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Electricity Prices Under Fire

An Empirical Assessment of Intermittent Renewable Energy Sources as a Remedy to High Gas Prices

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Abstract: Europe has experienced a drastic increase in electricity prices since fall 2021, and it is largely acknowledged that this extreme increase is a consequence of the natural gas supply crisis in Europe. Meanwhile, intermittent renewable energy sources (IRES) are playing an ever more important role in the electricity generation of many European countries. This paper assesses whether IRES can contribute to mitigating electricity's dependence on natural gas, despite the reliance on back-up generation technologies. We study the day-ahead electricity spot price in the German market during 2016-2020 using two empirical approaches. By comparing SARIMAX/GARCH models during peak and off-peak hours, we find evidence of a merit-order effect (MOE) of IRES in the German market, amounting to 0.23–0.30 €/MWh for a one GWh increase in IRES output. We also confirm that gas price has greater influence on electricity prices during peak hours. Although the MOE is endorsed by our secondary OLS approach, we cannot confirm that IRES significantly reduces the impact of the gas price on electricity prices.

Keywords: electricity price, renewables, gas price, intermittency, merit-order effect

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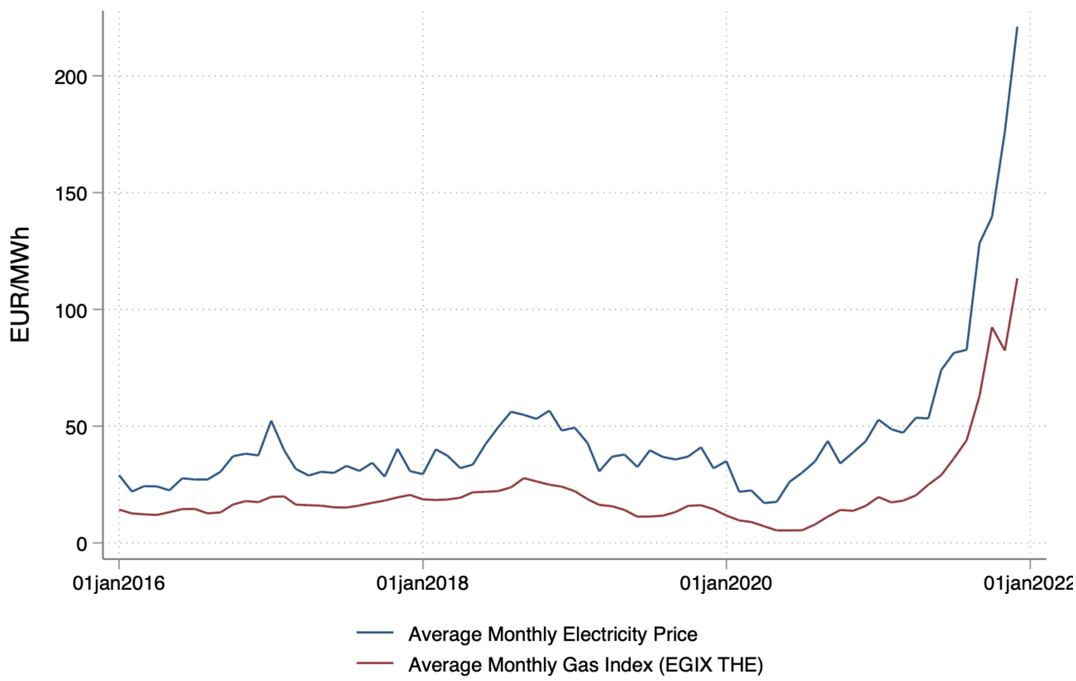
Any and all errors that remain in this paper are entirely our own.

Contents

1 Introduction

Europe has experienced drastically increased electricity prices since fall 2021. According to Eurostat (2022), 25 member countries of the European Union (EU) experienced a rise in household electricity prices in the latter half of 2021, compared to the corresponding period a year before. Estonia reports the largest increase of 50%, tightly followed by Sweden, sporting a rise of 49% in household electricity prices. Meanwhile, the highest household electricity prices for the same period were observed in Denmark and Germany, amounting to 34.50€/kWh and 32.30€/kWh, respectively.

Figure 1: Average Monthly German Electricity and Gas Prices



Note: The drastic increase in both gas and electricity in the latter half of 2021 can be seen on the German market. Data source: ENTSO-E Transparency Platform and Refinitiv Datastream. Graph by the authors.

It is largely acknowledged that the high electricity price is mainly driven by a huge increase in the price of natural gas (Batlle, Schittekatte, and Knittel 2022).

A natural gas supply crisis is spreading throughout Europe. 20 EU-countries simultaneously experienced gas price increases in the second half of 2021. For example, a rise of 70% in the gas price is seen in Sweden, along with a 67% increase in Denmark. Further tensions between Russia and the rest of Europe, heavily reliant on Russian gas deliveries, has highlighted additional risks of including natural gas in the energy production mix. Besides, demand increase due to the recovery from Covid-19 and technical challenge have also contributed to the gas supply shortage (Mišık 2022).

Existing literature addresses the impact of gas on the electricity producing sector. Linn, Muehlenbachs, and Wang (2014) point out that the cost and capital formation of the power sector leads to large and consistent effects on the generators when a natural gas price shock takes place. Mosquera-López and Nursimulu (2019) imply that the price of natural gas is one of the main price drivers at the long-term electricity futures market.

While gas price boasts a great influence on electricity price, other sources also play important roles in the electricity price setting process. Intermittent renewable energy sources (IRES) are increasingly employed for power generation in the EU. IRES also present a well-documented merit-order effect (Sensfuß, Ragwitz, and Genoese 2008; Tveten et al. 2013; Clò, Cataldi, and Zoppoli 2015; Gelabert, Labandeira, and Linares 2011), which encompasses the reducing effect on electricity prices from the usage of low marginal-cost IRES electricity production. Hence, IRES could be expected to dampen the price increase brought by along a spike in the gas price.

Nonetheless, the inherent variability in the production output of IRES has brought uncertainty to its expected effect to soothe gas price influence. The intermittency of IRES calls for the support of other technologies, so called back-up technologies, to generate electricity when IRES generation is not available or enough to meet demand. For this purpose, natural gas is known to be one of the major back-up technologies (Kolb et al. 2020). Therefore, we suspect that countries, e.g. Germany, that rely on natural gas as back-up technology are at greater risk when facing an exogenous gas price shock, compared to countries with access to cheaper back-up generation, e.g. the Nordic countries with access to hydropower (Dong et al. 2019).

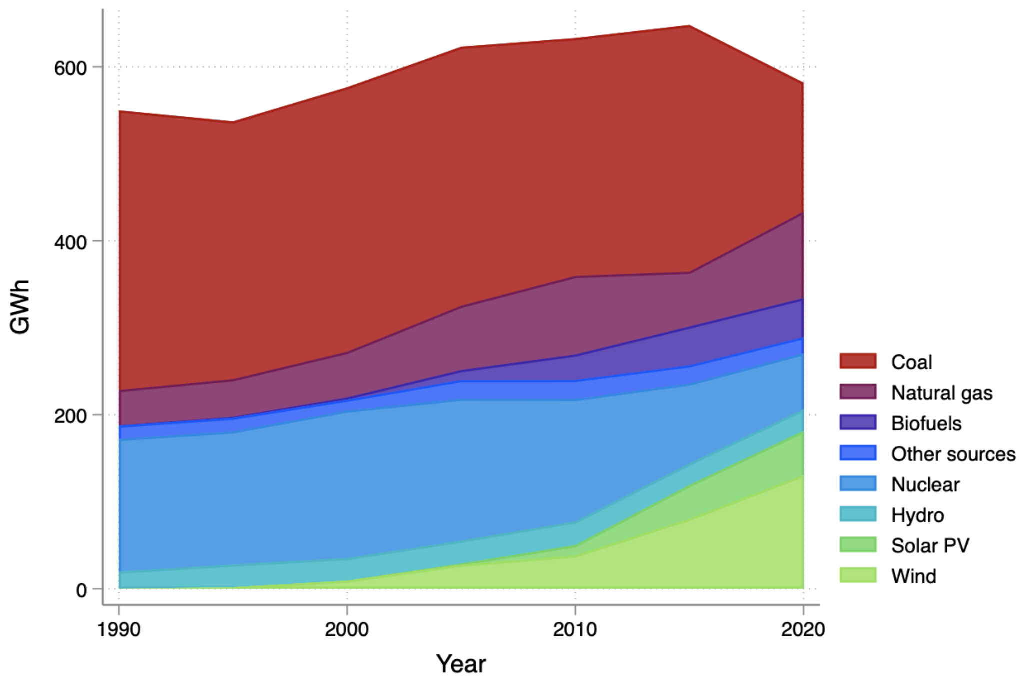
In this paper, we contribute to the literature by evaluating the joint effects of gas price and IRES generation. More precisely, we aim to answer the following research question: *Judging from its current reliance on back-up technologies, does IRES truly contribute to mitigating electricity's dependence on natural gas?*

This paper also contributes to the literature in electricity market study by employing two empirical approaches to reveal how gas price and IRES generation take part in the electricity market. To disentangle the relationship among electricity price, gas price and IRES generation, we proceed with the analysis in two steps, focusing on the German day-ahead electricity market during 2016-2020. Firstly, based on an integrated empirical approach (Duso, Szücs, and Böckers 2020; Macedo, Marques, and Damette 2021), we specify SARIMAX/GARCH models to assess the peak and off-peak differences of gas price influence on electricity prices. Secondly, we specify the interaction effect of gas price and IRES generation on electricity prices by developing OLS regression models with interaction terms (Clò, Cataldi, and Zoppoli 2015). Notably, day-ahead gas price is affected by electricity price from the demand side (Hulshof, Van Der Maat, and Mulder 2016) whereas gas price is mostly determined by fuel price in the long run (Nick and Thoenes 2014; Asche, Misund, and Sikveland 2013). In this study we employ the front month futures contracting price to indicate gas price, in order to mitigate the concern of reverse causality.

The focus on the German electricity market is founded upon its, for our purposes appropriate, energy profile. In addition to an upwards trend in IRES penetration, as seen in Figure 2, natural gas still covers a stable share of electricity supply in Germany.

Our study finds evidence of the merit-order effect of IRES in the German market and confirms that gas price has greater influence on electricity price during peak hours than off-peak hours. Nevertheless, the proposed mitigating effect of IRES on gas price influence on electricity prices remains unclear and cannot be established.

Figure 2: German Electricity Generation by Source



Note: Other sources include electricity generation from oil, waste, chemical heat, and other sources. Datasource: IEA (2022). Graph by the authors.

The paper proceeds as follows. Section 2 gives an introduction to the dynamics of electricity markets, further exemplified with the German electricity market. We proceed by presenting a review of related literature and our hypotheses, constituting our theoretical framework in Section 3. Sections 4 and 5 introduce the methodology and the data used in our analysis. The results are presented in Section 6 and further analysed in Section 7. Section 8 concludes.

2 Background

2.1 Electricity Market Design

Electricity can hardly be stored on a small scale, and unlikely at all on an industrial level. Electricity has historically been a monopolistic utility. However, the market has evolved with deregulation, development of generation technology and establishment of transmission networks (Stoft 2002; Kirschen and Strbac 2018). In order to understand a basic model of the electricity market, several concepts are important for understanding the institutional setup for the electricity market post-deregulation. Therefore, in accordance with the analysis of Cramton (2017), a detailed electricity market design is presented below.

The *system operator (SO)* is in charge of real-time grids and maintains the real-time balance of *supply (Generation)*, from generating companies and decentralized generation, and *demand (Load)*. The demand side includes final-end consumers (industry and household) and retailers that face these consumers. The demand presents a characteristic of time-dependency and low elasticity. *Power exchanges (PX)* offer the platform where trading happens and trading information, including positions, is provided to SO.

Moreover, there is the *wholesale market*. Trade takes place between generators and retailers at the wholesale market under two types of systems. Bilateral trading involves long-term contracts, over-the-counter contracts and short-term electronic trading contracts. Electricity pools allow companies and retailers to submit bids which are handled by SO and ranked to find the clearing price. The two systems are not in conflict and can exist in a hybrid model, which is employed in for example Nordpool and the European Power Exchange (EPEX). The *retail market* in turn involves the distribution networks from retailers to consumers.

The *day-ahead market* is a voluntary and financially binding model market where market participants acquire incentives and commitment for generation and operators efficiently plan units of the next day. Offers submitted by participants typically include three sections: start-up cost (the cost of starting a generator), minimum-energy cost (the lowest cost of running a generator), and an energy offer curve (the reflection of each unit's marginal cost).

