Price determinants in the German Intraday Power market

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Abstract

This thesis investigates the determinants of the price spread between the German day-ahead and intraday power markets, focusing on fundamental factors and identifying systematic patterns of behavior. Utilizing hourly price data from EPEX SPOT and relevant fundamental data from the years 2023-2024, the analysis employs econometric models including OLS, ARX, and GARCH to evaluate how forecast deviations in electricity demand (load) and renewable energy generation (wind and solar), unplanned generation outages, and cross-border electricity flows affect the price spread.

The findings show that forecast errors in wind and solar generation are highly significant in explaining the spread, with actual underproduction leading to higher intraday prices relative to day-ahead, and overproduction driving prices lower. Most results align with theoretical expectations, but load forecast errors surprisingly exhibit a negative relationship, indicating that excess demand lowers intraday prices, a deviation from standard assumptions. The interconnector DE $\leftrightarrow$ FR link stands out as the most statistically significant, reflecting its central role in cross-border balancing and market integration. The GARCH model provides additional insight into volatility dynamics, highlighting that variables like residual load and some of the other interconnectors become more influential during periods of market stress. Additionally, the analysis identifies clear intraday and weekly patterns. Wind forecast errors are the only significant factor during night hours, while solar deviations dominate midday. Load and net exports are mainly relevant during mid-peak hours, and outages primarily impact evening prices. On a weekly level, Monday exhibits the strongest sensitivity to forecast errors, suggesting elevated uncertainty after weekends.

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List of Abbreviations

Act	Actual observed value
ACF	Autocorrelation function
ADF	Augmented-Dickey-Fuller
ARCH	Autoregressive conditional heteroskedasticity
ARX	Autoregressive eXogenous
BRP	Balancing responsible party
DA	Day-ahead
df	Degrees of freedom
EPEX Spot	European Power Exchange
Fct	Forecast
FE	Forecast error
GARCH	Generalized autoregressive conditional heteroskedasticity
GW	Gigawatt
ID	Intraday
MW	Megawatt
OLS	Ordinary least squares
PACF	Partial autocorrelation function
RES	Renewable energy sources
SD	Standard deviation
TSO	Transmission system operator
VWAP	Volume-weighted average price

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1 Introduction

Over the past few decades, energy markets have undergone notable structural change. In Europe, the liberalization process initiated in the 1990's led to the restructuring of the previously vertically integrated electricity sector[1], into a deregulated and more competitive market framework. The current market landscape consists of various actors, such as power generators, distribution system operators, trading firms, and large-scale consumers, who interact either through bilateral contracts or organized platforms like the European Power Exchange (EPEX Spot). The transition towards a decarbonized energy system has significantly changed both the structure and operation of electricity markets. Germany has been at the forefront of this energy transition, and was the first European countries to implement feed-in tariffs in the 1990s. These tariffs provided guaranteed prices for renewable energy producers, fostering rapid deployment of wind, solar, and other renewable technologies. As a result, Germany quickly established itself as a frontrunner in renewable energy adoption, with its policy framework serving as a model for other European nations. After more than two decades of relying on feed-in mechanism, Germany replaced this strategy in the beginning of 2017, to compile with the preferences of the European Commission as the markets were moving towards a market-based structure that emphasized competition across Europe (Leiren and Reimer, 2021). Despite the shift away from traditional feed-in tariff policies, the share of renewable energy in Germany has continued to grow, reaching a new record in 2024 by accounting for 62.7% of net public electricity generation (Agora Energiewende and Ember, 2021). The German government has set a target for renewables to cover 80% of electricity generation by 2030, underlying the shift towards an even more renewable dominated grid in the future (Bömeke, 2024).

[1]The meaning of a vertically integrated electricity sector is that a single company in an area could provide the whole value chain, including generation of power, transmission and distribution, and retailing of power. Also considered a monopoly market structure

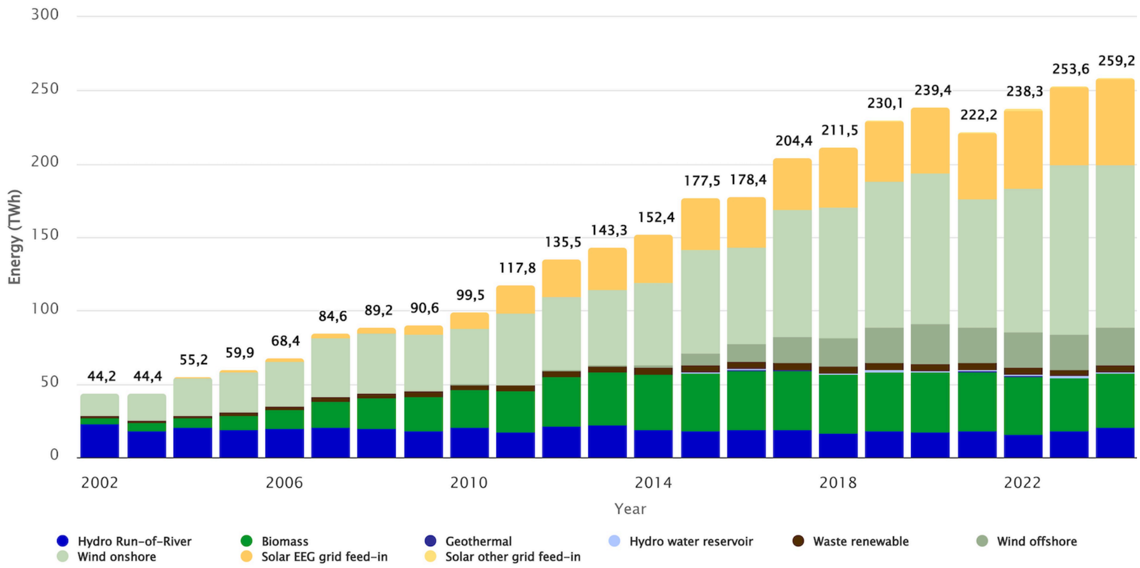


Figure 1: *Public net electricity generation from renewables. Source: Agora Energiewende and Ember, 2021*

The development of renewable energy sources (RES) in Germany has accelerated over the past two decades, as illustrated in the graph above. In particular, wind and solar power have experienced substantial growth and now constitute the dominant share of renewable electricity generation. Onshore wind has consistently been a key supply source, while offshore wind has expanded steadily since its introduction. Solar power has also grown significantly, driven by supportive policies such as the mentioned feed-in tariffs and later auction-based mechanisms. This consistent increase in RES reflects Germany's continued commitment to decarbonization. Unlike conventional thermal generation of power the output of RES is intermittent and often unpredictable, which introduce greater volatility and uncertainty into the power system. This intermittency of power generation requires market participants to continuously adjust their positions for forecasting errors and to maintain the balance of supply and demand. With the expectations of more RES in the systems, the electricity markets will get even more complex and volatile, as it leaves more room for forecasting errors, which will affect the intraday trading environment (Winter, 2023). In this context, the relationship between the day-ahead (DA) and intraday (ID) markets becomes increasingly important. While the DA market sets a forward-looking, auction based price using expected fundamentals, the ID market captures real-time market reactions to deviations from those expectations. Understanding how and why prices diverge between these two markets is not only critical for traders seeking to hedge or speculate, but also for system operators, regulators, and renewable asset managers aiming to maintain grid stability and optimize market performance.

Despite this relevance, existing literature often consider the DA and ID markets in isolation, or focuses on general price behavior without examining the direct interplay between the two. However, the growing importance of real-time balancing and continuous trading makes it important to understand which specific factors drive ID price movements relative to the DA benchmark. Germany, as Europe's most liquid and renewable driven electricity market, offers a particularly good setting to study these dynamics. With the DA market serving as the formal equilibrium expectation, the ID market reflects the "correction" process that unfolds as more accurate information becomes available. Hence studying the price spread between the two markets, while identifying the drivers behind these spreads could offer valuable insight into short-term market efficiency and the operational challenges of a renewable dominated grid.

1.1 Power market structure in Germany

This section provides a basic overview of the power market in Germany, considering the internal structure of the power system, tradable products and time ranges, while focusing on the differences between the DA and ID market.

Electricity is traded across multiple time horizons, ranging from long-term futures and forward contracts to real-time balancing markets. In that range, both physical and financial products are offered, but this thesis will only focus on physical products. In the short-term power market, the DA market and the ID market play an important role for the operations. The European Unions has in the past two decades implemented market coupling mechanism in both the DA and ID markets to facilitate a more seamless electricity trading across national borders in Europe. This has created a unified trading framework across Europe, increasing the competition and improving the overall efficiency of power allocation. Especially the implementation of Single Intraday Coupling (SIDC) in 2018 has been a key component to overcome the increasing share of intermittent renewables and ensure more balanced systems in all of Europe (ENTSO-E, 2025). A total of 868 Twh was traded on EPEX SPOT in 2024, surpassing the previous record from 2023 by 21%. The DA market contributed with 654 TWh (2023: 542 TWh), meanwhile the volume from ID market was 215 TWh (2023: 176 TWh). Within the context of Europe, the German electricity market is the largest and most liquid area (EPEX SPOT, 2025). Most of the short-term trading in Germany occurs on EPEX SPOT, which is one of the exchanges that hosts both the DA auctions and facilitate continuous ID trading.

1.1.1 The Day-Ahead Market

The DA market is a centralized auction that is conducted the day before delivery at 12:00 CET, acting as the main auction for supply and demand orders, setting the hourly price of the next day's electricity. A market clearing algorithm (PCR EUPHEMIA) is used to match the supply and demand across Europe, to determine a clearing price for every hour of all areas thar are a part of the Single Day-Ahead Coupling (SDAC). The algorithm will consider social welfare in it's price formation, as the goal is equal prices around all of Europe. The result of the auction is to be determined at 12.45 CET, often referred to as DA or spot prices. The spot price will reflect all area's expected supply and demand balance (equilibrium price) under the merit order principle, whereby the lowest-cost generators (RES) are dispatched to the system first, and then more expensive generations (e.g. gas, coal and oil plants) are delivering in periods of high demand or low availability of RES. The DA auction is critical for price setting and forms the baseline schedule of both consumption and generation for the following day (Winter, 2023). To enhance market efficiency and better integration of RES, the DA market will transition from a 60-minute auction to a 15-minute auction in 2025, if it gets approved. This will allow plant owners to adjust their hourly volumes for ramping periods and lead to a more stable and balanced market from DA perspective (EPEX SPOT, 2024b).

1.1.2 The Intraday Market

In Germany and coupled European markets, ID trading for the delivery of tomorrow opens in the afternoon at 15:00 CET, a couple of hours after DA results are published. The ID market allows for both trading hourly and quarterly products, and the contracts can be traded until 5 minutes before delivery in Germany. Trades are executed as soon as a buy- and sell order are to be matched in terms of price in the electronic orderbook. Besides the continuous trading, there is also three ID auctions called IDA1, IDA2 and IDA3, closing at 15:00, 22:00 and 10:00 the next day (IDA3 is therefore only an auction for delivery of 12:00 to 24:00) (EPEX SPOT, 2024a). Participants in the ID market engage in trading for a variety of reasons, below is some different needs of the flexibility that the ID market offer (Winter, 2023):

- Owners or balancing responsible parties (BRPs) of RES adjust their positions to account for forecast errors. As more accurate forecasts become available at ID level, these generators buy or sell power to make up the difference between DA forecasts and expected actual production. This helps them avoid imbalance penalties and contributes to system stability.
- Conventional power plants can adjust their operations based on updated market conditions. For instance, a gas-fired plant might ramp up or down and trade accordingly in ID if a sudden change in RES output or demand requires it to compensate. Such adjustments allow thermal generators to operate more economically and reliably, given that they have more information closer to dispatch.
- Different types of load serving entities will have to adjust their forecasted load to match their costumers' actual consumption. Especially deviations in temperature can push the demand for power in both directions and leave the need for adjustment.
- Exploiting short-term price discrepancies between the DA and ID market is of interest to traders as well. Traders will try to take advantage of their expectations to price behavior in the ID market or trade on new available information.

1.1.3 Potential of Intraday price spreads

To evaluate the potential of short-term electricity price dynamics, this study will investigate the hourly price spread between the German ID and DA electricity markets over the full calendar years 2023 and 2024[2].The key variable of interest is the ID return, defined as the difference between the volume-weighted average price (VWAP) of the intraday continuous market and the corresponding DA spot auction price. This spread captures the behavior of electricity prices as market participants update their positions based on for example, revised forecasts, system imbalances, and liquidity flows during the trading day.

Variable	**Mean**	**Median**	**SD**	**Min**	**Max**	**Skewness**	**Kurtosis**
Spot	86.81	88.83	50.94	-500.00	936.28	1.57	22.22
VWAP	89.11	89.78	59.70	-539.99	1168.15	4.22	64.84
Spread	2.30	0.68	29.72	-406.24	1021.94	13.65	364.92

Table 1: *Summary statistics for Spot, VWAP, and Spread (in EUR/MWh).*

The descriptive statistics for the DA spot price and the ID VWAP reveal broadly similar distributions. However, WVAP displays greater variability with a standard deviation (SD) of €8.76/MWh more than Spot and some slightly more extreme min and max values. Combining this with the higher skewness (4.22) and kurtosis (64.84) of the VWAP distribution relative to spot (1.57 and 22.22, respectively), further indicate that the ID market is exposed to more volatility and tail risk, skewed to the bull side.

While these differences between Spot and VWAP highlight the dynamics of price formation across market phases, the actual spread between them is more valuable to observe when assessing ID opportunities. Over the sample period, the average spread was €2.30/MWh, indicating a general upward adjustment of prices during the ID phase compared to the initial DAH benchmark. However, the median return is much lower, at €0.68/MWh, suggesting that the distribution is significantly right-skewed. This asymmetry is statistically confirmed by a positive skewness of 13.65, which reflects the presence of a right tail. Meanwhile, the kurtosis of 364.92 signals that the distribution is leptokurtic, with most spreads concentrated near the mean, but with fat tails and a higher likelihood of extreme price events. The

[2]2024-06-26 is excluded from the dataset due to decoupling. Further explanation about the full dataset will be provided in the methodology.

spread's volatility is also substantial, as evidenced by a SD of €29.72/MWh. While most values are clustered tightly around the center, the spread ranges over €1,428/MWh, with a minimum of –€406.24/MWh and a maximum of €1,021.94/MWh. These extreme values underscore the magnitude of price fluctuations that can arise within a single trading day. To better understand this distributional profile, the core and tail behavior of the spread are visualized separately. Figure 5 presents a histogram of the middle 98% of the spread's distribution where most trading activity occurs.

