Delft University of Technology

Assessing the Effect of Battery Storage on European Electricity Balancing Markets

An Empirical Approach

By

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Abstract

The transition to renewable energy sources is a key strategy in mitigating climate change, underscored by international agreements like the Paris Agreement and the European Union's target of sourcing 42.5% of its energy from renewables by 2030. However, integrating Variable Renewable Energy (VRE) sources, such as solar and wind, presents significant challenges for grid stability and balancing costs.

This study empirically investigates the impact of increasing Battery Energy Storage Systems (BESS) capacity on European balancing market prices. Using time-series data from five European countries between 2016 and 2019, multivariate regression models are applied to analyze the effects on three types of balancing services: Frequency Containment Reserve (FCR), Automatic Frequency Restoration Reserves (aFRR), and Manual Frequency Restoration Reserves (mFRR).

The results indicate that increased BESS capacity significantly reduces balancing prices, particularly in the FCR and aFRR markets. This research extends the findings from previous studies in Australia to the European context, highlighting the potential of BESS to offer cost-effective, CO_2-neutral solutions for grid stability.

These findings have important implications for Transmission System Operators (TSOs), policymakers, and stakeholders in the energy market, suggesting that specific policy and strategic investments in BESS could enhance the cost-efficiency and sustainability of future electricity systems.

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List of Abbreviations

API Application Programming Interface

aFRR Automatic Frequency Restoration Reserves

BESS Battery Energy Storage System

BP Balancing Price

BRP Balancing Responsible Party

BSP Balancing Service Provider

BESS battery capacity

CAES Compressed Air Energy Storage

CO_2 Carbon Dioxide

DAG Directed Acyclic Graph

Load Day-Ahead Load

DAM Day-Ahead Market

DG ENER The Directorate-General for Energy

DOE Department of Energy

DSO Distribution System Operator

EBGL Electricity Balancing Guideline

EC European Commission

EES Electrical Energy Storage

ENTSO-E European Network of Transmission System Operators for Electricity

EU European Union

FCR Frequency Containment Reserve

HAC Heteroskedasticity and Autocorrelation Consistent

HCSE Heteroscedasticity-Consistent Standard Errors

ISP Imbalance Settlement Period

mFRR Manual Frequency Restoration Reserves

OLS Ordinary Least Squares

PHS Pumped Hydroelectric Storage

PRP Program Responsible Party

PV Photovoltaics

SMP System Marginal Price

TSO Transmission System Operator

DSO Distribution System Operator

USA United States of America

VRE Variable Renewable Energy

Price Electricity Wholesale price

1 Introduction

There is widespread consensus that there is a pressing need to mitigate climate change. Growing public and political awareness of this urgent need, has led to global efforts aiming to, amongst others, reduce Carbon Dioxide (CO_2) emissions. These efforts have been channeled through various international agreements, most notably the Paris Agreement. These agreements underscore the urgency of transitioning from conventional carbon-intensive energy sources to cleaner alternatives, marking an era known as the energy transition. The European Union (EU) has further solidified this commitment by establishing a binding target for 2030 to source at least 42.5% of the European Union's overall energy mix from renewable energy sources (European Commision, 2022).

Solar and wind are the most important renewable energy sources to produce electricity given they are zero-carbon, low cost and widely applicable. These technologies have experienced a massive build out in recent years and were responsible for 27% of total electricity production in the EU in 2023 (Brown & Jones, 2024). This shift helps to meet the EU targets, but complicates the crucial task for Transmission System Operator (TSO) to balance supply and demand in real time– their primary responsibility. This is due to the fact that solar and wind generation are fully dependent on weather conditions, which has two inherent challenges. Firstly, their electricity supply is intermittent and non-dispatchable, meaning generation can't be increased or decreased on demand. In addition, their electricity supply is hard to perfectly predict. This means that solar and wind capacity needs to be complemented by flexible power plants to ensure supply and demand is in balance.

Traditionally, coals and gas-fired power generation have provided the lion's share of balancing services in most EU countries (Belmonte et al., 2023). If TSOs would continue to balance the grid with conventional energy sources in the future, these plants would have to keep operating at a consistent base level all year round to be able to ramp up and down as desired, even at moments in time when their marginal costs are above wholesale market price. This may not only be undesirable from a CO_2 reduction perspective, but would also cause TSOs to incur significant costs. Driven by these high marginal costs and CO_2 emissions, the role of these conventional power plants in the electricity system is set to change in many EU countries (Krafwerke, 2024). Grid-scale Battery Energy Storage System (BESS) emerge as a promising solution to offer dispatchable capacity without CO_2 emissions. BESS facilities are fundamentally different from conventional dispatchable assets in terms of capabilities and economics. Increased BESS capacity can therefore impact grid balancing operations and market dynamics, including the costs associated incurred by TSO's.

TSOs and Balancing Service Providers (BSPs) need to have insight into the future trends of balancing market prices. This information is crucial to them because it affects the societal costs and their business strategies respectively. Lower fees are positive for TSOs and society, as they reduce overall system balancing costs. However, lower fees may present a challenge for operators and investors in BESS as the balancing fees generally comprise an important revenue stream. Lower fees negatively impact their business case by potentially cannibalising the market.

This research aims to empirically investigate how BESS adoption affects the grid balancing prices in European balancing markets. Increased BESS capacity is expected to reduce balancing prices in two main ways. Firstly, the merit order, which determines balancing prices, may change since BESS typically has lower marginal costs than conventional flexible assets. Secondly, the widespread adoption of BESS for balancing services will likely boost competition in the balancing markets. This increased competition is expected to drive existing market players to lower their prices, indicating that the current market is imperfect. (Conejo, 2023). To study this effect, the following research question is formulated;

> "What is the effect of increasing grid-scale BESS capacity on balancing market prices in Europe?"

Sub-research questions To structure this research towards answering the research question, multiple sub-questions have been defined:

SRQ1: How do the three balancing markets in Europe differ from one another?

SRQ2: What is grid-scale BESS, and to what extent can BESS provide the different balancing services?

SRQ3: What are the specific mechanisms through which BESS is expected to impact the different balancing market prices?

SRQ4: What are other factors that impact balancing market prices and how do these relate to the effect of BESS on the balancing market prices?

A considerable amount of both theoretical and empirical research has been done into the impact of BESS on electricity prices in wholesale markets (Lamp & Samano, 2022, Zamani-Dehkordi et al., 2017). The impact of BESS on balancing market prices, however, has received less academic attention. Where applied to balancing markets, studies generally apply numerical simulations, such as Khalilisenobari & Wu (2022), Padmanabhan et al. (2019), and Rossi et al. (2019), rather than conduct empirical research on real balancing market price data.

Empirical research on the effect of BESS capacity on balancing markets has so far been limited to the Australian continent (Rangarajan et al., 2023). This thesis extends the Australian explorations to the European context and, therefore, complements existing literature with a new perspective. Extending this research to the European context not only broadens the scope of our understanding but also allows for a deeper examination of the geographical nuances shaping energy transition dynamics. Notably, European countries exhibit differing levels of BESS adoption and grid integration compared to Australia, stemming from distinct market structures, regulatory environments, and renewable energy profiles. Exploring these disparities provides valuable insights into BESS adoption and its implications for balancing markets across diverse regions.

By performing a regression analysis, I seek to discern the effects of BESS adoption on market prices. I use time-series data on BESS capacity and balancing market prices for five countries in the EU between 2016 and 2022. In the analysis, I differentiate between three different types of balancing services, Frequency Containment Reserve (FCR), Automatic Frequency Restoration Reserves (aFRR) and Manual Frequency Restoration Reserves (mFRR); the differences between these will be elaborated on in section 2. Data was primarily collected from the European Network of Transmission System Operators for Electricity (ENTSO-E) transparency platform and a database on storage facilities managed by EU.

The analysis reveals that increased BESS capacity significantly reduces balancing prices, particularly in the FCR and aFRR markets. Notably, the largest negative impacts were observed in Germany and Hungary for the FCR and aFRR markets. However, positive effects were found in some longer-term markets, like the mFRR in Germany, suggesting that fossil-fuel-based balancing market participants might have tried to recover costs in these markets. These findings underscore the potential of BESS to provide cost-effective, CO2-neutral solutions for grid stability, aligning with broader climate policy goals.

The rest of this paper will be structured as follows. To answer SRQ1 and SRQ2, first, the necessary background knowledge on the European electricity system, balancing mechanisms and BESS technology is provided in section 2. This provides the building blocks for the conceptual framework and helps to interpret existing literature. Hence,section 3 discusses existing literature and identifies relevant variables for the regression analysis. In section 4, the research method is described. This includes the conceptual framework - which provides answers to SRQ3 and SRQ4 -, causal inference, hypothesis and regression model specification. section 5 describes the data collection, management and manipulation to construct the database, providing transparency and reproducibility, and provides summary statistics and descriptives. Results are provided and discussed in section 6. The paper ends with a conclusion in section 7, providing summarising notes and implications for both stakeholders and academics.

2 Institutional Background

In this section, concepts that are important to understand in the context of this thesis will be discussed. Subsections 2.1 and 2.2 provide a broader introduction to the European electricity system. Subsections 2.3 and 2.4 focus on answering sub-questions SRQ1 (What are the different balancing markets in Europe?) and SRQ2 (What exactly is grid-scale BESS?).

2.1 The European Electricity System

In the 1990s, the EU initiated efforts to expand the internal market to include the energy sector, introducing the European electricity system. This initiative aimed to establish pan-European competitive and transparent energy markets, ultimately reducing costs for end-consumers and enhancing the security of energy supply (Next Krafwerke, 2023).

Today, the electricity systems of many European countries are physically interconnected, allowing for a flow of electricity between countries. An electron produced in Spain could theoretically travel and be consumed in Germany. Despite the physical interconnections, European electricity markets are still primarily organised along national lines due to historical, regulatory, and infrastructural reasons. However, they are strongly regulated by EU law to enable reliability, cost-effectiveness, and environmental sustainability.

One influential EU regulation relevant to this thesis is the regulation that requires unbundling of generation and distribution of energy markets since 2009[1]. This unbundling means no single company could operate a power network and generate or sell electricity with the aim of allowing fair access to transport infrastructure. Concretely, this means that in most markets, electricity is generated and supplied by private companies – allowing for competition to reduce societal costs – while a public company is in charge of electricity transport.

With the transition from an integrated to an unbundled system, the complexity of the electricity system has significantly increased. Figure 1 provides a schematic overview. I use the Dutch case to explain how electricity systems and the different markets that these systems comprise work, but a similar system exists for each European member state independently. A few key characteristics are relevant to understanding this paper's research question and analysis.

[1] The unbundling regards any energy market. The present research focuses on electricity markets specifically.

