00	-0.32	-0.19
	[-1.66 , 1.46]	[-3.55 , -0.21]	[-0.60 , 0.40]	[-2.99 , -1.00]	[-5.98 , 5.34]	[-1.20 , 0.83]
Observations	28,979	18,935	28,506	16,551	29,005	25,647
CH AR(1)	0.747	0.050	2.371	0.967	0.024	0.030
Lags	2	1	3	30	1	1

Note: Column titles refer to plantid from table 4.1. 99 percent confidence intervals in brackets are robust to HC3 heteroskedasticity. A dash (–) indicates that there is no sufficient variation in that variable to identify an effect. It is therefore omitted from the regression. Reported parameters are estimates from equation (4.8). All variables are first-difference transformed before estimation. Cumby-Huizinga test does not reject the null hypothesis of no first-order serial correlation in the error term. The number of lags required to make the model dynamically complete is reported in "Lags".

TABLE D.6: Full regression results of scheduled output on price III

	(19)	(20)	(21)	(22)	(23)
expPos	6.45	–	–	–	-2.51
	[-31.82 , 44.72]	–	–	–	[-31.28 , 26.25]
expNeg	–	-56.52	–	–	-21.33
	–	[-138.86 , 25.83]	–	–	[-57.68 , 15.03]
price	4.08	1.83	2.84	3.59	2.91
	[3.45 , 4.70]	[1.52 , 2.14]	[2.49 , 3.19]	[3.17 , 4.02]	[2.58 , 3.24]
eua	-126.89	9.58	-15.97	-9.27	-20.58
	[-264.55 , 10.77]	[-33.07 , 52.22]	[-57.16 , 25.22]	[-76.76 , 58.23]	[-71.26 , 30.11]
coal	-13.53	-2.09	-1.86	-7.98	1.09
	[-42.65 , 15.58]	[-9.94 , 5.75]	[-13.23 , 9.52]	[-22.74 , 6.78]	[-10.35 , 12.53]
gas	-16.07	-1.96	-1.13	-7.83	4.97
	[-47.07 , 14.92]	[-13.82 , 9.89]	[-4.77 , 2.51]	[-34.05 , 18.39]	[-8.75 , 18.69]
outcap	-0.07	0.02	-0.12	-0.01	-0.03
	[-0.19 , 0.06]	[-0.06 , 0.11]	[-0.39 , 0.15]	[-0.10 , 0.08]	[-0.15 , 0.09]
Constant	-3.45	-0.06	-1.62	-2.75	-4.65
	[-5.51 , -1.39]	[-1.18 , 1.05]	[-3.15 , -0.10]	[-4.32 , -1.17]	[-6.05 , -3.26]
Observations	7,110	28,979	18,608	14,691	17,222
CH AR(1)	1.124	0.528	1.408	1.288	0.737
Lags	1	2	10	3	1

Note: Column titles refer to plantid from table 4.1. 99 percent confidence intervals in brackets are robust to HC3 heteroskedasticity. A dash (–) indicates that there is no sufficient variation in that variable to identify an effect. It is therefore omitted from the regression. Reported parameters are estimates from equation (4.8). All variables are first-difference transformed before estimation. Cumby-Huizinga test does not reject the null hypothesis of no first-order serial correlation in the error term. The number of lags required to make the model dynamically complete is reported in "Lags".

TABLE D.7: Full regression results of scheduled output on price IV

	(1)	(2)	(3)	(4)	(5)	(6)
expPos	–	–	–	-19.75	28.20	–
	–	–	–	[-103.95 , 64.45]	[-28.88 , 85.28]	–
expNeg	–	6.78	–	2.53	-12.32	-1.26
	–	[-22.15 , 35.71]	–	[-59.52 , 64.57]	[-72.42 , 47.78]	[-35.90 , 33.38]
genWind	-30.69	-2.63	-5.46	-6.87	-16.53	-6.59
	[-35.39 , -26.00]	[-3.19 , -2.08]	[-6.94 , -3.99]	[-16.07 , 2.32]	[-19.68 , -13.38]	[-7.38 , -5.79]
genSolar	-21.71	-2.59	-3.19	-9.51	-9.63	-4.55
	[-23.32 , -20.11]	[-2.90 , -2.29]	[-3.65 , -2.74]	[-12.81 , -6.21]	[-10.77 , -8.48]	[-4.93 , -4.17]
load	33.04	3.16	4.54	19.62	15.11	7.36
	[31.28 , 34.81]	[2.91 , 3.41]	[4.09 , 4.99]	[16.49 , 22.75]	[14.08 , 16.13]	[7.03 , 7.69]
eua	78.33	-4.12	-1.12	-71.48	-34.38	-4.63
	[-46.32 , 202.98]	[-13.82 , 5.59]	[-35.78 , 33.55]	[-395.95 , 252.98]	[-137.83 , 69.08]	[-17.50 , 8.24]
coal	-0.57	-0.24	-3.12	7.58	2.63	-0.78
	[-17.48 , 16.34]	[-2.48 , 2.01]	[-12.59 , 6.35]	[-70.56 , 85.72]	[-36.43 , 41.69]	[-4.00 , 2.43]
gas	8.69	-2.97	0.96	2.63	-6.16	-0.93
	[-24.64 , 42.03]	[-9.36 , 3.42]	[-5.60 , 7.52]	[-130.34 , 135.61]	[-14.68 , 2.36]	[-4.51 , 2.66]
outcap	-0.05	-0.07	-0.07	–	-0.07	-0.01
	[-0.13 , 0.03]	[-0.21 , 0.07]	[-0.22 , 0.08]	–	[-0.17 , 0.03]	[-0.06 , 0.03]
Constant	-3.09	-0.18	-4.81	-19.53	-2.70	-0.28
	[-6.38 , 0.19]	[-0.60 , 0.24]	[-5.79 , -3.84]	[-26.93 , -12.13]	[-4.75 , -0.66]	[-0.88 , 0.32]
Observations	11,830	19,455	14,495	2,712	14,472	21,728
CH AR(1)	0.681	1.223	0.477	2.044	1.326	2.668
Lags	1	30	1	10	2	6

Note: Column titles refer to plantid from table 4.1. 99 percent confidence intervals in brackets are robust to HC3 heteroskedasticity. A dash (–) indicates that there is no sufficient variation in that variable to identify an effect. It is therefore omitted from the regression. Reported parameters are estimates from equation (4.9). All variables are first-difference transformed before estimation. Cumby-Huizinga test does not reject the null hypothesis of no first-order serial correlation in the error term. The number of lags required to make the model dynamically complete is reported in "Lags".

TABLE D.8: Full regression results of scheduled output on fundamentals I

	(7)	(8)	(9)	(10)	(11)	(12)
expPos	-31.48	-17.27	–	–	-4.43	–
	[-102.78 , 39.82]	[-117.93 , 83.40]	–	–	[-132.69 , 123.82]	–
expNeg	12.93	–	–	–	1.10	–
	[-59.57 , 85.43]	–	–	–	[-44.11 , 46.31]	–
genWind	-21.52	-5.88	-23.60	-3.41	-8.59	-11.12
	[-24.51 , -18.54]	[-6.79 , -4.98]	[-29.84 , -17.37]	[-5.37 , -1.45]	[-9.87 , -7.31]	[-13.65 , -8.59]
genSolar	-13.35	-3.70	-7.34	-2.40	-5.22	-6.79
	[-14.42 , -12.28]	[-4.23 , -3.16]	[-9.33 , -5.36]	[-2.95 , -1.86]	[-5.74 , -4.71]	[-7.75 , -5.82]
load	19.18	4.09	17.64	5.66	8.26	7.39
	[18.18 , 20.19]	[3.73 , 4.45]	[15.74 , 19.54]	[5.00 , 6.32]	[7.78 , 8.74]	[6.58 , 8.21]
eua	-33.60	2.98	85.83	-26.46	11.11	-52.47
	[-86.81 , 19.62]	[-8.83 , 14.79]	[-187.96 , 359.61]	[-71.78 , 18.86]	[-15.46 , 37.67]	[-119.22 , 14.29]
coal	-2.18	0.84	8.08	4.08	-3.51	-1.41
	[-15.99 , 11.63]	[-3.09 , 4.77]	[-65.25 , 81.41]	[-6.38 , 14.55]	[-9.44 , 2.41]	[-16.83 , 14.01]
gas	-0.50	-0.69	-21.61	4.25	-2.14	-3.33
	[-5.65 , 4.65]	[-3.08 , 1.71]	[-203.95 , 160.73]	[-13.83 , 22.34]	[-7.82 , 3.55]	[-17.39 , 10.73]
outcap	-0.00	0.01	-0.10	–	-0.02	-0.03
	[-0.07 , 0.06]	[-0.24 , 0.26]	[-0.30 , 0.09]	–	[-0.08 , 0.03]	[-0.10 , 0.04]
Constant	-1.72	-0.76	-0.81	-4.50	-0.18	-0.13
	[-3.57 , 0.13]	[-1.38 , -0.13]	[-4.96 , 3.34]	[-5.77 , -3.23]	[-1.10 , 0.74]	[-1.84 , 1.59]
Observations	16,007	15,047	7,020	10,987	27,057	28,965
CH AR(1)	2.592	1.153	0.792	0.312	0.012	0.186
Lags	2	40	1	2	1	2

Note: Column titles refer to plantid from table 4.1. 99 percent confidence intervals in brackets are robust to HC3 heteroskedasticity. A dash (–) indicates that there is no sufficient variation in that variable to identify an effect. It is therefore omitted from the regression. Reported parameters are estimates from equation (4.9). All variables are first-difference transformed before estimation. Cumby-Huizinga test does not reject the null hypothesis of no first-order serial correlation in the error term. The number of lags required to make the model dynamically complete is reported in "Lags".