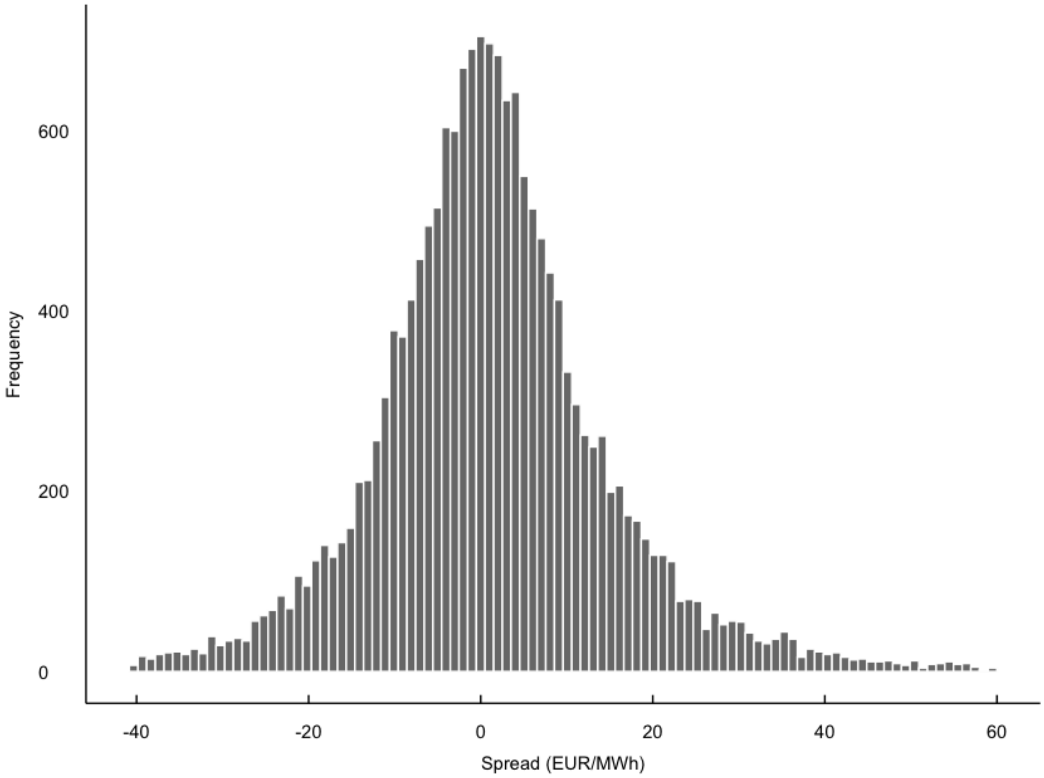


Figure 2: *Distribution of intraday spread (1% - 99%). Source: Generated in R*

Although the histogram provides clarity on the typical VWAP range, it omits the most extreme deviations. To complement this, Figure 3 plots only the bottom and top 1% of the observations, sorted by spread magnitude. This highlights the rare but significant outliers that represent ID volatility, which may have been the result of large forecast errors, unforeseen supply-demand imbalances, or market panic responses.

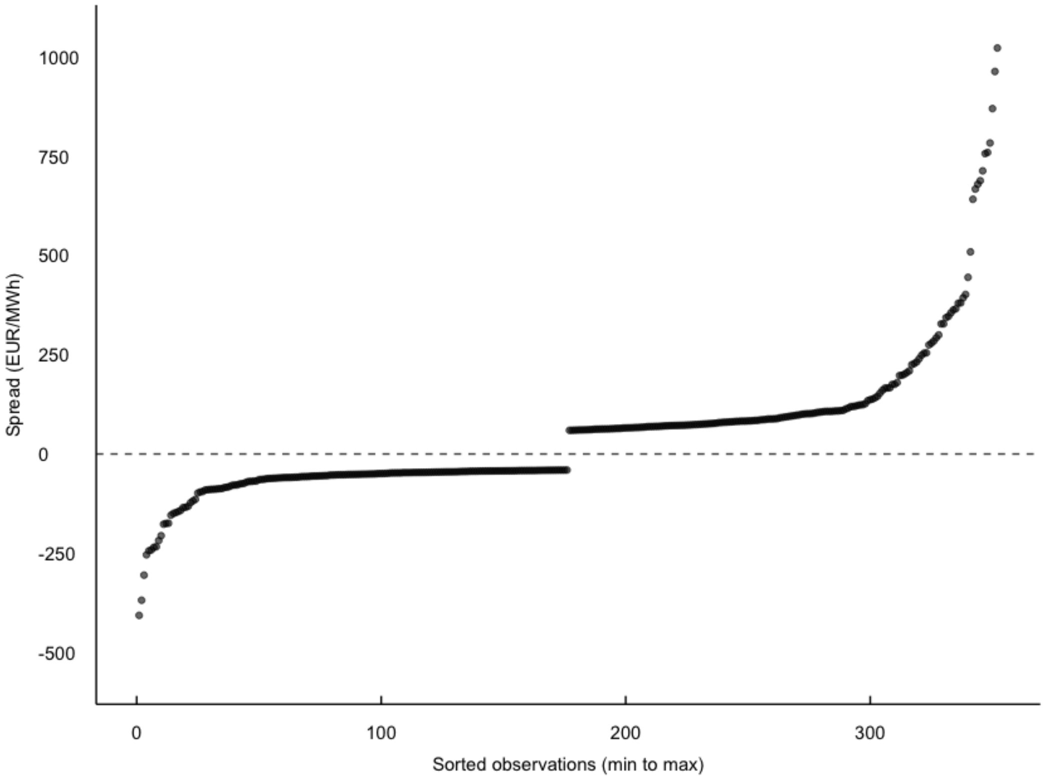


Figure 3: *Tail obs. of intraday spread (Bottom and top 1%). Source: Generated in R*

Together, these plots illustrate the behavior of the ID spread. For market participants, this signifies both opportunity and risk. Although the ID market can yield sizable returns in response to changing conditions, those same conditions can introduce abrupt losses if you are on the wrong side of the market. In that connection, it is important to acknowledge that not all market participants are pursuing profits based only on continuous trading (VWAP). A significant group of the participants, including BRPs, asset portfolio managers, and utility companies must continuously adjust their production and consumption forecasts to avoid imbalances. These actors are financially exposed to the imbalance price, which reflects the cost of real-time system balancing. In Germany, BRPs are required to balance their portfolios, and persistent deviations can lead to imbalance settlement charges or contractual risks. In contrast, speculative trading houses are required to operate a flat position, meaning they must not introduce physical imbalances into the system and therefore rely on spread capture between market phases or within the ID trading window.

2 Problem formulation

As outlined in the introduction, the ID market is expected to become even more important as the share of RES continues to grow. This will place additional pressure on the power systems, leading to greater uncertainty and increased volatility between the DA and ID markets. Building on that context, this thesis aim to answer the following research question:

“What are the main factors driving the price spread between the German day-ahead and intraday markets?”

This thesis is thus not about forecasting the actual spread, but about measuring the influence of different drivers (variables) for the price behavior from DA to ID. The study will therefore focus on the spread between DA and ID prices, and analyze the spread's sensitivity to fundamental changes up until delivery. To address the research question, it is essential to engage with existing literature and develop a set of guiding sub-questions. These sub-questions serve to structure the analysis and will be introduced in chapter 4 with added insights gained through the literature review.

The remainder of the thesis is structured as follows. **Chapter 3** presents a review of relevant literature within the field. **Chapter 4** outlines the data and methodology used to conduct the empirical analysis, including the process of variable selection and the econometric models that will be applied. **Chapter 5** presents the results of the analysis and addresses all sub-questions, while discussing the findings. Finally **Chapter 6** will review and conclude upon the research question, highlighting limitations and suggestions for future research.

3 Literature review

This section reviews findings from the literature on short-term electricity markets, with a focus on Germany. It covers fundamental price drivers in DA and ID markets in 3.1, observed ID trading patterns and volatility in 3.2, and the methodological approaches employed by previous studies in 3.3.

3.1 Fundamental factors in short-term power markets

Short-term power prices in both the DA and ID markets are largely determined by fundamental supply and demand conditions. In a competitive market, electricity price formation follows the merit-order principle, meaning generators bid in ascending order of their short-run marginal costs, and the market-clearing price is set by the last (costliest) unit needed to meet demand. Thus, the balance between available supply and demand is a primary driver of price at any given hour. When demand is high or supply is scarce, more expensive generation must come online, pushing prices up, whereas excess supply or low demand leads to lower-cost units setting the price, pushing prices down. Empirical studies confirm that short-term price movements respond strongly to these fundamental changes (Wolff and Feuerriegel, 2017). Immediately after the DA auction, ID prices initially align near the DA equilibrium, and then as time progresses, any ID deviations (e.g. unexpected changes in demand or generation) shift the supply–demand equilibrium and thus the price for continuous trading. Market participants have an incentive to trade in the ID market to handle such deviations (rather than rely on costly TSO imbalance settlements), which enhances overall system efficiency and security (Hagemann, 2015). A large body of literature has identified several fundamental factors that drive ID electricity price spreads. In particular, variations in renewable power generation (wind and solar), deviations in electricity demand (load), unexpected supply outages, and cross-border power exchanges (net exports or imports) are key determinants of hourly price differences (Shinde and Amelin, 2019). Empirical studies on the German ID market by Hagemann (2015) and others confirm that wind and solar forecast deviations, load forecast errors, power plant outages, and foreign supply/demand all have statistically significant impacts on ID price spreads. The direction of these effects aligns with expectations as positive supply shocks from wind or solar (more generation than anticipated) lead to lower prices, while demand surges or generation shortfalls lead to higher prices. In Hagemann's study from the trading period 2010-2011, crossborder trades between French-German is included and found to have no significant effect on German ID prices. But since his study, the influence of interconnectors have grown as European ID markets become more coupled. In todays market, interconnector availability and cross-border trades plays an important role by altering the supply–demand balance between borders, especially during periods of system stress. They will therefore be expected to have a significant impact on the spread.

3.2 Intraday trading patterns

In addition to real-time fundamentals, electricity price spreads exhibit strong seasonal patterns within the day and across the week. Intraday prices follow some cycles driven by typical demand patterns. Historically prices tend to be higher during morning and evening peak hours and lower during low demand hours (Abramova and Bunn, 2020). The introduction of intermittent renewables has modified these ID pattern slightly, as the share of RES within the day can push prices in both directions. To account for these recurring ID effects, researchers commonly include hour-of-day dummy variables or similar fixed-effect terms in their models (Wolff and Feuerriegel, 2017). In that connection volatility closer to delivery is also well documented, and especially how the volatility differs by delivery hour. For instance, contracts for hours with steep ramps in load (e.g., morning ramp-up or evening peak) or high renewable variability (e.g., solar peak) experience greater ID volatility. Baule and Naumann (2021) find these contract-specific effects significant, highlighting the importance of considering the delivery hour. Besides the hourly dynamics, electricity price spreads also vary systematically across weekdays and weekends. Lower demand on weekends and holidays typically results in different price dynamics compared to weekdays, often compressing the ID spreads due to flatter demand profiles. It is a standard practice in the literature to include day-of-week or weekend indicator variables to capture such intra week seasonal effects. This is also done in (Abramova and Bunn, 2020) study, as they include a weekend/holiday dummy to reflect the reduced demand and different supply mix in weekends.

3.3 Econometric approaches in the literature

Researchers have employed a range of econometric and statistical methods to investigate the above phenomena in electricity markets. One of common approach in the reviewed literature is to use time-series regression models to capture price dynamics and quantify the influence of explanatory variables. For example, Wolff and Feuerriegel (2017) adopt an autoregressive model with exogenous variables (ARX) to jointly model German DA and ID prices. In their two-step procedure, they first remove regular seasonal patterns (hourly and weekly seasonality) to avoid misleading results, and then estimate an ARX model including demand, wind and solar feed-in, fuel prices, and other factors. The autoregressive terms account for the autocorrelation in electricity prices (e.g. today's ID price is correlated with yesterday's), while exogenous terms capture fundamentals. Similarly, many studies rely on multiple linear regression (OLS) frameworks. Hagemann (2015), in the first analysis of ID price drivers, performed OLS regressions for different blocks of hours to see how outages, forecast errors, and other factors affect prices at various times of day. Pape et al. (2016) took a related but twofold approach as they built a detailed fundamental supply-stack model to compute theoretical prices, then used a linear regression on the difference between actual and fundamental price to identify the impact of factors like startup costs, market friction, and trading behavior. This combination of fundamental modeling and regression allowed them to explain which price variations fundamentals alone could not account for. In addition to these more standard econometrical approaches, several advanced or alternative methodologies have been explored in recent literature. One notable example is the use of panel data techniques by Gürtler and Paulsen (2018) employ a panel fixed-effects regression with 24 hourly cross-sections (one for each hour of the day) to analyze DA and ID prices from 2010–2016. Other studies are also exploring the use of machine learning (such as neural networks), aiming to capture complex patterns without requiring a specified parametric form.

4 Methodology

The methodology chapter outlines the empirical strategy, presents the dataset and selected variables, and introduces the theoretical basis for the diagnostic tools and econometric models that will be used in the study.

4.1 Empirical strategy

This section outlines the empirical framework used to investigate the drivers and patterns in the spread between the DA and ID electricity prices. Based on the insights from the literature review, the analysis is structured around two sub-questions:

1. *Which fundamental factors have an significant impact on the price spread between the day-ahead and intraday markets?*
2. *Are there observable weekly or daily patterns in the price spread and how are they related to the fundamental factors?*

To address the first sub-question, the analysis begins with a OLS estimation to establish a baseline mean model, before extending it to an ARX model that incorporates lagged spread terms and exogenous market fundamentals. Given the expected presence of volatility clustering and structural breaks during ramp periods, a GARCH(1,1) model is also implemented to capture time-varying volatility and conditional heteroskedasticity, to check if it deviates from the ARX results. This allows for a deeper understanding of both the mean and variance dynamics of the spread. To explore the second sub-question, dummy interactions are introduced to the mean model. Two sets of dynamic dummies are applied, one to capture the time-of-day effect and one to capture the day-of-week effect. These interactions are used to assess whether their is an effect of the fundamentals changes across time, and whether there are systematic ID or weekday-driven deviations that impact spread formation.

All analysis will be conducted in `R` using packages such as `tseries`, `lmtest`, and `FinTS`. `R` was chosen for its flexibility in statistical analysis and its strong visualization tools.

The relevant tests and the packages used to perform them are introduced throughout the methodology section

4.2 Data and variable description

The dataset used in the empirical analysis of this thesis is obtained via Centrica Energy's internal database, which collect data through API integration. The data sources will include official platforms such as EPEX spot and the ENTSO-E Transparency platform, as well as forecasts datasets that is accessible through subscription based services from Energy&Meteo Systems. The dataset consists of variables with varying resolutions, including both quarterly and hourly data. To ensure consistency, all quarterly values are converted to an hourly frequency by averaging each set of four quarter hours into a single hourly value. The final dataset spans the full period from 2023-01-01 to 2024-12-31 with a total of 17,520 hourly observations. Within this period, only a single full day, 2024-06-26, is excluded from the dataset. On this date, a technical incident led to a market decoupling, resulting in extreme outliers in the spread between the DA spot price and the ID market. Specifically, the DA price cleared as high as €2,325/MWh this day, while the corresponding ID VWAP for that hour was only €129/MWh. The average spread for all hours that day was -€403, illustrating the magnitude and abnormality caused by the event (EPEX SPOT, 2024c). In addition, the full dataset also contained 108 missing hourly observations, including those associated with daylight saving time adjustments. These missing values were replaced by the average of the two surrounding hours[1]. Table 2 below include an statistical overview of all the initial variables that will be used to form the independent variables. The DA forecast values is denoted (Fct) and actual production/consumption values by (Act). The use of them and further explanation will follow in the next sections. One thing to notice from the table below, is the degree of similarity between forecasted and actual values across all fundamental variables.

[1]All missing values for solar production occurred during nighttime hours and were therefore already "0".