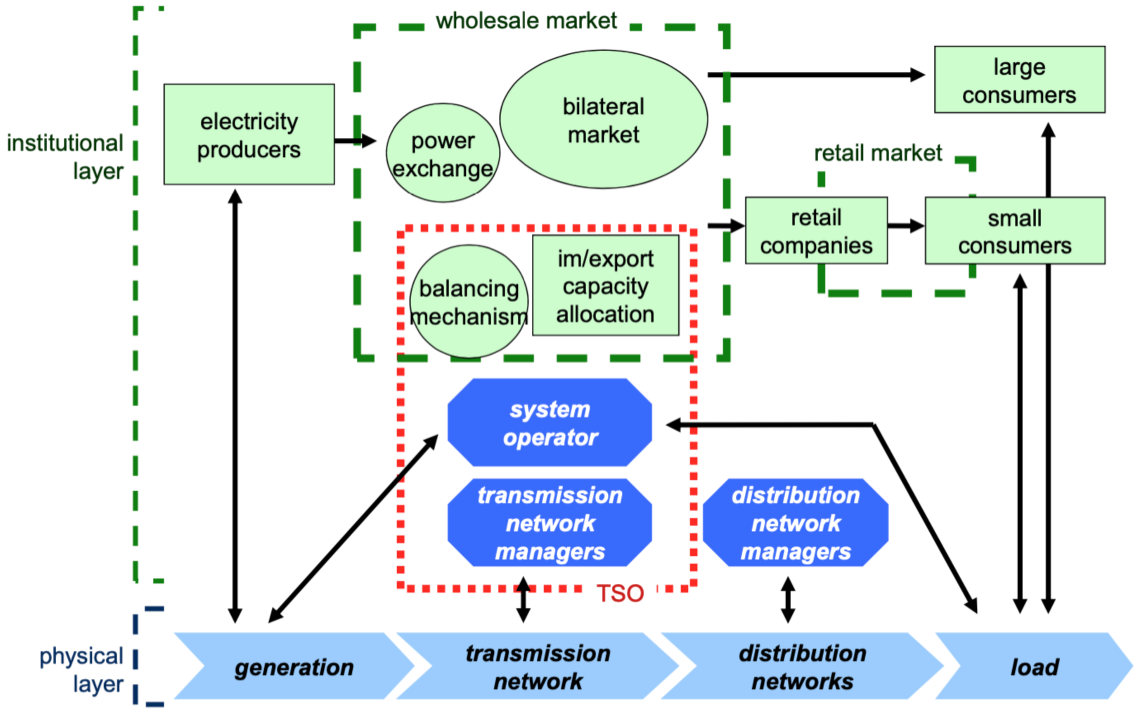


Figure 1: Diagram of the electricity system indicating the difference between technical and institutional components and the roles of different market participants. Source: (De Vries et al., 2020).

The system has two distinct layers: a physical and an institutional one. The physical layer includes the actual generation, distribution, and supply, whereas the institutional layer comprises of the buying and selling of electricity and balancing products.

Electricity producers and consumers interact with one another in two electricity markets: the wholesale market and the retail market. In the wholesale market, electricity is traded on power exchanges between producers, large consumers, and retail companies, and via bilateral markets, directly between generators and large consumers. In the retail market, small consumers buy electricity from retailers, such as Vattenfall or Eneco in the Netherlands, which produce the required amount of electricity with their own assets, or they buy it from the wholesale market.

Because of the unique characteristics of electricity, it is imperative to balance the system. In other words, the generation and consumption should be equal at every moment to ensure the stability of the network frequency. In Europe, this is 50 Hertz. Deviations in frequency caused by imbalances can lead to various issues, including blackouts and potential mechanical damage to rotating generators such as gas-fired power plants or wind turbines. As indicated by the red dashed square in Figure 1, balancing the grid is the responsibility of a TSO. To do so effectively, different balancing services and corresponding markets exist. This is this paper's central focus. Therefore, the following section further explains the different market players, balancing services, and price-setting mechanisms.

2.2 The balancing market: roles and responsibilities

Balancing markets have been developed to avoid the consequences of system frequency deviations. There are three actors involved: the Transmission System Operator (TSO), the Balancing

Responsible Party (BRP), and the Balancing Service Provider (BSP). Their interactions are depicted in Figure 2.

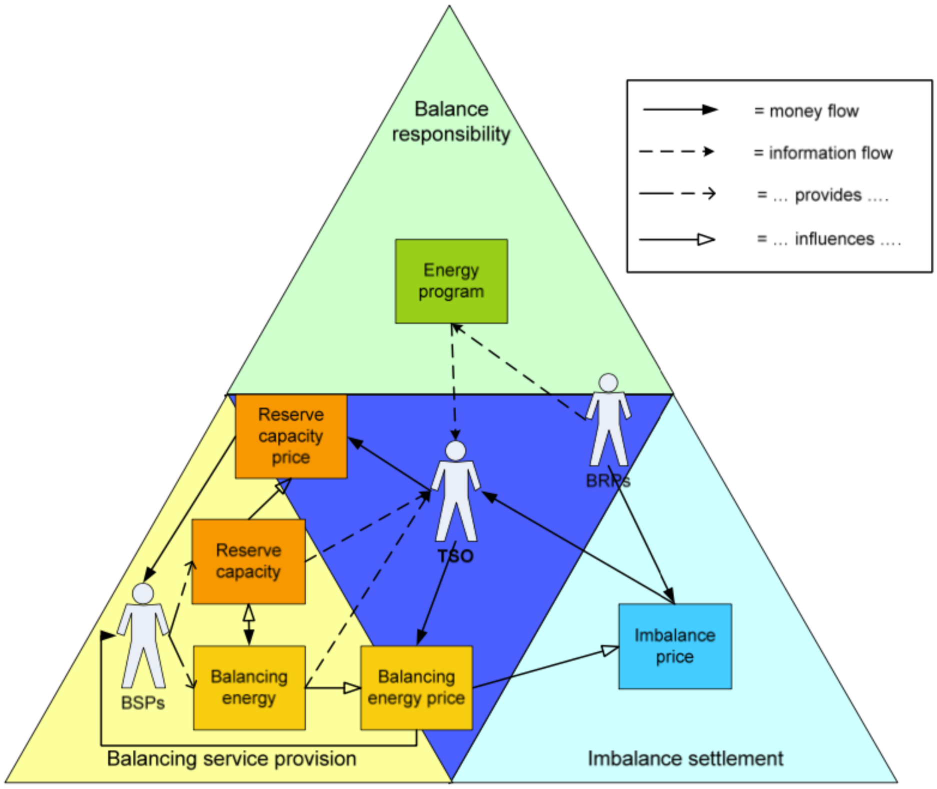


Figure 2: Schematic overview of the roles of the three relevant actors involved in the balancing market. Source: (De Vries et al., 2020).

Transmission system operator - TSO National TSOs are responsible for maintaining the grid frequency of 50 hertz at all times to balance the grid. It has a procedure to avoid imbalances through the support of BRPs and a market to respond to (forecasted or occurring) imbalances through the support of BSPs.[2]

Balancing Responsible Party – BRP Each supplier or buyer of electricity connected to the transmission grid carries balance responsibility and, therefore, needs to assign a Balance Responsible Party. Large consumers, retail companies, and electricity producers often act as BRPs themselves, while households or small businesses transfer the responsibility to the retail companies from whom they purchase electricity. Every day, BRPs submit their expected production or consumption program to the TSO for every quarter hour the next day. The BRP is financially responsible for any deviation from this program and, therefore, has an incentive to produce or consume exactly the amount of electricity as stated in the submitted program.

In reality, however, imbalances can arise due to, for example, forecasting errors in VRE generation, technical malfunctions in generation capacity, and unforeseen variations in demand. BRPs can rectify any imbalances in their allocations before the end of the imbalance settlement period (ISP), which lasts for 15 minutes, without incurring financial penalties. To do so, they

[2]In some countries, TSOs activate balancing products in response to forecasted imbalances (proactive), while in other countries, they are activated only when an imbalance occurs (reactive).

have the option to adjust their load or production at designated points or engage in trading with another BRP to achieve balance (Tennet, 2023c). Despite this mechanism, the total actual production and consumption of all BRPs may not consistently balance out for each period. To coordinate the balancing process, the TSO needs to ensure sufficient balancing capacity with the support of BSPs. This thesis will mainly focus on the relationship between the BSP and the TSO regarding the balancing market.

Balancing Service Provider – BSP Due to the unbundling of the electricity system, TSOs cannot own or operate the assets that perform these required balancing services. Instead, a balancing market has been set up where TSOs can procure these services from BSPs. BSPs are private companies that operate dispatchable generation assets like gas-fired power plants and BESS. Section subsection 2.4 describes BESS. BSPs have to prequalify to prove their ability to meet the technical requirements for the different balancing services. The interaction between the TSOs and the BSPs is the central focus of this paper.

The following sections describe the different types of balancing services, how these are procured and activated, and how their prices are formed.

2.3 The balancing process

Towards answering the first sub-research question, this subsection discusses the process of balancing and the roles that the three different balancing services play in this process.

Balancing services are reactive, short-term means to level out frequency deviations in the power grid.[3] These services can be upward or downward frequency regulation. In case of a shortage in power generation at a specific moment, the TSO must either boost generation or request consumers to reduce consumption – this is referred to as upward regulation. Conversely, if there's an excess in generation, the opposite measures are taken, known as downward regulation.

2.3.1 Three types of balancing services

There are three types of balancing services in the EU which cater to different purposes in addressing imbalances: Frequency Containment Reserves (FCR), Automatic Frequency Restoration Reserves (aFRR) and Manual Frequency Restoration Reserves (mFRR) (Tennet, 2023d). Each service has a distinct activation method, ramp-up rate and duration, reflecting when and how they are used to respond to different levels of imbalance. All services have a minimum bid capacity of 1 MW. Table 1 summarizes the types of services.

[3] A great variety of names are used for "balancing services." This inconsistent and diverging terminology is a significant problem in this field (Hirth & Ziegenhagen, 2015). This thesis stays as close as possible to the definitions stated in the EU's EBGL (European Commission, 2017). For this reason, I refer to "balancing services". 'Balancing reserve', 'frequency control', 'ancillary services', or 'reserve power' are other terms widely used in literature and by TSOs.

Table 1: Overview of the three different balancing markets.

Balancing service	Procurement and Balancing price-setting	Activation method	Full Activation Time
FCR - *primary control*	Procured internationally in a common European FCR market, each participating country contributes and share of FCR volume – set by EU regulation	Automatically, based on grid frequency deviations measured by the FCR	30 seconds
aFRR – *secondary control*	Procured via daily national auctions through bid-obligations, contracts for fixed moment in time	Automatically by an algorithm of the relevant TSO	5 minutes
mFRR – *tertiary* control	Procured via daily national auctions through capacity contracts	Manually by the TSO of the area of the imbalance	10-15 minutes

The Full Activation Time (FAT) is the maximum time allowed for fully activating or deactivating a standard aFRR energy bid. During the prequalification process, each BSP's adherence to the FAT requirement is verified and subsequently incorporated into local monitoring guidelines. When a BSP's bid is activated or deactivated, it must deliver the required volume within the FAT to remain compliant (ENTSO-E, 2018).

When an imbalance occurs in the European electricity grid, the FCR intervenes automatically within seconds to restore the balance in the entire synchronous (physically connected) grid. FCR works across borders and is considered the primary control reserve. Simultaneously, the TSO of the area where the imbalance occurs automatically requests the BSPs to activate automatic FRR. aFRR gradually replaces the FCR and is considered the secondary control. In cases of significant system imbalance during long-lasting periods, the TSO can activate the mFRR to 'free up' the aFRR for possible future imbalances. Figure 3 presents how the three balancing services are used over time following a drop in frequency due to some imbalance.