The *real-time market* is a mandatory as well as financially and physically binding market where the resource dispatch and energy prices throughout the operating day are determined. Energy offer curves or output schedules are required for resources. Bid curves can be submitted by load resources in response to dispatch instructions, in which lower prices are present with higher demand. Due to the fact that supply and demand are not able to be forecast in reality, adjustments are made efficiently at the real-time market by SO in order to meet the real-time deviations from the day-ahead planning.

Peak-load pricing is employed in the electricity market as a result of the interplay of time-varying demand, market power and electricity's nature of non-storability (Boiteux 1960). It describes a system where price shows within-day variations based on demand (Crew, Fernando, and Kleindorfer 1995).

Lastly, a merit order dispatch system is utilized in the electricity market. It ranks each unit of generation capacity by the bidding price. The dispatching capacity then meets demand, in terms of the bidding rank from lowest to the highest. In other words, the cheapest units that satisfy demand win the auction. Two main payment rules are deployed for winning bids. Uniform price suggests that all the winning bids receive the bidding price of the marginal bid (the highest winning bid) whereas pay-as-bid suggests that all the winning bids receive their own bidding prices (Akbari-Dibavar, Mohammadi-Ivatloo, and Zare 2020). In the case of uniform price, which is utilized in the European market (Van Bracht, Maaz, and Moser 2017), the price is determined by the bidding price of last unit demanded. As a consequence, low marginal-cost power generating sources are able to lower the spot price in the electricity market.

2.2 Electricity Supply

2.2.1 Energy Mix

The variety of electricity generation technologies has broaden the investment possibilities. According to Eurostat (2021b), at the year of 2020, the five most electricity generation sources in Europe are total petroleum products (35%), natural gas (24%), renewable energy (17%), nuclear energy (13%) and solid fossil fuels (12%). Generation sources vary in multiple aspects, including fixed and variable costs, carbon emission and installation difficulty. The choices of technology affect power market design, especially the auction form, and raise issues in various senses: greenhouse gas emissions (e.g. fossil fuels), nuclear security (e.g. nuclear), supply security (e.g. IRES), etc. (Fabra 2021).

Natural gas has gradually become the fuel choice for power plant investments and renewable energy sources have shown growing impact for generation in electricity markets in Europe. Their disparate natures lead to different risk profiles of gas-fired electricity contracts and renewable contracts. While natural gas generation is more resilient to short-run demand risks, renewable generation performs better at mitigating fuel price risks and environmental compliance risks (Wiser et al. 2004).

2.2.2 Transition to Renewable Energy Sources

The Energy Strategy and Energy Union in EU has addressed the importance of environmental issues and announced progressive targets in terms of renewable usage, notably achieving renewables generating 20 % of energy supply by 2020 and 32% by 2030 (European Union, n.d.).

The supply variability of renewable capacity in combination with the demand uncertainty at the power market calls for an integrated generation system, which provides a balanced production, flexible grids and distributed transmission infrastructure (Milstein and Tishler 2011; Zahedi 2011). Meanwhile, low-carbon sources present the characteristic of capital intensiveness, which indicates that it is more costly to promote renewables in emerging economies with higher capital costs than in more developed countries (Hirth and Steckel 2016). Therefore, varying energy security, economic situation and technology development have led to different speeds and motivation of energy transitioning among different countries within EU; While some countries prioritize developing renewables (e.g. Germany, Nordpool, and the Netherlands), others are not as enthusiastic about promoting renewables (e.g. Poland and Malta) (Pérez, Scholten, and Stegen 2019). To further promote renewable energies, a cointegrated system among countries to coordinate against the supply and demand fluctuation, as well as country-wise diversified generation, is much needed in the energy transition process (De Vries and Verzijlbergh 2018).

2.3 German Market

Despite the general trend of increasing usage of renewables in most European countries, we believe that Germany provides the most suitable energy mix setup for our study to analyze the combined effects of IRES and natural gas. In countries where IRES is developing, some still largely depend on nuclear energy (e.g. France), some are dominated by one major source (e.g. Norway) and some rely much more on natural gas than IRES (e.g. Italy). However, Germany serves better for our goal of untangling the relationship of IRES and its backup technology, notably natural gas in our case, and their joint effects on electricity prices. While IRES is gradually gaining more influence on power generation, natural gas still accounts for a crucial share of domestic German electricity supply.

2.3.1 Energiewende

Energiewende marks the energy transition in Germany. It entails a series of decisions including phasing out nuclear power by 2022, bringing down the share of electricity generation from fossil fuels from 80% to 20% while maintaining the economic development and increasing the share of renewable energy supply to 35% by 2020 and 80% by 2050 (Beveridge and Kern 2013). German government has created a feed-in-tariff model that consistently supports renewable sources and maintains adequate electricity supply despite the drastic decline in nuclear and fossil fuel generation (Gerhardt 2017). Meanwhile, various policy strategies are exercised to promote the supply of renewable energies, such as incentivizing photovoltaic installations in private households (Kratschmann and Dütschke 2021). On the other hand, the renewable energy companies show influence on the decision-making of the policy makers, which in turn further promotes renewable generation (Sühlsen and Hisschemöller 2014). The introduction of IRES has largely influenced the German electricity market. In 2020, solar and wind production account for more than 25% of electricity generation in Germany, compared with a share of less than 10% in 2010 (IEA 2021).

The policy makers have responded to the concern of nuclear safety and environmental concern by phasing out nuclear energy, reducing coal production, and expanding investments in renewable energy sources. However, the energy market is heavily subsidized to cover the gap between guaranteed prices to producers and market prices, with subsidies adding up to as much as 27 billion euro in 2014 (Chrischilles and Bardt 2015). Analysts are not positive about this situation and believe that German consumers do not have the ability to afford these enormous subsidies in the future (Renn and Marshall 2016). Hence, a call for mixed energy sources is raised in Germany, especially in terms of having a stable gas-fired production to mitigate the fluctuation of IRES supply. Having observed a previous decline, gas is now found to play an essential role in the Germany energy transition, resulting in a a recent increase of gas-fired generation (Hörnlein 2019; Graichen and Redl 2014).

3 Related Literature and Hypotheses

3.1 Related Literature

3.1.1 Natural Gas and Electricity Price

The gas market follows the scheme of coming spot trading with long-term contracts, which is the typical transaction approach of energy markets is followed. Spot trading indicates immediate delivery on the spot market while contracts are made with respect to a specific duration, location and price.

The gas price is a result of the interplay of supply and demand. Asche, Misund, and Sikveland (2013) discover that oil price is the most important price driver of the intergrated European gas market. The results of a study by Nick and Thoenes (2014) show that temperature, storage and supply shocks affect gas price in the short run, and coal and oil prices determines gas price in the long run. After analyzing the Dutch Gas Hub (TTF) day-ahead spot price from 2011 to 2014, Hulshof, Van Der Maat, and Mulder (2016) find that gas-market fundamentals including weather and storage are predominant on gas price. In other words, the supply side does not decide the daily gas price fluctuation. Meanwhile, they also find that wind production electricity price, which comes from the demand side, has a positive effect on gas price on the day-ahead market.

As a traditional source of power generation, natural gas is expected to show effects on electricity prices. Linn, Muehlenbachs, and Wang (2014) find strong evidence that electricity price is affected by natural gas prices in the US, and the similar indication is suggested by Alexopoulos (2017). He et al. (2018) come up with a two-stage adjustable model of a optimal coordinated system with power and gas, and argue that there exists interdependency of the two systems, which indicates that uncertainties from one side can also affect the other. The determinants of electricity price vary in the short run and in the long run (Everts, Huber, and Blume-Werry 2016), and natural gas is found to be one of the main price drivers at the long-term electricity futures market (Mosquera-López and Nursimulu 2019).

3.1.2 IRES and Electricity Price

With the employment of a merit-order dispatch system in the electricity market, low marginal-cost renewable electricity sources drive out expensive marginal plants (Fischer et al. 2006). Thus, merit-order effect describes this mechanism that the increasing usage of renewable energy sources in power generation decreases the electricity prices. The described phenomenon is found in multiple countries with empirical evidence. A marginal increase of 1 GWh in daily electricity production from solar and wind generation reduced the wholesale electricity prices respectively by 2.3€/MWh and 4.2€/MWh, and increased the volatility of the wholesale electricity prices in Italian market during the time period of 2005-2013 (Clò, Cataldi, and Zoppoli 2015). Similarly, a decrease of 2€/MWh is found in a ex-post study of renewable and co-generation production in the Spanish market (Gelabert, Labandeira, and Linares 2011). Wind energy generation is found to affect the day-ahead electricity spot price in the Danish market (Jónsson, Pinson, and Madsen 2010), as well as in the Irish market (O'Mahoney and Denny 2011). However, while most literature suggest a uniform direction of renewable energy sources, Oosthuizen, Inglesi-Lotz, and Thopil (2022) find that the increasing share of RES has significantly affected retail electricity prices in an upward direction in 34 OECD countries.

In the context of the setup of our paper, empirical evidence of merit-order effect in the German power market is presented in several studies. The renewable power generation lead to a decrease of 7.8 €/MWh of the unweighted average electricity price in 2006, and the estimated total merit-order effect increased from 1 billion euro in 2001, to 5 billion euro in 2006 (Sensfuß, Ragwitz, and Genoese 2008). Specifically, the solar generation on average reduces predicted prices by 7% in comparison with the predicted prices without solar production in 2011 (Tveten et al. 2013).

Furthermore, the analysis of Dillig, Jung, and Karl (2016) reveals that, along with the fact that renewable energy generation has reduced power market prices, renewables have saved German electricity consumers almost 30 billion euro, compared with the situation where only non-renewable sources are used. They conclude this is a consequence of a deficit of the capacity installation from non-renewable generation sources during 2011 and 2013. Their follow-up study in the time period 2014-2016 (Kolb et al. 2020) further argues that domestic non-renewable generation would not have been able to fulfill the electricity demand, which in turn addresses the importance of expanding the utilization of renewable energy sources. The studies imply electricity supply shortages in few years as a consequence of a series of events: time gap between renewable investments and actual production, decommission of conventional plants and fully shutting down or nuclear plants. Besides, considering IRES' characteristic of intermittency, there are times that solar or wind energy is not able to be put into use. Hence, a potential short-term solution to the deficits is to make use of backup capacities such as gas and hydro installation.

The employment of IRES not only affects power market prices, but also influences the price volatility. Intuitively, the intermittency nature of IRES leads to a less stable supply, for example, when the weather conditions fail to conduct wind or solar generation, and hence increases in price volatility. Nevertheless, previous studies have indicated various directions of the effects. The study of Ketterer (2014) shows that intermittent wind electricity generation increases the price volatility in the German market. This is in line with the analysis of Rintamäki, Siddiqui, and Salo (2017) in terms of the German market. However, they find that wind power generation decreases the price volatility in the Danish market. Similarly, Dong et al. (2019) also find that the Danish market presents a low price volatility with a major usage of wind generation, and they argue that this is potentially because Norway's hydro production is backing up the Danish system when wind generation is not able to fulfill the demand.

These findings regarding both electricity price mean and volatility above shed light on the importance of back-up technology in the increasing production of renewable sources. The analysis of Hirth (2013) addresses that complementary technologies, such as gas-fired plants and biomass, are crucial to fill the gap at mid and peak load hours when IRES is not able to fulfill the demand. After observing a declining trend in marginal effects of renewables on electricity prices in Spain, Gelabert, Labandeira, and Linares (2011) put forward one potential reason that, along with the growing renewable generation, the increasing participation of lower marginal cost gas power plants instead of higher cost coal production has contributed to flatten the supply curve.

3.1.3 Empirical Approach in Electricity Market Study

Various empirical approaches are applied to untangle the relationship between the employment of IRES and electricity prices. Some studies use fundamental models to simulate market prices, such as an agent-based approach (Wehinger, Galus, and Andersson 2010; Wang et al. 2008), an approach based on the economics of power production and consumption (Pirrong and Jermakyan 2008). Clò, Cataldi, and Zoppoli (2015) build an OLS regression model to examine the merit-order effect of solar and wind generation in the Italian electricity market during 2005-2013.

Many studies use econometric techniques including time series analysis. When analyzing electricity price series, its nature of high heteroskedasticity and high autocorrelation is often considered. Autoregressive moving average models (ARMA) and generalized autoregressive conditional heteroskedasticity models (GARCH) are widely used in electricity price studies. Worthington and Higgs (2010) undertake a comprehensive literature review on models used in electricity price studies, including both univariate and multivariate models, and this study suggests an increasing usage of ARCH and GARCH models to assess the persistence and volatility of electricity price series.

Based on time series analysis with seasonally adjusted autoregressive moving average (SARMA) models, Rintamäki, Siddiqui, and Salo (2017) compare Danish and German electricity market data at peak and off-peak hours, and assesses how variable renewable energy generation affects electricity price volatility. Macedo, Marques, and Damette (2021) measure the influence of wind power and cross-border electricity flow on the mean and volatility of electricity price, by building 24 hourly models with a SARMAX/GARCH method. To take the nature of electricity price into account, the SARMAX/GARCH model approach is used in this study to estimate the mean and volatility of electricity prices.