Variable	**Mean**	**Median**	**SD**	**Min**	**Max**	**Skew**	**Kurtosis**
Spot	86.81	88.83	50.94	-500.00	936.28	1.57	22.22
VWAP	89.11	89.78	59.70	-539.09	1168.15	4.22	64.84
Total Load$^{\mathrm{Fct}}$	53.10	52.83	9.13	30.89	74.04	0.02	-1.01
Total Load$^{\mathrm{Act}}$	53.21	53.16	9.22	31.28	76.30	0.06	-0.92
Wind$^{\mathrm{Fct}}$	16.38	13.60	11.83	0.03	53.20	0.80	-0.16
Wind$^{\mathrm{Act}}$	15.96	13.28	11.44	0.04	52.40	0.79	-0.16
Solar$^{\mathrm{Fct}}$	6.70	0.24	10.21	0.00	48.38	1.54	1.35
Solar$^{\mathrm{Act}}$	6.76	0.20	10.40	0.00	46.85	1.55	1.35

Table 2: *Summary statistics of variable starting point. Spot and VWAP is €/MWh, and all DA and Act variables is GW.*

4.2.1 Dependent variable

The focus of the thesis is to explain ID price movements relative to DA prices, the dependent variable is therefore constructed as the spread (or difference) between the ID and DA electricity prices for each hour. The dependent variable will be calculated as:

$$\mathrm{Spread}_t = P_t^{\mathrm{ID}} - P_t^{\mathrm{DA}}, \tag{1}$$

where P_t^{ID} is the ID VWAP and P_t^{DA} is the DA Spot price (both in EUR/MWh) for delivery hour t. A positive spread indicates that ID prices have increased relative to the DA market, while a negative spread suggests that ID prices have decreased. The ID price P_t^{ID} reflects continuous trading up to shortly before delivery, and is taken as the volume-weighted average of all trades for that hour on the EPEX continuous ID market. Using a weighted average smooths out individual trade volatility and provides a representative price for the hour and the full trading session. Alternatives to this would be to use the last traded price as one may argue that all information should be incorporated at that time, but this price would only be a equilibrium of that point in time and not a smoothing equilibrium of the full trading session as the VWAP. The data for VWAP and Spot prices is from EPEX spot.

4.2.2 Independent Variables

Based on the literature review and the refined sub questions, several independent variables are already identified as key drivers and will be included in this thesis as well to investigate the spread dynamics. A description and measure of each independent variable will follow below.

Demand

Unexpected changes in electricity demand (load) are accounted for by including the load forecast error (FE), defined as:

$$Load_t^{\mathrm{FE}} = Load_t^{\mathrm{Act}} - Load_t^{\mathrm{Fct}} \tag{2}$$

This measures whether actual electricity demand was higher or lower than anticipated in the DA timeframe. A higher than expected demand level would likely drive ID prices up as additional supply had to be drawn or scarcity prevailed. Conversely, lower than expected demand would put downward pressure on ID prices. The data for both the forecasted and actual demand is from ENTSO-E.

Solar and wind

Renewable energy forecast errors are a central driver of ID price movements. These errors will be included as independent variables defined as:

$$Wind_t^{\mathrm{FE}} = Wind_t^{\mathrm{Act}} - Wind_t^{\mathrm{Fct}} \tag{3}$$

$$Solar_t^{\mathrm{FE}} = Solar_t^{\mathrm{Act}} - Solar_t^{\mathrm{Fct}} \tag{4}$$

A positive FE for renewables would indicate a surplus of generation compared to DA forecast, whereas a negative FE is actual renewables coming in a deficit compared to forecast. These FE reflect unforeseen supply deviations that arise after the DA market. Based on prior findings, an excess supply from renewables should exert downward pressure on ID prices, while a shortfall should push ID prices above the DA level. The forecast for both wind and solar is provided by Energy&Meteo Systems, and the actual generation data is from ENTSO-E.

Residual load

Residual load reflects the net demand that must be met by dispatchable generation sources after accounting for renewable energy. It will be calculated from DA forecasts, representing the system operator's expectations prior to ID market. It is defined as:

$$\text{Residual load}_t^{\text{Fct}} = \text{Load}_t^{\text{Fct}} - \left(\text{Wind}_t^{\text{Fct}} + \text{Solar}_t^{\text{Fct}}\right) \tag{5}$$

From a DA point of view, this variable is crucial in shaping market expectations and bidding behavior. Higher residual load forecasts suggest a tighter supply-demand balance and may lead to upward pressure on prices in both the DA and ID markets. Whereas lower residual load forecasts imply a greater availability of renewable generation to meet demand, potentially pushing spot prices toward zero or even negative levels due to excess supply.

Unplanned outages

To capture unexpected supply-side events that may affect short-term electricity price dynamics, unplanned generation outages are included as an independent variable. These outages reflect the sudden unavailability of generation capacity due to unforeseen technical faults, accidents, or emergency shutdowns. The data is obtained from ENTSO-E's and specifically filtered to include only forced outages, which is events not scheduled in advance. Furthermore, only outages with a minimum capacity loss of 200 MW are retained to focus on systemically significant events. In order to isolate the short-term market impact, long term outages are excluded, and the dataset therefore only includes outages that occur and resolve within a day. This ensures that the variable reflects supply shocks rather than long-term capacity constraints. Such unplanned outages are expected to tighten supply conditions temporarily, which can drive ID price volatility and influence the spread between ID and DA market prices.

Cross-border flow

Germany is highly interconnected with neighboring countries, and cross-border electricity flows play a critical role in shaping domestic supply and price dynamics. To account for the effect of scheduled flows at DA, all of Germany's interconnectors are included as variables. The data is sourced from ENTSO-E, which publishes DA flow commitments based on capacity allocations. The variable is constructed for each interconnector i linked to Germany, measuring the scheduled net flow in MW from the DA market:

$$\text{NetExport}_{t,i} = \text{Export}_{t,i} - \text{Import}_{t,i}$$

Where a positive value of $\text{NetExport}_{t,i}$ indicates an export from Germany to country i, and a negative value indicates an import to Germany from country i. Each interconnector is treated as an independent variable in the model, resulting in 11 net export variables. This disaggregated approach captures the directional impact of specific cross-border flows on German ID price spreads, accounting for market coupling dynamics. Interconnectors may be aggregated later in the analysis, if necessary.

4.2.3 Dummies

To address ID trading patterns (sub-question 2), a set of time dummy variables is included to capture period-of-day, and day-of-week effects. The dummies will be used to capture any systematic ID price premium/discount patterns. The period-of-day dummies are constructed to capture variations in ID trading behavior throughout the day, based on operational patterns in electricity demand, renewable generation, and trading intensity. The 24-hour day is divided into the following five blocks:

- Night (00:00 – 06:00): Represents low-consumption hours with limited trading activity.
- Morning ramp (06:00 – 09:00): Captures the sharp increase in demand as the market transitions into peak hours. This is typically a volatile period.
- Mid peak (09:00 – 18:00): The period were solar is ramping up to it's peak point and also ramping down again. A period that can be very volatile.

- Evening ramp (18:00 – 22:00): This period captures the rise in demand after sunset, while solar output drops sharply. As a result, the system typically requires more flexible capacity and regulation to maintain balance.
- Late evening (22:00 – 00:00): Covers the final trading hours of the day, typically characterized by reduced liquidity and potential price noise.

In addition, day-of-week dummies (Monday to Sunday) are included to account for weekly seasonality in electricity market behavior. These fixed effects capture systematic differences in spread dynamics across weekdays and weekends, such as reduced industrial demand on weekends or behavioral shifts in trading activity.

In terms of modelling, the dummies will interact with each variable, as shown in equation 6 and 7:

$$\text{Spread}_t = \alpha + \sum_{b\in\mathcal{B}} \sum_{i=1}^{n} \beta_i^{(b)} \cdot x_{i,t} \cdot \text{Block}_b + \varepsilon_t \tag{6}$$

$$\text{Spread}_t = \alpha + \sum_{d\in\mathcal{D}} \sum_{i=1}^{n} \gamma_i^{(d)} \cdot x_{i,t} \cdot \text{Weekday}_d + \varepsilon_t \tag{7}$$

where,

$x_{i,t}$ are the i-th explanatory variables at time t

Block_b and Weekday_d are dummy indicators

$\beta_i^{(b)}$, $\gamma_i^{(d)}$ are interaction coefficients

α is the intercept and ε_t is the error term

4.2.4 Full variable overview

Below in table 3 is an overview of all variables that will be included in the analysis.

Variable	Mean	Median	SD	Min	Max	Skew	Kurtosis
Spread	2.30	0.68	29.72	-406.24	1021.94	13.65	364.92
Load^{FE}	109.27	65.57	2475.85	-9374.84	9325.87	0.09	0.21
Wind^{FE}	-417.08	-194.25	2317.94	-18524.00	9427.25	-0.91	4.03
Solar^{FE}	62.13	0.00	1134.22	-9939.50	7643.00	0.05	9.06
Residual Load	30.02	30.53	13.80	-14.94	66.82	-0.15	-0.21
Outages	71.90	0.00	186.16	0.00	1768.67	3.30	12.50
DE ↔ AT	0.82	0.84	1.40	-3.43	4.55	-0.14	-0.63
DE ↔ BE	-0.11	-0.09	0.80	-1.01	2.00	0.43	-0.97
DE ↔ CH	-0.37	-0.40	1.56	-4.00	2.00	-0.84	-0.56
DE ↔ CZ	0.19	0.25	0.91	-2.69	2.53	-0.30	-0.58
DE ↔ DK1	-1.13	-1.61	1.33	-2.50	2.50	1.25	0.80
DE ↔ DK2	-0.33	-0.42	0.47	-0.98	1.06	0.14	0.54
DE ↔ FR	-0.75	-1.52	2.50	-6.98	9.24	0.83	0.00
DE ↔ NL	-0.30	-0.26	1.53	-5.39	4.63	-0.24	-0.36
DE ↔ NO2	-0.52	-0.71	0.83	-1.40	1.40	0.96	0.00
DE ↔ PL	0.25	0.40	0.84	-2.90	2.40	-0.66	0.00
DE ↔ SE4	-0.32	-0.49	0.35	-0.62	0.62	0.98	-0.08

Table 3: *Descriptive statistics of all included variables. Spread and Reg Price are in €/MWh, all interconnectors and residual load is in GW and all other values are in MW.*

As already discussed in the introduction, the dependent variable Spread exhibits a high degree of variability, with extreme minimum and maximum values and pronounced positive skewness and kurtosis. This suggests the presence of outliers and fat tails, which motivates the need for robust estimation techniques and also volatility modeling using GARCH. Looking at the explanatory variables, FE for load, wind, and solar generation also display wide ranges and have some high standard deviations that could indicate some potential importance in explaining price corrections between the DA and ID markets. Both the mean and minimum value of wind FE seems extreme, but this is due to wind shutdowns, when DA clear below €0, leaving some days with large deficit of actual wind production compared to forecast. The observed range for residual load indicates substantial variation in the share of conventional generation running. This may have important implications for the spread behavior depending on whether the system is predominantly RES driven or reliant on conventional sources. Outages holds a lot of data without any volume, limiting the overall variation and thus their explanatory strength in a general regression setting.

Their impact is likely more relevant within specific ID windows, as further explored in the dynamic models. Finally, the net export flows between Germany and its neighbors vary both in magnitude and direction. The minimum and maximum values indicate that the largest available capacities are on the borders to FR and NL, with FR in particular expected to play the most significant role as an interconnector.

4.3 Econometric Model Specification

Before estimating any models, a series of diagnostics will be conducted to assess whether the data exhibits characteristics that may be unsuitable for modeling. These diagnostics include tests for stationarity and multicollinearity across all variables, as well as model testing for normality, autocorrelation, and conditional heteroskedasticity within the models.

4.3.1 Augmented Dickey-Fuller test

To test for stationarity, the Augmented Dickey-Fuller (ADF) test is performed. This test is widely applied in time series analysis to determine whether a series maintains a constant mean and variance over time, thus an essential assumption for econometric models. The ADF test assesses whether a unit root is present, which would indicate non-stationarity (Dickey & Fuller, 1979). The ADF is written as:

$$\Delta Y_t = \alpha + \beta t + \gamma Y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta Y_{t-i} + \varepsilon_t \tag{8}$$

In this equation, Y_t is the original time series, ΔY_t is its first differenced form of the time series, and $\alpha, \beta, \gamma, \delta$ are parameters to be estimated. The term ϵ_t denotes the error term. The hypotheses for the ADF is formulated as:

$$H_0 : \text{Non-stationary variable}$$
$$H_1 : \text{Stationary variable}$$

Identifying non-stationarity is critical, as it may otherwise result in misleading results. If non-stationarity is found, transformations such as differencing are typically applied. The test is implemented by using the `adf.test()` function from the `tseries` package in `R`.

4.3.2 Jarque-Bera test

To assess whether the residuals of the estimated model follow a normal distribution, the Jarque-Bera (JB) test is employed. Normality of residuals is an important assumption in classical linear regression, as non-normality may lead to inefficient estimators and invalid results in small samples (Tsay, 2010). The JB test is based on the sample skewness and kurtosis of the residuals. The test statistic is given by:

$$JB = n\left[\frac{S^2}{6} + \frac{(K-3)^2}{24}\right] \tag{9}$$

where n is the sample size, S is the sample skewness, and K is the kurtosis of the sample. Under the null hypothesis of normality, the JB statistic asymptotically follows a chi-squared distribution with 2 degrees of freedom (df). The hypotheses are formulated as follows:

H_0 : The residuals are normally distributed

H_1 : The residuals are not normally distributed

A rejection of H_0 implies that the residuals deviate from normality, suggesting the presence of asymmetry (skewness) and/or heavy tails (excess kurtosis). Detecting such deviations is important for validating model assumptions and ensuring reliable results. The test is implemented in `R` using the `jarque.bera.test()` function from the `tseries` package.

4.3.3 White test

To evaluate the presence of heteroskedasticity in the residuals of the regression models, the White test is applied (Wooldridge, 2016). This diagnostic assesses whether the variance of the residuals is constant across all levels of the independent variables. The null and alternative hypotheses are formally stated as:

H_0 : Homoskedasticity (constant error variance)

H_1 : Heteroskedasticity is present

The White test statistic follows a chi-squared distribution under the null hypothesis, with degrees of freedom equal to the number of auxiliary regression terms. The White test will be implemented in R using the `white()` function from the `skedastic` package.

4.3.4 Ljung-Box test

To assess the presence of autocorrelation in the residuals of a time series model, the Ljung-Box test is applied. This diagnostic is critical for verifying that the residuals behave like white noise, a key assumption in time series econometrics. If autocorrelation is present, it suggests model misspecification and the need for further adjustments (Tsay, 2010). The Ljung-Box statistic is defined as:

$$Q(m) = T(T+2)\sum_{\ell=1}^{m}\frac{\hat{\rho}_\ell^2}{T-\ell} \tag{10}$$

In this expression, T denotes the sample size, $\hat{\rho}_\ell$ is the estimated autocorrelation at lag ℓ, and m is the number of lags to test. The Q-statistic follows a chi-squared distribution with m df. The hypotheses for the Ljung-Box test are formulated as follows:

H_0 : The autocorrelations are all zero

H_1 : At least one autocorrelation is non-zero

A rejection of H_0 indicates that residual autocorrelation is present, which may violate key assumptions for consistent and efficient estimation. In addition to the formal Ljung-Box test, Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots are also inspected visually to support diagnostic evaluation of the residual dynamics. The Ljung-Box test is implemented in R using the `Box.test()` function with the `type = "Ljung-Box"` option from the `stats` package. The functions `acf()` and `pacf()` will be used from the same package, to plot ACF and PACF.