TABLE D.9: Full regression results of scheduled output on fundamentals II

	(13)	(14)	(15)	(16)	(17)	(18)
expPos	8.83	–	–	-1.83	–	-4.10
	[-60.07 , 77.74]	–	–	[-75.97 , 72.32]	–	[-15.97 , 7.76]
expNeg	–	-35.90	-23.11	-0.11	58.34	-0.24
	–	[-99.55 , 27.75]	[-74.46 , 28.23]	[-64.18 , 63.96]	[22.79 , 93.90]	[-27.17 , 26.69]
genWind	-11.89	-12.99	-2.25	-10.21	-57.70	-10.09
	[-14.26 , -9.53]	[-15.44 , -10.55]	[-2.90 , -1.60]	[-11.51 , -8.90]	[-66.07 , -49.33]	[-11.37 , -8.81]
genSolar	-8.28	-6.56	-3.75	-7.23	-34.58	-7.48
	[-9.20 , -7.36]	[-7.41 , -5.72]	[-4.03 , -3.46]	[-7.75 , -6.71]	[-38.17 , -30.99]	[-8.01 , -6.96]
load	7.66	10.72	6.12	8.86	30.04	10.17
	[6.94 , 8.37]	[9.91 , 11.52]	[5.79 , 6.45]	[8.44 , 9.28]	[27.29 , 32.80]	[9.58 , 10.75]
eua	-22.78	-5.64	4.45	17.41	-75.46	-7.42
	[-66.56 , 21.00]	[-72.07 , 60.79]	[-10.71 , 19.61]	[-4.81 , 39.63]	[-370.56 , 219.64]	[-40.88 , 26.05]
coal	-0.93	-15.65	-0.49	-5.55	-7.41	1.08
	[-11.71 , 9.84]	[-34.07 , 2.78]	[-4.11 , 3.13]	[-13.47 , 2.36]	[-82.83 , 68.01]	[-10.72 , 12.87]
gas	-2.62	0.99	0.50	0.74	34.42	0.01
	[-10.44 , 5.20]	[-5.61 , 7.59]	[-2.52 , 3.52]	[-1.63 , 3.11]	[-9.54 , 78.39]	[-5.02 , 5.04]
outcap	-0.01	-0.01	-0.06	-0.12	0.01	-0.01
	[-0.07 , 0.04]	[-0.06 , 0.03]	[-0.12 , -0.01]	[-0.20 , -0.03]	[-0.10 , 0.13]	[-0.05 , 0.03]
Constant	-0.09	-1.65	-0.07	-0.94	-0.30	-0.14
	[-1.63 - 1.46]	[-3.27 - -0.03]	[-0.55 - 0.41]	[-1.82 - -0.05]	[-5.88 - 5.29]	[-1.11 - 0.82]
Observations	28,979	18,751	28,547	21,881	29,005	25,647
CH AR(1)	0.107	0.158	0.299	1.288	0.040	0.765
Lags	2	2	2	1	1	1

Note: Column titles refer to plantid from table 4.1. 99 percent confidence intervals in brackets are robust to HC3 heteroskedasticity. A dash (–) indicates that there is no sufficient variation in that variable to identify an effect. It is therefore omitted from the regression. Reported parameters are estimates from equation (4.9). All variables are first-difference transformed before estimation. Cumby-Huizinga test does not reject the null hypothesis of no first-order serial correlation in the error term. The number of lags required to make the model dynamically complete is reported in "Lags".

TABLE D.10: Full regression results of scheduled output on fundamentals III

	(19)	(20)	(21)	(22)	(23)
expPos	-1.73	–	59.48	–	-0.48
	[-36.64 , 33.18]	–	[-105.65 , 224.61]	–	[-28.50 , 27.54]
expNeg	–	-56.59	–	–	-18.20
	–	[-139.13 , 25.94]	–	–	[-55.03 , 18.64]
genWind	-13.68	-6.60	-11.05	-15.58	-9.76
	[-17.10 , -10.26]	[-8.32 , -4.88]	[-13.47 , -8.63]	[-18.36 , -12.81]	[-11.68 , -7.83]
genSolar	-8.98	-3.90	-5.95	-8.61	-6.62
	[-10.11 , -7.86]	[-4.57 , -3.24]	[-6.76 , -5.14]	[-9.44 , -7.78]	[-7.41 , -5.84]
load	14.53	3.88	8.76	11.92	10.34
	[13.53 , 15.53]	[3.37 , 4.38]	[8.00 , 9.52]	[11.12 , 12.71]	[9.67 , 11.01]
eua	-129.38	9.14	-11.38	-7.89	-9.87
	[-272.41 , 13.65]	[-33.29 , 51.57]	[-51.24 , 28.48]	[-70.65 , 54.87]	[-59.31 , 39.56]
coal	-14.28	-2.26	-1.67	-8.41	-0.28
	[-44.31 , 15.76]	[-10.06 , 5.54]	[-12.76 , 9.41]	[-23.16 , 6.33]	[-11.37 , 10.81]
gas	-13.34	-2.13	-1.75	-7.47	4.67
	[-44.09 , 17.42]	[-13.96 , 9.70]	[-5.85 , 2.35]	[-30.21 , 15.27]	[-8.00 , 17.35]
outcap	-0.07	0.02	-0.16	-0.02	0.02
	[-0.23 , 0.09]	[-0.06 , 0.10]	[-0.37 , 0.05]	[-0.09 , 0.05]	[-0.21 , 0.25]
Constant	-2.76	-0.06	-1.28	-1.89	-4.19
	[-4.62 , -0.89]	[-1.16 , 1.05]	[-2.77 , 0.21]	[-3.37 , -0.40]	[-5.51 , -2.87]
Observations	6,985	28,979	18,987	14,842	16,371
CH AR(1)	0.860	0.157	2.804	1.181	2.207
Lags	2	2	6	2	3

Note: Column titles refer to plantid from table 4.1. 99 percent confidence intervals in brackets are robust to HC3 heteroskedasticity. A dash (–) indicates that there is no sufficient variation in that variable to identify an effect. It is therefore omitted from the regression. Reported parameters are estimates from equation (4.9). All variables are first-difference transformed before estimation. Cumby-Huizinga test does not reject the null hypothesis of no first-order serial correlation in the error term. The number of lags required to make the model dynamically complete is reported in "Lags".

TABLE D.11: Full regression results of scheduled output on fundamentals IV

Realized output as dependent variable

	(1)	(2)	(3)	(4)	(5)	(6)
expPos	–	–	–	44.43	64.91	–
	–	–	–	[-9.67 , 98.53]	[-25.97 , 155.80]	–
expNeg	–	2.95		6.87	-43.10	-14.41
	–	[-25.40 , 31.31]		[-31.51 , 45.25]	[-187.25 , 101.04]	[-39.58 , 10.75]
price	5.89	0.93	1.28	2.99	3.58	1.35
	[4.63 , 7.16]	[0.79 , 1.06]	[1.10 , 1.47]	[2.23 , 3.74]	[3.17 , 3.99]	[1.17 , 1.52]
eua	17.08	0.28	-1.67	-35.36	-3.47	-7.31
	[-70.54 , 104.70]	[-9.27 , 9.83]	[-27.99 , 24.65]	[-250.65 , 179.93]	[-56.99 , 50.05]	[-20.33 , 5.70]
coal	-0.56	-0.67	-1.86	3.31	-1.46	-1.30
	[-19.71 , 18.59]	[-2.89 , 1.54]	[-9.23 , 5.51]	[-32.75 , 39.36]	[-18.50 , 15.57]	[-4.35 , 1.75]
gas	-5.98	-2.95	-0.01	1.58	-1.85	-1.30
	[-53.52 , 41.56]	[-9.27 , 3.37]	[-3.53 , 3.50]	[-65.02 , 68.19]	[-6.36 , 2.67]	[-6.34 , 3.74]
outcap	-0.00	-0.05	-0.06	-0.19	-0.01	-0.03
	[-0.14 , 0.13]	[-0.18 , 0.08]	[-0.20 , 0.08]	[-0.61 , 0.23]	[-0.09 , 0.07]	[-0.08 , 0.03]
Constant	-11.35	-0.20	-6.03	-14.54	-3.41	-0.52
	[-15.55 , -7.16]	[-0.62 , 0.23]	[-6.99 , -5.08]	[-18.78 , -10.29]	[-5.22 , -1.60]	[-1.14 , 0.11]
Observations	6,163	19,455	14,495	4,769	14,472	19,661
CH AR(1)	2.205	1.7	1.465	0.187	2.478	0.619
Lags	30	30	1	2	2	30

Note: Column titles refer to plantid from table 4.1. 99 percent confidence intervals in brackets are robust to HC3 heteroskedasticity. A dash (–) indicates that there is no sufficient variation in that variable to identify an effect. It is therefore omitted from the regression. Reported parameters are estimates from equation (4.10). All variables are first-difference transformed before estimation. Cumby-Huizinga test does not reject the null hypothesis of no first-order serial correlation in the error term. The number of lags required to make the model dynamically complete is reported in "Lags".