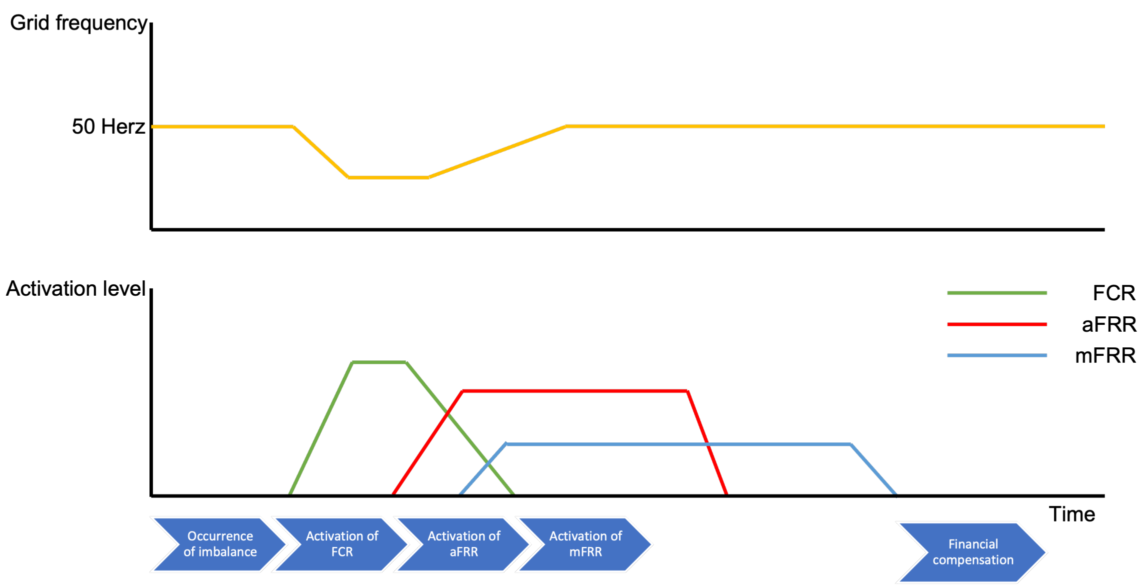


Figure 3: Schematic overview of the process of balancing the grid in case of an imbalance, exemplifying the first three balancing products and their different applications. Source: (Tennet, 2023a).

Figure 3 presents an example of a drop in frequency due to an imbalance, for example, the failure of a power plant. The initial drop in frequency is immediately arrested by activating the FCR service. The frequency is then stabilised using a combination of aFRR and mFRR services to recover it within its standard operating band of 50 hertz.

2.3.2 Bidding processes

The three types of European balancing markets differ slightly from one another in terms of bidding processes but are organised similarly in the broader context. All three balancing markets are split up in periods called Imbalance Settlement Period (ISP). The ISP length has been different between countries and has been subject to changes over time within countries, but nowadays, it is 15 minutes throughout Europe. Previously, the duration of balancing capacity contracts could run over multiple ISPs, but today, the duration of the balancing contracts is matched with ISP length at 15 minutes. The implications of these variations in ISP length and contract duration over time will be further discussed in section 5.

The TSO organises separate bidding processes for each of the three services to reserve a minimum amount of the upward and downward balancing capacity. This minimum amount is determined by EU regulation, taking into account factors such as the size of the power system, expected VRE output, historical consumption patterns, and generation forecast variability (European Parliament & Council of the European Union, 2009).

Prequalified BSPs put in a bid to reserve capacity, submitting either upward, downward, or synchronised bids for every ISP. Upon award, the TSO secures the option to purchase balancing energy in the future, much like a financial options contract. During the duration of the balancing contract, the TSO can decide whether or not to lift that option depending on balancing service requirements (De Vries et al., 2020).

FCR The bidding process for FCR involves daily auctions where BSPs submit bids to provide FCR services. The bids, which are for symmetric products that must be available throughout the entire delivery period, are then evaluated by the Transmission System Operators (TSOs).

An optimization algorithm selects the most cost-effective combination of bids, taking into account constraints such as export limits and the need to maintain grid stability. Successful bidders are then paid based on their bid price in a paid-as-bid mechanism. This daily auction process encourages the participation of various market players, promoting competition and ensuring a reliable supply of frequency containment reserves. This results in country-specific local marginal prices for FCR, based on the merit order and cross-regional constraints.

aFRR and mFRR For aFRR, there are two possibilities for participation as a BSP, either through contracting or free bidding. Contracted bidding means that certain BSPs are obliged to place reserve balancing capacity bids to the TSO for specified periods. Second, BSPs can participate through free bidding. Bids from both contracted and free-bidding BSPs compete on the same merit order (Tennet, 2023c). Bid obligation contracts guarantee the availability of ample balancing bids at all times, with their prices dictated by the market.

Figure 4 shows a typical example of the bidladder of such a merit order, including some information regarding price setting. The coloured boxes represent the accepted bids, corresponding to the predetermined minimum volume of balancing capacity that the TSO must contract. Such a bid ladder is created and cleared for every ISP.

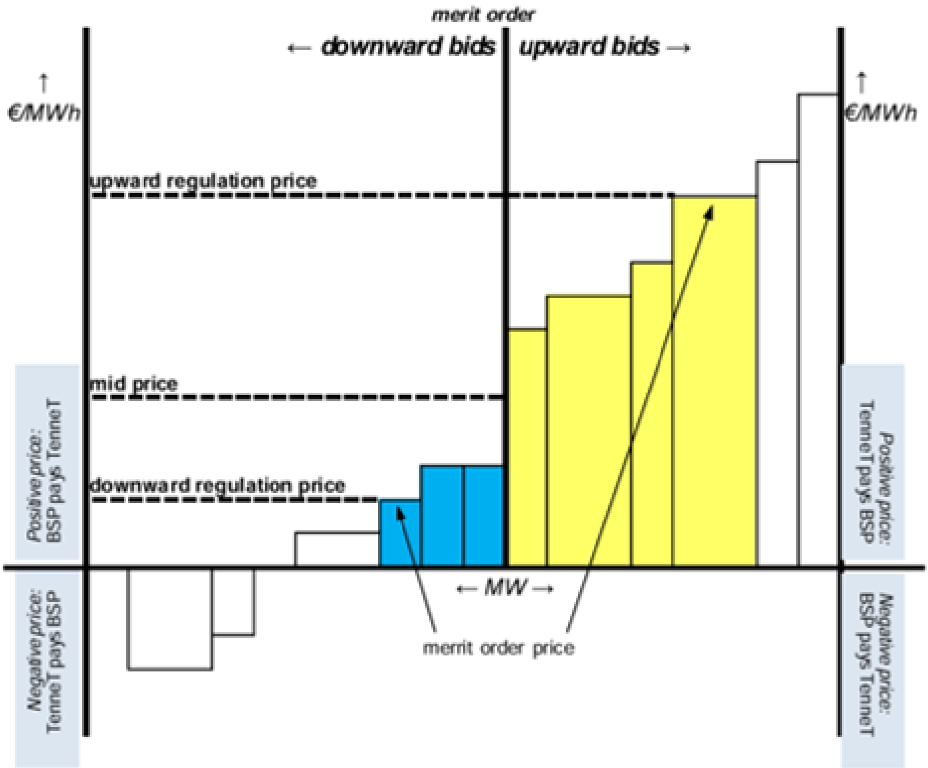


Figure 4: Typical bid ladder for upward and downward regulation. Source: (Tennet, 2021).

The TSO starts accepting low bids until the predetermined amount of necessary reserved balancing capacity is reached. A downward regulation bid implies the amount of money a BSP is willing to pay to the TSO to be allowed to reduce its production or increase its consumption relative to the submitted program. Such action is likely to save the BSP money on fuel in the case of a conventional power plant or store "free" electricity in the battery in the case of a BESS.

Downward regulation bids are often negative, reversing the monetary flow: the TSO pays that price to the BSP to reserve downward balancing capacity. BSPs are remunerated to reserve balancing capacity with a uniform fee corresponding to the last accepted bid. This fee is depicted by the horizontal dashed lines in Figure 4.
Additionally, with aFRR and mFRR, the BSPs can potentially receive financial compensation in the form of the imbalance price for the actual amount of balancing energy if the TSO activates the reserved capacity to address imbalances during that ISP. In contrast, for FCR reserves, BSPs are remunerated only for the capacity they reserve, with no additional payment for the activation of this capacity.

2.4 Battery Energy Storage Systems

In this subsection grid-scale BESS will be discussed in more detail with regard to their suitability to provide the different balancing services to answer sub-research question 2.

The balancing services described in the preceding sections are performed by prequalified BSPs. To qualify as a BSP, one must meet a series of requirements set out by the relevant TSO (Tennet, 2023b). These requirements are specified differently for each of the balancing services such that, for example, BSPs prequalified for FCR services can indeed respond within the required time frame and prequalified BSPs are indeed able to sustain the balancing power for the required duration, among others.

Traditionally, conventional power plants have performed balancing services. However, as has been indicated before, such power plants will be phased out in the future to reduce power system-related CO_2 emissions. The same balancing services will, therefore, need to be performed by other types of BSPs. They can be performed by Electrical Energy Storages (EESs) if they meet the requirements as stated in the prequalification documents of the relevant balancing service.

Different EES technologies, in general, are characterised by a number of different attributes. With regard to what functions these ees technologies can perform in the broader sense of the electricity system, there are two important characteristics: Energy capacity, denoting the maximum energy a storage device can hold, and power capacity, representing the maximum transfer rate of energy. These two concepts can also be approached as discharge duration and power requirement. Figure 5 places a number of different EES applications and technologies along these two axes. This figure indicates which specific types of EES are fit for which specific application of EES. From this figure, the overlap between voltage and frequency regulation on the application side and batteries on the technology side implies that BESS is indeed suitable for balancing services with regard to the power requirement and discharge duration.

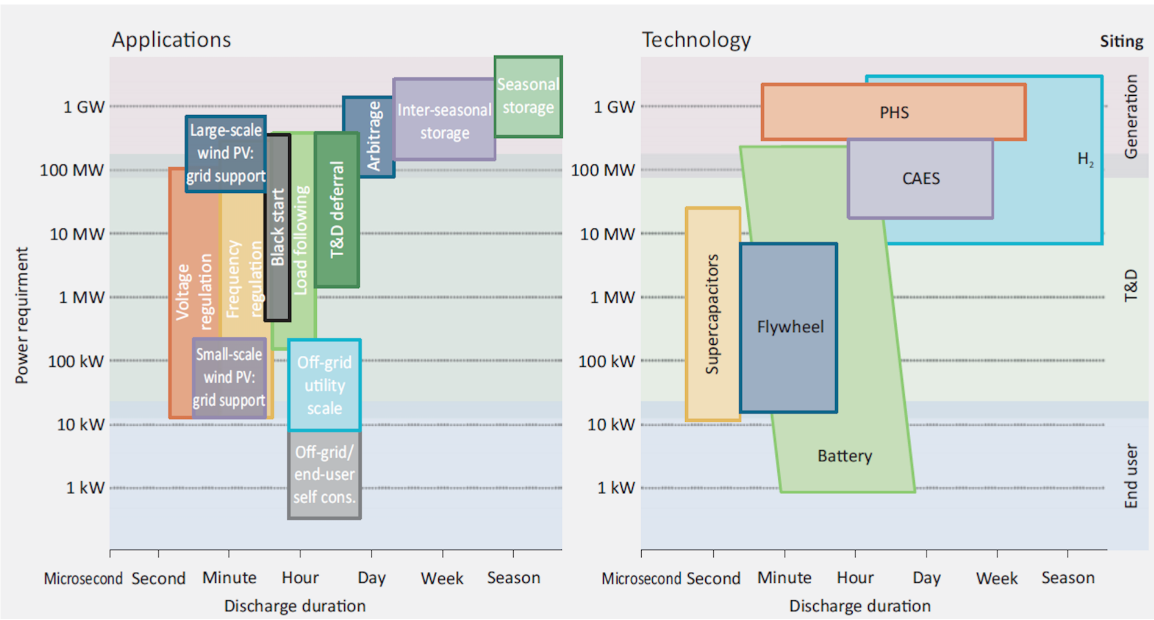


Figure 5: Energy storage applications and technologies. Different applications require different technologies. Source: (IEA, 2015).

With regard to suitability to perform the different specific balancing services and comply with prequalification requirements, two additional characteristics of EES and BESS specifically are important: Ramp rates and response times (Luo et al., 2015). BESSs prove to be the most suited EES for balancing services due to their fast response times and ramp rates and sufficiently large power and energy capacity. For these reasons, most research on storage in balancing markets focuses on BESS (Figgener et al., 2023, Rangarajan et al., 2023). Luo et al. (2015) specifically state that BESS are especially suited for the shorter-term balancing services: FCR and aFRR, as opposed to the longer-term balancing service mFRR. This aligns with the information presented in Table 1.