4.3.5 ARCH-LM Test

To examine the presence of autoregressive conditional heteroskedasticity (ARCH) in the residuals of the estimated model, the ARCH-LM test introduced by Engle (1982) is employed. This diagnostic is important for identifying whether the error variance is constant over time or exhibits time-varying volatility. The test is conducted by regressing the squared residuals $\hat{\varepsilon}_t^2$ on their own lags in the following auxiliary regression:

$$\hat{\varepsilon}_t^2 = \alpha_0 + \alpha_1 \hat{\varepsilon}_{t-1}^2 + \cdots + \alpha_m \hat{\varepsilon}_{t-m}^2 + u_t \tag{11}$$

where $\hat{\varepsilon}_t$ denotes the residuals from the mean equation, m is the number of lags to be tested, and u_t is a white noise error term. The regression is tested by:

$$H_0 : \alpha_1 = \alpha_2 = \cdots = \alpha_m = 0$$

$$H_1 : \alpha_1 = \alpha_2 = \cdots = \alpha_m \neq 0$$

Rejection of the null hypothesis suggests the presence of conditional heteroskedasticity, indicating that a GARCH-type model may provide a better fit to account for time-varying volatility. The test statistic follows a chi-squared distribution with m df, and is implemented in this study using the `ArchTest()` function from the `FinTS` package in R.

4.3.6 Autoregressive exogenous model

To model the dynamics of the electricity price spread while accounting for both its own past values and external influencing factors, an Autoregressive model with Exogenous inputs (ARX) can be employed. The ARX model extends the traditional Autoregressive (AR) framework by incorporating exogenous variables (Tsay, 2010). The ARX(p, q) model is specified as:

$$Y_t = \alpha + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=1}^{q} \beta_j X_{t-j} + \varepsilon_t \tag{12}$$

where,

Y_t represents the dependent variable at time t (spread)

X_{t-j} denotes the j-th lag of an exogenous predictor at time t

The coefficients ϕ_i and β_j correspond to the autoregressive and exogenous components, respectively.

α is a constant term (intercept)

ε_t is the error term assumed to be white noise.

An ARX model will be estimated only if significant autocorrelation is detected in the residuals of the preliminary OLS model, ensuring that lagged dependent terms are meaningfully incorporated. The ARX model estimation is performed using the `dynlm` package in `R`, which allows for efficient handling of dynamic linear models with exogenous variables.

4.3.7 GARCH Model

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model can capture the time-varying volatility in a time series, also knowns as volatility clustering (Tsay, 2010). A common feature in financial and energy time series where large changes in a variable tend to be followed by further large changes. The GARCH(m, s) model extends the ARCH framework by incorporating both past squared residuals and past conditional variances. It consists of the following two equations:

$$\begin{aligned} a_t &= \sigma_t \epsilon_t, \qquad \epsilon_t \sim \mathcal{N}(0,1) \\ \sigma_t^2 &= \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2 \end{aligned} \tag{13}$$

where,

a_t is the residual at time t

ϵ_t is a standard normal white noise error term

σ_t^2 is the conditional variance at time t

α_0 is a constant

α_i are the coefficients for the ARCH terms (a_{t-i}^2)

β_j are the coefficients for the GARCH terms (σ_{t-j}^2)

The model assumes that current volatility depends both on past forecast errors and its own past values, allowing it to effectively capture clustering and persistence in volatility. A GARCH model will be estimated only if the ARCH-LM test confirms significant ARCH effects in the residuals of the mean model, ensuring the relevance of conditional heteroskedasticity modeling. The GARCH model will be implemented in `R` using the `rugarch` package that includes `ugarchspec()` and `ugarchfit()`.

5 Empirical analysis and discussion

The analysis chapter begins with a preliminary assessment of the data, including checks for stationarity and multicollinearity. It then proceeds to address the sub-questions, first by identifying the fundamental drivers of the spread in 5.2, and subsequently by exploring seasonality patterns in 5.3.

5.1 Preliminary assessment

Before estimating any econometric models, a preliminary assessment of the dataset is conducted to ensure it meets the necessary statistical requirements for time series modeling. This includes evaluating the stationarity of the variables and testing for potential multicollinearity. These diagnostics provide an important foundation for ensuring the validity of the models used later in the analysis.

Stationarity

Since non-stationary time series can produce unreliable regression results, the stationarity of all variables is assessed using the Augmented Dickey-Fuller (ADF) test. The test results, displayed in table 6 in appendix B, indicate that all variables are stationary at the 1% significance level. The null hypothesis of a unit root is rejected for each series, suggesting that mean and variance stability over time can be assumed throughout the modeling process. This satisfies a key assumption required for linear regression and time series models.

Multicollinearity

To detect multicollinearity, Variance Inflation Factor (VIF) scores were calculated for the full set of independent variables. The results for the base model[1] are provided in appendix B, table 7. While most variables present acceptable VIF values below the commonly accepted threshold of 5, the variable representing net scheduled cross-border flow from

[1]Base OLS model, including all independent variables.

the Czech Republic (DE $\leftrightarrow$ CZ) exhibits a VIF of 14.81, indicating strong collinearity with other variables, particularly DE $\leftrightarrow$ AT. To mitigate this, a revised specification was introduced, combining DE $\leftrightarrow$ AT and DE $\leftrightarrow$ CZ into a single aggregate variable (DE $\leftrightarrow$ ATCZ). This adjustment reduced the VIF to a manageable level of 4.29. The effect of this revision is visualized in the updated correlation matrix in appendix A.2, figure 10.

The final dataset used for model estimation therefore includes only stationary variables and exhibits no problematic multicollinearity, providing a reliable basis for the subsequent analysis.

5.2 Drivers of Intraday spread

5.2.1 Mean model construction

The analysis begins with the estimation of a baseline OLS model to examine the linear relationship between the selected fundamental variables and the dependent variable. This serves as an initial benchmark to assess the directional impact and statistical significance of the explanatory variables under standard linear assumptions. While the preliminary assessment in section 5.1 ensured the inclusion of only stationary and non-collinear variables, it is necessary to examine the residual structure of the OLS model to validate its adequacy as a mean equation. The Ljung-box test is performed on the residuals baseline model and indicate highly significant autocorrelation, with the test rejecting the null hypothesis. This is further substantiated by the autocorrelation and partial autocorrelation function (ACF and PACF) plots of the residual series, which display persistent lag structures that do not dissipate immediately. Test results and plots can be found in appendix C.1. These findings suggest that the spread series exhibits time dependent dynamics that are not adequately captured by a static OLS specification.

Consequently, the model is extended to account for autoregressive structure in the dependent variable, leading to the implementation of an ARX model. The first version of the ARX will include the first lag of the dependent variable, as the PACF plot of the OLS residuals showed a prominent spike at lag 1, suggesting that the current value of the spread is partially dependent on the first past value. The estimation results from the ARX model reveal several key improvements. Most notably, the lagged variable $spread_{t-1}$ is highly significant ($p < 0.01$), with a large positive coefficient. This confirms the presence of meaningful autocorrelation in the dependent series that the static OLS model could not capture. Incorporating this autoregressive structure substantially improves the model fit, as reflected in the increase in R^2 from 0.275 in the OLS model to 0.603 in the ARX model. The diagnostics of the residuals also show improvements, although autocorrelation is still present when running the Ljung-box test, but the test statistic dropped from 12.571 to 182.54. Looking at the ACF and PACF plots of the ARX's residuals, it's clear that the dominant autocorrelation of the OLS has been effectively addressed by adding a lagged variable. However, despite the improvements there is still autocorrelation present. To adress this, the model got extended by including additional lags of the dependent variable at strategically selected intervals ($spread_{t-2}$, $spread_{t-3}$, $spread_{t-24}$, $spread_{t-168}$), to account for more of the past, including daily and weekly cyclical effects that may influence the behavior of ID trading. The extended ARX model improved marginally on adjusted R^2 (0.6054), the Ljung-box statistic reduced considerably to 69.36 and most lags falling within the confidence bounds in both ACF and PACF. Nevertheless, the Ljung-Box test still indicates some remaining autocorrelation. While this suggests that the model does not fully capture all temporal dynamics, the magnitude and structure of the residual autocorrelation are sufficiently reduced to proceed. Further diagnostics of the residuals include a Jarque-Bera test and White test. The result of the Jarque-bera test, with a test statistic of 3.94×10^{8} and a p-value $< 2.2\times10^{-16}$, strongly rejects the null hypothesis of normal distribution. While normality is not a strict requirement, non-normal residuals may affect the model results. The results of White's test for heteroskedasticity also confirms the presence of non-constant variance in the residuals. To address this issue and ensure valid results, heteroskedasticity-consistent standard errors (HC robust) are computed. The full results of that, can be found in appendix C.1, table 15, but all the variables that remains statistically significant can be found below in table 4. The lagged dependent variable L(Spread, 1) is highly significant and positively signed (0.71161), suggesting a strong degree of persistence in the spread series. This implies that a 1€ increase in the spread during the previous hour leads, on average, to a 0.71€ increase in the current spread, highlighting the similarity of behavior from hour to hour in the ID market. The $Load^{FE}$ carries a negative and significant coefficient (-0.00012). This indicates that when actual load is higher than forecasted by 1GW (a positive forecast error), the spread is expected to decrease by approximately €0.12. This somewhat contradicts the intuitive expectation that underforecasted demand would push up ID prices and thus widen the spread. One possible explanation is that load forecast errors are typically small or mitigated in real time through balancing mechanisms.

Variable	**Estimate**	**Std. Error**	**t-Value**	**Signif.**
Intercept	-1.38500	0.48074	-2.8815	**
L(Spread, 1)	0.71161	0.11268	6.3154	***
Load^{FE}	-0.00012	0.00005	-2.5231	**
Wind^{FE}	-0.00106	0.00018	-5.9800	***
Solar^{FE}	-0.00102	0.00029	-3.5731	***
Outages	0.00177	0.00079	2.2486	*
DE ↔ BE	0.00053	0.00025	2.1427	*
DE ↔ DK1	-0.00040	0.00016	-2.5692	**
DE ↔ FR	-0.00029	0.00006	-4.4725	***

Table 4: *ARX model results with robust standard errors (significant variables only). Source: Generated in R*

The Wind^{FE} and Solar^{FE} both exhibit negative and highly significant coefficients, with values of -0.00106 and -0.00102, respectively. This implies that an overestimation of wind or solar generation by 1GW leads to a reduction in the spread by approximately €1.06 and €1.02, respectively. Outages are positively signed (0.00177) and significant at the 5% level. This suggests that the loss of generation capacity exerts upward pressure on ID prices, thereby increasing the spread, but only by €1.7 per 1 GW outages. Three cross-border flow variables also show significance. Increased scheduled exports from Germany to Belgium are positively associated with the spread (0.00053), suggesting that greater outflows to Belgium contribute to tighter local conditions and upward ID price pressure. In contrast, increased exports to Denmark (DK1) and France are negatively associated with the spread (-0.00040 and -0.00029, respectively), indicating that these interconnectors are putting more downside pressure to the German Intraday market, when exporting more at DA state.

Lastly, to assess the presence of autoregressive conditional heteroskedasticity, the ARCH LM test is applied to the extended model's residuals. The null hypothesis of no ARCH effects is rejected at the 1% level, with a test statistic of 1682 (df = 24, $p < 2.2 \times 10^{-16}$).

This result indicates the presence of time-varying volatility in the residuals, which justify the transition to a GARCH framework in the following section.

5.2.2 GARCH

Following the ARX analysis in section 5.2.1, a GARCH(1,1) will now be estimated to capture time-varying volatility in the spread. This GARCH model includes the same set of exogenous regressors in the mean equation as the ARX model, allowing a direct comparison of the drivers identified previously while adding an additional layer of insight through the conditional variance. Below in table 5 is all the significant results from the GARCH(1,1), the full table can be found in appendix C.1.

Variable	**Estimate**	**Std. Error**	**t-Value**	**Signif.**
Intercept (mu)	-1.97339	0.60162	-3.2801	***
L(Spread, 1) (ar1)	0.79021	0.00837	94.4108	***
Wind^{FE}	-0.00154	0.00009	-16.3203	***
Solar^{FE}	-0.00216	0.00012	-18.5095	***
Residual load	0.00004	0.00002	1.94892	*
DE $\leftrightarrow$ ATCZ	0.00076	0.00011	6.6854	***
DE $\leftrightarrow$ CH	0.00065	0.00009	6.9101	***
DE $\leftrightarrow$ FR	-0.00039	0.00006	-5.8903	***
DE $\leftrightarrow$ NO2	-0.00046	0.00020	2.2667	**
DE $\leftrightarrow$ PL	-0.00076	0.00021	-3.3518	***
ω	2.85134	0.12842	22.2065	***
$\alpha 1$	0.79975	0.06687	11.9631	***
$\beta 1$	0.19916	0.02240	8.8680	***
shape	2.85172	0.08355	34.1320	***

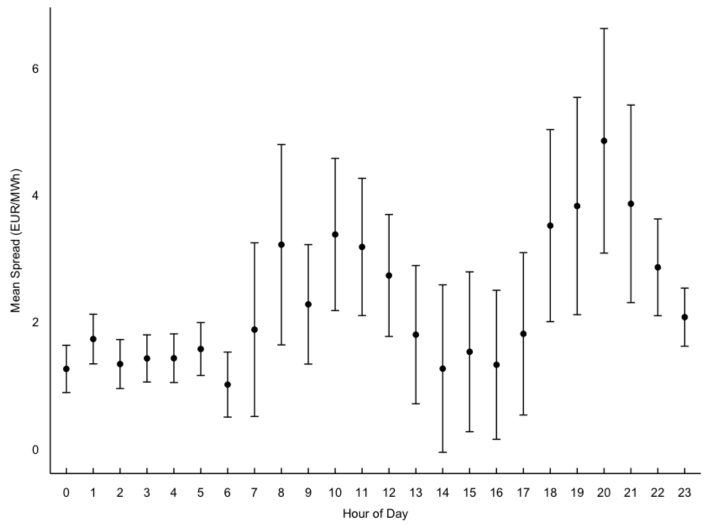
Table 5: *GARCH(1,1) model results with robust standard errors (significant variables only). Source: Generated in R*

The volatility dynamics captured by the GARCH(1,1) model also provide important insights. The parameter ω is significantly positive, indicating a stable baseline level of conditional variance in the spread. The ARCH term $\alpha 1$ is large and highly significant, suggesting that recent shocks to the spread, such as unexpected renewable forecast errors or price spikes, have a strong and immediate impact on future volatility. Meanwhile, the GARCH term $\beta 1$ is also significant, indicating that once volatility rises, it tends to persist across multiple trading intervals. This meaning that periods of high uncertainty tend to be followed by further uncertainty. From a trading perspective, these dynamics are crucial. Traders should be aware that ID market conditions are not independent from past volatility. In addition, diagnostic testing supports the robustness of the model specification. The ARCH LM test results show that all p-values are close to 1 across multiple lags, indicating no remaining ARCH effects in the standardized residuals. This suggests that the GARCH(1,1) model adequately captures the time-varying volatility present in the spread, and that conditional heteroskedasticity has been successfully modeled.