TABLE D.12: Full regression results of realized output on price I

	(7)	(8)	(9)	(10)	(11)	(12)
expPos	20.87	-9.37	–	–	-9.40	–
	[-27.54 , 69.28]	[-63.78 , 45.04]	–	–	[-42.30 , 23.49]	–
expNeg	16.89	–	–	–	-1.79	–
	[-69.74 , 103.52]	–	–	–	[-57.17 , 53.58]	–
price	3.85	1.06	4.13	1.54	2.84	3.11
	[3.33 , 4.36]	[0.92 , 1.21]	[3.41 , 4.84]	[1.26 , 1.82]	[2.57 , 3.11]	[2.65 , 3.57]
eua	-6.17	7.35	39.86	-2.45	12.57	-37.93
	[-59.48 , 47.14]	[-4.29 , 18.98]	[-41.19 , 120.91]	[-28.19 , 23.30]	[-14.53 , 39.68]	[-89.79 , 13.93]
coal	-1.49	0.12	-7.78	1.05	-3.63	1.38
	[-15.90 , 12.91]	[-3.53 , 3.77]	[-24.94 , 9.37]	[-6.57 , 8.67]	[-9.51 , 2.26]	[-9.33 , 12.09]
gas	0.16	-0.28	-5.61	0.87	-1.45	-4.71
	[-6.74 , 7.06]	[-2.52 , 1.95]	[-36.08 , 24.86]	[-9.55 , 11.30]	[-6.35 , 3.45]	[-21.87 , 12.45]
outcap	0.02	0.01	-0.05	–	-0.02	-0.02
	[-0.08 , 0.12]	[-0.24 , 0.26]	[-0.24 , 0.13]	–	[-0.08 , 0.04]	[-0.09 , 0.06]
Constant	-3.99	-0.71	-3.68	-5.35	-0.16	-0.14
	[-5.90 , -2.07]	[-1.29 , -0.14]	[-7.08 , -0.28]	[-6.67 , -4.02]	[-1.12 , 0.79]	[-1.78 , 1.49]
Observations	14,287	16,030	7,020	10,987	27,057	28,965
CH AR(1)	1.108	1.323	1.191	0.709	0.941	0.808
Lags	10	30	1	2	1	2

Note: Column titles refer to plantid from table 4.1. 99 percent confidence intervals in brackets are robust to HC3 heteroskedasticity. A dash (–) indicates that there is no sufficient variation in that variable to identify an effect. It is therefore omitted from the regression. Reported parameters are estimates from equation (4.10). All variables are first-difference transformed before estimation. Cumby-Huizinga test does not reject the null hypothesis of no first-order serial correlation in the error term. The number of lags required to make the model dynamically complete is reported in "Lags".

TABLE D.13: Full regression results of realized output on price II

	(13)	(14)	(15)	(16)	(17)	(18)
expPos	0.12	–	–	4.71	–	-2.78
	[-117.01 , 117.26]	–	–	[-25.44 , 34.86]	–	[-76.61 , 71.04]
expNeg	–	-37.58	-5.08	-36.35	-14.17	0.84
	–	[-116.32 , 41.17]	[-24.47 , 14.31]	[-122.11 , 49.41]	[-40.05 , 11.71]	[-28.25 , 29.94]
price	3.63	2.79	1.34	1.83	12.08	3.32
	[3.17 , 4.10]	[2.45 , 3.13]	[1.19 , 1.49]	[1.59 , 2.07]	[10.31 , 13.85]	[3.01 , 3.62]
eua	-12.75	4.55	2.46	16.17	-65.94	0.11
	[-52.65 , 27.14]	[-42.03 , 51.14]	[-9.13 , 14.05]	[-6.89 , 39.22]	[-213.26 , 81.38]	[-28.71 , 28.93]
coal	-1.14	-3.03	-1.31	-6.04	-3.29	2.79
	[-10.31 , 8.03]	[-17.56 , 11.50]	[-4.19 , 1.58]	[-15.74 , 3.65]	[-26.20 , 19.61]	[-6.23 , 11.80]
gas	-0.97	2.47	0.49	-0.63	27.88	-0.37
	[-7.70 , 5.76]	[-1.72 , 6.67]	[-3.17 , 4.14]	[-4.09 , 2.83]	[-38.35 , 94.11]	[-5.01 , 4.26]
outcap	-0.01	0.01	-0.04	-0.09	0.05	0.02
	[-0.06 , 0.05]	[-0.04 , 0.06]	[-0.10 , 0.03]	[-0.26 , 0.09]	[-0.03 , 0.14]	[-0.02 , 0.06]
Constant	-0.10	-2.11	-0.10	-1.92	-0.41	-0.18
	[-1.63 , 1.42]	[-3.56 , -0.66]	[-0.54 , 0.33]	[-2.87 , -0.97]	[-5.02 , 4.20]	[-1.18 , 0.81]
Observations	28,979	18,751	28,219	16,551	29,005	25,647
CH AR(1)	0.666	0.906	1.858	0.639	0.122	0.004
Lags	2	2	10	30	1	1

Note: Column titles refer to plantid from table 4.1. 99 percent confidence intervals in brackets are robust to HC3 heteroskedasticity. A dash (–) indicates that there is no sufficient variation in that variable to identify an effect. It is therefore omitted from the regression. Reported parameters are estimates from equation (4.10). All variables are first-difference transformed before estimation. Cumby-Huizinga test does not reject the null hypothesis of no first-order serial correlation in the error term. The number of lags required to make the model dynamically complete is reported in "Lags".

TABLE D.14: Full regression results of realized output on price III

	(19)	(20)	(21)	(22)	(23)
expPos	4.60	–	–	–	-0.77
	[-14.81 , 24.00]	–	–	–	[-20.36 , 18.82]
expNeg	–	-52.20	–	–	-17.29
	–	[-131.72 , 27.31]	–	–	[-40.12 , 5.54]
price	3.58	1.81	2.80	3.33	2.52
	[3.01 , 4.15]	[1.51 , 2.12]	[2.46 , 3.15]	[2.94 , 3.71]	[2.24 , 2.81]
eua	-15.54	4.46	-17.23	-3.73	-0.72
	[-64.22 , 33.14]	[-35.50 , 44.42]	[-57.52 , 23.07]	[-55.69 , 48.24]	[-32.04 , 30.60]
coal	-4.21	-0.43	-1.32	-6.55	-0.06
	[-13.95 , 5.52]	[-6.52 , 5.67]	[-11.88 , 9.25]	[-18.18 , 5.09]	[-7.48 , 7.36]
gas	-9.35	-1.64	-0.99	-1.13	5.00
	[-27.26 , 8.56]	[-13.37 , 10.09]	[-4.43 , 2.46]	[-6.50 , 4.24]	[-7.67 , 17.68]
outcap	-0.04	0.03	-0.12	-0.01	-0.03
	[-0.19 , 0.11]	[-0.06 , 0.11]	[-0.39 , 0.16]	[-0.10 , 0.08]	[-0.15 , 0.10]
Constant	-2.87	-0.06	-1.63	-2.76	-5.09
	[-4.72 , -1.03]	[-1.17 , 1.04]	[-3.15 , -0.12]	[-4.26 , -1.27]	[-6.31 , -3.87]
Observations	6,985	28,979	18,608	14,691	17,222
CH AR(1)	0.911	0.509	1.360	1.830	0.737
Lags	2	2	10	3	2

Note: Column titles refer to plantid from table 4.1. 99 percent confidence intervals in brackets are robust to HC3 heteroskedasticity. A dash (–) indicates that there is no sufficient variation in that variable to identify an effect. It is therefore omitted from the regression. Reported parameters are estimates from equation (4.10). All variables are first-difference transformed before estimation. Cumby-Huizinga test does not reject the null hypothesis of no first-order serial correlation in the error term. The number of lags required to make the model dynamically complete is reported in "Lags".