Moreover, over the past decade, cost reductions have been realised in BESS production processes due to scale advantages. These economies of scale have been driven by increasing demand for electric vehicles (Figgener et al., 2023). Prequalification documentation for various balancing products states that BSPs, including BESS, must reserve at least 1MW of power (Tennet, 2023b). Therefore, this research excludes BESS facilities with rated power smaller than 1MW.

3 Literature Review

This section presents a state-of-the-art review of the literature on electrical energy storage in general and its impact on balancing prices. The aim is to provide a comprehensive overview that synthesizes existing research and highlights key theories and recent findings in the field while identifying a knowledge gap. This positions this thesis within the existing literature, emphasizing its relevance. Subsequently, I focus on distilling critical variables that may be causally related to storage capacity and balancing prices.

3.1 State-of-the-Art

Previous academic explorations within the domains of both EES in general and BESS specifically have taken a variety of angles. In this subsection, the literature is discussed by theme.

Optimal EES operation A predominant part of the literature delved into EES operation within the wholesale market, i.e., buy low sell high strategies, also referred to as energy arbitrage. Researchers have sought to determine optimal EES energy and power capacity to maximize gains from energy arbitrage.

Bradbury et al. (2014) find that Pumped Hydroelectric Storage (PHS) and Compressed Air Energy Storage (CAES) have the greatest potential for arbitrage. Their analysis also states that these technologies are optimally sized at 7-8 hours of storage. While most other EESs are optimal at 1-4 hours, the optimal power capacity cannot be captured in a simple figure as it depends on the relevant market. They additionally state that ancillary service markets offer the economic potential for certain EESs and emphasize EESs' pivotal role in large-scale power systems, which, according to them, is much broader than arbitrage.

Variable Renewable Energy Moreover, studies have focused on the influence of Variable Renewable Energy (VRE) sources on BESS energy arbitrage revenue from the wholesale markets.

Tuohy & O'Malley (2011) apply a unit commitment model to study the Irish power system with and without high levels of PHS, accounting for uncertainty in wind power. It is shown that as wind penetration increases beyond 50%, the economics will justify capital costs and energy losses. Interestingly, they find that at wind penetrations below 60% the addition of storage increases the system's carbon emissions. This is because coal plants would primarily be used to charge the additional battery storage in that scenario, according to the authors. Of course, whether or not this statement still holds today or in the future depends on the characteristics of the power system.

Foley & Lobera (2013) study the impacts of CAES on an electricity market with renewable energy penetration of 40% with a simulation model. They find that the increase in storage would decrease system CO_2 emissions and support the integration of renewables by decreasing curtailment. However, it also comes at a cost; they find that the increase in storage would negatively impact the System Marginal Price (SMP) and consequently increase the wholesale price of electricity.

Hartner & Permoser (2018) use dispatch models to simulate hourly prices based on varying Photovoltaics (PV) production in Austria and Germany to investigate the impact of solar PV on electricity prices and storage plant revenue. Because of a relatively high correlation between solar radiation and demand peaks, storage facilities only start to make revenue at PV penetrations higher than 5%, significantly increasing for penetrations larger than 10%. The authors directly relate the PV penetration to storage investment incentives.

Wholesale price spreads A substantial amount of literature also examines how energy arbitrage with BESS affects the spread of wholesale market prices. Focusing on large-scale BESS in California, Lamp & Samano (2022) explore the growth of VRE in the system. They reveal that battery deployment had reduced the average intra-day wholesale price spreads by analyzing the charging and discharging patterns of grid-scale BESS. Zamani-Dehkordi et al. (2017) take a slightly broader approach in the same direction by not only examining wholesale price spreads but also the price level as a whole and how the arbitrage operation of storage facilities affects the revenue of other generation units in the market.

Theoretical research on Balancing Markets Contrary to these three research themes, the effect of BESS capacity on balancing market prices is studied relatively sparsely, and efforts have predominantly taken a theoretical or simulation approach, as opposed to an empirical approach. To find the effects, these studies simulate energy systems with and without the operations of such BESS.

For instance, Khalilisenobari & Wu (2022) present an optimization framework for optimal market operations of a BESS in wholesale and balancing markets. Based on their synthetic system, they perform case studies to study the interaction between BESS profit maximization strategies and their operations in various markets for varying market conditions. In doing so they reveal that BESS can significantly add to the balancing market capacity and reduce overall system costs.

Padmanabhan et al. (2019) present a novel BESS operational cost model that considers the state of charge and degradation costs based on the depth of discharge and discharge rates, specifically for lithium-ion batteries. The authors develop a bid/offer participation strategy from this cost model. Based on this strategy, three case studies are presented to study the effect of BESS participation system operation and market settlement.

Similarly, Rossi et al. (2019) engaged in an extensive theoretical analysis by simulating a network comprising battery facilities actively participating in the broader ancillary services market. This network of BESS facilities demonstrated a consistent ability to lower overall balancing costs. Thereby emphasizing the importance of BESS participation in balancing markets.

Badeda et al. (2020) explores the impact of Battery Energy Storage Systems (BESS) on the German FCR market. The study uses agent-based market simulation to show how increasing BESS installations can drive down FCR prices. Results indicate that higher BESS penetration can significantly reduce average prices, with price sensitivity dependent on BESS cost and lifetime assumptions.

Fleer et al. (2016) provides a model-based economic assessment of stationary BESS providing primary control reserve (PCR), similar to FCR. It assesses the economic feasibility of BESS for primary control provision using two case studies based on a 2 MWh BESS. The results indicate that a BESS with a power-to-energy ratio of 1:2 is not economically feasible under the current framework, while a BESS with a power-to-energy ratio of 1:1 can break even after approximately nine years of operation. The study also highlights the potential for decreasing battery prices to increase price pressure on the PCR market, leading to decreasing revenues for PCR supply.

Kondziella et al. (2020) examines the role of battery storage in enhancing the flexibility of power systems dominated by renewable energy. It looks at the economic and operational benefits of integrating BESS with renewable energy sources. The paper indicates that increased system flexibility, particularly through battery storage, can reduce capacity prices specifically for the shorter-term balancing reserves like FCR and aFRR, due to the lower opportunity cost compared to fossil-fueled power plants.

Empirical research on Balancing Markets Rangarajan et al. (2023), however, seek to address a notable gap by empirically investigating the impact of grid-scale BESS on overall balancing costs for the first time. Their study specifically focused on Australia. Still, they mention that the results are not limited to their continent and are expected to be extendable to other regions because of high-level similarities between balancing market design globally. In their paper, Rangarajan et al. first study two Australian regions separately. The installed BESS capacity increased significantly during the study period in these two regions. In their research design, this significant increase is considered as the treatment. A medical analogy for this research design would be administering medication to a patient. Then, while controlling for a number of variables, they estimated the effect of the increased BESS capacity and the treatment on the balancing market prices by applying a time series regression model.

Subsequently, to control for other exogenous effects not captured by the control variables, the authors present a Difference-in-Differences regression model which also included a control group of states where there had been no increase in BESS capacity during the study period. Regarding the same medical analogy, they included a group of patients in the data set to whom no treatment was administered during the sample period. Their analysis shows that the introduction of grid-scale BESS into the system significantly reduced the overall balancing costs, in line with theory and simulation studies. Their analysis specifically shows that, on average, for an additional MW of battery capacity, the prices for the Australian counterparts of the FCR and aFRR balancing services decreased by AUD0.11/MWh and AUD0.63/MWh, respectively.

3.2 Variable Exploration

Following our state-of-the-art literature analysis in the previous section, I assemble a list of relevant variables. Firstly, key themes are distilled from the literature already discussed. Subsequently, further literature is presented to unveil additional variables not extensively covered. This proactive exploration ensures a comprehensive identification of variables. At this point, no further selection is being made other than potential relevance to the effect of storage capacity on balancing prices.

Identified Relations In subsection 3.1 the following causal effects have been identified. The business case for VRE can benefit from an increase in EES capacity because of an increase in wholesale prices during VRE generation hours (Foley & Lobera, 2013). As a result, an increase in EES capacity can cause the amount of installed VRE in the future to increase as well. Hartner & Permoser (2018) find that the reverse holds as well: an increase in installed VRE capacity today can cause in increase in installed EES capacity in the future. Hartner & Permoser also point out that an increase in VRE decreases overall average Day-Ahead Market (DAM) wholesale market prices.

Foley & Lobera (2013) find evidence supporting that an increase in storage capacity can cause the wholesale prices to increase in the DAM. Zamani-Dehkordi et al. (2017), however, find in their case study that the increase of storage capacity in fact deceased the wholesale prices. The direction of this effect depends on the shape of the relevant merit order, i.e., the difference in slope at off-peak hours and high-demand hours, when the battery charges and discharges, respectively. In other words, the price increase can be moderate in off-peak hours when that slope is relatively flat, and the price decrease in high-demand hours can be significant if the slope there is larger, or vice versa. Not only the overall wholesale market price levels are affected by increasing storage capacity, Lamp & Samano (2022), state that the intra-day market spreads can be reduced. Moreover, the negative effect that BESS capacity has on balancing market prices is demonstrated theoretically (Badeda et al., 2020, Fleer et al., 2016, Khalilisenobari & Wu, 2022, Kondziella et al., 2020, Padmanabhan et al., 2019, Rossi et al., 2019) and empirically (Rangarajan et al., 2023).

Further Relations Additionally I identify the causal relations between the following variables. Hirth & Ziegenhagen (2015) state that balancing markets interact with VRE through the impact of VRE forecast errors on balancing reserve requirements and the supply of balancing services by VRE generators. They find that increasing penetration of VRE impacts the volumes and costs of balancing markets. However, they note that the impact is smaller than sometimes believed, stating that other factors play a role as well, e.g., VRE forecast errors. Results from Sirin & Yilmaz (2021) also show that an increase in VRE implies higher balancing market prices.

Batalla-Bejerano & Trujillo-Baute (2016) emphasize the importance of accounting for balancing costs when assessing the economic implications of a growing integration of VRE in electricity markets. This consideration becomes especially relevant when such integration leads to substantially higher demands for balancing services. Gianfreda et al. (2018), in the same line of reasoning state that balancing services needed for the proper integration of VRE causes system costs to rise, working its way through into the consumers' electricity bill. Hurta et al. (2022) show, among others, that increasing wholesale and balancing prices causes future EES capacity to increase as well.

Keles & Dehler-Holland (2022) evaluate the impact of large-scale photovoltaic (PV) storage systems on energy markets using stochastic dynamic programming. The study highlights that increased renewable energy production affects electricity prices, creating opportunities for storage systems to engage in arbitrage trading. The research shows that higher price spreads enhance the market potential for PV storage systems, indicating a promising business case under conditions of increased market volatility

Mwampashi et al. (2021) analyze the effects of wind power generation on electricity prices in Australia's National Electricity Market (NEM). Using an eGARCH model, the study finds that increased wind generation decreases daily electricity prices while increasing price volatility. The research underscores the importance of strategic investment in cross-border interconnectors and regulatory interventions to ensure reliable renewable energy delivery and mitigate price volatility in the NEM.

Table 2 gives an overview of all relations that have been identified and their sources by theme. The direction of the effect is given in the last column.

Table 2: Overview of Literature Relevant to relations between variables.