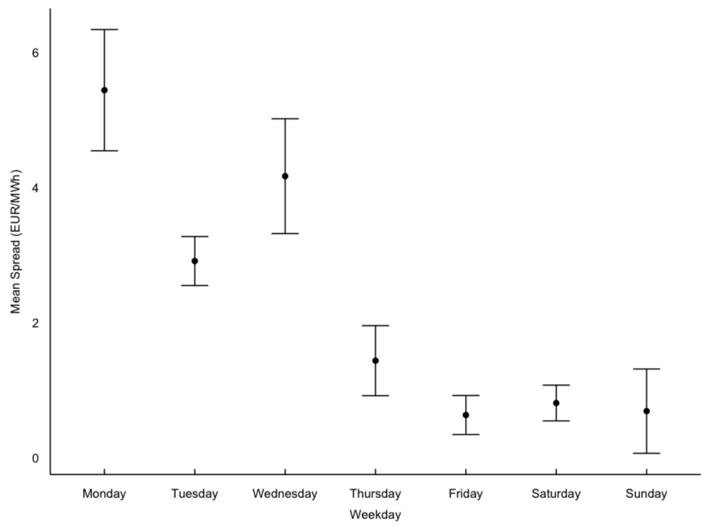
Comparing the results from the extended ARX and the GARCH, several differences in terms of significance can be captured. The variables Load^{FE}, DE $\leftrightarrow$ BE, and DE $\leftrightarrow$ DK1 are not significant anymore. Meanwhile the variables residual load, DE $\leftrightarrow$ ATCZ, CH, NO2 & PL, did not appear significant in the ARX model, they became statistically significant in the GARCH framework. This highlights that their contribution to the spread is more prominently linked to periods of heightened volatility. For example, interconnector flows may not strongly affect the average spread but becomes more critical when markets are under stress or reacting to forecast surprises.

5.3 Seasonality

Intraday price spreads in electricity markets are inherently shaped by recurring temporal patterns. These seasonal effects often stem from systematic behavioral trends, market operation routines, demand patterns, and fluctuations in renewable energy production.



Mean spread and standard error for hourly timeframe



Mean spread and standard error for weekdays

Figure 4: *Mean spread and it's standard error. Source: Generated in R*

In figure 4 above, it is clear that the mean spread and it's standard error vary throughout the day and week. This visual evidence suggests the presence of time-dependent pricing behavior, particularly with elevated spreads and uncertainty during specific hours and on early weekdays. In the two following sections 5.3.1 and 5.3.2 the time-dependent spread behavior will be addressed by estimating models with dummies included.

5.3.1 Daily effect

To capture the ID dynamics of the spread, the day was segmented into five distinct blocks, which include, night (00:00–06:00), morning ramp (06:00–09:00), mid peak (09:00–18:00), evening ramp (18:00–22:00), and late evening (22:00–00:00). The OLS regression was specified with interaction terms between these time blocks and the key independent variables, including forecast errors[2] and market fundamentals, using the night block as reference. Before interpreting the results, it is important to acknowledge that residual diagnostics reveal the presence of both autocorrelation and heteroskedasticity. The Ljung-Box test strongly rejects the null hypothesis of no autocorrelation ($p < 2.2 \times 10^{-16}$), and White's test similarly rejects the null of homoskedasticity ($p = 1.91 \times 10^{-24}$). Consequently, robust standard errors (HC) are applied using the `coeftest` function. The results of that can be found in Appendix C.2, table 21.

Looking at the results, a number of interesting patterns emerge. Interestingly, the base effect of the time blocks themselves (Block_FactorMP) is not statistically significant, suggesting that the conditional spread level alone does not shift markedly throughout the day once the explanatory variables are accounted for. Then looking at the fundamentals, load FE are only significant during the mid peak, and interestingly enough not the ramps. This suggests that during the central hours of the day, when demand is relatively stable and solar generation is at its peak, deviations in expected load can have an effect on the spread. In contrast, during the ramping periods, system flexibility and increased dispatch activity may buffer the impact of load forecast errors, making the influence on price spreads statistically insignificant. Wind FE are significantly negative across all time blocks (and the only variable that is significant in the night) but notably less significant in the mid peak. This aligns with the dominance of solar during this period, which may reduce the marginal influence of wind forecast errors on the spread. With solar generation driving much of the supply variability in mid peak hours, the system's pricing sensitivity may shift away

[2]Solar is not included in this setup, as the production is limited to the two mid peak blocks, and thus not as informative

from wind deviations, explaining the relative drop in significance. Outages are positively significant during the evening ramp and late evening blocks, when system flexibility is generally more constrained. This is intuitive, as reduced generation availability during these hours heightens reliance on more expensive balancing mechanisms, thus widening the spread. It would have been expected, that outages also had a significant effect on the morning ramp, but that is not the case. Net export is only significant during the mid peak hours, reflecting the complexity of this period in the European power system where RES deviate a lot between countries. The results suggest that when Germany exports more in the DA market, the ID price tends to trade lower than the spot price during these hours, possibly due to over scheduled exports amplifying supply side pressure that is later corrected in ID market.

5.3.2 Weekday effect

To examine whether the spread dynamics vary systematically across the days of the week, the model is extended with interaction terms between weekday dummies and the explanatory variables, using monday as reference. The regression thus captures not only the direct weekday effect, but also whether the influence of forecast errors and fundamentals varies depending on the day. As with the daily block model, the residual diagnostics indicate a clear presence of both autocorrelation and heteroskedasticity. The Ljung-Box test strongly rejects the null of no autocorrelation ($p < 2.2 \times 10^{-16}$), while the White test similarly rejects the null of homoskedasticity ($p = 3.39 \times 10^{-63}$). Hence, the `coeftest` function with heteroskedasticity-consistent standard errors (HC) is again employed to ensure more valid results. The results can be found in appendix C.2, table 24 and 25.

The model reveals several patterns. First, the weekday dummy coefficients, particularly for Tuesday, Thursday, and Friday are statistically significant, indicating that the average spread on these days differs from Monday even when controlling for all other variables. In contrast, Wednesday and the weekend are not statistically significant, implying that the average spread on these days does not differ meaningfully from monday after accounting for market fundamentals. Among the fundamentals, the load FE only show slightly sign of significance for some of the days. This suggests that FE in load are not systematically associated with spread variations on specific days of the week, likely due to the relatively predictable nature of demand patterns across the week. Wind FE exhibit a particularly interesting weekday pattern. The baseline coefficient for Monday (the reference category) is highly significant and strongly negative, indicating that on Mondays, wind FE tend to reduce the ID prices relative to the spot price (if supply surplus). Meanwhile the rest of the week is also significant (besides Wednesday), but with positive coefficients. Notably, the strongest effects compared to Monday are seen on weekends (Saturday and Sunday), which may reflect less flexible generation portfolios and lower trading volumes. Solar FE exhibit the same behavior as wind, with Monday being highly significant and strongly negative. The interaction terms for the other weekdays for solar FE are also generally positive, but only marginally significant, suggesting a weakening of this negative effect from Monday. Residual load is different from wind and solar FE, as it have a significant and positive base effect on Mondays, indicating that spreads are strongly influenced by the level of conventional generation early in the week. However, the interaction terms for rest of the week is only significant for Tuesday, Thursday and Friday, but with negative coefficients. Outages are mostly insignificant across the weekdays, indicating that their effect on the spread is not strongly tied to the day of the week. This aligns with earlier findings showing that outages matter more in specific time windows, such as the evening ramp, where system flexibility is limited, rather than exhibiting a consistent weekday pattern. Finally, net export is very similar to wind FE in terms of weekly interactions. Net export is highly significant and negatively signed on the Monday reference, suggesting that increased DA exports are associated with lower ID prices relative to spot on that day. Then for rest of the week, net export have positive coefficients that gets even more significant as we approach Friday to Sunday. This is implying that the price impact of net exports intensifies during the end of the week and especially in the weekends.

6 Conclusion

This study identifies some of the fundamental factors driving the price spread between the German DA and ID electricity markets. It finds that the spread is significantly affected by discrepancies between forecasted and actual electricity supply by wind and solar, forecast deviations for demand, combined with scheduled DA interconnector flows also proven significant on certain borders.

When addressing the first sub-question, the results from the ARX model aligned with expectations for most significant variables. However, the load FE deviated from theoretical expectations, showing a negative coefficient. This indicates that when actual demand exceeds forecasts it led to lower ID prices compared to DA prices, contradicting standard theoretical assumptions. Among the interconnectors, the net export for DE $\leftrightarrow$ FR was found to be the most statistically significant, which aligns with its high capacity and strategic role in balancing the German market, especially during system stress or large forecast deviations. Considering the insights from the GARCH(1,1) model further reveals that factors such as residual load and additional interconnector flows becomes signifant during periods of heightened market volatility, even if their average effect on the spread is limited. Regarding the second sub-question, the analysis reveals some patterns in the price spread, both ID and across the week. From a daily perspective, wind forecast error is the only variable that shows a significant effect during the night hours (also significant for the rest of the day, but less in mid peak, where solar deviations kick in), indicating that unexpected wind deviations overnight have a measurable impact on ID prices, possibly due to low liquidity and limited flexibility in those hours. Additionally, both the load and net export is only significant during the mid peak block, suggesting that load FE and cross-border flows play a more active role in price formation during the most liquid and operationally intensive part of the trading day, but are less relevant during ramping or off-peak hours. Besides that, outages is only significant in the evening. On a weekly level, interaction effects show that both wind and solar forecast errors are most impactful on Mondays, where they are highly significant and negatively signed. This implies that on Mondays, forecast errors tend to drive ID prices below DA levels (if in a surplus or above DA levels if in a deficit). The pattern for Monday is likely due to higher system uncertainty and residual adjustments from the weekend. For the remainder of the week, the coefficients turn positive, suggesting a shift in market behavior and improved alignment between forecasts and actual conditions.

While the findings of this study offer meaningful insights into the drivers of ID price spreads, certain limitations should be acknowledged. The results are based on historical data from a specific period, and the applied econometric models involve simplifications that may limit generalizability. Dynamics such as market liquidity and strategic trading behavior were not quantified and used in this study. However, these limitations also point towards opportunity of future research, which could be with the use of more advanced modeling from machine learning. Developing a forecasting model for spread behavior could provide valuable tools for short-term trading and operational decision-making.

7 Bibliography

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Appendicer

A Plots

A.1 Variables

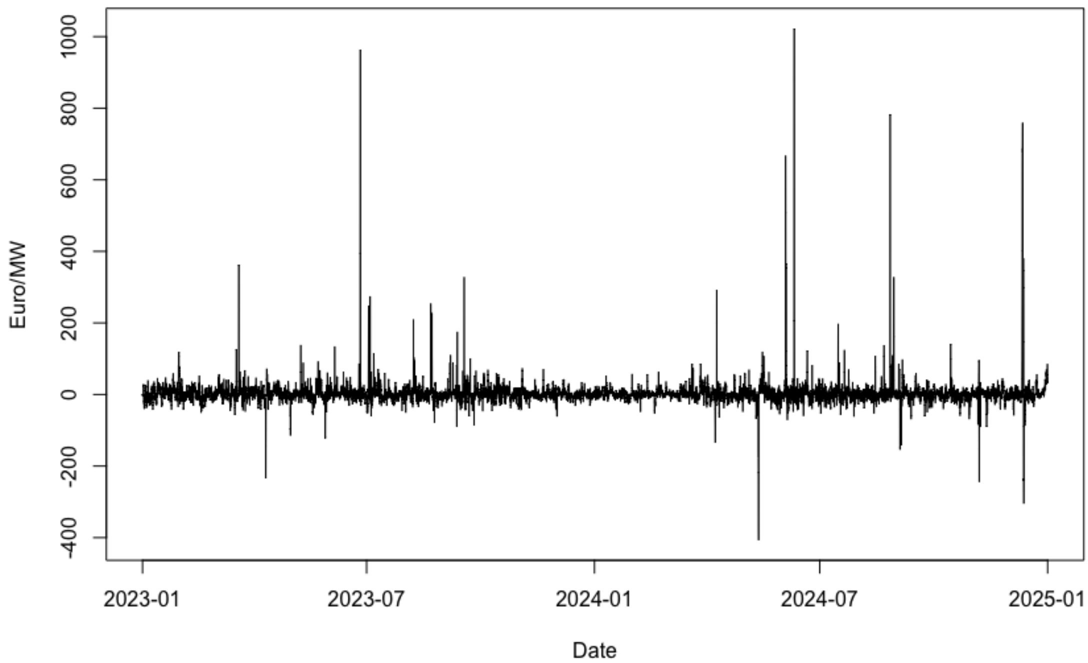
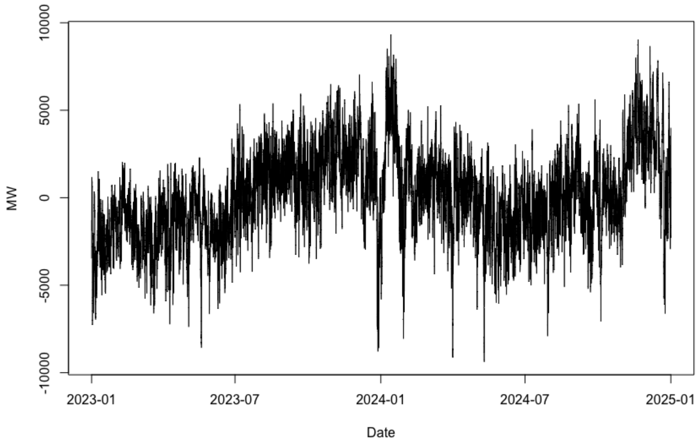
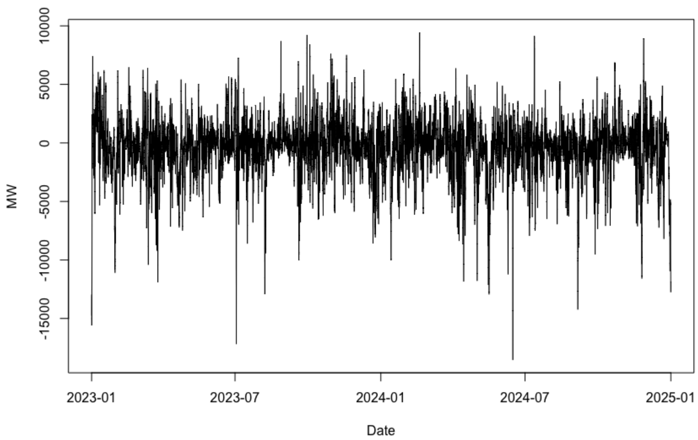


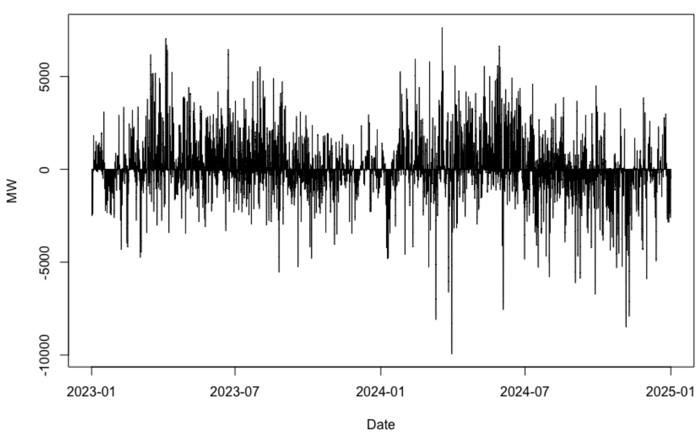
Figure 5: *Lineplot for the spread. Source: Generated in R*