TABLE D.15: Full regression results of realized output on price IV

	(1)	(2)	(3)	(4)	(5)	(6)
expPos	–	–	–	-6.50	42.77	–
	–	–	–	[-36.91 , 23.90]	[-26.97 , 112.50]	–
expNeg	–	6.35	–	2.20	-25.21	-8.99
	–	[-26.93 , 39.63]	–	[-44.02 , 48.41]	[-124.01 , 73.58]	[-36.45 , 18.46]
genWind	-29.53	-2.59	-5.50	-1.75	-12.53	-6.37
	[-34.11 , -24.95]	[-3.14 , -2.05]	[-6.84 , -4.15]	[-14.60 , 11.09]	[-15.03 , -10.02]	[-7.13 , -5.60]
genSolar	-21.70	-2.58	-3.40	0.79	-8.11	-4.43
	[-23.29 , -20.10]	[-2.88 , -2.28]	[-3.81 , -2.99]	[-2.89 , 4.47]	[-9.09 , -7.13]	[-4.80 , -4.06]
load	32.82	3.12	4.20	5.49	13.08	7.25
	[31.07 , 34.58]	[2.87 , 3.37]	[3.78 , 4.62]	[1.39 , 9.59]	[12.20 , 13.97]	[6.92 , 7.57]
eua	60.79	-0.79	-2.80	119.54	-1.56	-3.87
	[-47.23 , 168.82]	[-9.68 , 8.09]	[-28.79 , 23.19]	[-127.06 , 366.13]	[-54.20 , 51.07]	[-15.95 , 8.21]
coal	2.49	-0.39	-1.81	-5.47	-2.86	-0.93
	[-11.37 , 16.35]	[-2.47 , 1.68]	[-9.42 , 5.79]	[-43.28 , 32.35]	[-19.10 , 13.37]	[-3.89 , 2.03]
gas	3.83	-3.45	0.25	-32.80	-1.89	-1.28
	[-51.70 , 59.36]	[-9.54 , 2.64]	[-3.20 , 3.71]	[-178.43 , 112.83]	[-5.22 , 1.45]	[-4.42 , 1.87]
outcap	-0.04	-0.06	-0.06	–	-0.03	-0.01
	[-0.12 , 0.04]	[-0.20 , 0.07]	[-0.21 , 0.08]	–	[-0.10 , 0.05]	[-0.05 , 0.03]
Constant	-3.02	-0.19	-5.31	-14.54	-2.61	-0.27
	[-6.26 , 0.21]	[-0.61 , 0.22]	[-6.22 , -4.40]	[-23.21 , -5.86]	[-4.33 , -0.90]	[-0.86 , 0.31]
Observations	11,830	19,455	14,495	761	14,472	21,728
CH AR(1)	0.310	1.236	1.626	0.169	1.010	2.092
Lags	1	30	1	30	2	6

Note: Column titles refer to plantid from table 4.1. 99 percent confidence intervals in brackets are robust to HC3 heteroskedasticity. A dash (–) indicates that there is no sufficient variation in that variable to identify an effect. It is therefore omitted from the regression. Reported parameters are estimates from equation (4.11). All variables are first-difference transformed before estimation. Cumby-Huizinga test does not reject the null hypothesis of no first-order serial correlation in the error term. The number of lags required to make the model dynamically complete is reported in "Lags".

TABLE D.16: Full regression results of realized output on fundamentals I

	(7)	(8)	(9)	(10)	(11)	(12)
expPos	21.47	-14.55	–	–	-4.48	–
	[-20.91 , 63.84]	[-60.91 , 31.82]	–	–	[-132.60 , 123.64]	–
expNeg	14.30	–	–	–	0.17	–
	[-58.06 , 86.66]	–	–	–	[-45.19 , 45.52]	–
genWind	-20.12	-5.78	-24.38	-3.01	-8.56	-10.87
	[-22.78 , -17.47]	[-6.61 , -4.96]	[-29.73 , -19.03]	[-4.90 , -1.11]	[-9.84 , -7.28]	[-13.31 , -8.43]
genSolar	-11.74	-3.54	-7.39	-2.45	-5.22	-6.37
	[-12.71 , -10.77]	[-4.04 , -3.04]	[-8.96 , -5.81]	[-2.98 , -1.92]	[-5.73 , -4.70]	[-7.31 , -5.42]
load	17.35	3.69	15.05	5.59	8.24	6.92
	[16.41 , 18.28]	[3.36 , 4.01]	[13.50 , 16.60]	[4.94 , 6.25]	[7.76 , 8.72]	[6.15 , 7.68]
eua	-13.77	5.83	34.78	-3.43	12.63	-38.26
	[-59.55 , 32.01]	[-5.47 , 17.12]	[-42.76 , 112.32]	[-29.59 , 22.73]	[-13.50 , 38.77]	[-89.36 , 12.85]
coal	-3.58	-0.00	-9.23	0.61	-4.20	1.19
	[-16.35 , 9.18]	[-3.73 , 3.73]	[-27.14 , 8.68]	[-7.14 , 8.37]	[-9.96 , 1.56]	[-9.41 , 11.80]
gas	-1.19	-0.13	-4.49	-0.33	-2.19	-4.80
	[-5.98 , 3.59]	[-2.38 , 2.12]	[-34.94 , 25.97]	[-11.08 , 10.41]	[-7.83 , 3.45]	[-20.84 , 11.24]
outcap	-0.00	0.01	-0.07	–	-0.02	-0.02
	[-0.06 , 0.06]	[-0.25 , 0.27]	[-0.25 , 0.12]	–	[-0.08 , 0.03]	[-0.09 , 0.05]
Constant	-1.80	-0.58	-2.46	-4.56	-0.18	-0.13
	[-3.48 , -0.12]	[-1.15 , -0.01]	[-5.70 , 0.78]	[-5.80 , -3.31]	[-1.10 , 0.74]	[-1.76 , 1.50]
Observations	16,007	15,047	7,020	10,987	27,057	28,965
CH AR(1)	0.073	1.616	0.142	1.628	0.012	0.212
Lags	2	40	1	2	1	2

Note: Column titles refer to plantid from table 4.1. 99 percent confidence in-
tervals in brackets are robust to HC3 heteroskedasticity. A dash (–) indicates
that there is no sufficient variation in that variable to identify an effect. It
is therefore omitted from the regression. Reported parameters are estimates
from equation (4.11). All variables are first-difference transformed before es-
timation. Cumby-Huizinga test does not reject the null hypothesis of no first-
order serial correlation in the error term. The number of lags required to make
the model dynamically complete is reported in "Lags".

TABLE D.17: Full regression results of realized output on fundamentals II

	(13)	(14)	(15)	(16)	(17)	(18)
expPos	8.93	–	–	-1.79	–	-4.05
	[-58.83 , 76.68]	–	–	[-71.49 , 67.90]	–	[-15.48 , 7.39]
expNeg	–	-35.91	1.40	-10.11	-1.45	2.93
	–	[-101.85 , 30.03]	[-19.08 , 21.87]	[-59.72 , 39.51]	[-26.25 , 23.35]	[-23.42 , 29.28]
genWind	-11.60	-9.69	-1.88	-9.03	-67.87	-9.81
	[-13.92 , -9.29]	[-11.74 , -7.64]	[-2.41 , -1.35]	[-10.27 , -7.79]	[-76.16 , -59.58]	[-11.07 , -8.56]
genSolar	-8.08	-5.57	-3.37	-6.88	-36.54	-7.35
	[-8.99 , -7.18]	[-6.31 , -4.82]	[-3.60 , -3.14]	[-7.38 , -6.37]	[-40.33 , -32.75]	[-7.87 , -6.83]
load	7.52	9.23	5.49	8.32	20.93	10.07
	[6.81 , 8.22]	[8.54 , 9.92]	[5.23 , 5.74]	[7.91 , 8.74]	[18.29 , 23.56]	[9.49 , 10.65]
eua	-13.70	4.98	2.35	21.72	-69.49	-1.98
	[-53.40 , 25.99]	[-40.70 , 50.66]	[-7.59 , 12.28]	[0.94 , 42.51]	[-216.76 , 77.78]	[-31.09 , 27.13]
coal	-1.34	-3.59	-0.99	-5.94	-3.39	2.88
	[-10.38 , 7.69]	[-18.03 , 10.84]	[-3.36 , 1.39]	[-13.76 , 1.88]	[-25.49 , 18.72]	[-6.33 , 12.10]
gas	-1.29	2.57	0.20	0.07	23.62	-0.32
	[-8.02 , 5.44]	[-1.32 , 6.45]	[-2.27 , 2.66]	[-2.04 , 2.18]	[-32.32 , 79.55]	[-5.84 , 5.20]
outcap	-0.01	0.00	-0.05	-0.11	0.05	-0.00
	[-0.06 , 0.04]	[-0.05 , 0.05]	[-0.11 , 0.00]	[-0.19 , -0.02]	[-0.03 , 0.14]	[-0.04 , 0.04]
Constant	-0.09	-1.75	-0.06	-0.91	-0.39	-0.14
	[-1.60 , 1.42]	[-3.15 , -0.35]	[-0.48 , 0.36]	[-1.76 , -0.05]	[-4.89 , 4.12]	[-1.08 , 0.81]
Observations	28,979	18,751	28,547	21,881	29,005	25,647
CH AR(1)	0.06	0.104	0.272	0.008	0.207	1.018
Lags	2	2	2	1	1	1

Note: Column titles refer to plantid from table 4.1. 99 percent confidence intervals in brackets are robust to HC3 heteroskedasticity. A dash (–) indicates that there is no sufficient variation in that variable to identify an effect. It is therefore omitted from the regression. Reported parameters are estimates from equation (4.11). All variables are first-difference transformed before estimation. Cumby-Huizinga test does not reject the null hypothesis of no first-order serial correlation in the error term. The number of lags required to make the model dynamically complete is reported in "Lags".