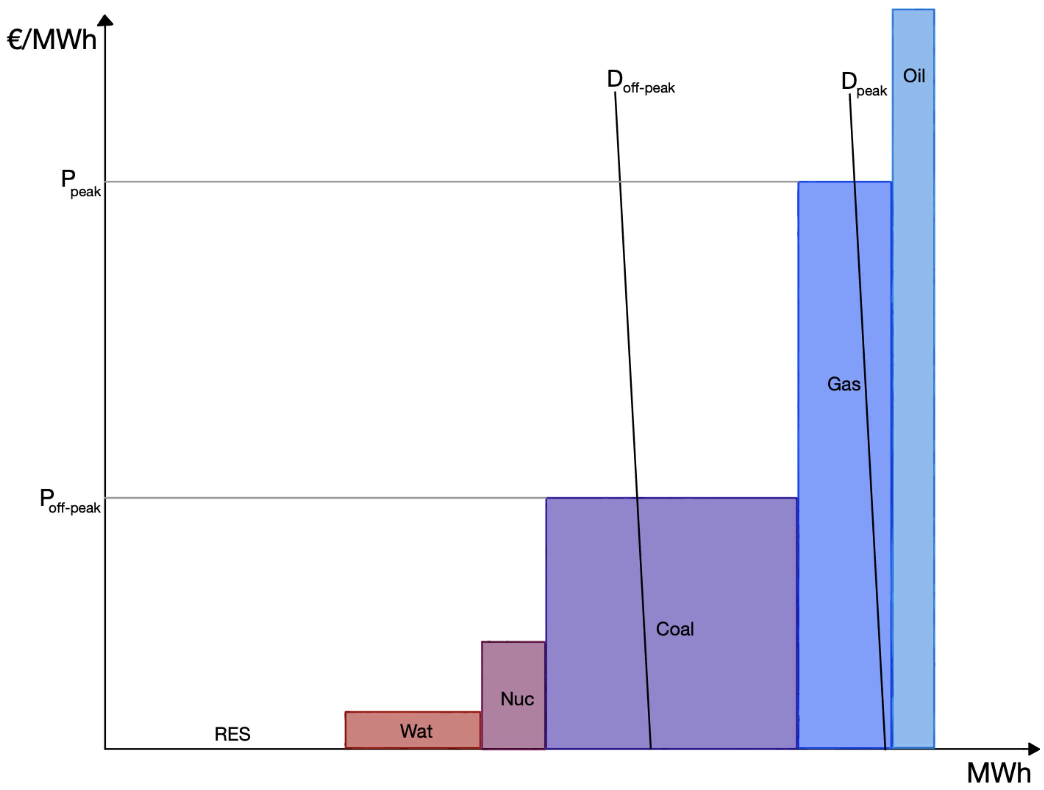
3.2 Hypotheses

As is presented in existing literature, there is a well-documented relationship between gas and electricity price, as well as between IRES and electricity price. EU's energy transition, in which IRES plays a major role, aims to mitigate the reliance of electricity production on fossil fuels and improve energy security against fluctuating supply of fossil fuels. However, judging from its current reliance on backup technologies, does IRES truly contribute to mitigating electricity's dependence on natural gas?

More precisely, we aim to analyze how IRES affect gas price fluctuations' influence on electrity price. To untangle this relationship, we proceed with two steps. Firstly, we test whether gas price presents different effects on electricity price under the usage of IRES.

We apply an identification strategy on the basis of intraday demand variation and merit-order dispatch. We expect to see gas price present different effects between peak and off-peak hours. This strategy is inspired by the observation of Duso, Szücs, and Böckers (2020) in Germany. While off-peak prices reflect marginal cost of the highest-cost plant, energy providers possess stronger market power during peak hours. As shown in Figure 3, electricity supply curve presents high convexity, and it intersects the peak demand curve at a steeper fragment than the off-peak one. That is to say, a shock from supply side renders a larger effect during peak hours.

Figure 3: Visualization of the Dispatch System in Germany



Note: Stylized visualization of the German dispatch system, inspired by Gugler and Haxhimusa (2019). Graph by the authors.

During off-peak hours with a lower demand, IRES with low cost profiles are used first whereas the more expensive gas is only used if IRES and other, cheaper, back-up generation technologies, e.g. hydro, cannot provide the marginal demanded unit. During peak hours with a higher demand, IRES and gas are likely to produce electricity simultaneously to fulfill the high demand. Hence, we specify two models separately for peak and off-peak hours and expect to see gas price present a lower or zero effect on electricity price mean and volatility at off-peak hours than at peak hours.

Secondly, we further study the interaction of IRES generation and gas price. Directions of the interaction can be divergent. To identify the scale of the effects, we specify an OLS regression model including an interaction term of IRES production and gas price. We expect a negative coefficient of the interaction term, because even though increasing IRES emphasizes the role of natural gas as back-up technology, its merit-order effect might still serve to reduce the overall influence of gas price on electricity price.

4 Method

Based on the different hypotheses we aim to test, two methods are employed accordingly. Firstly, we use SARIMAX/GARCH models to explain the characteristics of electricity price series and compare the differences of explanatory variables between peak and off-peak hours. Secondly, we use OLS estimations with interaction terms to capture the joint effect of gas price and IRES.

4.1 SARIMAX/GARCH Model

The SARIMAX model belongs to the autoregressive moving average (ARMA) model family. ARMA stands out in time series study for its flexibility and capacity to describe most features of a stationary time series (Woodward, Gray, and Elliott 2017). The autoregressive parts of these models explain how consecutive observations are influenced by their own previous values while the moving average parts capture some possible unobserved shocks. In this research, to include the seasonality feature of electricity and exogenous regressors accounting for price formation, we use the SARMAX framework proposed by Box et al. (2015). Considering the results of the unit root tests later reported in Section 5, we incorporate an integration order, which gives us the final SARIMAX structure. We follow the notation of Macedo, Marques, and Damette (2021) and present their model below. The SARIMAX model we pursue is essentially the same as the SARMAX model shown below, with the addition that the variables are differenced.

$$P_{t,h} = + \sum_{j=1}^{p_h} \phi_j P_{t-j} + \sum_{i=1}^{P_h} \Phi_j P_{t-s_h} + \sum_{i=1}^{P_h} \Phi_i \sum_{j=1}^{p_h} \phi_i P_{t-j-s_h} + \sum_{j=1}^{q_h} \varphi_j \varepsilon_{t-j} + \sum_{z=1}^{Q_h} \Psi_z \varepsilon_{t-s_h} + \sum_{z=1}^{Q_h} \Psi_z \sum_{j=1}^{q_h} \varphi_z \varepsilon_{t-j-s_h} + \sum_{l \in k} \delta_l X_{t,l} + \varepsilon_t, \tag{4.1}$$

$P_{t,h}$ is our dependent variable, the average day-ahead electricity price for peak and off-peak hours respectively, which are denoted by h. Furthermore, s represents the seasonal term, k represents the information set, ϕ_p and φ_q respectively denote the non-seasonal AR- and MA-parameters, whereas Φ_P and Ψ_Q respectively denote the seasonal AR- and MA-parameters. X stands for the vector of the exogenous variables, δ their coefficients and l indicates the summation index of the exogenous regressors.

The GARCH model is introduced by Bollerslev (1986) to model time-varying volatility. GARCH models capture the error variance in ARMA models, and allow for past conditional variances in the current conditional variances. We use the same model proposed by Macedo, Marques, and Damette (2021) for the corresponding GARCH(p,q) variance equation:

$$\sigma_t^2 = \gamma + \beta \sigma_{t-1}^2 + \alpha \varepsilon_{t-1}^2 + \sum_{m \in r} \lambda_m Z_{t,m}, \tag{4.2}$$

where Z represents the vector of the exogenous variables and λ are the coefficients of them, m is the information set, and r stands for the summation index. The exogenous regressors include total load, cross-border flows, wind and solar generation, as well as gas price.

The GARCH error parameter α, also known as the ARCH parameter, assesses the impact of new shocks in a time series. The GARCH lag parameter β evaluates the impact of past shocks on future volatility. Combining both parameters, $\alpha+\beta$ measures the persistence of volatility, which indicates whether a shock has long-lasting influence in a time series. The stationarity of GARCH models is undermined when the value of $\alpha+\beta$ is greater than 1. The persistence of volatility is high if the value of $\alpha+\beta$ is around 1 and suggests that a shock possibly tend to revert slowly in a time series. The persistence of volatility is low if the value of $\alpha+\beta$ is substantially lower than 1 and indicates that a shock is likely to diminish quickly.

4.2 OLS Regression Model

We incorporate a secondary OLS approach to include interaction terms and nuance the results of the SARMAX models, and loosely establish our models on the basis of Clò, Cataldi, and Zoppoli (2015).

We firstly build a model including gas price and IRES generation as the explanatory variables. We then control for total load, inflow and outflow, denoted in the vector of exogenous regressors, X.

$$P_t = \alpha + \beta_1 IRES_t + \beta_2 Gas\,Price_t + \sum_{l \in k} \delta_l X_{t,l} + \varepsilon_t \tag{4.3}$$

We further add an interaction term between gas price and IRES generation, which is our main variable of interest, to assess the joint effects of them.

$$P_t = \alpha + \beta_1 IRES_t + \beta_2 IRES_t \times Gas\,Price_t + \beta_3 Gas\,Price_t + \sum_{l \in k} \delta_l X_{t,l} + \varepsilon_t \tag{4.4}$$

On the basis of above equations, we separate IRES generation into wind and solar to distinguish their individual effect on electricity price.

$$P_t = \alpha + \beta_1 Solar_t + \beta_2 Wind_t + \beta_3 Gas\,Price_t + \sum_{l \in k} \delta_l X_{t,l} + \varepsilon_t \tag{4.5}$$

Lastly, we incorporate interaction terms of gas price and wind and solar respectively, aiming to identify their influence separately.

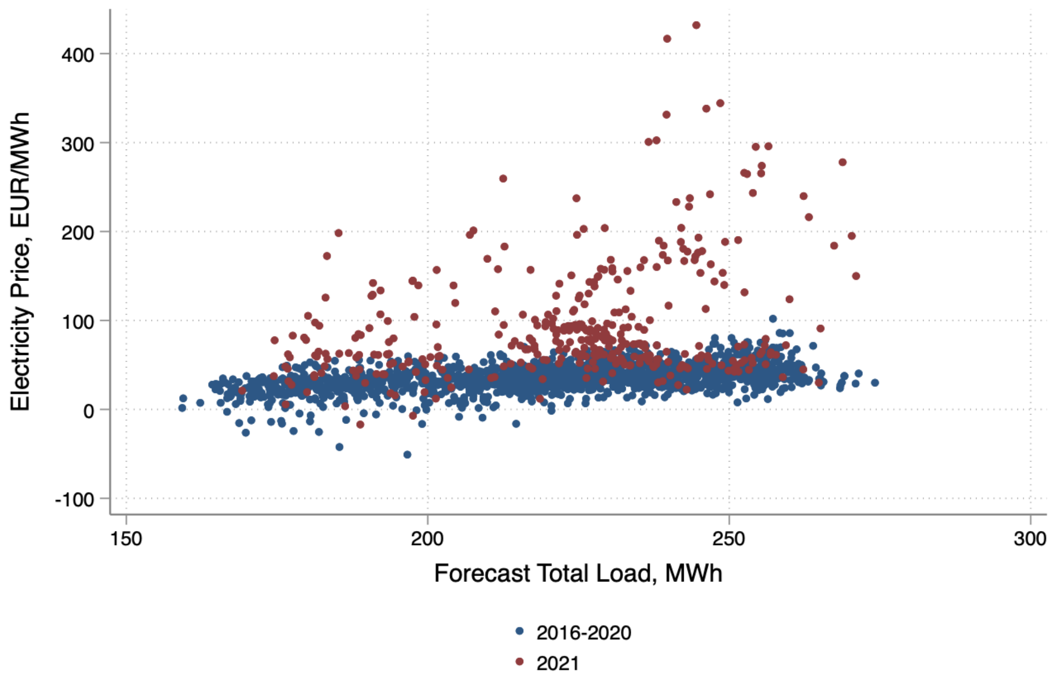
$$\begin{gathered} P_t = \alpha + \beta_1 Solar_t + \beta_2 Solar_t \times Gas\,Price_t + \beta_3 Wind_t \\ + \beta_4 Wind_t \times Gas\,Price_t + \beta_5 Gas\,Price_t + \sum_{l \in k} \delta_l X_{t,l} + \varepsilon_t \end{gathered} \tag{4.6}$$

5 Data

For our empirical analysis, time series for the German electricity market from January 1, 2016 to December 31, 2020 are used. The time series included are hourly electricity spot prices on the day-ahead market, the day-ahead forecast total quarter-hourly load, day-ahead forecast for hourly wind and solar generation, as well as actual cross-border flows of electricity, all obtained from the ENTSO-E Transparency Platform (ENTSO-E 2022). Additionally, the European Gas Index for Trade Hub Europe (EGIX THE) was obtained for the corresponding time period from Refinitiv Datastream. The electricity price is our dependent variable, with IRES generation, i.e. wind and solar generation, along with gas price as the main explanatory variables. As Clò, Cataldi, and Zoppoli (2015) note, IRES are non-programmable and therefore exogenous. Likewise, they claim our control variable for demand, total load, is exogenous as consumption is generally inelastic in response to electricity price. We refrain from including additional generation technologies as control variables out of worry for collinearity with existing generation and consumption variables. Front month futures gas price is used in this study as gas price in the long run is mostly affected by fuel price (Nick and Thoenes 2014; Asche, Misund, and Sikveland 2013), thus exogenous to electricity price. All time series are further defined in the variable description below.