Load FE

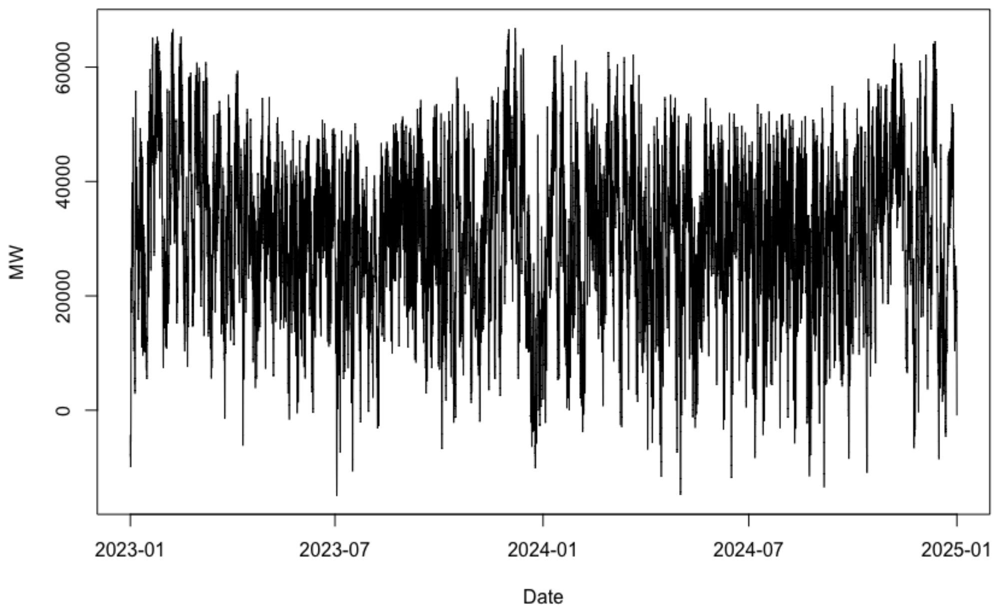


Wind FE

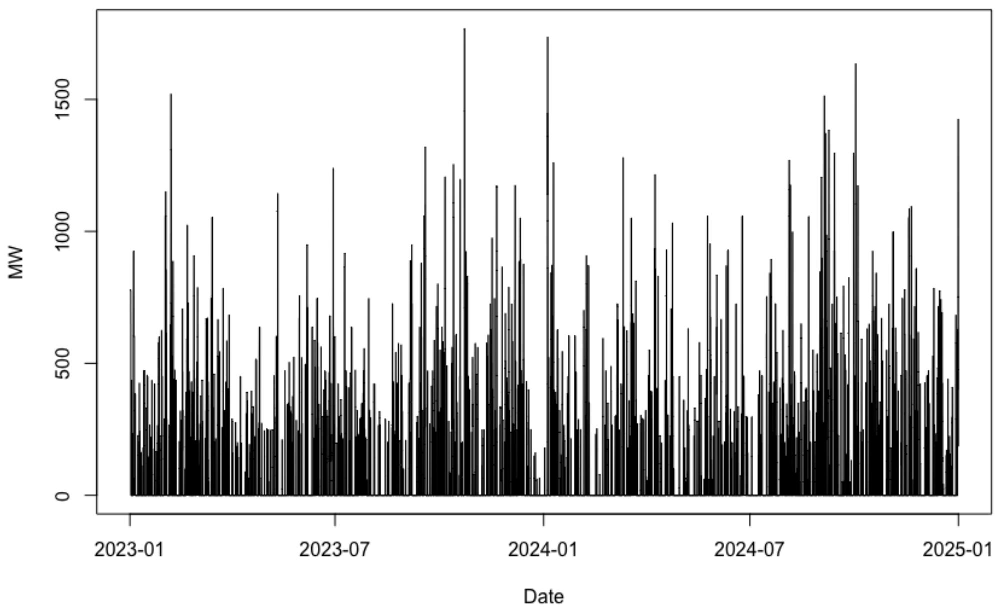


Solar FE

Figure 6: *Lineplots of Load FE, Wind FE, and Solar FE. Source: Generated in R*

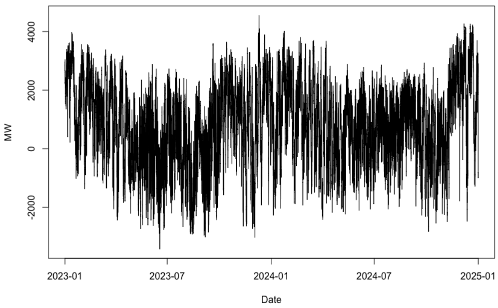


Residual load Fct

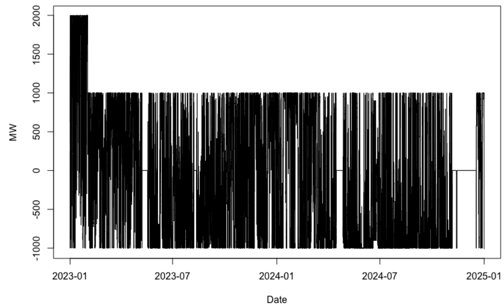


Unplanned outages

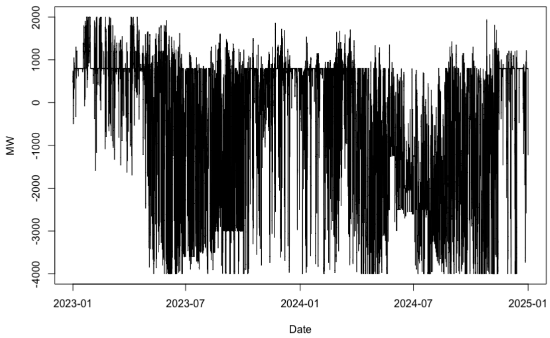
Figure 7: *Lineplots of Residual load and unplanned outages. Source: Generated in R*



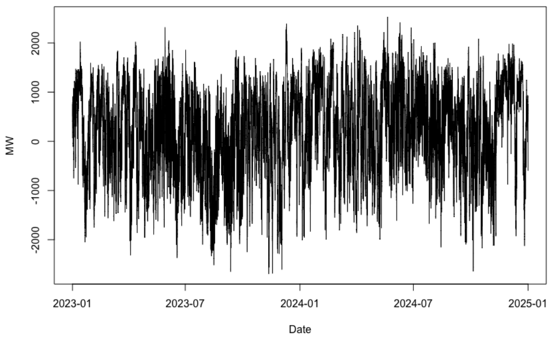
DE ↔ AT



DE ↔ BE



DE ↔ CH



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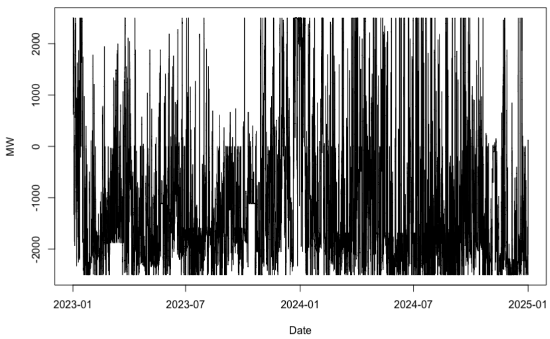
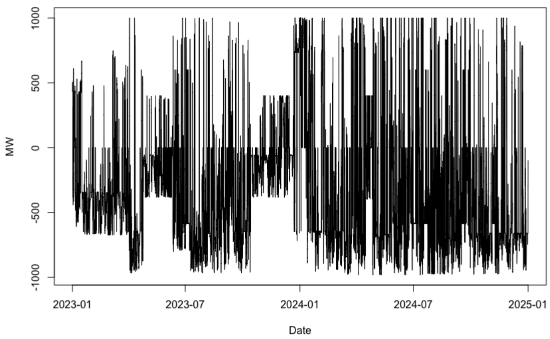
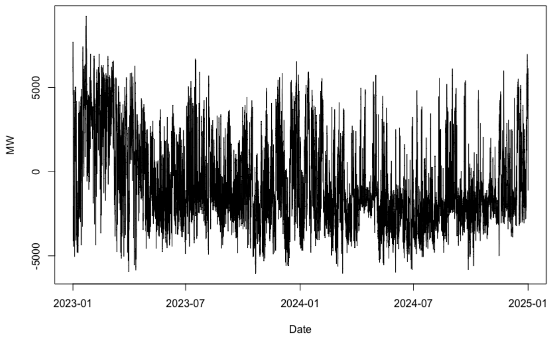


DE ↔ DK1

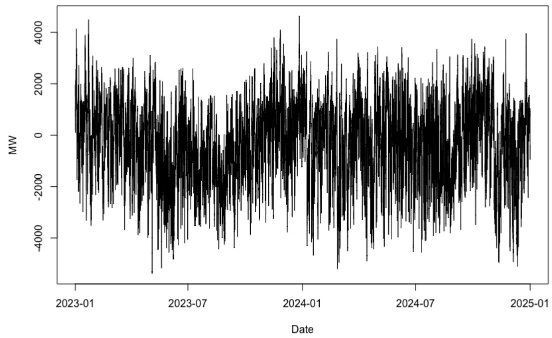


DE ↔ DK2

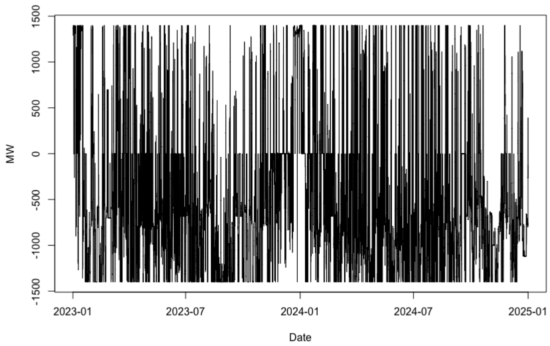
Figure 8: *Lineplots of the net export for all interconnectors. Figure (1/2). Source: Generated in R*



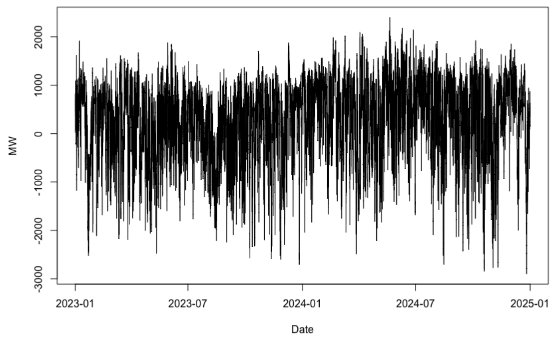
$DE \leftrightarrow FR$



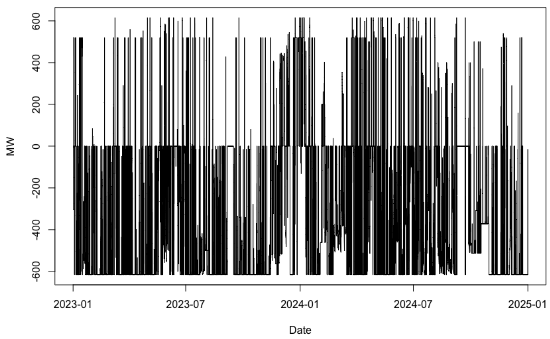
$DE \leftrightarrow NL$



$DE \leftrightarrow NO2$



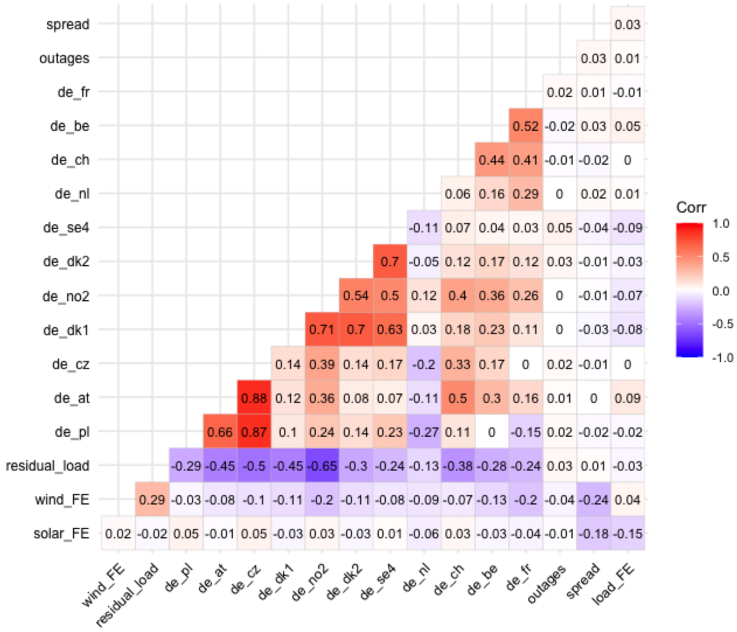
$DE \leftrightarrow PL$



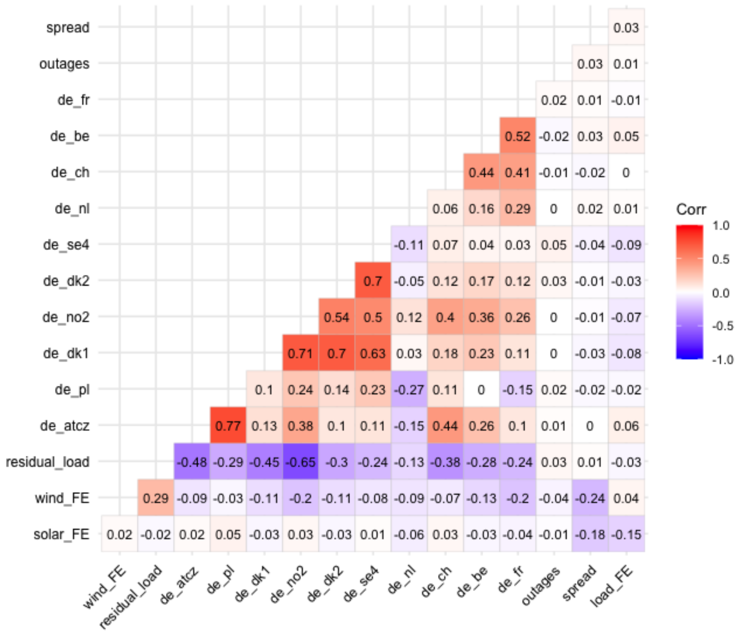
$DE \leftrightarrow SE4$

Figure 9: *Lineplots of the net export for all interconnectors. Figure (2/2). Source: Generated in R*

A.2 Correlation



Correlation matrix, version 1



Correlation matrix, version 2

Figure 10: *Correlation matrix with and without variable update. Source: Generated in R*

B Tables

B.1 Preliminary diagnostics

Variable	**ADF Statistic**	**p-value**
Spread	-22.779	< 0.01
Load$^{\mathrm{FE}}$	-10.460	< 0.01
Wind$^{\mathrm{FE}}$	-18.808	< 0.01
Solar$^{\mathrm{FE}}$	-17.041	< 0.01
Residual Load	-16.892	< 0.01
Outages	-21.691	< 0.01
DE $\leftrightarrow$ AT	-13.357	< 0.01
DE $\leftrightarrow$ BE	-13.458	< 0.01
DE $\leftrightarrow$ CH	-11.467	< 0.01
DE $\leftrightarrow$ CZ	-15.356	< 0.01
DE $\leftrightarrow$ DK1	-14.378	< 0.01
DE $\leftrightarrow$ DK2	-13.617	< 0.01
DE $\leftrightarrow$ FR	-12.821	< 0.01
DE $\leftrightarrow$ NL	-15.214	< 0.01
DE $\leftrightarrow$ NO2	-13.657	< 0.01
DE $\leftrightarrow$ PL	-16.800	< 0.01
DE $\leftrightarrow$ SE4	-12.812	< 0.01