TABLE D.18: Full regression results of realized output on fundamentals III

	(19)	(20)	(21)	(22)	(23)
expPos	-4.90	–	62.37	–	-0.40
	[-24.26 , 14.47]	–	[-141.79 , 266.52]	–	[-19.71 , 18.91]
expNeg	–	-52.30	–	–	-20.34
	–	[-132.46 , 27.87]	–	–	[-41.51 , 0.83]
genWind	-11.85	-6.61	-11.00	-16.67	-7.22
	[-14.71 , -9.00]	[-8.32 , -4.91]	[-13.41 , -8.59]	[-19.14 , -14.21]	[-8.80 , -5.64]
genSolar	-8.02	-3.89	-5.91	-8.38	-6.76
	[-9.07 , -6.96]	[-4.55 , -3.23]	[-6.72 , -5.11]	[-9.16 , -7.60]	[-7.41 , -6.11]
load	13.18	3.84	8.69	11.00	8.85
	[12.29 , 14.07]	[3.34 , 4.34]	[7.94 , 9.45]	[10.25 , 11.75]	[8.26 , 9.45]
eua	-15.09	4.03	-12.88	-2.77	7.21
	[-57.55 , 27.38]	[-35.69 , 43.74]	[-51.87 , 26.11]	[-50.96 , 45.42]	[-21.24 , 35.66]
coal	-5.69	-0.60	-1.16	-7.16	-0.64
	[-15.14 , 3.77]	[-6.65 , 5.44]	[-11.47 , 9.14]	[-19.58 , 5.26]	[-7.10 , 5.82]
gas	-4.44	-1.81	-1.61	-0.86	4.68
	[-20.49 , 11.61]	[-13.52 , 9.90]	[-5.52 , 2.29]	[-5.53 , 3.80]	[-6.64 , 16.00]
outcap	-0.05	0.02	-0.16	-0.02	-0.02
	[-0.21 , 0.10]	[-0.06 , 0.11]	[-0.37 , 0.06]	[-0.09 , 0.05]	[-0.26 , 0.23]
Constant	-2.59	-0.06	-1.29	-1.95	-4.39
	[-4.26 , -0.92]	[-1.16 , 1.04]	[-2.77 , 0.20]	[-3.36 , -0.55]	[-5.52 , -3.27]
Observations	6,985	28,979	18,987	14,842	16,371
CH AR(1)	1.325	0.180	2.568	0.206	0.234
Lags	2	2	6	2	3

Note: Column titles refer to plantid from table 4.1. 99 percent confidence intervals in brackets are robust to HC3 heteroskedasticity. A dash (–) indicates that there is no sufficient variation in that variable to identify an effect. It is therefore omitted from the regression. Reported parameters are estimates from equation (4.11). All variables are first-difference transformed before estimation. Cumby-Huizinga test does not reject the null hypothesis of no first-order serial correlation in the error term. The number of lags required to make the model dynamically complete is reported in "Lags".

TABLE D.19: Full regression results of realized output on fundamentals IV

D.2   Robustness

Specification including polynomials of weather

	(2)	(6)	(11)	(17)	(18)	(19)	(20)
expPos	–	–	-6.35	–	-4.54	-0.18	–
	–	–	[-86.76 , 74.06]	–	[-15.37 , 6.29]	[-34.80 , 34.45]	–
expNeg	5.48	3.61	-0.21	53.44	0.28	–	-56.25
	[-25.60 , 36.56]	[-30.14 , 37.36]	[-45.76 , 45.33]	[17.96 , 88.91]	[-26.20 , 26.77]	–	[-138.48 , 25.98]
genWind	-2.56	-7.24	-2.72	21.53	-2.78	-16.65	6.29
	[-4.57 , -0.55]	[-10.02 , -4.46]	[-6.99 , 1.55]	[-3.52 , 46.57]	[-6.84 , 1.27]	[-26.16 , -7.14]	[1.34 , 11.25]
genWind2	-0.01	0.02	-0.31	-4.17	-0.46	0.09	-0.70
	[-0.14 , 0.13]	[-0.16 , 0.19]	[-0.62 , 0.00]	[-6.01 , -2.34]	[-0.73 , -0.19]	[-0.82 , 1.00]	[-1.11 , -0.30]
genWind3	0.00	0.00	0.00	0.05	0.01	0.00	0.01
	[-0.00 , 0.00]	[-0.00 , 0.00]	[-0.00 , 0.01]	[0.02 , 0.09]	[0.00 , 0.01]	[-0.02 , 0.02]	[0.00 , 0.02]
genSolar	-3.38	-4.25	-7.57	-23.69	-9.08	-5.76	-3.45
	[-4.18 , -2.57]	[-5.31 , -3.19]	[-9.14 , -6.00]	[-33.93 , -13.46]	[-10.61 , -7.54]	[-8.80 , -2.72]	[-5.25 , -1.66]
genSolar2	0.08	0.01	0.33	-0.40	0.25	-0.08	0.04
	[0.00 , 0.17]	[-0.11 , 0.12]	[0.17 , 0.50]	[-1.46 , 0.66]	[0.08 , 0.41]	[-0.42 , 0.26]	[-0.16 , 0.24]
genSolar3	-0.00	-0.00	-0.01	-0.00	-0.01	-0.00	-0.00
	[-0.00 , 0.00]	[-0.00 , 0.00]	[-0.01 , -0.00]	[-0.04 , 0.03]	[-0.01 , -0.00]	[-0.01 , 0.01]	[-0.01 , 0.00]
load	-29.78	-41.75	19.89	283.43	4.50	14.63	30.10
	[-37.71 , -21.86]	[-52.97 , -30.52]	[-0.34 , 40.11]	[175.50 , 391.35]	[-15.17 , 24.18]	[-34.90 , 64.16]	[7.21 , 52.98]
load2	0.59	0.94	-0.18	-4.08	0.25	0.22	-0.41
	[0.44 , 0.73]	[0.74 , 1.14]	[-0.54 , 0.19]	[-6.04 , -2.12]	[-0.10 , 0.60]	[-0.64 , 1.08]	[-0.82 , -0.00]
load3	-0.00	-0.01	0.00	0.02	-0.00	-0.00	0.00
	[-0.00 , -0.00]	[-0.01 , -0.00]	[-0.00 , 0.00]	[0.01 , 0.03]	[-0.00 , -0.00]	[-0.01 , 0.00]	[-0.00 , 0.00]
eua	-4.39	-4.67	7.67	-69.74	-6.84	-129.43	9.98
	[-14.01 , 5.22]	[-17.58 , 8.24]	[-18.37 , 33.72]	[-365.60 , 226.12]	[-40.24 , 26.55]	[-273.72 , 14.86]	[-32.42 , 52.38]
coal	-0.38	-0.93	-3.11	-4.71	1.09	-13.75	-1.95
	[-2.59 , 1.83]	[-4.16 , 2.29]	[-9.08 , 2.86]	[-80.75 , 71.32]	[-10.65 , 12.84]	[-44.43 , 16.93]	[-9.79 , 5.89]
gas	-2.82	-1.00	-0.88	33.61	-0.09	-12.39	-2.20
	[-9.23 , 3.59]	[-4.46 , 2.46]	[-6.72 , 4.96]	[-10.82 , 78.03]	[-5.04 , 4.86]	[-42.96 , 18.18]	[-13.98 , 9.59]
outcap	-0.06	-0.01	-0.03	0.02	-0.01	-0.07	0.02
	[-0.20 , 0.07]	[-0.06 , 0.03]	[-0.09 , 0.03]	[-0.10 , 0.14]	[-0.05 , 0.03]	[-0.24 , 0.11]	[-0.06 , 0.10]
Constant	-0.18	-0.27	-0.39	-0.35	-0.15	-2.79	-0.06
	[-0.60 , 0.24]	[-0.87 , 0.33]	[-1.34 , 0.55]	[-5.91 , 5.21]	[-1.11 , 0.80]	[-4.64 , -0.95]	[-1.17 , 1.05]
Observations	19,455	21,728	24,949	29,005	25,647	6,985	28,979
CH AR(1)	0.871	1.652	0.903	0.011	0.713	1.266	0.235
Lags	30	6	30	1	1	2	2

Note: Column titles refer to plantid from table 4.1. 99 percent confidence intervals in brackets are robust to HC3 heteroskedasticity. A dash (–) indicates that there is no sufficient variation in that variable to identify an effect. It is therefore omitted from the regression. Reported parameters are estimates from equation (4.12). All variables are first-difference transformed before estimation. Cumby-Huizinga test does not reject the null hypothesis of no first-order serial correlation in the error term. The number of lags required to make the model dynamically complete is reported in "Lags".