The selected period of study is based on a combination of data availability and analysis feasibility. By going back to 2016, a sufficiently large sample for analysis is secured. The original sample included daily data up until the end of 2021, however the full year of 2021 was dropped because of the difficulty of studying it. The unprecedented spikes in both electricity and gas prices in 2021, shown in Figure 1, violate the stationary assumption of many time series approaches, further elaborated on in Section 5.4. Furthermore, 2021 seemingly constitute an outlier, as it is primarily the price variables that are affected by the spike, whereas load, generation, and cross-border flow variables remain fairly stable across the years. This is exemplified in Figure 4, showing the scatter plot of average daily electricity prices and average daily forecast total load for 2016–2020 and 2021 separately. Scatter plots of electricity prices and the rest of the variables are available in Appendix A.

Figure 4: Scatter Plot of Electricity Price and Forecast Total Load



Note: Data source: ENTSO-E Transparency Platform. Plot by the authors.

5.1 Variable Description

Electricity Price

The day-ahead hourly spot price (*Electricity Price*, €/MWh) used is the spot price for the German-Austrian-Luxembourgian bidding zone up until September 31, 2018, and for the German-Luxembourgian from October 1, 2018 onwards. This is a consequence of the German-Austrian bidding zone split due to congestion in the Austrian direction around the country border (APG, n.d.). Both series are obtained from the ENTSO-E Transparency Platform and combined to create a continuous price time series for the period of study.

Total Load Forecast

Forecast total load (*Total Load*, GWh) is the forecast total consumption, or demand for a given time period. We sum up the quarter-hourly observations to hourly data. The forecast total load is estimated based historic consumption and other demand-driving factors, such as weather conditions.

Wind, Solar, and IRES Generation Forecast

For the forecast wind and solar generation (*Wind*, GWh, and *Solar*, GWh), the quarter-hourly prognosis are summed up to hourly projected generation. The solar and wind generation is separated, the latter combining the prognosis for both onshore and offshore generation. The forecast generation is used instead of realized generation to better account for the formation of the spot price. For part of the analysis, a third variable (*IRES*, GWh) summing up the total of both the forecast wind and solar generation is created.

Cross-border Electricity Flows

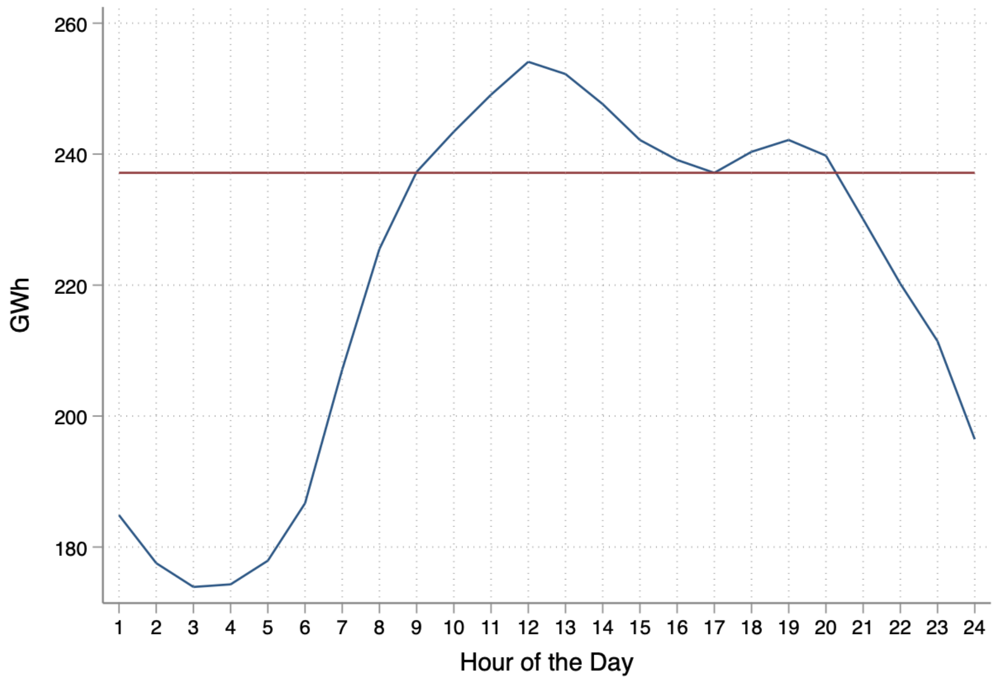
The actual cross-border electricity flows are included in two separate time series for inflow and outflow respectively (*Inflow*, GWh, and *Outflow*, GWh) across the German borders. The variables sum up the total actual flows to and from the connected grids in Austria, Belgium, the Czech Republic, Denmark, France, Luxembourg, the Netherlands, Norway, Poland, Sweden, and Switzerland. Although scheduled cross-border flows, rather than the actual flows, would be more relevant for the formation of the spot price, the latter is used due limited availability of the scheduled flows.

Gas Price

For the gas price (*Gas Price*, €/MWh), the daily European Gas Index for Trade Hub Europe (EGIX THE) is used. The daily index is a volume-weighted average price of all trades of front month natural gas futures on the specific Trade Hub Europe contract (EEX 2021).

5.2 Identifying Peak Hours

Figure 5: Average Day-ahead Forecast Total Load Across the Day



Note: Red line represents the median. Data source: ENTSO-E Transparency Platform. Graph by the authors.

We study daily averages, as well as averages for peak and non-peak hours separately, based on the hourly consumption patterns in Germany. Figure 5 shows the average day-ahead forecast for total load across the day. We note there is a strong pattern with electricity consumption peaking between 9 a.m. and 9 p.m. We use this graphical analysis to define peak hours as the 12 hours starting 9 a.m. – 8 p.m. Thus the remaining hours starting at 9 p.m. – 8 a.m. are regarded as off-peak hours. This definition is also in line with definitions used in previous research using a similar separation, such as Duso, Szücs, and Böckers (2020), who define their peak hours as the period between 8 a.m. and 8 p.m. in their study on the German electricity market. Similarly, in their study on the Swedish SE3 bidding zone, Macedo, Marques, and Damette (2021) consider the hours starting from 7 a.m. to 7 p.m. as peak hours.

5.3 Descriptive Statistics

Table 1: Descriptive Statistics

	Mean	Std.Dev.	Min.	Max.	Skewness	Kurtosis
Off-peak Hours						
Electricity Price	32.029	12.053	-56.388	73.659	-0.583	6.159
Total Load	196.464	20.197	148.555	253.043	-0.090	2.493
Inflow	3.763	1.973	0.628	12.009	1.204	4.273
Outflow	7.941	2.935	2.011	15.509	0.177	2.056
IRES	51.008	33.042	5.594	175.788	1.088	3.686
Solar	0.849	1.003	0.000	3.962	1.000	2.716
Wind	50.159	33.370	4.919	175.763	1.086	3.666
Gas Price	15.778	5.030	4.050	29.220	0.080	2.950
Peak hours						
Electricity Price	38.277	17.168	-65.941	130.184	-0.130	6.737
Total Load	243.257	28.683	167.862	297.204	-0.522	2.326
Inflow	3.117	1.842	0.337	11.133	1.181	4.508
Outflow	8.346	2.347	2.224	16.059	0.245	2.633
IRES	83.606	35.258	6.738	206.961	0.541	3.151
Solar	35.589	22.714	1.557	88.974	0.236	1.850
Wind	48.017	37.011	2.300	184.240	1.094	3.591
Gas Price	15.778	5.030	4.050	29.220	0.080	2.950
Total						
Electricity Price	35.153	15.156	-65.941	130.184	-0.040	7.063
Total Load	219.860	34.098	148.555	297.204	0.203	2.052
Inflow	3.440	1.935	0.337	12.009	1.180	4.403
Outflow	8.143	2.665	2.011	16.059	0.152	2.328
IRES	67.307	37.853	5.594	206.961	0.648	2.949
Solar	18.219	23.669	0.000	88.974	1.116	2.871
Wind	49.088	35.249	2.300	184.240	1.084	3.637
Gas Price	15.778	5.030	4.050	29.220	0.080	2.950

Note: The number of observations is 1,827 for all variables in every sample.

Table 1 reports the descriptive statistics of the calculated daily averages for peak and off-peak hours respectively, based on the definitions specified above, as well as for the total sample. We notice immediately that all of the electricity price time series take on negative values. A closer look at the data confirms that this is the case in 37 days for the peak series and 20 days for the off peak series, for a total of 45 days in the full sample. These observations are spread out evenly across the months of the year and the years in the sample with no apparent pattern. Negative prices are common in electricity market, due to the fact that for some generators it is more cost-efficient to continue producing at negative prices than shutting down and restarting again (Stanwell 2021). In addition to that, the forecast solar generation shows a minimum value of 0 in off-peak hours, as can be expected as there should be no solar generation in nighttime in winter.

5.4 Unit Root Tests

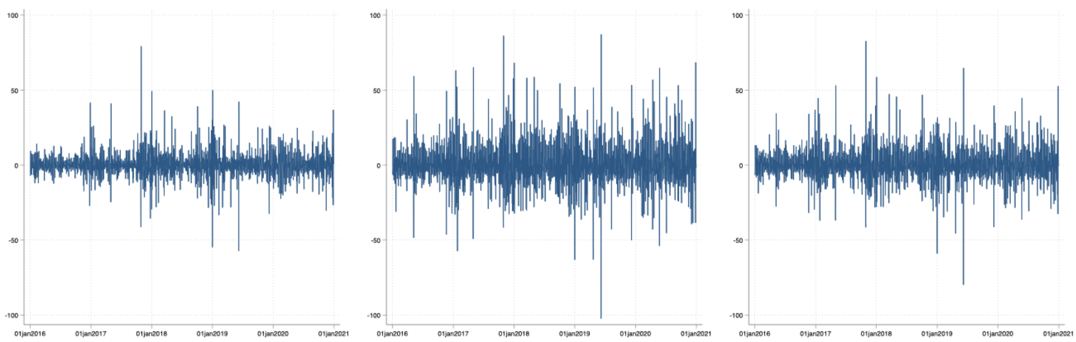
Classical regression models require both dependent and independent variables to be stationary, else there is risk for a so called spurious regression, whereby significant parameter estimates and high explanatory power might be achieved despite no actual, consistent effect existing (Enders 2015). Therefore we test all variable time series for the full sample, as well as for the peak and off-peak subsamples, for presence of unit roots using the Augmented Dickey-Fuller (ADF) test, as suggested by e.g. Clò, Cataldi, and Zoppoli (2015). The ADF tests the null hypothesis of a unit root in the time series against the alternative of a stationary time series.

The test statistics for the unit root tests are reported in detail in Appendix A. The results suggest that most variables are mean-stationary. In the full sample, forecast solar generation is the only variable not significant on a 1% level, but it is on a 5% level. This is also the case for the peak and off-peak samples, with the addition of the off-peak forecast total load series. The exception to all this is the gas price, which neither is mean-, nor trend-stationary, for any of the samples, providing difficulty for the progression of the analysis.

Transformations of time series are common in order to circumvent problems with non-normality and noise in data that can result in non-stationarity. The logarithmic transformation has desirable qualities when it comes to result interpretation, as parameter estimates are expressed as elasticities. However, the presence of subzero observations hinder this transformation of the data. Macedo, Marques, and

Damette (2021) face the same challenge, but circumvent this problem by adding a constant of one to all variables, as suggested by Lagarde and Lantz (2018). Noteworthy is that the Swedish electricity prices studied by Macedo, Marques, and Damette (2021) never fall below –1 €/MWh, rendering the effect of such a transformation on the subsequent analysis limited. In our sample, a similar transformation would involve adding a constant of a minimum of 66, whereas the means of electricity price samples range in the 30s. Lagarde and Lantz (2018) likewise face larger negative values and point out that adding a larger value to make the time series strictly positive risk compressing higher price values and shifting more weight to the lower prices. Given the importance of a continuous time series we cannot remove the days for which negative prices appear, although they only make up approximately 2.5% of the sample. Therefore, we proceed with taking the first difference of all variables instead, effectively studying the daily changes in them.