Theme	Source	Finding		
		Cause	Outcome	Direction
Variable Renewable Energy	Foley & Lobera (2013)	BESS	VRE_{t+1}	+
	Hartner & Permoser (2018)	VRE	$BESS_{t+1}$	+
Wholesale Electricity Price	Foley & Lobera (2013) Zamani-Dehkordi et al. (2017)	BESS	WP	+/-
	Lamp & Samano (2022)	BESS	WP spreads	-
	Hurtha et al. (2022)	BP & EP	$BESS_{t+1}$	+
Balancing Price	Hirth & Ziegenhagen (2015) Sirin & Yilmaz (2021)	VRE	BP	+
	Badeda et al. (2020) Fleer et al. (2016) Khalilisenobari & Wu (2022) Kondziella et al. (2020) Padmanabhan et al. (2019) Rossi et al. (2019) Rangarajan et al. (2023)	BESS	BP	-

4 Methods

The main research question in this thesis is: "What is the effect of increasing grid-scale BESS capacity on balancing market prices in Europe?" In this section, the research method is set out. Subsection 4.1 discusses the conceptual framework, which serves as a cornerstone in this thesis, along with an elaboration on the roles of the covariates, answering SRQ3 and SRQ4 respectively. Subsequently, the economic methods applied in the analysis and the regression model specification are discussed in subsections 4.4 and 4.5. Table 3 provides an overview of the names and abbreviations of the variables that are discussed in the previous section.

Table 3: Included variables.

Type	Variable	Abbreviation
Outcome	Balancing Prices	BP
	• Frequency Containment reserve	FCR
	• Automatic Frequency Restoration Reserves	aFFR
	• Manual Frequency Restoration Reserves	mFFR
Treatment	Battery Energy Storage System Capacity	BESS
Covariates	Electricity Wholesale prices	Price
	Total Load	Load
	VRE generation	VRE

4.1 Conceptual Framework

Based on findings in academic literature and in the context of my understanding of power markets and nuances between the three balancing services, I will present the conceptual framework. This framework provides a structured approach to empirically investigate the causal relationship between installed battery capacity and balancing market prices, contributing to a deeper understanding of the role of energy storage in electricity markets.

The dependent variable, balancing market prices, is conceptualized to be influenced by various factors through their impact on the market's supply-demand dynamics. Figure 6 visualises this. The idea conveyed by this figure is strongly based on the merit order principle showing how supply and demand of balancing services interact to set prices in the balancing markets, as was discussed in detail in section 2.

4.1.1 Explanatory variable

Increased BESS capacity affects the supply side of the balancing market in two distinct ways. The first way in which BESS participation in balancing markets affect balancing prices arises from the BESS facility providing balancing services at lower costs than current market participants, therefore shifting the existing merit order horizontally and decreasing the balancing price. Differently, similar impact might occur if conventional BSPs adjusts their bids downward upon market entry of BESS and consequently decrease the balancing price. This would imply that previous to BESS market entry BSPs set bid prices above marginal costs, signalling an imperfect market.

4.1.2 Covariates

Another factor impacting the supply side is the wholesale price. The rationale is that BSPs must chose to allocate capacity to either balancing markets or wholesale markets. During hours

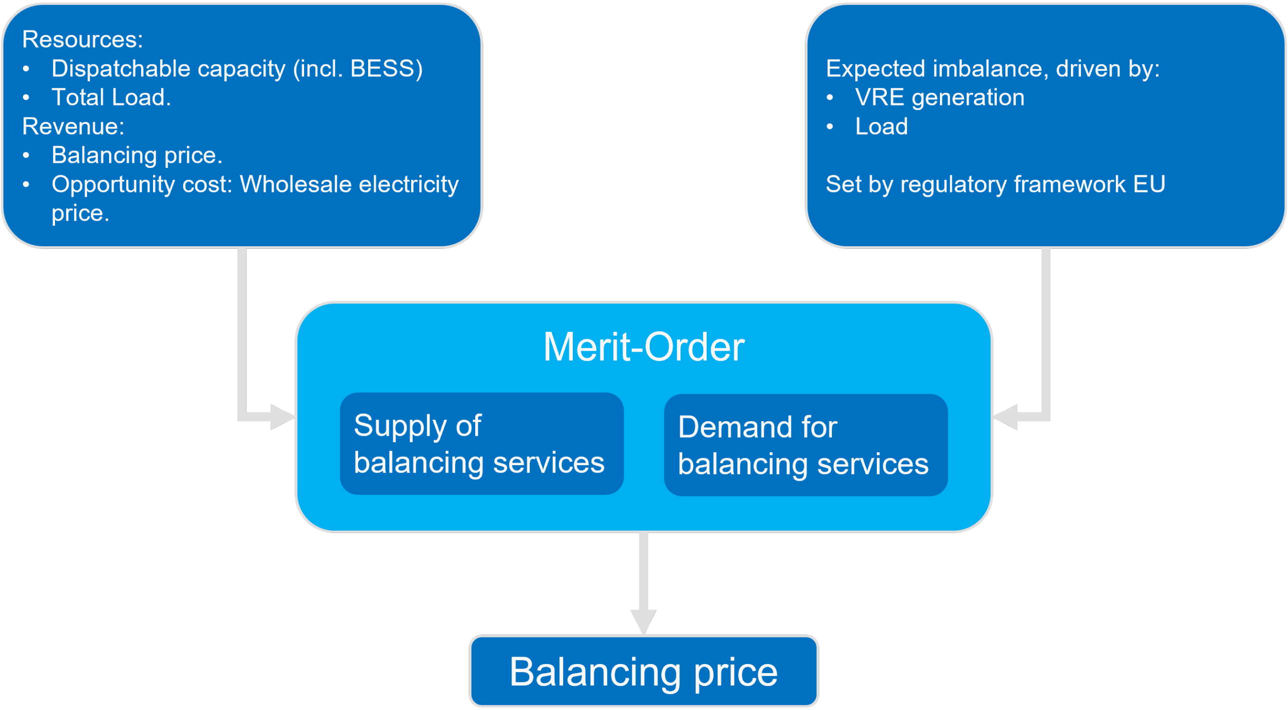


Figure 6: Conceptual framework showing the interaction between BESS capacity, wholesale prices, load, VRE generation and balancing prices.

of high electricity wholesale prices, there will be less incentive for BSP to alocate capacity to the balancing markets. Consequently, the volume of generation capacity available for balancing is limited.

Higher shares of VRE during a given period can increase the need for balancing capacity. VRE output cannot be forecasted perfectly day-ahead, potential forecast errors must be accomodated for. Therefore the EU requires TSOs to reserve more balancing capacity in times of higher expected VRE output. In addition, a high total load can put strain on the grid and potentially lead to imbalances between generation and consumption. In such situations, grid operators may need additional balancing services to ensure grid stability.

4.2 Causal Inference

In addition to the conceptual framework presented above, a Directed Acyclic Graph (DAG) is depicted in Figure 7 and shows all hypothesized causal relations between the dependent and independent variables and the covariates. A DAG serves two purposes. First, it visualises the exact hypothesised effects between each individual variable more specifically than Figure 6 does. And secondly, a DAG is useful to determine which of the covariates should be controlled for in the the regression analysis. Including or excluding an effect in the DAG is crucial because a missing effect could create alternative causal pathways, known as backdoor paths, leading to biased models. Biased models can overestimate or underestimate true relationships between variables.

4.2.1 DAG

Based on previous paragraphs the effects of the three covariates and BESS on the balancing price can be included. To make the DAG meaningful it has to contain all hypothesised effects. This is done by further identifying other relations in the following paragraphs.

Cunningham (2021) state that the choice of not including an effect is at least as important as including an effect. This is because a falsely left-out effect between any two variables could potentially form an alternative causal pathway between the dependent and independent variables. Such a pathway is called a backdoor path and, if left open, can cause the model to be biased. Therefore, a critical look is taken at potential additional relations between all variables. After all effects in the DAG are identified, I will discuss how to deal with these backdoor paths.

Firstly, in subsection 3.2, I identified that BESS can have a positive or negative effect on electricity prices, depending on the shape of the merit order in the relevant country. Secondly, I also identified that the VRE can affect electricity prices. Thirdly, the effect of the total load on the electricity prices is included since this is how the electricity wholesale price is set with the merit order. These three additional relations are included in Figure 7.

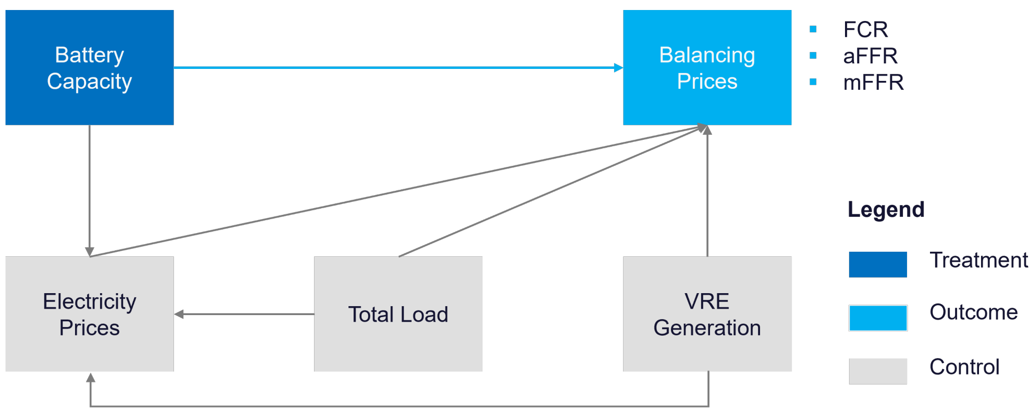


Figure 7: Directed Acyclic Graph (DAG) visualising hypothesized causal relations between variables. The directions of the arrows represent the hypothesised causal direction of the effects.

There is also a number of relations that are not included in Figure 7. For example one could logically reason that the total load increases with lower electricity prices, i.e. wholesale electricity prices would have a negative effect on the total load. However, the short-term price elasticity for electricity in Europe is very low, ranging in the literature between -0.05 and 0.12 (Csereklyei, 2020, Hirth et al., 2022, Labandeira et al., 2017). This implies that electricity consumers barely change their consumption patterns because of a price change. Therefore, the total load is assumed not to be affected by the electricity prices.

Moreover, one could argue that VRE generation is affected by electricity prices and by total load since VRE could be curtailed when the price is below zero or when the load is smaller than the VRE generation respectively. However, curtailment in, e.g. Germany has been below 3% during the sample period (IEA, 2023). Therefore, VRE generation is assumed not to be affected by the Load or by the electricity prices.

Lastly, VRE, the balancing prices and the electricity prices impact the business case of BESS, therefore impacting it. However, these are long term effects and impact the battery capacity in the future. Since future BESS capacity cannot effect todays balancing price, these effects are not included in the DAG.

4.2.2 Direct and Indirect Effect

From the completed DAG in Figure 7, I see that BESS affects the balancing prices in two ways, directly and through a mediator, electricity price. The causal path of the direct effect is $BESS \rightarrow Balancing\ Price$. The causal pathway of BESS's indirect effect on the balancing prices through the electricity prices is $BESS \rightarrow Electricity\ Price \rightarrow Balancing\ Price$. Estimating the total effect or the direct effect has different implications for closing backdoor paths.

From the literature review, it has become clear that the effect of electricity prices on balancing prices can be either negative or positive, depending on the shape of the merit order. To address the research question, "What is the effect of increasing grid-scale BESS capacity on balancing market prices in Europe?", it is therefore more effective to focus on the direct effect of BESS on balancing prices rather than the total effect. This approach enables a consistent and comparable analysis across different markets and countries, minimizing the variability introduced by country-specific wholesale electricity price determinants. By isolating the direct effect, the study provides clearer insights into the immediate impacts of BESS deployment, which are essential for policymakers and market operators. This focus also allows for a fairer comparison between countries, as it accounts for differences in electricity wholesale merit order effects and other local factors, providing a more precise understanding of how BESS directly influences BP.

4.2.3 Causal Paths and Closing Back Doors

Having established that this thesis will focus on the direct effect of BESS on balancing prices, the next step is to identify which covariates need to be controlled for in the analysis.