TABLE D.20: Full regression results of scheduled output on fundamentals including polynomials

	(2)	(6)	(11)	(17)	(18)	(19)	(20)
expPos	–	–	-5.84	–	-4.47	-3.73	–
	–	–	[-133.11 , 121.43]	–	[-14.92 , 5.97]	[-22.59 , 15.14]	–
expNeg	4.97	-4.16	-0.34	-5.71	3.42	–	-51.96
	[-30.29 , 40.23]	[-29.19 , 20.88]	[-45.81 , 45.13]	[-30.46 , 19.04]	[-22.49 , 29.33]	–	[-131.94 , 28.03]
genWind	-2.46	-7.10	-3.11	-2.69	-2.47	-19.36	6.18
	[-4.46 , -0.47]	[-9.81 , -4.39]	[-7.26 , 1.04]	[-23.55 , 18.17]	[-6.45 , 1.51]	[-27.05 , -11.68]	[1.25 , 11.10]
genWind2	-0.01	0.03	-0.30	-3.58	-0.46	0.51	-0.70
	[-0.15 , 0.12]	[-0.14 , 0.19]	[-0.60 , 0.01]	[-5.08 , -2.09]	[-0.73 , -0.20]	[-0.15 , 1.16]	[-1.10 , -0.30]
genWind3	0.00	0.00	0.00	0.05	0.01	-0.01	0.01
	[-0.00 , 0.00]	[-0.00 , 0.00]	[-0.00 , 0.01]	[0.02 , 0.08]	[0.00 , 0.01]	[-0.02 , 0.01]	[0.00 , 0.02]
genSolar	-3.37	-4.14	-8.02	-33.23	-9.08	-5.29	-3.50
	[-4.18 , -2.57]	[-5.17 , -3.10]	[-9.52 , -6.52]	[-42.08 , -24.38]	[-10.60 , -7.56]	[-8.16 , -2.43]	[-5.28 , -1.71]
genSolar2	0.09	0.01	0.33	0.31	0.26	-0.04	0.04
	[0.00 , 0.17]	[-0.10 , 0.12]	[0.17 , 0.49]	[-0.59 , 1.21]	[0.10 , 0.43]	[-0.36 , 0.29]	[-0.16 , 0.24]
genSolar3	-0.00	-0.00	-0.01	-0.02	-0.01	-0.01	-0.00
	[-0.00 , 0.00]	[-0.00 , 0.00]	[-0.01 , -0.00]	[-0.05 , 0.00]	[-0.01 , -0.00]	[-0.02 , 0.01]	[-0.01 , 0.00]
load	-28.92	-38.92	30.05	319.14	6.50	16.29	29.99
	[-36.76 , -21.08]	[-49.96 , -27.88]	[10.69 , 49.42]	[225.34 , 412.95]	[-12.94 , 25.94]	[-29.14 , 61.71]	[7.16 , 52.82]
load2	0.57	0.89	-0.33	-4.94	0.21	0.17	-0.41
	[0.43 , 0.71]	[0.69 , 1.09]	[-0.68 , 0.02]	[-6.63 , -3.25]	[-0.14 , 0.56]	[-0.62 , 0.96]	[-0.81 , -0.00]
load3	-0.00	-0.01	0.00	0.03	-0.00	-0.00	0.00
	[-0.00 , -0.00]	[-0.01 , -0.00]	[-0.00 , 0.00]	[0.02 , 0.04]	[-0.00 , -0.00]	[-0.01 , 0.00]	[-0.00 , 0.00]
eua	-1.06	-3.90	12.37	-64.02	-1.41	-15.26	4.86
	[-9.85 , 7.73]	[-16.06 , 8.26]	[-13.75 , 38.49]	[-210.73 , 82.68]	[-30.45 , 27.63]	[-57.91 , 27.39]	[-34.80 , 44.53]
coal	-0.54	-1.09	-4.07	-0.57	2.91	-5.20	-0.29
	[-2.60 , 1.52]	[-4.06 , 1.89]	[-9.83 , 1.68]	[-22.98 , 21.83]	[-6.26 , 12.08]	[-15.04 , 4.63]	[-6.36 , 5.77]
gas	-3.30	-1.35	-2.59	22.76	-0.41	-3.23	-1.88
	[-9.44 , 2.83]	[-4.40 , 1.71]	[-8.65 , 3.46]	[-31.29 , 76.80]	[-5.82 , 5.00]	[-20.21 , 13.74]	[-13.53 , 9.78]
outcap	-0.06	-0.01	-0.03	0.06	-0.00	-0.05	0.02
	[-0.20 , 0.08]	[-0.05 , 0.03]	[-0.09 , 0.03]	[-0.02 , 0.14]	[-0.04 , 0.04]	[-0.22 , 0.13]	[-0.06 , 0.11]
Constant	-0.19	-0.27	-0.20	-0.44	-0.15	-2.65	-0.06
	[-0.60 , 0.22]	[-0.85 , 0.32]	[-1.12 , 0.72]	[-4.92 , 4.05]	[-1.09 , 0.79]	[-4.30 , -1.00]	[-1.16 , 1.04]
Observations	19,455	21,728	26,976	29,005	25,647	6,985	28,979
CH AR(1)	0.654	1.560	1.683	0.151	0.948	1.716	0.216
Lags	30	20	20	1	1	1	2

Note: Column titles refer to plantid from table 4.1. 99 percent confidence intervals in brackets are robust to HC3 heteroskedasticity. A dash (–) indicates that there is no sufficient variation in that variable to identify an effect. It is therefore omitted from the regression. Reported parameters are estimates from equation (4.13). All variables are first-difference transformed before estimation. Cumby-Huizinga test does not reject the null hypothesis of no first-order serial correlation in the error term. The number of lags required to make the model dynamically complete is reported in "Lags".

TABLE D.21: Full regression results of realized output on fundamentals including polynomials

Specification including local load proxy variables

	(2)	(6)	(11)	(17)	(18)	(19)	(20)
expPos	–	–	–	–	4.66	5.90	–
	–	–	–	–	[-68.47 , 77.78]	[-32.25 , 44.05]	–
expNeg	2.27	-9.42	0.80	47.35	-0.66	–	-59.13
	[-21.51 , 26.05]	[-41.27 , 22.43]	[-52.77 , 54.37]	[11.29 , 83.40]	[-30.05 , 28.74]	–	[-142.07 , 23.81]
price	0.57	0.92	1.73	13.32	2.24	2.41	2.00
	[0.43 , 0.70]	[0.74 , 1.10]	[1.45 , 2.01]	[10.87 , 15.77]	[1.93 , 2.55]	[1.77 , 3.06]	[1.57 , 2.44]
eua	-2.26	-6.23	9.00	-71.85	-7.26	-126.51	8.35
	[-12.71 , 8.19]	[-19.82 , 7.37]	[-17.77 , 35.77]	[-371.41 , 227.70]	[-41.03 , 26.52]	[-263.79 , 10.78]	[-34.63 , 51.33]
coal	-0.41	-0.69	-1.67	-3.48	2.01	-12.70	-1.82
	[-2.74 , 1.92]	[-3.92 , 2.55]	[-7.63 , 4.29]	[-79.77 , 72.81]	[-9.83 , 13.85]	[-41.35 , 15.96]	[-9.68 , 6.04]
gas	-1.86	-1.17	-2.68	38.54	-0.28	-15.45	-2.11
	[-8.56 , 4.84]	[-6.38 , 4.04]	[-9.03 , 3.67]	[-9.76 , 86.84]	[-4.95 , 4.39]	[-46.17 , 15.27]	[-14.00 , 9.78]
outcap	-0.06	-0.03	-0.03	0.01	0.01	-0.06	0.02
	[-0.19 , 0.08]	[-0.08 , 0.03]	[-0.10 , 0.03]	[-0.10 , 0.13]	[-0.03 , 0.05]	[-0.20 , 0.07]	[-0.06 , 0.11]
flowATDE	-0.01	-0.02	-0.02	-0.08	-0.04	-0.05	-0.00
	[-0.01 , -0.01]	[-0.02 , -0.01]	[-0.03 , -0.02]	[-0.11 , -0.04]	[-0.04 , -0.03]	[-0.06 , -0.04]	[-0.01 , 0.00]
flowCZDE	0.01	0.03	0.04	0.04	0.06	0.08	0.00
	[0.01 , 0.02]	[0.02 , 0.03]	[0.03 , 0.04]	[0.00 , 0.08]	[0.05 , 0.07]	[0.06 , 0.09]	[-0.01 , 0.01]
flowPLDE	-0.00	-0.01	-0.00	0.27	-0.00	-0.02	0.02
	[-0.01 , 0.00]	[-0.01 , -0.00]	[-0.01 , 0.01]	[0.22 , 0.33]	[-0.01 , 0.01]	[-0.04 , -0.00]	[0.01 , 0.03]
flowDKDE	-0.00	-0.00	-0.02	-0.06	-0.01	-0.01	-0.01
	[-0.00 , 0.00]	[-0.00 , -0.00]	[-0.02 , -0.02]	[-0.08 , -0.04]	[-0.02 , -0.01]	[-0.02 , -0.00]	[-0.01 , -0.00]
flowNLDE	-0.00	-0.01	-0.00	0.02	-0.01	-0.02	0.02
	[-0.01 , -0.00]	[-0.01 , -0.00]	[-0.01 , 0.00]	[0.00 , 0.04]	[-0.01 , -0.00]	[-0.03 , -0.01]	[0.01 , 0.02]
flowFRDE	0.00	0.01	0.01	-0.03	0.01	0.02	-0.01
	[0.00 , 0.01]	[0.01 , 0.01]	[0.01 , 0.01]	[-0.04 , -0.01]	[0.00 , 0.01]	[0.01 , 0.03]	[-0.01 , -0.01]
flowCHDE	-0.00	0.00	0.01	0.06	0.01	0.01	0.01
	[-0.00 , 0.00]	[0.00 , 0.01]	[0.01 , 0.01]	[0.04 , 0.09]	[0.01 , 0.02]	[0.00 , 0.02]	[0.01 , 0.02]
Constant	-0.19	-0.53	-0.29	-0.42	-0.14	-3.52	-0.06
	[-0.62 , 0.24]	[-1.16 , 0.10]	[-1.25 , 0.68]	[-6.11 , 5.27]	[-1.13 , 0.86]	[-5.51 , -1.52]	[-1.18 , 1.06]
Observations	19,106	19,587	25,219	28,470	25,539	7,084	28,452
CH AR(1)	2.472	1.039	2.546	0.058	0.302	0.004	0.982
Lags	30	30	20	1	1	1	2