Figure 6: First Difference of Off-peak, Peak, and Total Electricity Price Time Series



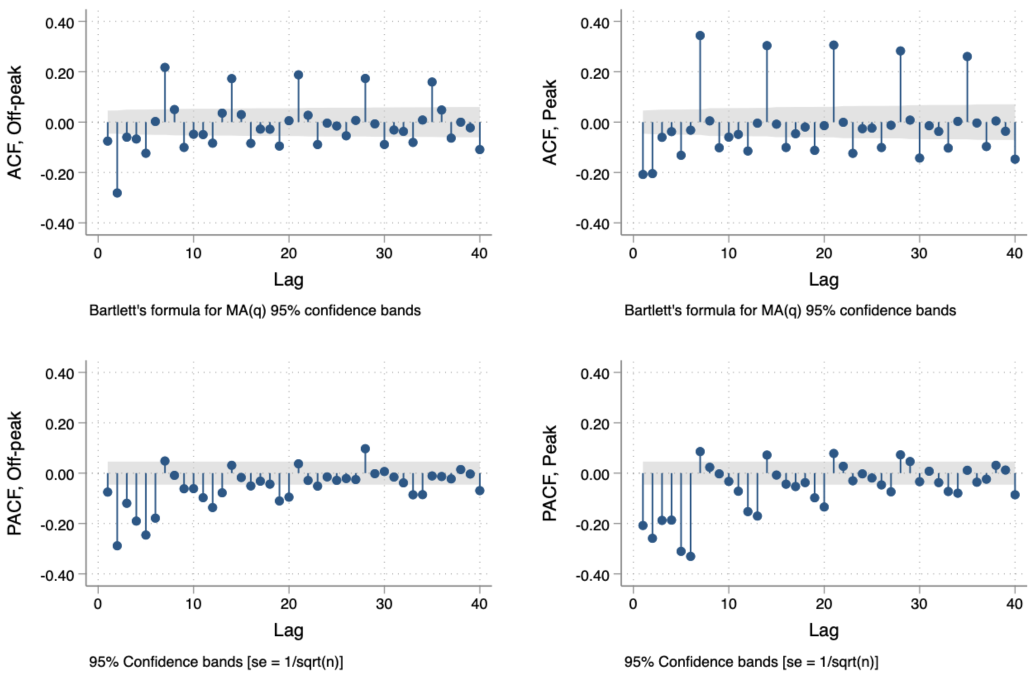
Note: Panels graph the first-differenced electricity price for off-peak, peak and total time series, in order from left to right. Data source: ENTSO-E Transparency Platform. Graph by the authors.

The first differences of all variables, including gas price, are suggested to be stationary in ADF tests, also reported in Appendix A, and used in subsequent analysis. The transformed electricity price time series are presented in Figure 6 and we can see that the average off-peak electricity price (Panel 1) seems to be substantially less volatile than the average peak electricity price (Panel 2). The full sample average electricity price (Panel 3) reasonably seems to smooth out the differences between the subsample averages.

5.5 SARIMAX Model Selection

In order to determine the SARIMAX model we use in our analysis, we first plot autocorrelation (ACF) and partial autocorrelation functions (PACF) of the time series. In Figure 7 the ACF and PACF plots for the respective differenced German off-peak and peak average electricity price time series are displayed. The ACF plots display a recurring seasonal pattern, corresponding to the day of the week, as there are spikes at 7, 14, 21, and 35, with the data being of daily frequency. The PACF plots shows the partial autocorrelation, controlled for other lags, where mentioned seasonality is less pronounced. However, there seems to exist some significant negative autocorrelation over the first seven days.

Figure 7: Autocorrelation and Partial Autocorrelation Function Plots of Differenced Off-peak and Peak Time Series



Note: Data source: ENTSO-E Transparency Platform. Plots by the authors.

The model selection used for the analysis of the respective time series is based on the Bayesian information criterion (BIC), also known as the Schwarz information criterion (SIC, SBIC). The model with a lower information criterion value than alternative models is supposed to be the most appropriate. An alternative information criterion often employed in time series analysis is the Akaike information criterion (AIC). Enders (2015) note that although both criteria punish additional regressors lacking explanatory power, the BIC is more restrictive on adding additional regressors. However, Enders (2015) concludes that the BIC is superior to the AIC in large samples. As our sample might be deemed to be with 1,826 observations (reduced by one from 1,827 due to the first-differencing), the AIC is prone to overfitting. Since the BIC favors a simpler model, we must be careful to check that the residuals of the model selected actually passes as white noise, which we do after our model selection.

Finding the best fitting model is a process of trial and error in minimizing the BIC-value. We start by estimating simple AR(1) and MA(1) models and thereafter add more lags until we find a model that results in the lowest BIC-value. As we are using a SARIMAX framework, we also allow for seasonal lags primarily set to 7 days, corresponding to a weekly lag, in the models, supported by the presence of such lags in the ACF and PACF plots.

For the off-peak electricity price time series, the BIC suggests a SARIMAX(0, 1, 1/2)(0, 0, 1) model out of the multitude of model specifications that we test. The first parentheses define the normal ARIMA-lags and the order of integration, which is one, since we are dealing with first-differenced data. The second pair of brackets set the seasonal lags, set to a seasonality of 7. For the peak electricity price time series modelling the model selection results in a SARIMAX(10, 1, 1/2)(1, 0, 0). The estimated models are presented in full in Table 2 in Section 6.

After model selection we study the ACF and PACF plots of the predicted residuals, to make sure we cannot detect any autocorrelation. These plots are presented in Appendix B. We also carry out the Ljung-Box Q-test for serial correlation in the standardized residuals for up to 40 lags. We cannot reject the null hypothesis of the residuals behaving like white noise and not being serially autocorrelated. Finally, we check the inverse roots of the ARMA polynomials, likewise available in Appendix B, and find that they all lie within the unit circle for both models, which indicates that the estimated models are stationary. We therefore conclude the models to be appropriate for our analysis.

6 Results

6.1 SARIMAX/GARCH

We first present the results from the SARIMAX model estimations in Table 2 and the GARCH model estimations in Table 3. As all variables have been first-differenced, the interpretation of the estimated coefficients represent the effect of a one unit increase in the daily change of the independent variable on the daily change of the dependent variable, electricity price, conditional on the lagged variables of the SARIMAX estimation. The results suggest there are differences in the explanatory power of the exogenous variables on the daily change in average electricity price across peak and off-peak hours. All exogenous regressors, as well as the lagged ARMA-parameters, are significant on a 1% significance level across both the off-peak and peak electricity price mean equations, with the exception of forecast solar generation and outflow.

The results show that electricity price is significantly positively driven by the daily increase of gas price at both off-peak and peak hours. Nonetheless, the magnitude of gas price's influence on the electricity price is substantially larger at peak than off-peak hours. While a 1 €/MWh rise of daily change in gas price increases the daily change of electricity price by 0.572 €/MWh at off-peak hours, the increase is 0.862 €/MWh at peak hours. Meanwhile, the daily increase of gas price makes electricity price more volatile in both peak and off-peak hours, and shows a similar pattern as how it affects the mean price, where a larger influence is observed at peak hours and off-peak hours.

The daily change of forecast load is shown to have a significant increasing effect on the electricity price mean, and the effects are of similar magnitude between peak and off-peak hours. When the daily change of forecast load shift positively for 1

Table 2: Mean Equation

	Off-Peak	Peak
D.Total Load	0.270***	0.294***
	(0.008)	(0.008)
D.Inflow	-0.467***	-0.504***
	(0.103)	(0.144)
D.Outflow	0.731***	-0.386***
	(0.093)	(0.124)
D.Solar	-0.243	-0.241***
	(0.404)	(0.019)
D.Wind	-0.295***	-0.274***
	(0.005)	(0.008)
D.Gas Price	0.572***	0.862***
	(0.167)	(0.248)
Constant	0.009	0.009
	(0.018)	(0.023)
ARMA		
L.ma	-0.535***	-0.661***
	(0.011)	(0.013)
L2.ma	-0.319***	-0.205***
	(0.018)	(0.016)
L10.ar		-0.084***
		(0.021)
ARMA7		
L.ma	0.060***	
	(0.022)	
L.ar		0.086***
		(0.019)
sigma		
Constant	4.120***	6.350***
	(0.037)	(0.056)
Observations	1826	1826
AIC	10375.629	11957.747
BIC	10436.238	12023.865
$Q_{LB}(40)$	39.256	26.446
	[0.504]	[0.951]

Standard errors in parentheses. Daily change in day-ahead electricity prices. Electricity and gas price measured in €/MWh, all other variables in GWh. P-value of Q-statistic in square brackets.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Volatility Equation

	Off-Peak	Peak
D.Total Load	0.242***	0.282***
	(0.006)	(0.007)
D.Inflow	-0.421***	-0.382***
	(0.098)	(0.131)
D.Outflow	0.567***	-0.316**
	(0.079)	(0.124)
D.Solar	-0.714***	-0.245***
	(0.276)	(0.017)
D.Wind	-0.264***	-0.266***
	(0.004)	(0.007)
D.Gas Price	0.590***	0.885***
	(0.160)	(0.227)
Constant	-0.008	-0.013
	(0.017)	(0.023)
ARCH		
L.arch	0.401***	0.228***
	(0.030)	(0.023)
L.garch	0.183***	-0.069
	(0.049)	(0.046)
Constant	7.456***	34.196***
	(0.529)	(1.622)
Observations	1826	1826
AIC	9983.974	11814.380
BIC	10055.602	11891.519

Standard errors in parentheses. Dependent variable: Conditional variance of daily change in day-ahead electricity prices. Electricity and gas price measured in €/MWh, all other variables in GWh.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

GWh, the daily change of electricity price increases by 0.270 €/MWh at off-peak hours and 0.294 €/MWh at peak hours. Similarly, daily change of forecast load increases electricity daily change volatility homogeneously at peak and off-peak hours.

Increasing forecast solar generation presents different effects between peak and off-peak hours. As expected, forecast solar generation is not significant in explaining the electricity in off-peak hours, mainly because of definition of off-peak hours as 9 p.m. - 8 a.m., hours where there would be no sunshine in Germany for large parts of the year. In contrast, a 1 GWh increase of its daily change brings down electricity price daily change by 0.241 €/MWh at peak hours. Meanwhile, even though forecast solar generation decreases the volatility of the electricity price in general, it shows a larger effect at off-peak hours than peak hours. This could perhaps be due to the fact that any solar generation in off-peak hours would coincide with early mornings and late evenings in summertime. These are also the hours of the highest load during the off-peak hours, as can be seen in Figure 5, and any solar generation could suppress prices during relatively high loads, compared to the rest of off-peak sample.

However, increasing forecast wind generation displays homogeneous effects between peak and off-peak hours. A 1 GWh increase of forecast wind generation change decreases the electricity price change by 0.295 €/MWh at off-peak hours and 0.274 €/MWh at peak hours. Besides, increasing forecast wind generation decreases volatility of the electricity price daily change similarly at off-peak and peak hours.

Inflow likewise appears to have homogeneous decreasing effects on both mean and volatility of the electricity price at off-peak and peak hours. However, the influence of outflow on electricity price daily change show distinctly different directions between off-peak and peak hours. While an increase of 0.731 €/MWh is seen at off-peak hours, a decrease of 0.386€/MWh is observed at peak hours, in response of a 1 GWh rise of the change in outflow. Similarly, cross-border outflows increases the electricity price volatility at off-peak hours but decreases the volatility at peak hours.

Both the α and the β estimates are higher during off-peak hours than peak hours, with β not even being significantly different from null for the peak hour estimation. The α parameter, measuring the impact of new shocks, is larger than β, measuring the impact of past shocks, the in both peak and off-peak hours. The persistence of volatility, measured as the sum of α and β, in daily change in day-ahead electricity price is on a relatively low level, not even close to 1, during both peak and off-peak hours, which means the electricity price series presents a short memory pattern. A higher degree of persistence is found during off-peak hours ($\alpha+\beta = 0.584$) than peak hours ($\alpha + \beta = 0.228$, as β is not significant), so a shock is likely to have a larger effect on off-peak volatility.

Although the estimates from the SARIMAX model are generally in line with expectations, the interpretation of them suffers from some non-intuitivity because of the lagged variables that condition them. Therefore we proceed with an OLS regression, in order to compare estimates and nuance them with a different approach.