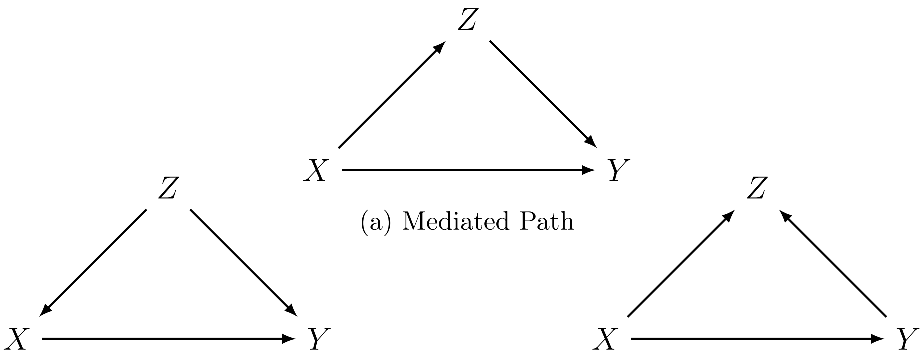
For this next step, it is key to understand the concept of causal paths and closing backdoors. In the context of DAGs and causal inference, different types of causal paths can influence the relationship between variables. The primary types of causal paths include:

a. Mediated Path: A path where a variable mediates the effect between the explanatory variable and the dependent variable. For example, $X \rightarrow Z \rightarrow Y$ in Figure 8a.

b. Backdoor Path: A path that creates a non-causal association between the explanatory variable and the dependent variable due to confounding variables. For example, $X \leftarrow D \rightarrow Y$ in Figure 8b.

c. Collider Path: A path where controlling for a variable opens up a new path of influence that did not seem relevant before. For example, $X \rightarrow Z \leftarrow Y$ in Figure 8c.

In causal analysis using DAGs, controlling for specific variables is essential to accurately determine the effect of an explanatory variable on a dependent variable (Huntington-Klein, 2022).



(a) Mediated Path

(b) Backdoor Path

(c) Collider Path

Figure 8: Different Types of Paths in a DAG

Mediators Mediators are variables that transmit the effect from the explanatory variable to the dependent variable along a directed path. For example, in the path $X \rightarrow Z \rightarrow Y$, Z is a mediator. Controlling for Z helps to isolate the direct effect of X on Y by blocking the mediated path. This allows the analysis to determine how X influences Y directly, without the intermediate influence of Z.

Confounders Confounders are variables that create a backdoor path, leading to non-causal associations. For example, in the path $X \leftarrow D \rightarrow Y$, D is a confounder because it influences both X and Y. Controlling for D blocks this backdoor path, ensuring that the observed relationship between X and Y is not due to D's influence. This helps isolate the true causal effect of X on Y.

Colliders Colliders are variables that are influenced by two or more variables in a causal path. In the path $X \rightarrow Z \leftarrow Y$, Z is a collider. Controlling for a collider like Z can open a path that introduces bias, as it creates a false association between X and Y. This happens because Z now allows information to flow between X and Y, which were otherwise independent. Therefore, controlling for colliders is generally avoided to prevent introducing new confounding paths.

In summary, controlling for mediators helps isolate the direct effects, controlling for confounders blocks backdoor paths, and avoiding controlling for colliders prevents the introduction of new biases, ensuring accurate and unbiased causal inference.

In the DAG in Figure 7, there are there causal paths from BESS to balancing prices, in addition to the direct path between BESS and Balancing prices.

1. $BESS \rightarrow Electricity\ Price \rightarrow Balancing\ Price$
2. $BESS \rightarrow Electricity\ Price \leftarrow Total\ Load \rightarrow Balancing\ Price$
3. $BESS \rightarrow Electricity\ Price \leftarrow VRE \rightarrow Balancing\ Price$

To estimate the direct effect of BESS on Balancing Prices using DAGs, addressing backdoor paths is essential, such as path 1. In this path, EP mediates the effect of BESS on BP. To isolate the direct effect of BESS on BP, controlling for EP is necessary, blocking this mediation path.

Paths 2 and 3 were initially closed by the since EP acts as a collider. However, controlling for EP opens new collider-induced backdoor paths, allowing Load and VRE to confound the relationship between BESS and BP. Therefore, controlling for Load and VRE is also necessary to prevent this confounding.

4.3 Hypothesis

Drawing from the conceptual framework and DAG analysis, I posit the following hypothesis:

> "Increasing the capacity of BESS in European electricity grids will lead to a consequential decrease in balancing market prices."

In other words, I expect increased BESS capacity to have a negative effect on balancing prices. This hypothesis emerges from the understanding that BESS, with their ability to store and discharge electricity rapidly, offer a flexible solution for grid stabilization and load balancing. By augmenting grid-size BESS capacity, I anticipate more competition in balancing service markets. This hypothesis not only aligns with theoretical expectations but also reflects the empirical observations presented by (Rangarajan et al., 2023) which show a strong inverse correlation between BESS capacity and balancing market prices in the Australian context.

To specify this hypothesized effect of BESS on the balancing market price, I can differentiate between the three distinct balancing services: FCR, aFRR and mFRR. As discussed in section 2 in more detail, these services are differ from one another based on ramp rate and response time. Batteries are better suited for the shorter term balancing markets, FCR and aFRR, and therefore I expect the effect to be more pronounced for these services.

Additionally, I expect that the balancing price is positively effected by load and electricity prices because of the reduced available capacity and higher opportunity costs that impact the supply side of the balancing markets. Moreover, I expect the VRE to have a positive effect on the balancing prices as well, because it increases the amount of required balancing services for that ISP.

4.4 Econometric Method

In order to test the hypothesis that increasing BESS capacity has a negative impact on the balancing price, I conduct a multivariate regression analysis. Regression is a useful tool for understanding relationships between variables.

In this section I discuss the methodological implications of using time series data, I discuss the applied estimation method, specify hypothesis testing lastly I discuss limitations to the methods applied.

4.4.1 Regression Analysis

Time-series I aim to study multiple countries to make the findings more general. While I have considered to analyse a set of countries as a whole as panel data, I have left this out of the scope of this research. I have decided to follow single countries over time separately. This implies that I do a time-series analysis, allowing me to estimate the effect of BESS capacity on

Balancing Price (BP)(Hyndman & Athanasopoulos, 2018).

In the context of this research, the variables discussed in subsection 4.1 can be observed periodically over time for individual countries. For each country that will be included in the analysis I will do a total of three independent time-series regression analyses, one for each balancing market.

Estimation The purpose of estimation is to calculate the $\hat{\beta}_i$ for the sample data, which is an estimate for the population coefficient β_i. There are various methods to estimate the coefficients, applicability depends on the model definition. In my research I apply Ordinary Least Squares (OLS) to estimate my models numerically. OLS is a widely-used method because it is simple, efficient, and provides easily interpretable results. It works by minimizing the differences between observed and predicted values, referred to as residuals.

Numerous different software programs exist for this end, three most commonly used are R, Python or SPSS. In this study, R is used to define and estimate the models. Specific packages that are used in this thesis are "Sandwich" and "Stargazer", which are used to compute robust standard errors and to create latex tables for the regression results (Hlavac, 2022, Zeileis, 2004).

Hypotheses testing Subsequently to estimating the model coefficients $\hat{\beta}_i$, I test whether or not the results are statistically significant. This is done on model level with F-tests and on coefficient level with t-tests.

The F Statistic examines the collective significance of the regression model by testing whether any of the independent variables have coefficients that are not zero. In essence, it assesses whether the independent variables, as a group, significantly contribute to explaining the variations observed in the dependent variable.

The estimated coefficients, $\hat{\beta}_i$, are theoretically distributed around the population coefficient β_i, implying there is a certain chance that I found a $\hat{\beta}_i$ that is different from the β_i.

I will utilize t-tests to calculate p-values based on t-test statistics. The t-test statistic measures the difference between the estimated coefficient and the hypothesized population value (i.e. $H_1 : \beta_{Storage} \neq 0$), relative to the variability in the data as represented by the standard error.

The significance level (α) sets the threshold for accepting or rejecting the null hypothesis. If the p-value (probability of observing $\hat{\beta}_1$, by random chance alone, i.e. given H_0 is true) is below α, typically 0.05, H_0 is rejected.

4.4.2 Assumptions

Regression analysis is powerful but relies on several assumptions. These assumptions, such as normality of residuals, linearity, no perfect multicollinearity, independence among observations, and homoscedasticity, ensure the reliability and validity of results. Violations of these assumptions can lead to biased estimates and misleading conclusions.

Normality of residuals Firstly, regression models rely on the assumption for the residuals to be normally distributed around a mean value with a certain standard error.

Deviations from normality in the residuals can affect the accuracy of hypothesis tests and confidence intervals. Non-normal residuals can lead to incorrect p-values and confidence intervals, particularly in small samples. However, if the sample size is very large, deviations from normality are no problem. Which is the case in this research.

Linearity Another concern lies in the assumption of linearity. Regression models presume a linear relationship between the dependent and independent variables. If the actual relationship is nonlinear, the model's accuracy diminishes.

This can be solved by transforming a variable, e.g. take the log, square or square root, this will be further discussed in the model specification.

Perfect multicolinearity Multicollinearity occurs when two or more independent variables in a regression model are highly correlated with each other (of Science, 2018). Perfect multicollinearity occurs when one independent variable can be perfectly predicted by a linear combination of other variables.

This can pose challenges in isolating the individual direct effects of the independent variables on the dependent variable and can inflate standard errors.

Independence among observations Observations in the dataset should be independent of each other. This means that the value of one observation should not depend on the value of another observation. Observations may, for example, be correlated over time, this is known as autocorrelation.

This violation is likely to underestimate standard errors of estimates, leading to overly optimistic assessments of statistical significance. This results in narrower confidence intervals and an increased risk of Type I errors (false positives). Potentially yielding misleading conclusions about the significance of variables.

Homoscedasticity Moreover, regressions assume homoscedasticity as opposed to heteroscedastisity. Heteroscedasticity refers to the situation where the variance of the residuals is not constant across all levels of the independent variables. In other words, the spread of the residuals varies throughout the range of the independent variables.

When heteroscedasticity is present, the standard errors of the coefficient estimates may be overestimated, leading to overly conservative estimates of uncertainty and wider confidence intervals. This can potentially lead to lower likelihoods of detecting true effects (Type II errors).

HAC Standard Errors To correct for autocorrelation and heteroscedasticity and in the data set, Newey & West (1986) have developed a simple method of calculating a heteroskedasticity and autocorrelation consistent (HAC) covariance matrix that is positive semi-definite by construction. The HAC standard errors are then calculated by taking the square root of the diagonal from this covariance matrix.

4.5 Model specification

With the conceptual framework and econometric methods defined, I now specify the exact regression model. It is key to specify my hypothesis that the balancing prices will be affected negatively by BESS and positively by Load, Price, and VRE.

Fixed effects are represented by dummy variables that capture systematic variations in the dependent variable associated with different categories or periods. In time series datasets, fixed effects can account for regular patterns or cycles that repeat at known intervals, such as weekly or monthly cycles. For fixed effects with n different categories or periods, $n-1$ dummy variables are included to represent each category or period. The effect of the n-th category or period is captured in the residual term. In this research, I control for systematic variations in the dependent variable associated with different times of the day, weekdays, months, or years.

Specifically, I control for potential diurnal variation by including dummy variables for five 4-hour periods, i.e. 00:00-04:00, 04:00-08:00, etc. Also, a dummy variable is added to indicate whether the observation is on a working day rather than on a Saturday or Sunday. To capture potential seasonal effects, eleven dummy variables are included for the months of the year. Lastly, dummy variables are included for the four years to control for underlying trends, potential policy changes, and external factors that vary annually, ensuring more accurate estimation of the effect of BESS capacity on balancing prices.