Note: Column titles refer to plantid from table 4.1. 99 percent confidence intervals in brackets are robust to HC3 heteroskedasticity. A dash (–) indicates that there is no sufficient variation in that variable to identify an effect. It is therefore omitted from the regression. Reported parameters are estimates from equation (4.14). All variables are first-difference transformed before estimation. Cumby-Huizinga test does not reject the null hypothesis of no first-order serial correlation in the error term. The number of lags required to make the model dynamically complete is reported in "Lags".

TABLE D.22: Full regression results of scheduled output on price including proxy variables for local load

	(2)	(6)	(11)	(17)	(18)	(19)	(20)
expPos	–	–	–	–	1.76	4.45	–
	–	–	–	–	[-13.88 , 17.40]	[-31.80 , 40.69]	–
expNeg	6.64	-7.16	-2.59	59.74	0.47	–	-60.39
	[-26.78 , 40.07]	[-37.85 , 23.53]	[-49.06 , 43.88]	[24.33 , 95.15]	[-24.65 , 25.59]	–	[-144.58 , 23.79]
genWind	-3.11	-8.12	-10.68	-81.66	-13.83	-17.37	-10.69
	[-3.72 , -2.51]	[-8.99 , -7.24]	[-12.10 , -9.27]	[-91.03 , -72.28]	[-15.27 , -12.40]	[-21.02 , -13.71]	[-12.64 , -8.74]
genSolar	-2.91	-5.28	-7.51	-64.36	-11.45	-13.35	-9.27
	[-3.35 , -2.46]	[-5.92 , -4.65]	[-8.44 , -6.58]	[-70.36 , -58.36]	[-12.39 , -10.50]	[-15.17 , -11.52]	[-10.60 , -7.95]
load	3.07	5.81	8.93	46.55	11.76	15.46	7.44
	[2.75 , 3.39]	[5.35 , 6.27]	[8.23 , 9.62]	[42.24 , 50.86]	[11.02 , 12.51]	[14.14 , 16.79]	[6.52 , 8.35]
eua	-2.94	-6.49	9.06	-68.91	-7.99	-128.68	8.68
	[-12.85 , 6.97]	[-19.40 , 6.43]	[-16.84 , 34.96]	[-366.40 , 228.58]	[-41.11 , 25.13]	[-272.31 , 14.94]	[-33.88 , 51.25]
coal	-0.07	-0.79	-2.08	-1.78	1.93	-13.37	-1.78
	[-2.34 , 2.21]	[-3.98 , 2.41]	[-7.87 , 3.71]	[-78.09 , 74.52]	[-9.75 , 13.61]	[-44.53 , 17.79]	[-9.60 , 6.04]
gas	-2.36	-1.05	-3.23	35.57	-0.28	-11.27	-2.30
	[-8.86 , 4.15]	[-5.81 , 3.72]	[-9.97 , 3.51]	[-11.69 , 82.82]	[-5.31 , 4.76]	[-42.07 , 19.53]	[-14.21 , 9.61]
outcap	-0.07	-0.03	-0.04	0.01	-0.01	-0.08	0.02
	[-0.21 , 0.08]	[-0.08 , 0.02]	[-0.11 , 0.03]	[-0.11 , 0.13]	[-0.04 , 0.03]	[-0.23 , 0.06]	[-0.07 , 0.10]
flowATDE	-0.00	-0.00	0.01	0.11	0.00	0.00	0.02
	[-0.01 , -0.00]	[-0.01 , 0.00]	[0.00 , 0.01]	[0.08 , 0.15]	[-0.00 , 0.01]	[-0.01 , 0.01]	[0.02 , 0.03]
flowCZDE	0.01	0.02	0.01	-0.01	0.03	0.03	-0.01
	[0.00 , 0.01]	[0.01 , 0.02]	[0.01 , 0.02]	[-0.05 , 0.03]	[0.03 , 0.04]	[0.02 , 0.05]	[-0.02 , -0.00]
flowPLDE	0.00	-0.00	0.00	0.30	0.01	-0.01	0.02
	[-0.00 , 0.01]	[-0.01 , 0.00]	[-0.00 , 0.01]	[0.25 , 0.36]	[-0.00 , 0.01]	[-0.03 , 0.01]	[0.01 , 0.03]
flowDKDE	0.00	0.01	-0.01	0.03	0.00	0.01	0.01
	[0.00 , 0.01]	[0.01 , 0.01]	[-0.01 , -0.00]	[0.01 , 0.06]	[-0.00 , 0.01]	[0.00 , 0.02]	[0.00 , 0.01]
flowNLDE	-0.00	0.00	0.01	0.10	0.01	0.01	0.03
	[-0.00 , 0.00]	[-0.00 , 0.00]	[0.01 , 0.01]	[0.08 , 0.12]	[0.01 , 0.01]	[-0.00 , 0.01]	[0.02 , 0.03]
flowFRDE	0.00	0.01	0.01	0.01	0.01	0.01	-0.01
	[0.00 , 0.01]	[0.01 , 0.01]	[0.01 , 0.01]	[-0.00 , 0.03]	[0.00 , 0.01]	[0.00 , 0.02]	[-0.01 , -0.00]
flowCHDE	0.00	0.01	0.02	0.06	0.02	0.02	0.01
	[-0.00 , 0.00]	[0.00 , 0.01]	[0.01 , 0.02]	[0.04 , 0.09]	[0.02 , 0.02]	[0.01 , 0.03]	[0.01 , 0.02]
Constant	-0.19	-0.48	-0.25	-0.38	-0.12	-3.54	-0.05
	[-0.61 , 0.23]	[-1.08 , 0.13]	[-1.19 , 0.69]	[-5.95 , 5.19]	[-1.07 , 0.83]	[-5.40 , -1.69]	[-1.16 , 1.06]
Observations	19,106	19,587	25,219	28,470	25,539	7,084	28,452
CH AR(1)	1.494	1.002	2.497	0.000	0.257	1.885	0.851
Lags	30	30	20	1	1	1	2

Note: Column titles refer to plantid from table 4.1. 99 percent confidence intervals in brackets are robust to HC3 heteroskedasticity. A dash (–) indicates that there is no sufficient variation in that variable to identify an effect. It is therefore omitted from the regression. Reported parameters are estimates from equation (4.15) . All variables are first-difference transformed before estimation. Cumby-Huizinga test does not reject the null hypothesis of no first-order serial correlation in the error term. The number of lags required to make the model dynamically complete is reported in "Lags".