6.2 OLS Regression with Interaction Terms

Table 4 presents the results of the complimentary OLS regression analysis. We use the same variables as in the previously presented SARIMAX/GARCH estimation, with the addition of the IRES variable, summing up the wind and solar generation. Instead of separating the analysis into different models for peak and off-peak hours, we use interaction terms of gas price and wind and solar generation, and IRES generation respectively, in order to estimate the magnitude of the joint effect. We also employ a set of dummies (DMY) for the day of the week, month of the year, as well as year, to control for time fixed effects.

To check for serial correlation in the regression residuals, we employ the Durbin-Watson test and Durbin's alternative test, as suggested by Clò, Cataldi, and Zoppoli (2015). The Durbin-Watson test statistic range from 0 to 4, with a statistic of 0 indicating perfect positive correlation, and a statistic of 4 suggesting perfect negative correlation of the error terms. A test statistic close to 2 suggest no serial correlation of the residuals. The Durbin-Watson test on the original

Table 4: Regressions of Differenced Time Series

	(1)	(2)	(3)	(4)
D.Total Load	0.293***	0.293***	0.293***	0.293***
	(0.027)	(0.027)	(0.027)	(0.027)
D.Inflow	-0.225	-0.227	-0.210	-0.213
	(0.179)	(0.179)	(0.182)	(0.183)
D.Outflow	0.071	0.071	0.067	0.065
	(0.152)	(0.152)	(0.152)	(0.153)
D.Gas Price	0.444	0.426	0.443	0.434
	(0.325)	(0.338)	(0.325)	(0.338)
D.IRES	-0.278***	-0.278***		
	(0.010)	(0.010)		
D.IRES × D.Gas Price		0.004		
		(0.014)		
D.Solar			-0.257***	-0.257***
			(0.026)	(0.026)
D.Wind			-0.277***	-0.277***
			(0.010)	(0.010)
D.Solar × D.Gas Price				-0.030
				(0.045)
D.Wind × D.Gas Price				0.005
				(0.014)
Constant	-1.036	-1.041	-1.032	-1.042
	(0.666)	(0.667)	(0.667)	(0.668)
DMY Dummies	YES	YES	YES	YES
R^2	0.761	0.761	0.761	0.761
Adjusted R^2	0.758	0.758	0.758	0.757
F	121.601	117.093	116.934	108.839
rho	-0.312	-0.312	-0.311	-0.311
Durbin-Watson	2.163	2.163	2.163	2.162
Durbin-Watson, orig.	2.620	2.620	2.616	2.616
Observations	1826	1826	1826	1826

Robust standard errors in parentheses. Dependent variable: Daily change in day-ahead electricity price. Electricity and gas prices measured in €/MWh, all other variables in GWh.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

regression, which statistic is found in 4, denoted as Durbin-Watson, orig., shows sign of negative serial correlation across all four models. Likewise, we reject the null hypothesis of no serial correlation with Durbin's alternative test. Like Clò, Cataldi, and Zoppoli (2015), we mitigate this problem by using the Prais-Winsten estimation, which models the residuals to follow a first-order autoregressive model as follows:

$$\varepsilon_t = \rho\varepsilon_{t-1} + \omega_t \tag{6.1}$$

where $|\rho| < 1$ and ω resembles a white noise process. The presented results are the rerun results and the new Durbin-Watson test statistic (denoted Durbin-Watson in Table 4), very close to 2, suggests the serial correlation is amended. The values of ρ are also in the required range.

Models 1 and 2 of Table 4 show the regressions using first IRES, and then IRES in combination with an interaction term with the gas price. The corresponding specifications are run in Models 3 and 4 for the wind and solar variables separately. Comparing the coefficient estimates to those of the mean equation of the SARI-MAX models, we see that the estimates for total load, as well as wind and solar, showcase significant coefficients of a similar magnitude. The coefficient for total load is estimated to 0.293 (0.242 and 0.282 respectively in Table 2). Solar and wind are estimated to –0.257 and –0.277 respectively (–0.241 and –0.295/–0.274).

In contrast, inflow, outflow, and gas price, and in extension the interaction terms of the gas price, are not significant in explaining the daily change in the electricity price. The insignificance of the inflow and outflow estimates are further elaborated on in Section 7. Although the direction of the gas price is as expected, the lack of significance is worrying. Natural gas-burning being one of Germany's major power generation technologies, the gas price is expected to have a significant, positive effect on electricity prices, as the price of the input should influence the end price. Taking first differences of the variables reduces the variance in the series, which means that we in our transformation lose information that could be of importance.

The combination of natural gas being storable and our usage of a daily index for next month gas deliveries for our gas price suggest that we have less volatility in the gas prices than electricity prices. The daily change in the gas index does not appear to explain daily changes in the German electricity price, but eyeing Figure 1 suggests there is still certain correlation between gas and electricity prices, as previous literature has established, e.g. Clò, Cataldi, and Zoppoli (2015). Thus, we proceed with estimating the mean electricity price with the non-transformed variables, but take caution in the interpretation of the results.

Table 5 reports the results of the OLS regression with the variables in levels. The corresponding model specifications tested in Table 4 are presented in the same order. The Durbin-Watson test and Durbin's alternative test are carried out again and show similar results, despite indicating positive serial correlation this time around, motivating the repeated use of the Prais-Winsten estimation. Comparing Tables 4 and 5, we see that the adjusted R^2 values barely change, increasing from 76% to 77%, suggesting that the non-transformation of the variables does not radically change explanation of variance in the dependent variable.

The coefficent estimates for total load, as well as forecast IRES, wind, and solar generation remain significant on a 1% level and of approximately the same magnitude. That is reassuring, as estimates of the first-differenced series should reflect the relationship of the non-differenced variables. The electricity price is increasing in total load, and decreasing in IRES, wind, and solar generation. The coefficient estimates of inflow and outflow remain significant, as before.

However, the coefficient of gas price is now significant and positive, which suggests that the day-ahead electricity spot price is increasing in gas price. Likewise are the interaction terms, interacting gas price with IRES, wind, and solar, respectively, significant. The interaction estimates range from -0.006 for forecast IRES and wind generation, to -0.017 for solar generation. These results suggest IRES dampen the effect of gas price on electricity price, supported by the increase of 0.434 (0.703) in the pure gas price coefficient estimate moving from the first (third) to the second (fourth) regression specification.

Focusing on the second regression specification, the interaction term estimate of -0.006 might seem very small. However, both interaction variables are continuous, which complicates the interpretation of the coefficient, as the marginal effect of

Table 5: Regressions of Non-differenced Time Series

	(1)	(2)	(3)	(4)
Total Load	0.277***	0.271***	0.279***	0.274***
	(0.027)	(0.026)	(0.027)	(0.026)
Inflow	-0.137	0.037	-0.108	0.041
	(0.148)	(0.139)	(0.150)	(0.142)
Outflow	0.193	0.181	0.188	0.181
	(0.148)	(0.147)	(0.149)	(0.147)
Gas Price	1.537***	1.971***	1.549***	2.252***
	(0.153)	(0.145)	(0.153)	(0.181)
IRES	-0.281***	-0.182***		
	(0.009)	(0.026)		
IRES × Gas Price		-0.006***		
		(0.001)		
Solar			-0.230***	0.014
			(0.026)	(0.063)
Wind			-0.280***	-0.181***
			(0.009)	(0.026)
Solar × Gas Price				-0.017***
				(0.004)
Wind × Gas Price				-0.006***
				(0.001)
Constant	-43.475***	-49.543***	-44.154***	-54.648***
	(6.314)	(6.297)	(6.359)	(6.365)
DMY Dummies	YES	YES	YES	YES
R^2	0.772	0.778	0.773	0.780
Adjusted R^2	0.769	0.774	0.769	0.777
F	154.232	162.690	148.528	154.651
rho	0.509	0.502	0.509	0.494
Durbin-Watson	2.089	2.083	2.085	2.073
Durbin-Watson, orig.	1.020	1.035	1.020	1.055
Observations	1827	1827	1827	1827

Robust standard errors in parentheses. Dependent variable: Day-ahead electricity price.
Electricity and gas prices measured in €/MWh, all other variables in GWh.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Interaction Term Effect

IRES	Interaction Size	Marginal Gas Price Effect
0	0.000	1.971
50	-0.300	1.671
100	-0.600	1.371
150	-0.900	1.071
200	-1.200	0.771

Calculations based on coefficients of IRES and gas price interaction term from Model 2 in Table 5. IRES denoted in GWh and interaction size and marginal gas price effect given in €/MWh.

one of the interacting variables increases in the other variable. Table 6 shows the estimated effect of the interaction coefficient, as well as the estimated total effect, for a one euro increase the gas price, for different levels of IRES generation. As can be seen in the descriptive statistics (Table 1), forecast IRES generation ranges between roughly 6 and 207 GWh, with a mean of 67 GWh. We therefore calculate the estimated effects for forecast IRES generation in 50 GWh intervals between 0 and 200 GWh. For a below mean IRES generation of 50 GWh, the marginal effect of gas price is reduced by 0.30 €/MWh to 1.67 €/MWh. A forecast IRES generation of 150 GWh almost halves the marginal gas price effect.

6.3 Robustness to Oil Price and Year-effects

The concern for oil price being the underlying driver of the positive effect of gas price on electricity price warrant the inclusion of oil price in our regression specifications. Given studies like that by Asche, Misund, and Sikveland (2013), which credits the influence of oil prices on European natural gas prices, the concern is not unfounded. We obtain the daily European spot price for Brent oil, along with the average daily euro-dollar exchange rate, from Refinitiv Datastream in order to create our oil price control variable (*Oil Price*, €/bbl). The regression results for the variables of interest are presented in Table 7, with complete regression tables available in Appendix C. Oil price appears to have a signifcant and positive effect on electricity price, as could be expected, as oil is an input good to oil-fired power production. The results also suggest that the previously mentioned gas price and

Table 7: Regressions of Non-differenced Time Series, Including Oil Price

	(1)	(2)	(3)	(4)
Gas Price	1.422***	1.854***	1.433***	2.201***
	(0.164)	(0.156)	(0.163)	(0.180)
IRES	-0.281***	-0.186***		
	(0.009)	(0.026)		
IRES × Gas Price		-0.006***		
		(0.001)		
Solar			-0.228***	0.072
			(0.025)	(0.061)
Wind			-0.280***	-0.185***
			(0.009)	(0.026)
Solar × Gas Price				-0.021***
				(0.004)
Wind × Gas Price				-0.006***
				(0.001)
Oil Price	0.126***	0.112***	0.127***	0.155***
	(0.043)	(0.041)	(0.043)	(0.039)

Robust standard errors in parentheses. Dependent variable: Day-ahead electricity price. Electricity and gas prices measured in €/MWh, all other variables in GWh, except for oil price, which is denoted in €/barrel. Full Table available in Appendix C.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Yearly Regressions of Non-differenced Time Series

	(1) 2016	(2) 2017	(3) 2018	(4) 2019	(5) 2020
Gas Price	2.078***	3.266***	1.033**	0.133	1.118**
	(0.446)	(1.256)	(0.488)	(0.620)	(0.481)
IRES	0.285***	0.122	-0.205***	-0.270**	-0.230***
	(0.097)	(0.162)	(0.055)	(0.114)	(0.055)
IRES × Gas Price	-0.035***	-0.025***	-0.005**	-0.000	-0.001
	(0.007)	(0.008)	(0.002)	(0.006)	(0.005)

Robust standard errors in parentheses. Dependent variable: Day-ahead electricity price. Electricity and gas prices measured in €/MWh, all other variables in GWh. Full table available in Appendix C.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

interaction effects are not driven by oil price.

Lastly, we run the second regression specification, using the forecast IRES generation and its interaction term rather than the separate wind and solar generation variables, separately on the yearly samples. Despite including year-fixed effects in the previous regressions, we also want to acknowledge that the rapidly increasing share of IRES in the German electricity production, as shown in Figure 2, could result in changing effects of IRES on electricity price over time. A selection of the results is presented in Table 8 and the complete regression results can be found in Appendix C. The results are ambiguous, but indicate that the full sample regression results could be driven by effects found in 2016 and 2017, for which the gas price coefficient is relatively high and significant on a 1% level. The interaction term coefficient is negative and significant only for the years 2016-2018. The IRES coefficient estimate remains the most stable one, corresponding to the levels observed in our previous approaches, except for in 2017.

7 Discussion

The results presented in the previous section have three major implications. Firstly, we can confirm the already established merit-order effect (MOE) in our specific sample. Secondly, we find different effects of gas price on electricity prices in peak and off-peak consumption hours. Thirdly, we cannot confirm our hypothesis of IRES reducing the impact of gas prices on electricity prices.