Table 6: *ADF test results for all variables. P-value is smaller than the printed p-value. Source: Generated in R*

(a) Base Model VIF

Variable	**VIF**
Load^{FE}	1.09
Wind^{FE}	1.14
Solar^{FE}	1.05
Residual Load	2.43
Outages	1.01
DE $\leftrightarrow$ AT	6.80
DE $\leftrightarrow$ BE	1.64
DE $\leftrightarrow$ CH	1.83
DE $\leftrightarrow$ CZ	**14.78**
DE $\leftrightarrow$ DK1	3.29
DE $\leftrightarrow$ DK2	2.60
DE $\leftrightarrow$ FR	1.70
DE $\leftrightarrow$ NL	1.25
DE $\leftrightarrow$ NO2	3.40
DE $\leftrightarrow$ PL	5.74
DE $\leftrightarrow$ SE4	2.39

(b) Revised Model VIF (after combining `de_atcz`)

Variable	**VIF**
Load^{FE}	1.07
Wind^{FE}	1.13
Solar^{FE}	1.04
Residual load	2.20
Outages	1.01
DE $\leftrightarrow$ ATCZ	4.29
DE $\leftrightarrow$ BE	1.63
DE $\leftrightarrow$ CH	1.79
DE $\leftrightarrow$ DK1	3.20
DE $\leftrightarrow$ DK2	2.59
DE $\leftrightarrow$ FR	1.66
DE $\leftrightarrow$ NL	1.24
DE $\leftrightarrow$ NO2	3.35
DE $\leftrightarrow$ PL	3.43
DE $\leftrightarrow$ SE4	2.39

Table 7: *Comparison of Variance Inflation Factor (VIF) before and after variable reduction. Source: Generated in R*

C Models

For all models, the following significance levels is applied:

$$*** \ p < 0.01, ** \ p < 0.05, * \ p < 0.1$$

C.1 SQ1

OLS

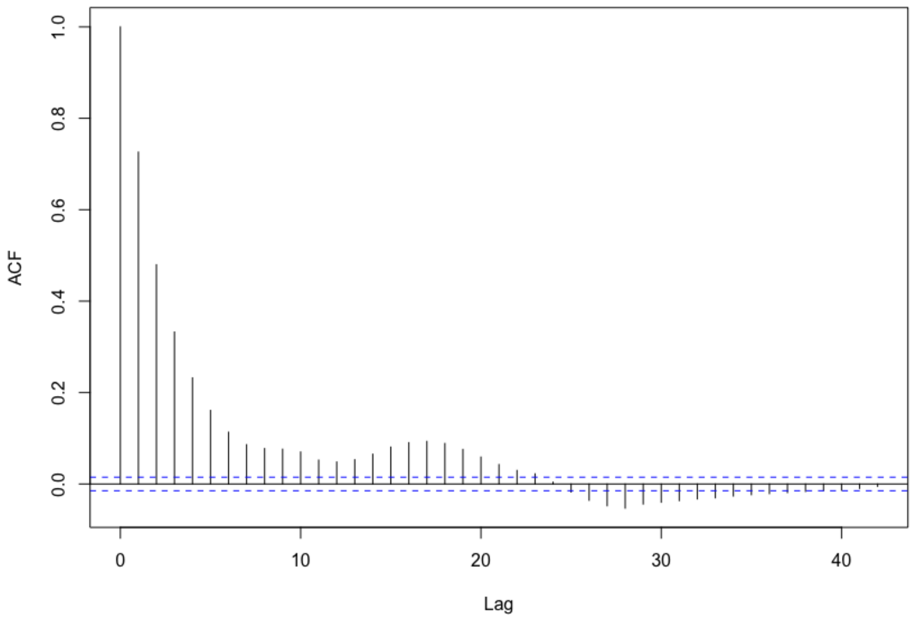
Variable	Estimate	Std. Error	t-Value	Signif.
Intercept	-6.203e+00	7.199e-01	-8.617	***
Load^{FE}	9.859e-05	8.890e-05	1.109	
Wind^{FE}	-3.418e-03	9.878e-05	-34.918	***
Solar^{FE}	-4.555e-03	1.917e-04	-23.764	***
Residual Load	1.808e-04	2.287e-05	7.908	***
Outages	2.947e-03	1.150e-03	2.563	*
DE $\leftrightarrow$ ATCZ	3.538e-04	1.965e-04	1.801	
DE $\leftrightarrow$ BE	1.370e-03	3.408e-04	4.020	***
DE $\leftrightarrow$ CH	-2.176e-04	1.828e-04	-1.189	
DE $\leftrightarrow$ DK1	-1.214e-03	2.858e-04	-4.246	***
DE $\leftrightarrow$ DK2	2.760e-04	1.593e-04	1.732	
DE $\leftrightarrow$ FR	-6.478e-04	1.098e-04	-5.901	***
DE $\leftrightarrow$ NL	-1.221e-04	1.546e-04	-0.790	
DE $\leftrightarrow$ NO2	1.734e-03	4.696e-04	3.693	***
DE $\leftrightarrow$ PL	-9.519e-04	4.724e-04	-2.015	*
DE $\leftrightarrow$ SE4	-3.358e-03	9.296e-04	-3.641	***

Table 8: *Baseline OLS regression results. Source: Generated in R*

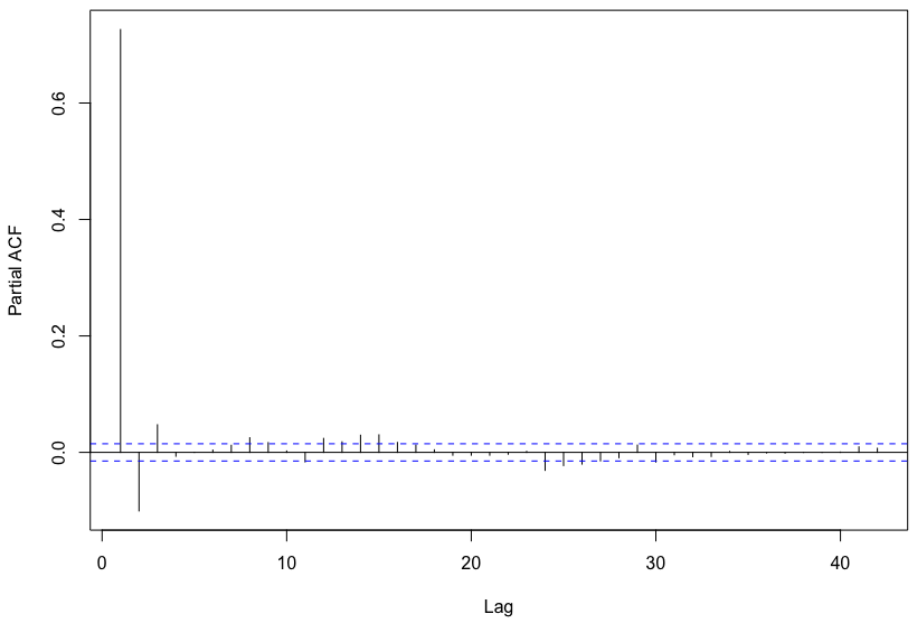
Note: Residual Std. Error: 28.19 on 17,504 df. $R^2 = 0.1011$, Adj. $R^2 = 0.1003$. F-statistic = 131.2 on 15 and 17,504 df, $p < 2.2 \times 10^{-16}$.

Test Statistic	Degrees of Freedom	p-value
12,571	20	$< 2.2 \times 10^{-16}$

Table 9: *Ljung-Box test result for residual autocorrelation in baseline OLS model. Source: Generated in R*



ACF of the OLS's residuals



PACF of the OLS's residuals

Figure 11: *ACF and PACF for the baseline OLS model. Source: Generated in R*

ARX

1. version

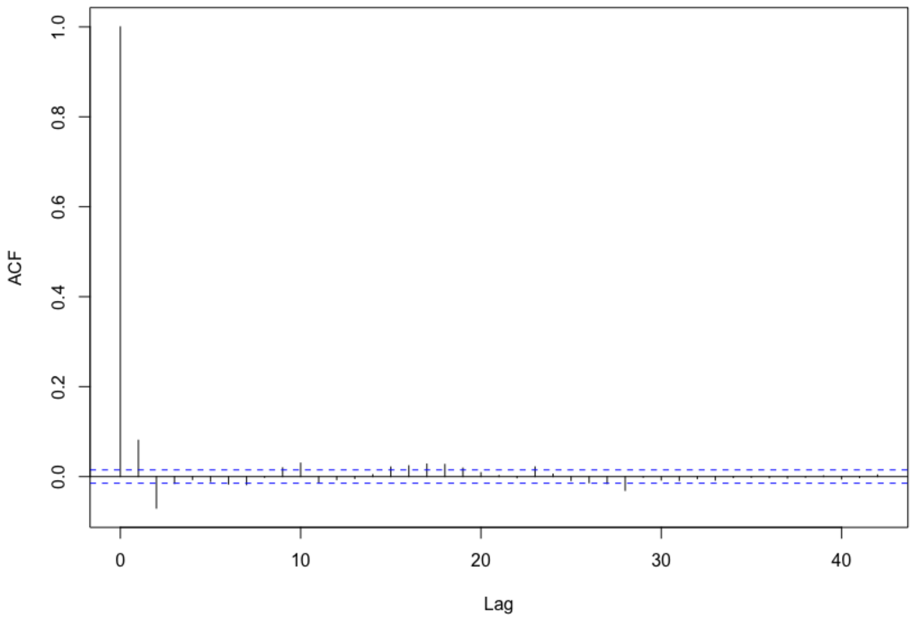
Variable	Estimate	Std. Error	t-Value	Signif.
Intercept	-1.606e+00	4.958e-01	-3.240	**
L(Spread, 1)	7.245e-01	5.182e-03	139.825	***
Load^{FE}	-5.495e-05	6.110e-05	-0.900	
Wind^{FE}	-9.732e-04	6.957e-05	-13.990	***
Solar^{FE}	-1.424e-03	1.336e-04	-10.658	***
Residual Load	1.692e-04	1.575e-05	10.740	**
Outages	1.624e-03	7.906e-04	2.055	*
DE $\leftrightarrow$ ATCZ	1.741e-04	1.354e-04	1.285	
DE $\leftrightarrow$ BE	3.661e-04	2.348e-04	1.560	
DE $\leftrightarrow$ CH	-1.196e-04	1.253e-04	-0.953	
DE $\leftrightarrow$ DK1	-4.414e-04	1.965e-04	-2.249	*
DE $\leftrightarrow$ DK2	4.823e-04	5.004e-04	0.965	
DE $\leftrightarrow$ FR	-2.198e-04	7.552e-05	-2.911	**
DE $\leftrightarrow$ NL	-1.034e-04	1.063e-04	-0.970	
DE $\leftrightarrow$ NO2	5.414e-04	3.229e-04	1.677	.
DE $\leftrightarrow$ PL	-6.534e-04	3.247e-04	-2.012	*
DE $\leftrightarrow$ SE4	-4.031e-04	6.393e-04	-0.631	

Table 10: *ARX regression results including first lag. Source: Generated in R*

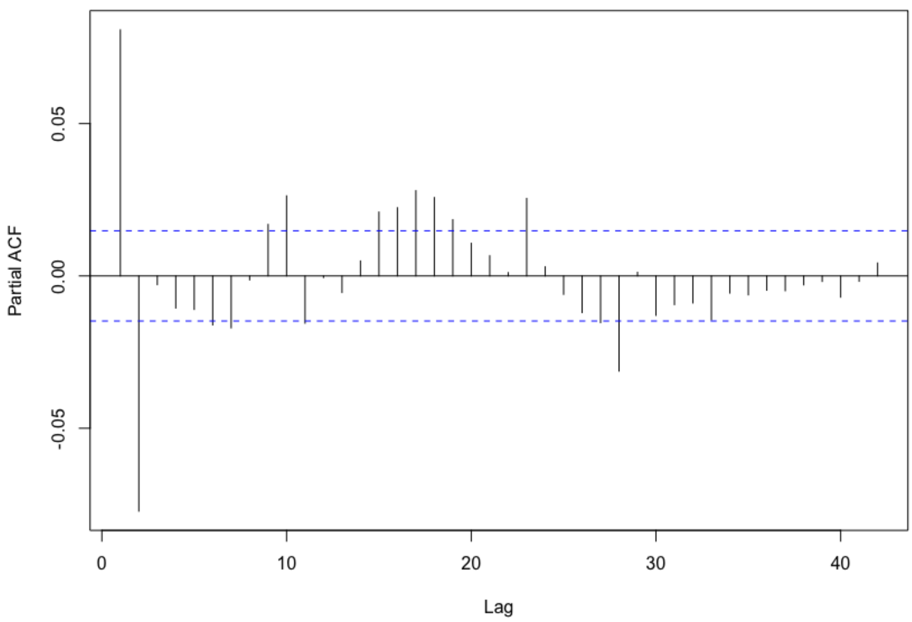
Note: Residual Std. Error: 19.37 on 17,502 df. $R^2 = 0.5754$, Adj. $R^2 = 0.5751$. F-statistic = 1483 on 16 and 17,502 df, $p < 2.2 \times 10^{-16}$.