The primary reason for not including transformations in the regression model is to maintain simplicity and interpretability. The variables have already been standardized, and introducing transformations would add another level of complexity that goes beyond the project's scope. Standardization, while altering the direct interpretation of coefficients in terms of one-unit changes on the original scale, still allows for a meaningful assessment of each variable's relative importance.

Initial exploratory data analysis and the theoretical background do not provide strong suggestions that there are substantial non-linear patterns, suggesting that a linear approach is sufficient. This simplification helps avoid model complexity and reduces the risk of overfitting, ensuring that the main predictors' effects are clear and comprehensible.

Moreover, the inclusion of dummy variables for time, weekday, month, and year effectively captures non-linear patterns by representing categorical effects without requiring data transformations. This method accommodates daily, weekly, seasonal, and yearly variations in balancing prices without assuming a specific functional form. Dummy variables enable the model to handle complex patterns without resorting to logarithmic or polynomial transformations, which further mitigates the risk of overfitting and maintains model simplicity and interpretability. Each coefficient in this context directly relates to the impact of the categorical variables on the balancing price.

In summary, the exclusion of transformations in the linear regression model is justified by the desire to maintain simplicity, interpretability, and robustness, consistent with the scope of this project. Standardization and the use of dummy variables adequately address the complexities and non-linearities in the data, providing a clear and straightforward analytical approach. The time series regression equation is therefore defined by Equation 1.

$$
\begin{aligned}
BP_t = \beta_0 + \beta_1 \cdot BESS_t + \beta_2 \cdot Load_t + \beta_3 \cdot Price_t + \beta_4 \cdot VRE_t \\
+ \gamma_1 \cdot Time_t + \gamma_2 \cdot Weekday_t + \gamma_3 \cdot Month_t + \gamma_4 \cdot Year_t + \epsilon_t
\end{aligned} \tag{1}
$$

Where:

- BP_t is the respective balancing price at time t, the dependent variable,
- $BESS_t$ is the installed battery capacity at time t, the independent variables,
- $Load_t$ is the total load at time t,
- $Price_t$ is the electricity wholesale price at time t,
- VRE_t is the variable renewable energy generation at time t,
- $Time$ represents five binary dummy variables for the time of day,
- $Weekday$ is a binary dummy variable which indicates the weekday or weekend,
- $Month$ represents 11 binary dummy variables for the months,
- $Year$ represents three binary dummy variables for years,
- ϵ is the error term,
- β_i are the coefficients associated with the respective variables.
- and γ_i are the coefficients associated with the respective dummy variables.

The way I have specified the model and the dummy variables will be tested by doing a robustness analysis. This entails that a number of variations of the defined model will be estimated to find out whether or not this changes the outcomes. The robustness analysis will be presented along with the results in subsection 6.3.

5 Data

In the previous sections, I identified relevant variables for my research question and defined the regression model. As discussed in section 4, I am performing several independent regression analyses to study the relationships between BESS capacity and FCR, aFRR and mFRR for a set of EU countries. To perform the regression analyses, I have therefore constructed separate time-series datasets for each country, based on similar sources and the same process. This section describes the data collection and preparation process, with the aim of providing relevant information so other researchers can have confidence in the quality of the dataset and the possibility of replicating the research. In addition, this section presents selected summary statistics and data descriptives to get a better understanding of the variables.

5.1 Sample

Table 10 in Appendix A provides an overview of available data. For the decision on the sample, a trade-off was made between including more countries and having a longer sample period. The screening process around available data for the relevant variables finally led to a sample of five EU countries: Belgium, Czech Republic, Germany, Hungary and the Netherlands. I am using hourly time-series data between 2016 and 2020.

5.2 Data collection and preparation

I primarily used two data sources for the country datasets. I have used the 'Transparency Platform' for the Balancing prices, Total load, VRE generation and wholesale prices, the control and outcome variables. I have used a specific EU database for BESS capacity, the treatment variable.

In the following two subsections, the data source, data collection and preparation of the associated variables are therefore addressed in these two groups.

5.2.1 Dependent and Control Variables

Data Source and Collection For the prices of all three balancing services, total load, VRE generation and electricity prices, I have used the 'Transparency Platform' [4], the online data portal from ENTSO-E. [5]

The control variables are available on the Transparency Platform in different data forms. Across the control variables, ENTSO-E reports day-ahead (i.e. forecasted, expected) as well as actual data. I have opted to include day-ahead data for two reasons. First, this is the data on which the amount of required reserved balancing capacity is determined. This volume, in turn, impacts balancing prices through the merit-order system as described in subsection 4.1. And secondly, this resembles the data based on which BSPs place their bids. The precise data forms

[4]The Transparency Platform is a central collection and publication of electricity generation, transmission and consumption data from Enstso-e member countries. The data is provided and, as necessary, aggregated by the local TSOs. ENTSO-E aims to collect and publish the data in a uniform manner across member countries. Through various online articles, they have defined exactly what data the TSOs must submit and in what format the data must be submitted. This push for consistency supports the reliability, comparability and interpretation of the data used in this research across countries.

[5]The ENTSO-E is the association for the cooperation of the 40 TSOs from 36 European countries, including countries not part of the EU, and is a critical institution of the EU electricity system.

as available on the Transparency Platform for each corresponding variables are presented in Table 4.

Table 4: Specific Data Sources within the Transparency Platform.

Type	Abbreviation	ENTSO-E Data Source
Outcome	BP	Price of Reserved Balancing Reserves [17.1.C]
Covariates	Price	Day-Ahead Prices [12.1.D]
	Load	Total Load – Day – Ahead Forecast [6.1.B]
	VRE	Day-Ahead Generation Forecast for Wind and Solar [14.1.D]

For the data used for the control variables (Total Load, VRE Generation and Electricity Wholesale Prices), the transparency platform allows to easily select and download the relevant data for the country and period of interest in csv-format. For the balancing prices however, the portal does not allow to export the data directly. The balancing prices were downloaded through a python script that heavily relies on ENTSO-E Application Programming Interface (API), in combination with an open-source third party python client, by Pecinovsky & Boerman (2022). The python script, including queries for Germany with relevant comments, and can be found in subsection B.1.

Raw Data and Preparation The structure and nature of the ENTSO-E database meant I had to modify the raw data before analysing it – the exact preparations varied by variable. All preparations were made in Python. In the following paragraphs, I describe the form of the raw data and the respective preparations by variable.

The data sources for Total Load, VRE generation and Electricity Wholesale Price are very complete. Scarce missing values in the data of these variables have been filled with the average value of the hour before and after the missing data.

Balancing market prices The lack of uniformity for which the data for the outcome variable was available caused the data preparation process to be pervasive. One difficulty encountered during the downloading process was the consistency of the time interval during which the data was available on the transparency platform.

Inconsistent time intervals of the available data for balancing prices caused problems with the data in two separate ways. Firstly, both the ISP length and the related contract duration have changed throughout 2016-2022. This is because balancing markets have developed throughout the years to stimulate competition and form uniform European markets to reduce society's costs. These varying isp lengths and the contract durations for each included country are presented in Appendix A.2. The relatively long contract durations observed in the earlier parts of the sample period have resulted in uninterrupted periods with a single constant balancing price, limiting the variance in the dependent variable. Today, both the ISP and contract duration are uniformly set at 15 minutes across Europe.

Secondly, the duration of contracts at times overlapped. In other words, sometimes, both weekly and hourly contracts existed for the same hour in time. Where this was the case, I considered the shortest duration as the key data point. Given this adjustment, the dataset had no missing data.

Total Load
The primary key of the load data was consistently 15 minutes for all countries across 2016-2020. Therefore, average values are taken of the four 15-minute intervals to obtain one new hourly data point. The units for total load were scaled from MW to GW for ease of exposition of the regression results; this was done in Python as well.

VRE generation
Generation data from a variety of generation sources (e.g. coal, gas, solar run of river, among others) is available on the transparency platform for both actual values and forecasts. For solar, onshore wind and offshore wind, there is also an additional option with the day ahead forecast for just those sources. These represent all variable renewable energy sources. The forecasted generation volumes for the two types of wind and solar are aggregated into one variable.

Somewhat counterintuitively, the data for the generation by source is provided by the transparency platform in units of power, MW, rather than energy, MWh. This data is also published for 15 minutes time intervals instead of 1 hour. I therefore averaged the values of the four 15 minute intervals to obtain one hourly data points. Similarly to the total load, the units of VRE generation were scaled from MW to GW.

Electricity Wholesale Price
The electricity wholesale prices is published for 15 minute time intervals for all countries across 2016-2020. The unit for this variable is €/MWh. To end up with hourly data, I therefore averaged the values for the four 15 minute intervals .

Standardisation All dependent and independent variables are standardised, i.e. first centered around 0 and then scaled to have a standard deviation of 1.This is done such that the estimated coefficients are comparable across countries and across variables. This standardisation, however, does make the result interpretation less intuitive; this is further elaborated on in subsection 6.1 where the regression results are discussed.

5.2.2 Explanatory variable

The Transparency Platform does not collect or report on installed storage capacity data at all. Therefore, I have used a different database for the explanatory variable, the BESS capacity.

Description of data source Two governmental databases were used to construct the battery capacity variable: the Database of the European energy storage technologies and facilities' (the EU database) and 'DOE Global Energy Storage Database' (the US database).

The EU database is used as the primary source. The database was constructed as part of a study on the contribution of energy storage to the security of supply in Europe and is managed by the Department of Energy of the European Commission (EC)(Directorate-General for Energy, 2020). This database presents a wide variety of information on single storage facilities. The US database, is a similar dataset managed by the United States Department of Energy with a global scope, it was used as a secondary source of information to both validate the information as well as extend it.

Raw data The goal of the BESS capacity variable is to obtain the installed capacity in each country for every hour in the sample period. Unfortunately, this data was not directly available. Instead, the datasets provided an overview of a great number of storage facilities along with a variety of information on those facilities.

The two most relevant data points for each facility for our study are the installed capacity [MW] and the date of commissioning. I only used data on BESS, as versus other storage technologies like CAES or PHS. Moreover, I limited my selection to BESS facilities with a capacity larger than 1MW in order to include only grid-scale storage facilities that are connected to the transmission grid, as opposed to smaller facilities that are connected to the distribution grid and can, therefore, not perform balancing services.

Preparation While a useful database, a main limitation is that the database contained missing data, which I needed to resolve and which might impact the quality of the results of the study. The missing data was on two levels.
Firstly, for many facilities, either or both the date of commissioning or the power capacity rating were missing. I have gotten in contact with employees of the relevant department of the EC, in an effort to collect the missing data, however they were not able to provide me with an updated table. I, therefore, completed the dataset manually. This was done by supplementing the EU database with relevant data from the US database, which had the same problem of missing data points in various columns. In addition, I performed specifically targeted web searches and mainly found data from news articles about the facilities using available reference data such as facility name, developer, location, and owner. These online web sources have been carefully documented in the adapted version of the original database in Excel.

Secondly, the dataset does not present data on storage facilities commissioned after 2020, even though the web page through which it is available notes it was last updated on the 14th of December, 2022. In other words, the dataset seems to suggest that no storage facilities were commissioned between 2020 and 2022. It has become clear from web searches and other (national) storage datasets that new storage facilities, in fact, have gone operational in the countries relevant to this study. This leads me to assume the database is not properly maintained, contrary to what the web page suggests. For this reason, the initially foreseen end date for the sample period of 2023 was changed to 2020.

5.2.3 In sum

After all data was downloaded, all variables were combined in a separate Excel file for each country. The dummy variables defined in section 4 were also constructed in these Excel files. Subsequently, the Excel files were loaded in the R-code to run the regression models. This code is provided in subsection B.2.