The MOE entails IRES, with low to no marginal costs in power production, offsetting more expensive electricity generation technologies, such as fossil fuel burning, and thus reducing the electricity price (Krohn, Morthorst, Awerbuch, et al. 2009; Woo et al. 2011; Sensfuß, Ragwitz, and Genoese 2008). We estimate the MOE per 1 GWh increase of forecast wind and solar generation to ranges of 0.277–0.295 €/MWh and 0.230–0.257 €/MWh respectively, and to 0.278–0.281 €/MWh per 1 GWh increase for the summed up forecast IRES generation, across both our SARIMAX and OLS regression models. The mitigating, negative effect of wind generation on the level of electricity prices is already proved for electricity prices in the Swedish BZ3 (Macedo, Marques, and Damette 2021), as well as in Germany during the period from 2006 to 2012 (Ketterer 2014). Considering the nature of solar energy, and our definitions of peak and off-peak hours, it is well-anticipated that solar generation shows distinct effects between peak and off-peak hours, as seen in Table 2. While it has a significant, reducing effect on electricity price during peak hours, it does not show any significant effect during off-peak hours, which are mostly times without daylight. Comparing our estimates for the MOE to a study by Clò, Cataldi, and Zoppoli (2015) on the Italian electricity market from 2005 to 2013, we find that their estimates for the suppressing effects are roughly 10–15 times larger than ours. They estimate a 1 GWh increase in wind and solar generation to reduce electricity prices with 4.2€/MWh and 2.3€/MWh respectively. The sizeable difference in the estimates could be tied to either the different markets of study, or to the fact that we study different time periods. The IRES technologies have developed rapidly over the last decade and differences in the technology mixes as well as in the IRES penetration of the electricity generation can result in remarkably different effects due to the merit-order dispatch system.

Volatility of IRES generation is often a concern when it comes its effects on electricity prices. We find that both forecast wind and solar generation reduce the volatility of Germany electricity prices, as shown in Table 3. This in line with the finds of Rintamäki, Siddiqui, and Salo (2017) for the Danish market 2010-2014. However, the same study find that wind generation increases electricity price volatility in Germany 2012-2014, as the impact is stronger during off-peak hours. Ketterer (2014) also finds that wind generation drives volatility in 2011 and 2012. Meanwhile, Rintamäki, Siddiqui, and Salo (2017) claim solar generation reduces volatility in Germany. The accessibility to back-up electricity generation is vital for an integrated power system with a large share of IRES. For example, hydro production from Norway backs up the Danish market (Dong et al. 2019), which could explain why intermittency in Danish wind production does not increase electricity price volatility. The volatility effect of wind production is inconclusive in the study of the Swedish BZ3 by Macedo, Marques, and Damette (2021). They report that nuclear production is still vital in Sweden and also provides electricity at low marginal costs, but it is not very fit as back-up. The stable supply of relatively cheap electricity, however, could explain why there is neither a clear positive, nor negative effect on electricity price volatility from wind generation. Our contrasting results of the volatility effect of wind generation on the German market, as compared to previous studies, could either be a result of more mature and diversified IRES infrastructure evolved over time, as we study a later time period. With combinations of on-shore and off-shore wind parks in different regions, wind generation is diversified. Increased solar generation, supported by Figure 2 reducing peak load electricity prices, also suggests the skewed impact of wind generation on off-peak hours is reduced.

Our analysis based on the SARIMAX/GARCH model suggest that gas prices are positively correlated with electricity price, similar to the findings of Linn, Muehlenbachs, and Wang (2014) and Alexopoulos (2017) on the U.S. market. Mosquera-López and Nursimulu (2019) also find a positive effect of gas prices on electricity prices, although they find the impact is larger on electricity futures, rather than on the day-ahead electricity market. Furthermore, the estimated effect in our sample is larger during peak hours than in off-peak hours. This is in line with our hypothesis, as we base our peak hour definition on the average total load. The merit-order dispatch system in the electricity market determines that while IRES is used first in both peak and off-peak hours, the more expensive natural gas only comes into play as back-up production when IRES or other non-intermittent renewables, such as hydro, cannot fulfill the demand. Arguably, this results in different influence of gas price on electricity price during peak and off-peak hours.

Nonetheless, the fact that gas price has a significant and non-negligible effect on electricity price during off-peak hours implies generation without natural gas is not sufficient enough to deliver the off-peak demand. We think this might be explained in two ways. One is related to inherent nature of volatility IRES generation. While solar generation is generally not available in evenings, wind generation also experiences unpredictable fluctuations. For example, nights in summer are in generally less windy than other times due to air temperature conditions (Brown, Katz, and Murphy 1984). Thus, the difficulty to generate electricity in the evening- and nighttime, which our off-peak hours analysis accounts for, requires natural gas-fuelled electricity production. The other possible explanation is that the current IRES penetration in Germany is not adequate for off-peak, following our definition, demand at all hours.

However, the influence of gas price is less clear in our OLS regression approach. The coefficient estimates are positive, suggesting high gas prices are consistent with higher electricity prices, but they are not consistently statistically significant, which is further proved in the robustness checks. This also translates into ambiguity into interpreting the effect of the interaction of gas price and IRES generation. The direction of the interaction estimates suggest that IRES generation reduces the magnitude of gas price influence on electricity prices, but we cannot confirm this effect is statistically significant across all model specifications across all years of our sample.

Despite our inability to confirm a negative joint effect of gas price and IRES generation, there are indications of some dynamic at play. Comparing the results of Models 3 and 4 in Table 5, we discover that while wind generation retain a statistically significant effect, solar generation loses significance after including an interaction term with gas price, which has a negative coefficient. The interaction coefficient is, however, estimated larger than for both IRES and wind. Arguably, this could be because wind and solar face different production patterns. Wind is employed for generation throughout the day when there is sufficient wind, regardless of the level of demand. However, solar is limited due to its obvious dependence on sunlight and only therefore can only generate electricity during the day, which coincides with peak hours of high electricity demand. Meanwhile, natural gas is mostly utilized in response to the high demand during peak hours. It is likely that both solar and gas generation is concentrated to peak hours. Hence, solar generation main effect on electricity prices comes from offsetting the need for gas-fired power generation during some peak hours. In other words, in our model specification including an interaction term of solar generation and gas price, solar generation only affects electricity price through reducing the influence of gas price.

Of our control variables, total load shows a consistent, statistically significant and positive effect on electricity prices among all the models, which is in line with the economical intuition of price and demand. Inflow and outflow, on the other hand, do not present the same effects in the SARIMAX/GARCH models. Whilst daily change of inflow shows simultaneous reducing effects across peak and off-peak hours in both mean and volatility equations, daily change of outflow has divergent effects between peak and off-peak hours. Two possible scenarios can happen with electricity inflow and outflow, conditional on whether power transmission lines are congested. When the interconnections are not congested, electricity flows from markets with lower prices to markets with higher prices, which increases prices in the exporting areas and decrease prices in the importing area (Keles et al. 2020). In the case of Germany, lower-price electricity imports from wind generation in Denmark or nuclear generation in France can reduce the German domestic spot price. On the other hand, as one of the biggest electricity exporters in Europe (Statista 2021), Germany experiences increasing electricity price from exporting to areas with a higher market price until power prices get almost equalized. That being said, neither inflow or outflow appear to be significant in the results of our OLS regressions. Considering Germany as the biggest electricity producer and consumer in Europe (Eurostat 2021a), it is reasonable that electricity trade, against a larger scale of domestic production and consumption, has relatively low explanatory power for German electricity prices.

The combination of two different approaches to determine the relationships between the German day-ahead electricity price and our set of explanatory variables strengthens the internal validity of our analysis. Likewise, the effects of IRES, total load and cross-border flows are in line with previous literature on the area and intuition. However, the relationship between the electricity and gas prices, and in extension also that of the electricity price and the interaction of IRES generation and gas price, remain ambiguous. The non-stationarity of the gas price variable, one of our main variables of interest provides some difficulties in the analysis and requires caution in our interpretation. The relatively large coefficient estimates reported in Table 5 compared to those of our SARIMAX approach could indicate that the former are overestimated.

While the homogeneity of electricity market setup throughout Europe enhances the external validity of our study, the extent to which our findings can be generalised is limited by the accessibility to diversified production technologies and the importance of the generation mix in price determination for each electricity market. Germany has seen an increasing share of IRES generation in the last decade, resulting in a need for back-up generation to compensate for occasional shortfall in IRES generation. The Nordic electricity market Nordpool, on the other hand, has access to large hydropower generation, which to some extent is storable and feasible as cheap back-up generation to volatility in IRES generation (Dong et al. 2019). Moreover, in some markets other factors play a more pronounced role, such as in Lithuania, a country which is currently heavily dependent on electricity imports (Norvaiša and Galinis 2016). All these differences in electricity generation technology mixes result in different effects of the variables studied in this paper.

8 Conclusion

The price of natural gas has been drastically increasing since early fall 2020, coupled with the ongoing European gas supply crisis spurred by recovery from Covid-19 (Mišık 2022). Moreover, the threatened gas supply from Russia due to geopolitical situation has further undermined the natural gas supply security in Europe. In the power sector, diversified generation profiles are believed to relieve the risk from fluctuations in the supply side, which is the gas supply deficit in our case. Under the trend of energy transitioning, IRES has gradually grown to play an essential role in electricity mix. While strong evidence of merit-order effect is found with IRES (Sensfuß, Ragwitz, and Genoese 2008; Clò, Cataldi, and Zoppoli 2015), the current level of IRES penetration and electricity storage technology are not able to fully account for domestic electricity demand, which is why backup technology comes into play. In the case of Germany, the goal of Energiewende to phase out nuclear has shifted its energy profile and made natural gas an importance source of back-up production.

Our paper extends on existing literature by not only studying IRES and natural gas, and their respective effects on electricity prices, but also analysing their joint effect on electricity prices. Specifically, we assess whether increasing IRES generation in fact mitigates the influence of gas price on day-ahead electricity prices in the German market. By creating and analysing SARIMAX/GARCH models, we confirm the existence of a merit-order effect (MOE), of a magnitude of 0.23–0.30 €/MWh per one GWh increase in IRES output, in the German market. We also find evidence of different magnitudes of gas price influence on electricity price between peak and off-peak hours. OLS regression models with interaction terms are further evaluated in order to distinguish the joint effect of gas price and IRES generation on electricity prices. However, we cannot find solid evidence that IRES reduces the impact of gas price on electricity prices. The two approaches used in this paper coordinate and complement each other. While the SARIMAX/GARCH models are able to capture the time varying characteristics of electricity price series, the OLS regression models constitute second approach to confirm the results and offers more intuitive effect estimates.

Our findings suggest that IRES generation does reduce electricity prices, which can be beneficial on a societal level. However, careful concern has to be taken to what generation technology is available to provide back-up generation to compensate for the volatility in IRES generation. In the case of Germany, employing gas-fired generation as the main source of back-up generation, the MOE does not seem to extend to actively reducing gas price influence on electricity prices. Thus, the German electricity market is especially vulnerable to price spikes of natural gas, such as has been experienced in late 2021 – early 2022. As long as there is no feasible technology available for large-scale storage of electricity, other alleys would have to be evaluated in order to mitigate said vulnerability. This could for example entail increased interconnections to other markets, such as Nordpool, that can compensate for IRES generation shortfalls in Germany with cheaper, semi-programmable hydro-generated electricity.

Lastly, in this paper we solely study the effect of IRES and gas prices on day-ahead electricity prices. The effects of the level of electricity prices on the monetary incentives of producers is not part of our analysis, but nonetheless of importance. Despite providing electricity at basically no marginal cost, IRES requires substantial investments that have to be repaid, which has motivated subsidy schemes for IRES. These have been studied by Chrischilles and Bardt (2015) and Renn and Marshall (2016). However, how price spikes on input goods for back-up generation affects the incentives for IRES investors could be interesting for future research to evaluate.