Test Statistic	Degrees of Freedom	p-value
296.58	20	$< 2.2 \times 10^{-16}$

Ljung-Box test result for residual autocorrelation in ARX model. Source: Generated in R



ACF of the ARX's residuals



PACF of the ARX's residuals

Figure 12: *ACF and PACF for the first ARX model. Source: Generated in R*

2. version

Variable	Estimate	Std. Error	t-Value	Signif.
Intercept	-1.681e+00	4.969e-01	-3.382	***
L(Spread, 1)	8.053e-01	7.602e-03	105.932	***
L(Spread, 2)	-1.399e-01	9.701e-03	-14.416	***
L(Spread, 3)	4.450e-02	7.533e-03	5.908	***
L(Spread, 24)	-1.534e-02	4.955e-03	-3.097	**
L(Spread, 168)	-1.907e-02	4.949e-03	-3.853	***
Load^{FE}	-1.415e-05	6.181e-05	-0.229	
Wind^{FE}	-1.039e-03	7.082e-05	-14.667	***
Solar^{FE}	-1.493e-03	1.338e-04	-11.158	***
Residual Load	5.022e-05	1.584e-05	3.170	**
Outages	2.015e-03	8.008e-04	2.516	*
DE $\leftrightarrow$ ATCZ	1.985e-04	1.358e-04	1.462	
DE $\leftrightarrow$ BE	4.852e-04	2.368e-04	2.049	*
DE $\leftrightarrow$ CH	-1.299e-04	1.253e-04	-1.036	
DE $\leftrightarrow$ DK1	-4.461e-04	1.973e-04	-2.261	*
DE $\leftrightarrow$ DK2	4.600e-04	5.004e-04	0.919	
DE $\leftrightarrow$ FR	-2.282e-04	7.582e-05	-3.010	**
DE $\leftrightarrow$ NL	-9.859e-05	1.066e-04	-0.925	
DE $\leftrightarrow$ NO2	5.124e-04	3.248e-04	1.578	
DE $\leftrightarrow$ PL	-6.865e-04	3.255e-04	-2.109	*
DE $\leftrightarrow$ SE4	-4.382e-04	6.415e-04	-0.683	

Table 11: *ARX regression results including multiple lags of spread. Source: Generated in R*

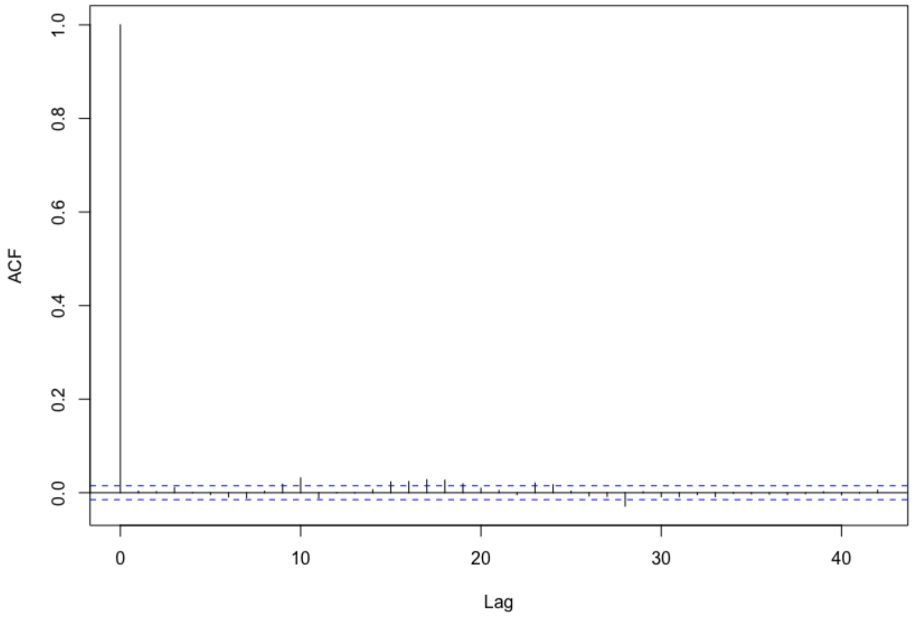
Note: Residual Std. Error: 19.31 on 17,331 df. $R^2 = 0.5811$, Adj. $R^2 = 0.5806$. F-statistic = 1202 on 20 and 17,331 df, $p < 2.2 \times 10^{-16}$.

Test Statistic	Degrees of Freedom	p-value
85.335	20	4.792×10^{-10}

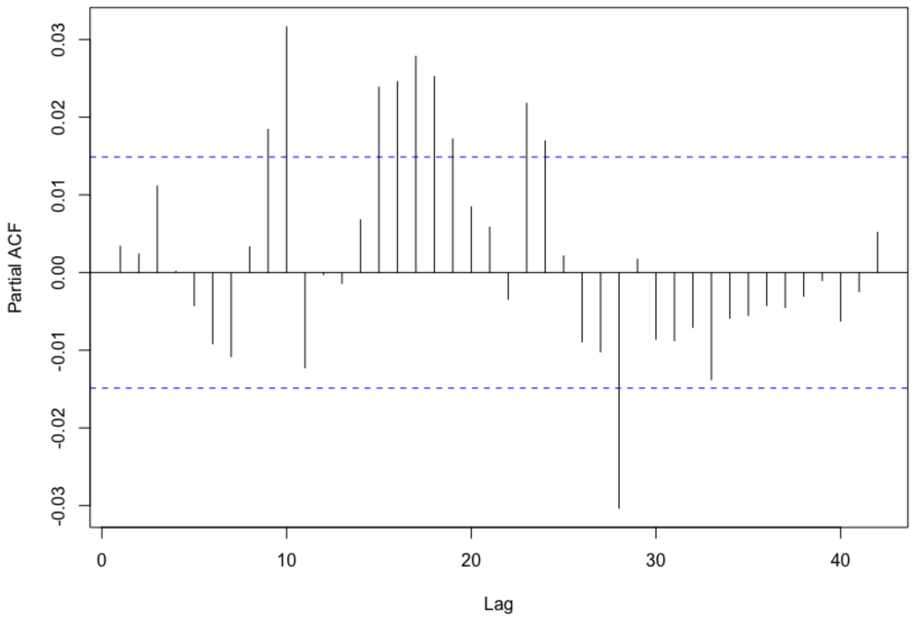
Table 12: *Ljung-Box test result for residual autocorrelation in extended ARX model. Source: Generated in R*

Test Statistic	Degrees of Freedom	p-value
450748324	2	$< 2.2 \times 10^{-16}$

Table 13: *Jarque-Bera test result for residual normality in extended ARX model. Source: Generated in R*



ACF of the extended ARX's residuals



PACF of the extended ARX's residuals

Figure 13: *ACF and PACF for the extended ARX model. Source: Generated in R*

Test Statistic	Degrees of Freedom	p-value
1546	40	1.54×10^{-298}

Table 14: *White's test result for heteroscedasticity in extended ARX model. Source: Generated in R*

Variable	Estimate	Std. Error	t-Value	Signif.
Intercept	-1.6807	0.47005	-3.5756	***
L(Spread, 1)	0.8533	0.10564	7.6233	***
L(Spread, 2)	-0.1399	0.09138	-1.5008	
L(Spread, 3)	-0.0493	0.05493	-0.9022	
L(Spread, 24)	-0.1535	0.13918	-1.1025	
L(Spread, 168)	-0.2862	0.15375	-1.8630	
Load^{FE}	-0.00005	0.00047	-0.2849	
Wind^{FE}	-0.00157	0.00027	-5.7806	***
Solar^{FE}	-0.00285	0.00029	-5.1870	***
Residual load	0.00022	0.00006	3.4825	***
Outages	0.00082	0.00034	2.3998	*
DE↔ATCZ	0.00124	0.00079	1.5640	
DE↔BE	0.00085	0.00044	1.9436	.
DE↔CH	-0.00111	0.00058	-1.9140	
DE↔DK1	-0.00118	0.00047	-2.6158	**
DE↔DK2	0.00046	0.00055	0.8355	
DE↔FR	-0.00213	0.00061	-3.4897	***
DE↔NL	-0.00098	0.00161	-0.9256	
DE↔NO2	-0.00135	0.00052	-2.5966	*
DE↔PL	-0.00186	0.00073	-2.5318	*
DE↔SE4	-0.00083	0.00104	-0.7953	

Table 15: *Extended ARX model results with robust standard errors. Source: Generated in R*

Test Statistic	Degrees of Freedom	p-value
1093.9	24	$< 2.2 \times 10^{-16}$

Table 16: *ARCH LM test result for ARCH effects in extended ARX model residuals. Source: Generated in R*

GARCH

Variable	Estimate	Std. Error	t-Value	Signif.
Intercept (μ)	-1.91029	0.60150	-3.1759	***
AR(1) (ϕ_1)	0.79137	0.00825	95.9398	***
Load^{FE}	-0.00002	0.00006	-0.3302	
Wind^{FE}	-0.00154	0.00009	-16.5271	***
Solar^{FE}	-0.00212	0.00011	-18.6785	***
Residual load	0.00004	0.00002	2.8513	***
Outages	0.00003	0.00007	0.4526	
DE↔ATCZ	0.00076	0.00011	6.4502	***
DE↔BE	0.00088	0.00020	4.3383	
DE↔CH	0.00065	0.00009	6.9384	***
DE↔DK1	-0.00004	0.00003	-1.9631	
DE↔DK2	-0.00046	0.00029	-1.5673	
DE↔FR	-0.00075	0.00013	-5.9094	***
DE↔NL	-0.00018	0.00019	-0.9866	
DE↔NO2	-0.00044	0.00020	-2.1663	**
DE↔PL	-0.00044	0.00022	-1.9830	***
DE↔SE4	0.00035	0.00036	0.9692	
ω	31.89182	2.90161	10.9917	***
α_1	0.80047	0.06715	11.9206	***
β_1	0.19854	0.02292	8.6621	***
shape	2.84222	0.08297	34.2583	***

Table 17: *GARCH(1,1) model results with robust standard errors and labeled external regressors. Source: Generated in R*

ARCH Lag	Statistic	Shape	p-value
5	2.441e-05	0.500	0.9961
13	5.268e-03	1.440	0.9998
20	8.983e-03	2.315	1.0000

Table 18: *ARCH LM test results for standardized residuals from GARCH(1,1) model. Source: Generated in R*

C.2 SQ2

Daily effect

Test Statistic	Degrees of Freedom	p-value
19,348	20	$< 2.2 \times 10^{-16}$

Table 19: *Ljung-Box test result for the block dummy model. Source: Generated in R*

Test Statistic	Degrees of Freedom	p-value
217	48	2.01×10^{-23}

Table 20: *White's test result for the block dummy model. Source: Generated in R*

Variable	Estimate	Std. Error	t-Value	Signif.
Intercept	0.60331	0.19210	3.1396	**
Load^{FE}	0.00003	0.00020	0.3818	
Block_Morningramp	-0.09120	0.05869	-0.1566	
Block_MP	0.05134	0.05320	0.9960	
Block_Eveningramp	-0.08147	0.05105	-1.6246	
Block_Lateevening	-0.03331	0.06956	-0.7094	
Wind^{FE}	-0.00227	0.00012	-18.8728	***
Outages	-0.00188	0.00108	-1.6674	.
Net export	-0.00028	0.00025	-1.1358	
$\text{Load}^{\text{FE}} \times$ Morningramp	-0.00027	0.00033	-0.8175	
$\text{Load}^{\text{FE}} \times$ MP	0.00048	0.00015	3.1131	***
$\text{Load}^{\text{FE}} \times$ Eveningramp	0.00105	0.00023	4.5763	.
$\text{Load}^{\text{FE}} \times$ Lateevening	0.00060	0.00032	1.8961	.
$\text{Wind}^{\text{FE}} \times$ Morningramp	-0.00273	0.00065	-4.2078	***
$\text{Wind}^{\text{FE}} \times$ MP	-0.00079	0.00024	-3.7122	*
$\text{Wind}^{\text{FE}} \times$ Eveningramp	-0.00399	0.00195	-1.2493	***
$\text{Wind}^{\text{FE}} \times$ Lateevening	-0.00268	0.00064	-4.1971	***
Outages $\times$ Morningramp	-0.00548	0.00227	-0.2411	
Outages $\times$ MP	-0.00131	0.00192	-0.6854	
Outages $\times$ Eveningramp	0.00583	0.00195	2.9989	***
Outages $\times$ Lateevening	0.00286	0.00029	5.7585	***
Net export $\times$ Morningramp	-0.00133	0.00018	-7.0830	.
Net export $\times$ MP	-0.00460	0.00046	-9.9461	***
Net export $\times$ Eveningramp	-0.00370	0.00042	-8.7430	
Net export $\times$ Lateevening	-0.00197	0.00015	-1.3462	

Table 21: *OLS model with block-wise interaction terms and robust standard errors. Source: Generated in R*

Weekday effect

Test Statistic	Degrees of Freedom	p-value
17,484	20	$< 2.2 \times 10^{-16}$

Table 22: *Ljung-Box test result for residual autocorrelation in the weekday interaction model. Source: Generated in R*

Test Statistic	Degrees of Freedom	p-value
541	96	3.39×10^{-63}

Table 23: *White's test result for heteroskedasticity in the weekday interaction model. Source: Generated in R*

Variable	Estimate	Std. Error	t-Value	Signif.
Intercept	-7.30200	1.73560	-4.2073	***
Weekday Tuesday	1.21060	1.96380	6.1661	***
Weekday Wednesday	-4.51610	4.30220	-1.0497	
Weekday Thursday	6.69380	2.41730	2.7342	**
Weekday Friday	8.97840	1.97530	4.5435	***
Weekday Saturday	2.91660	1.87180	1.5586	
Weekday Sunday	-0.73910	1.32720	-0.3176	
Load^{FE}	-0.00264	0.00139	-1.8969	
Wind^{FE}	-0.00494	0.00043	-11.6204	***
Solar^{FE}	-0.00771	0.00175	-4.4090	***
Residual load	0.00031	0.00006	5.3192	***
Outages	-0.00159	0.00219	-0.7253	
Net export	-0.00041	0.00011	-3.7386	***
Tuesday $\times$ Load^{FE}	0.00075	0.00337	0.2226	
Wednesday $\times$ Load^{FE}	0.00115	0.00054	2.1508	*
Thursday $\times$ Load^{FE}	0.00385	0.00352	1.0942	
Friday $\times$ Load^{FE}	0.00563	0.00332	1.6985	.
Saturday $\times$ Load^{FE}	0.00352	0.00289	1.0703	
Sunday $\times$ Load^{FE}	0.00089	0.00301	0.2960	.
Tuesday $\times$ Wind^{FE}	0.00171	0.00045	3.7749	***
Wednesday $\times$ Wind^{FE}	-0.00132	0.00048	-2.7612	
Thursday $\times$ Wind^{FE}	0.00218	0.00048	2.6283	**
Friday $\times$ Wind^{FE}	0.00189	0.00045	4.2023	***
Saturday $\times$ Wind^{FE}	0.00266	0.00045	2.9272	***
Sunday $\times$ Wind^{FE}	0.00276	0.00046	4.9544	***

Table 24: *OLS model results with weekday interaction terms and robust standard errors (1/2). Source: Generated in R*

Variable	**Estimate**	**Std. Error**	**t-Value**	**Signif.**
Tuesday × Solar^{FE}	0.00412	0.00175	2.3538	*
Wednesday × Solar^{FE}	0.00252	0.00179	1.4072	
Thursday × Solar^{FE}	0.00237	0.00184	2.3063	*
Friday × Solar^{FE}	0.00439	0.00176	2.4811	*
Saturday × Solar^{FE}	0.00251	0.00176	2.4175	*
Sunday × Solar^{FE}	0.00282	0.00176	1.6047	
Tuesday × Residual Load	-0.00044	0.00006	-6.8302	***
Wednesday × Residual Load	0.00070	0.00006	2.6803	
Thursday × Residual Load	-0.00028	0.00008	-3.3400	***
Friday × Residual Load	-0.00036	0.00007	-5.5235	***
Saturday × Residual Load	-0.00011	0.00006	-1.7444	.
Sunday × Residual Load	0.00028	0.00008	0.3168	
Tuesday × Outages	0.00399	0.00274	1.4579	
Wednesday × Outages	0.00692	0.00398	1.5820	
Thursday × Outages	0.00287	0.00292	0.9866	
Friday × Outages	0.00433	0.00246	1.7520	.
Saturday × Outages	0.00405	0.00345	1.1344	
Sunday × Outages	0.00701	0.00553	1.2671	
Tuesday × Net Export	0.00043	0.00019	2.0284	*
Wednesday × Net Export	0.00042	0.00014	1.5121	
Thursday × Net Export	0.00039	0.00012	3.5872	*
Friday × Net Export	0.00038	0.00012	3.3058	***
Saturday × Net Export	0.00032	0.00013	2.3422	***
Sunday × Net Export	0.00047	0.00014	3.3149	***

Table 25: *OLS model results with weekday interaction terms and robust standard errors (2/2). Source: Generated in R*