TABLE D.23: Full regression results of scheduled output on fundamentals including proxy variables for local load

Specification disregaring overlapping redispatch observations

	(2)	(6)	(11)	(17)	(18)	(19)	(20)
expPos	–	–	-1.09	–	-2.83	6.42	–
	–	–	[-29.33 , 27.15]	–	[-77.57 , 71.90]	[-31.88 , 44.71]	–
expNeg	3.35	-9.57	-0.47	51.50	-3.40	–	-121.95
	[-20.75 , 27.45]	[-39.93 , 20.80]	[-55.42 , 54.49]	[13.28 , 89.73]	[-34.09 , 27.28]	–	[-299.68 , 55.78]
price	0.94	1.36	2.49	13.79	3.36	4.07	1.82
	[0.80 , 1.08]	[1.18 , 1.54]	[2.24 , 2.74]	[11.87 , 15.71]	[3.05 , 3.67]	[3.44 , 4.69]	[1.51 , 2.13]
eua	-2.91	-6.65	10.21	21.21	-3.82	-126.92	9.63
	[-13.40 , 7.57]	[-20.33 , 7.03]	[-16.63 , 37.06]	[-267.39 , 309.81]	[-36.66 , 29.01]	[-264.57 , 10.74]	[-32.22 , 51.49]
coal	-0.54	-1.43	-2.62	-4.06	-1.61	-13.54	-0.85
	[-2.95 , 1.88]	[-4.64 , 1.77]	[-8.61 , 3.37]	[-72.89 , 64.78]	[-11.59 , 8.37]	[-42.65 , 15.56]	[-7.84 , 6.14]
gas	-2.44	-1.34	-1.95	38.00	-0.55	-16.10	-2.35
	[-9.07 , 4.20]	[-6.43 , 3.76]	[-7.58 , 3.69]	[-28.63 , 104.62]	[-4.69 , 3.60]	[-47.12 , 14.92]	[-14.40 , 9.69]
outcap	-0.05	-0.03	-0.03	0.03	0.01	-0.07	0.03
	[-0.19 , 0.08]	[-0.08 , 0.03]	[-0.09 , 0.04]	[-0.09 , 0.14]	[-0.03 , 0.05]	[-0.19 , 0.06]	[-0.06 , 0.11]
Constant	-0.17	-0.50	-0.29	-10.10	-0.15	-3.36	-0.13
	[-0.60 , 0.27]	[-1.13 , 0.13]	[-1.26 , 0.68]	[-15.73 , -4.47]	[-1.16 , 0.86]	[-5.42 , -1.30]	[-1.24 , 0.99]
Observations	19,429	19,634	25,596	25,675	25,634	7,094	28,887
CH AR(1)	1.489	0.973	1.832	0.082	0.010	1.106	0.453
Lags	30	30	20	1	1	1	2

Note: Column titles refer to plantid from table 4.1. 99 percent confidence intervals in brackets are robust to HC3 heteroskedasticity. A dash (–) indicates that there is no sufficient variation in that variable to identify an effect. It is therefore omitted from the regression. Reported parameters are estimates from equation (4.8), disregarding observations with overlapping redispatch mandates. All variables are first-difference transformed before estimation. Cumby-Huizinga test does not reject the null hypothesis of no first-order serial correlation in the error term. The number of lags required to make the model dynamically complete is reported in "Lags".

TABLE D.24: Full regression results of scheduled output on price disregarding overlapping observations

	(2)	(6)	(11)	(17)	(18)	(19)	(20)
expPos	–	–	-0.47	–	-4.09	-1.76	–
	–	–	[-59.86 , 58.93]	–	[-15.77 , 7.59]	[-36.68 , 33.16]	–
expNeg	6.79	-5.43	0.61	61.94	-0.25	–	-120.10
	[-22.28 , 35.86]	[-36.17 , 25.31]	[-44.75 , 45.96]	[24.48 , 99.39]	[-27.18 , 26.68]	–	[-299.19 , 58.98]
genWind	-2.63	-6.33	-8.46	-51.98	-10.06	-13.62	-6.59
	[-3.18 , -2.08]	[-7.14 , -5.52]	[-9.78 , -7.13]	[-60.78 , -43.17]	[-11.33 , -8.78]	[-17.04 , -10.20]	[-8.31 , -4.87]
genSolar	-2.60	-3.62	-4.51	-33.45	-7.48	-8.96	-3.90
	[-2.90 , -2.30]	[-4.08 , -3.16]	[-5.08 , -3.95]	[-37.11 , -29.79]	[-8.00 , -6.95]	[-10.09 , -7.84]	[-4.56 , -3.23]
load	3.17	5.34	7.52	29.82	10.13	14.52	3.88
	[2.92 , 3.42]	[4.97 , 5.71]	[7.02 , 8.02]	[26.92 , 32.73]	[9.55 , 10.71]	[13.52 , 15.53]	[3.37 , 4.38]
eua	-4.11	-6.43	10.09	21.32	-5.12	-129.41	9.19
	[-13.84 , 5.61]	[-19.74 , 6.87]	[-16.03 , 36.21]	[-265.60 , 308.24]	[-37.91 , 27.66]	[-272.43 , 13.61]	[-32.45 , 50.83]
coal	-0.21	-1.70	-3.19	-3.74	-1.49	-14.28	-1.03
	[-2.50 , 2.08]	[-4.83 , 1.44]	[-9.08 , 2.69]	[-71.92 , 64.44]	[-11.46 , 8.48]	[-44.31 , 15.74]	[-7.98 , 5.92]
gas	-2.96	-1.22	-2.63	33.22	-0.58	-13.36	-2.52
	[-9.36 , 3.44]	[-5.94 , 3.49]	[-9.33 , 4.08]	[-26.80 , 93.24]	[-5.46 , 4.29]	[-44.13 , 17.41]	[-14.54 , 9.49]
outcap	-0.07	-0.03	-0.04	0.02	-0.00	-0.07	0.02
	[-0.21 , 0.07]	[-0.08 , 0.02]	[-0.10 , 0.03]	[-0.10 , 0.14]	[-0.04 , 0.03]	[-0.23 , 0.09]	[-0.06 , 0.10]
Constant	-0.16	-0.46	-0.24	-10.01	-0.10	-2.67	-0.12
	[-0.58 , 0.26]	[-1.07 , 0.15]	[-1.18 , 0.70]	[-15.57 , -4.45]	[-1.06 , 0.86]	[-4.54 , -0.81]	[-1.23 , 0.99]
Observations	19,429	19,634	25,596	25,675	25,634	6,969	28,887
CH AR(1)	0.989	1.175	1.546	0.394	0.907	0.919	0.150
Lags	30	30	20	1	1	2	2

Note: Column titles refer to plantid from table 4.1. 99 percent confidence intervals in brackets are robust to HC3 heteroskedasticity. A dash (–) indicates that there is no sufficient variation in that variable to identify an effect. It is therefore omitted from the regression. Reported parameters are estimates from equation (4.9), disregarding observations with overlapping redispatch mandates. All variables are first-difference transformed before estimation. Cumby-Huizinga test does not reject the null hypothesis of no first-order serial correlation in the error term. The number of lags required to make the model dynamically complete is reported in "Lags".

TABLE D.25: Full regression results of scheduled output on fundamentals disregarding overlapping observations

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Erklärung

Hiermit erkläre ich, Philip Christopher Schnaars, dass ich keine kommerzielle Promotionsberatung in Anspruch genommen habe. Die Arbeit wurde nicht schon einmal in einem früheren Promotionsverfahren angenommen oder als ungenügend beurteilt.

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Eidesstattliche Versicherung

Ich, Philip Christopher Schnaars, versichere an Eides statt, dass ich die Dissertation mit dem Titel:

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selbst und bei einer Zusammenarbeit mit anderen Wissenschaftlerinnen oder Wissenschaftlern gemäß den beigefügten Darlegungen nach § 6 Abs. 3 der Promotionsordnung der Fakultät für Wirtschafts- und Sozialwissenschaften vom 18. Januar 2017 verfasst habe. Andere als die angegebenen Hilfsmittel habe ich nicht benutzt.

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Selbstdeklaration bei kumulativen Promotionen

Fachbereich Sozialökonomie

Konzeption / Planung: Formulierung des grundlegenden wissenschaftlichen Problems, basierend auf bisher unbeantworteten theoretischen Fragen inklusive der Zusammenfassung der generellen Fragen, die anhand von Analysen oder Experimenten / Untersuchungen beantwortbar sind. Planung der Experimente / Analysen und Formulierung der methodischen Vorgehensweise, inklusive Wahl der Methode und unabhängige methodologische Entwicklung.

Durchführung: Grad der Einbindung in die konkreten Untersuchungen bzw. Analysen.

Manuskripterstellung: Präsentation, Interpretation und Diskussion der erzielten Ergebnisse in Form eines wissenschaftlichen Artikels.

Die Einschätzung des geleisteten Anteils erfolgt mittels Punkteinschätzung von 1 %-100 %.

Für den in Kapitel 2 vorliegenden Aufsatz (”**The real substitution effect of renewable electricity: An empirical analysis for Germany**”) liegt die Eigenleistung bei **100** %.

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