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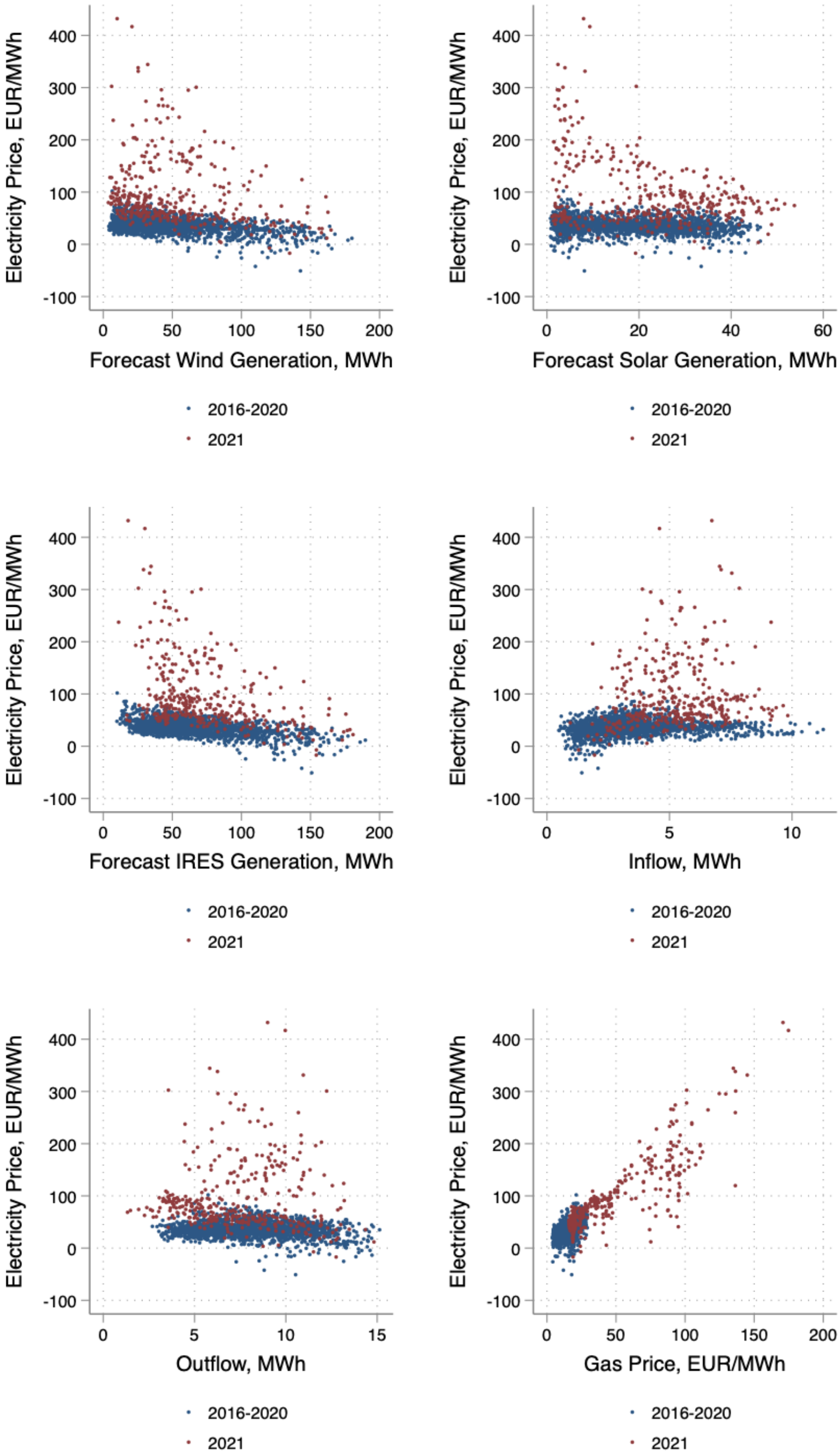
Appendix A: Data Analysis

Figure 8: Scatter Plots



Note: Data source: ENTSO-E Transparency Platform. Plots by the authors.

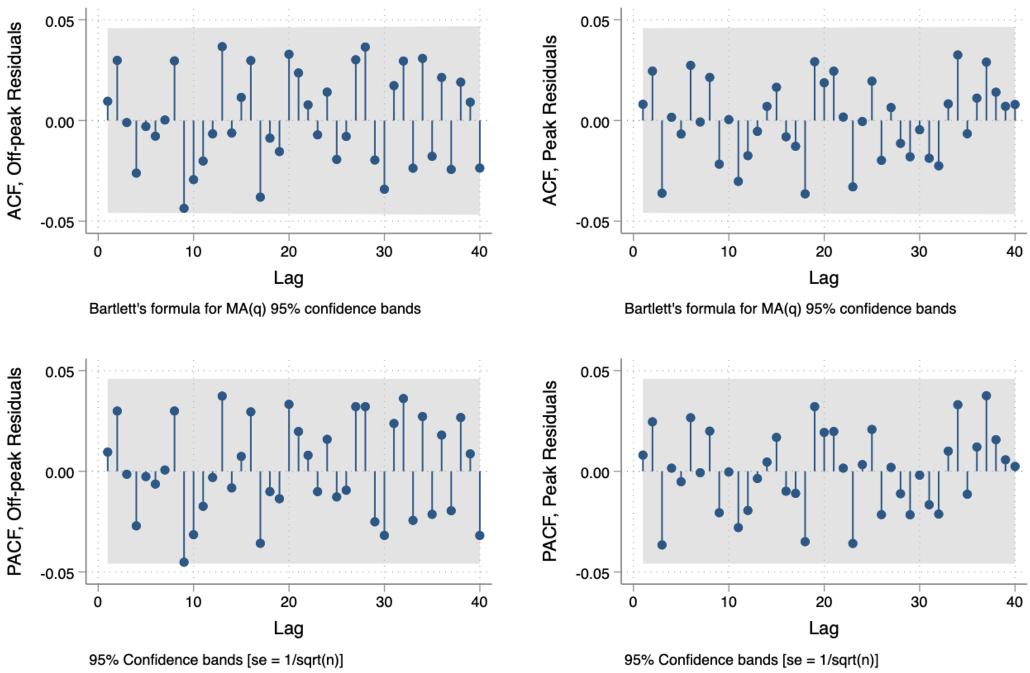
Table 9: Unit Root Tests

	Non-differenced Series		Differenced Series	
	Lags	ADF Test Statistic	Lags	ADF Test Statistic
Off-peak Hours				
Electricity Price	13	-4.775	13	-17.245
Total Load	50	-3.338	49	-7.461
Inflow	8	-4.900	13	-16.563
Outflow	7	-4.393	6	-24.368
IRES	3	-12.876	11	-19.303
Solar	5	-2.887	4	-25.904
Wind	3	-12.689	11	-19.292
Gas Price	N.A.	N.A.	N.A.	N.A.
Peak hours				
Electricity Price	22	-3.549	21	-13.321
Total Load	50	-3.626	49	-7.921
Inflow	7	-6.480	13	-17.978
Outflow	7	-6.667	13	-18.184
IRES	1	-18.958	15	-17.407
Solar	10	-3.038	9	-20.354
Wind	1	-9.988	11	-19.231
Gas Price	N.A.	N.A.	N.A.	N.A.
Total				
Electricity Price	22	-3.651	21	-13.616
Total Load	50	-3.461	49	-7.736
Inflow	8	-5.377	13	-17.153
Outflow	7	-5.141	21	-12.849
IRES	3	-14.700	11	-19.428
Solar	10	-2.984	9	-20.350
Wind	3	-13.195	10	-20.340
Gas Price	2	-1.558	1	-30.023

Note: The MacKinnon (1996) critical values are -3.430, -2.860, and -2.570 for confidence levels of 1%, 5%, and 10% respectively. A test statistic less than the critical value means we can reject the null hypothesis of presence of a unit root in the time series.

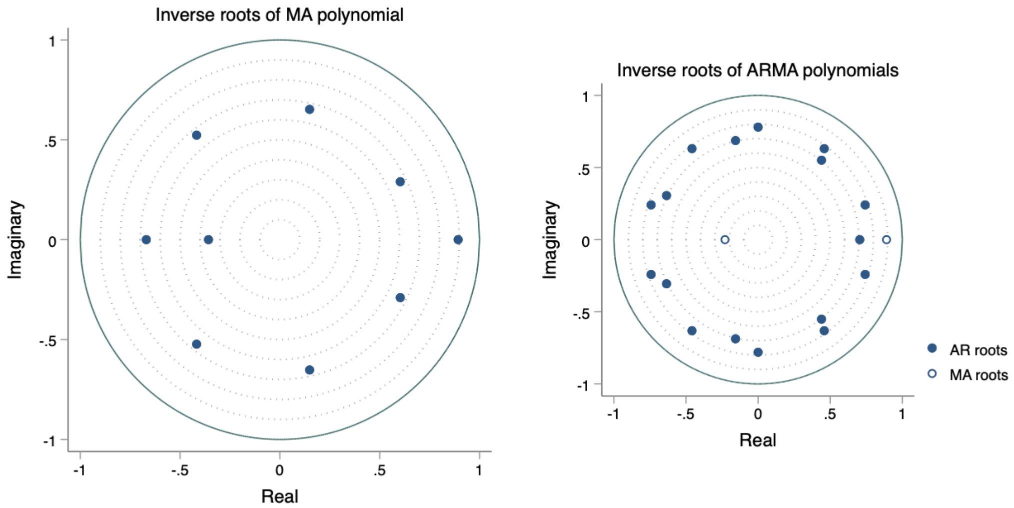
Appendix B: SARIMAX Model Fit

Figure 9: Autocorrelation and Partial Autocorrelation Function Plots of Off-peak and Peak Model Residuals



Note: Lag observations within the confidence band indicate no autocorrelation.

Figure 10: Inverse roots of ARMA-polynomials



Note: Plots of the inverse roots of the ARMA-polynomials from the respective off-peak and peak SARIMAX-models. Inverse roots within the unit circle indicate model stationarity.

Appendix C: Robustness Check Regression Tables

Table 10: Yearly Regressions of Non-differenced Time Series

	(1) 2016	(2) 2017	(3) 2018	(4) 2019	(5) 2020
Total Load	0.146***	0.241***	0.355***	0.350***	0.277***
	(0.036)	(0.057)	(0.058)	(0.063)	(0.035)
Inflow	-0.552**	-1.219***	-0.365	-0.238	-0.170
	(0.251)	(0.412)	(0.374)	(0.358)	(0.223)
Outflow	-0.212	-0.216	0.534*	0.352	-0.054
	(0.176)	(0.497)	(0.319)	(0.305)	(0.244)
Gas Price	2.078***	3.266***	1.033**	0.133	1.118**
	(0.446)	(1.256)	(0.488)	(0.620)	(0.481)
IRES	0.285***	0.122	-0.205***	-0.270**	-0.230***
	(0.097)	(0.162)	(0.055)	(0.114)	(0.055)
IRES × Gas Price	-0.035***	-0.025***	-0.005**	-0.000	-0.001
	(0.007)	(0.008)	(0.002)	(0.006)	(0.005)
Constant	-20.830**	-49.670***	-55.154***	-15.112	-20.906**
	(10.568)	(16.661)	(13.745)	(13.331)	(9.471)
DM Dummies	YES	YES	YES	YES	YES
R^2	0.850	0.815	0.873	0.784	0.861
Adjusted R^2	0.840	0.802	0.864	0.770	0.852
F	71.663	40.304	106.206	40.879	60.925
rho	0.312	0.342	0.433	0.165	0.287
Durbin-Watson	1.938	1.893	2.011	1.921	2.011
Durbin-Watson, orig.	1.378	1.321	1.199	1.635	1.450
Observations	366	365	365	365	366

Robust standard errors in parentheses. Dependent variable: Day-ahead electricity price.
Electricity and gas prices measured in €/MWh, all other variables in GWh.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Regressions of Non-differenced Time Series, Including Oil Price

	(1)	(2)	(3)	(4)
Total Load	0.275***	0.269***	0.276***	0.272***
	(0.026)	(0.026)	(0.026)	(0.026)
Inflow	-0.133	0.034	-0.104	0.028
	(0.146)	(0.138)	(0.149)	(0.140)
Outflow	0.198	0.186	0.193	0.191
	(0.148)	(0.147)	(0.148)	(0.146)
Gas Price	1.422***	1.854***	1.433***	2.201***
	(0.164)	(0.156)	(0.163)	(0.180)
IRES	-0.281***	-0.186***		
	(0.009)	(0.026)		
IRES × Gas Price		-0.006***		
		(0.001)		
Solar			-0.228***	0.072
			(0.025)	(0.061)
Wind			-0.280***	-0.185***
			(0.009)	(0.026)
Solar × Gas Price				-0.021***
				(0.004)
Wind × Gas Price				-0.006***
				(0.001)
Oil Price	0.126***	0.112***	0.127***	0.155***
	(0.043)	(0.041)	(0.043)	(0.039)
Constant	-46.245***	-51.811***	-46.996***	-59.597***
	(6.445)	(6.426)	(6.495)	(6.487)
DMY Dummies	YES	YES	YES	YES
R^2	0.774	0.779	0.775	0.784
Adjusted R^2	0.771	0.776	0.772	0.781
F	150.646	158.393	145.424	153.696
rho	0.503	0.498	0.503	0.481
Durbin-Watson	2.083	2.079	2.079	2.062
Durbin-Watson, orig.	1.032	1.044	1.032	1.082
Observations	1827	1827	1827	1827

Robust standard errors in parentheses. Dependent variable: Day-ahead electricity price. Electricity and gas prices measured in €/MWh, all other variables in GWh, except for oil price, which is denoted in €/barrel.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$