Table 5 provides an overview of the included data, their source and data preparations.

Table 5: Overview of the variables.

Type	Variable	Definition	Unit	Data source	Data preparation
Dependent	Balancing prices	FCR, aFRR and mFRR market prices	€/MW/ISP	ENTSO-E	API-Collection Resampling for separate sub periods
Explanatory	BESS	Total of Battery Energy storage system capacity larger than 1 MW	MW	EU Energy Storage Database	Complete database Transform facility data to hourly time series
Control	Electricity Price	Prices from the Day-Ahead Wholesale Electricity Market	€/MWh	ENTSO-E	Resample from quarterly to hourly time series
	Load	Day-ahead total load forecast. The total expected amount of power drawn from the grid	MW	ENTSO-E	Resample from quarterly to hourly time series
	VRE	Day ahead forecast solar, onshore wind and offshore wind	MW	ENTSO-E	Aggregate Resample from quarterly to hourly time series

5.3 The Final Dataset

Throughout this section, the data for Germany will be used to illustrate various trends and patterns in the constructed dataset. Germany is generally considered an important energy hub in Europe.

5.3.1 Overview of Summary Statistics

Table 6 provides the summary statistics for Germany; the summary statistics of the other four countries are provided in Appendix A.3.

Table 6: Summary Statistics for Germany

	Sd	Mean	min	q1	median	q3	max
FCR	4.02	11.89	4.16	7.73	11.80	14.32	28.18
aFRR	15.37	16.31	0.00	3.52	13.14	25.18	353.24
mFRR	6.90	2.28	0.00	0.00	0.34	1.87	168.30
BESS	95.15	287.50	137.90	190.90	273.40	378.40	425.40
Price	16.69	36.39	-130.09	27.51	35.53	45.23	163.52
Load	9.47	55.18	33.36	47.37	55.06	63.27	75.91
VRE	10.15	21.28	2.44	13.14	19.51	28.24	59.05

From Table 6, several observations can be made. First, the FCR prices are moderately spread with some variation, indicating potential predictability and variability, which might be captured by BESS and other control variables.

Secondly, there are many observations for which the mFRR price is zero. Both aFRR and mFRR have maximum values (353.24 and 168.30, respectively) that are significantly higher than their third quartiles (Q3), indicating the presence of extreme values or outliers. Also, the standard deviations for both variables are relatively large compared to their means, suggesting a wide spread in the data. Moreover, the median values are much lower than the means, and the data is skewed to the right. This skewness typically results in a long tail on the right side of the distribution. The suggested presence of outliers and the skewed distribution can affect the assumption of normality. However, this is not expected to cause problems due to the large sample size of the dataset. The tables in appendix A.3 show that, generally, the same observations can be made on aFRR and mFRR in the other countries.

Thirdly, Table 6 shows that installed BESS capacity was 137.90MW at the beginning of 2016 and has gradually increased to 424.40MW, knowing that the capacity has only increased in the sample period.

And lastly, the three control variables appear to follow a normal distribution. The table shows that wholesale electricity prices in the sample period have been negative. Additionally, the first and third quartiles, Q1 and Q3, are relatively close together. Load shows a relatively narrow range, indicating consistent demand, which could be a stable control variable in the regression models. VRE has a moderate mean and standard deviation, suggesting some variability in renewable energy generation, which can influence balancing prices.

5.3.2 Analysis of Key Variables over Time

In this subsection, various time series plots of the variables from the final dataset are presented. These figures will be analysed to identify and discuss the observed trends and patterns in the data.

Figure 9 shows the installed BESS capacity for all countries. In addition to the sample period, the data for the years after 2020 are included in the plot as well.

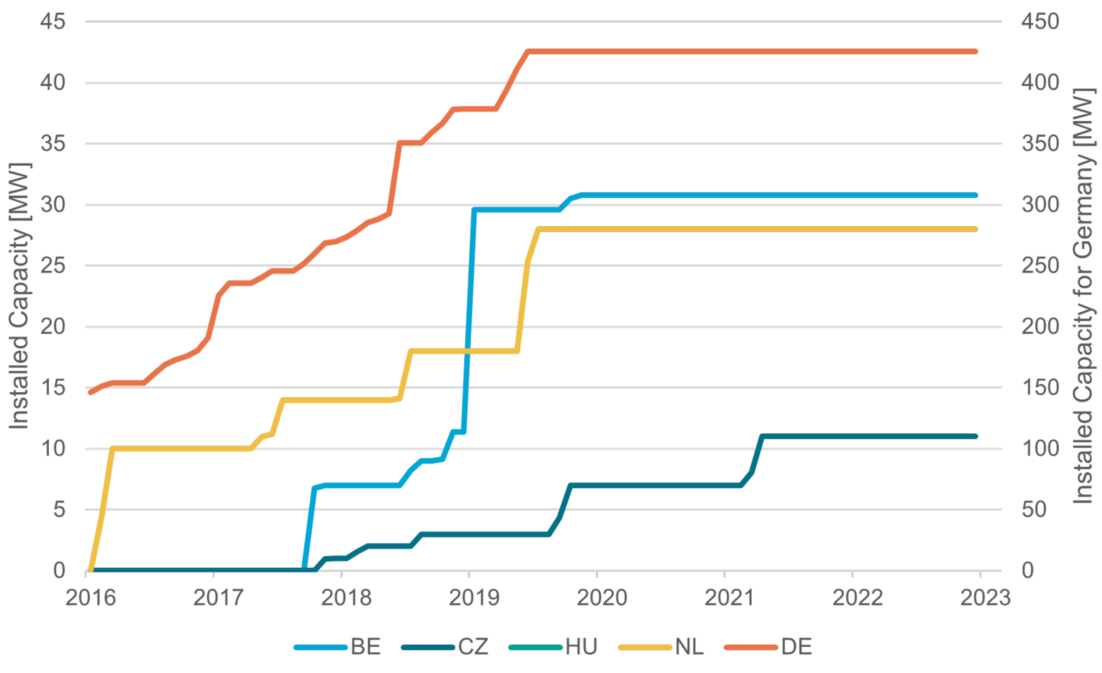
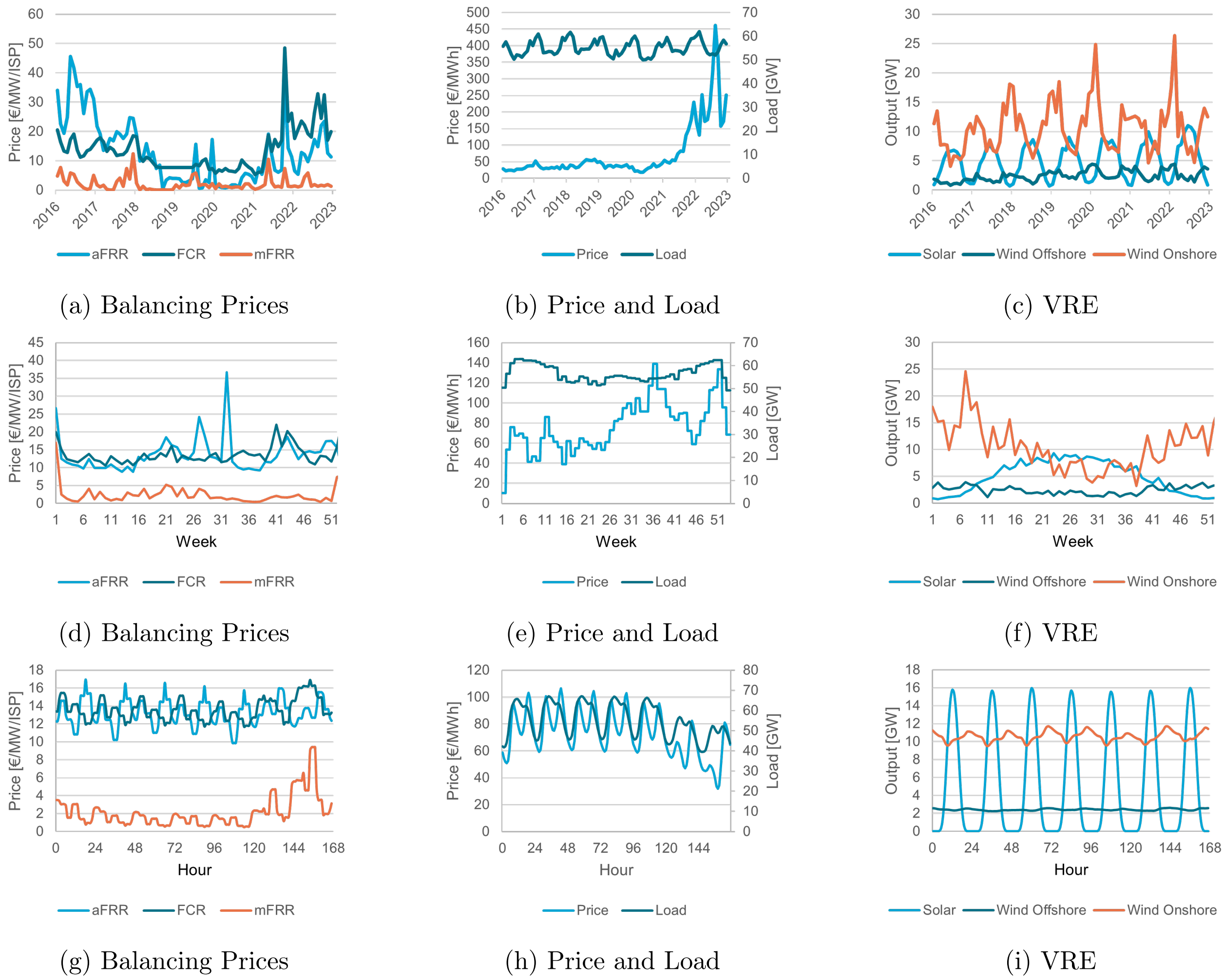


Figure 9: Installed BESS capacity over time. Note: Because of the much larger installed BESS capacity in Germany, a secondary axis was added on the right of the figure.

The step-wise growth of installed BESS capacity is clearly depicted by Figure 9. This figure also clearly shows that the volumes of installed BESS capacity greatly vary across countries, with Germany having substantially more installed BESS capacity. Further, it can be seen that, in principle, the dataset stops after 2020, with an exception for one additional BESS facility in 2021 in the Czech Republic, which was added to the dataset manually in an effort to complete it. This further supports the decision to shorten the sample period to 2016-2020.

Figure 10 provides data plots of the main variables for Germany for three different time horizons. The same plots for the other four countries are provided in Appendix A.3. To show trends in and after the sample period, subfigures 10a, 10b and in Figure 10 show weekly averaged data for the period between 2016 and 2022. Figures 10d, 10e, and 10f depict the average daily data aggregated for one year to visualise seasonal variation in the dataset. To show daily and weekly patterns, subfigures 10g, 10h, and 10i show average hourly data aggregated for one week.



(a) Balancing Prices (b) Price and Load (c) VRE

(d) Balancing Prices (e) Price and Load (f) VRE

(g) Balancing Prices (h) Price and Load (i) VRE

Figure 10: Time series plots of all variables for Germany.

From Figure 10a, it can be observed that the mFRR balancing price stays relatively constant throughout the entire period. However, the aFRR and FCR prices show more variation and seem to move roughly together over time. They first decreased between 2016 and 2019 and later increased at the end of 2021. In the same period as the latter, the electricity wholesale prices have increased dramatically as seen in Figure 10b. This is in line with the 2021 Global

Energy Crisis, which resulted from the aftermath of the COVID-19 crisis and geopolitical turmoil due to the Russian invasion of Ukraine. These observations hint at a positive relation between the electricity wholesale prices and the FCR and aFRR balancing prices. However, it is important to note that the sample period concludes before 2020, implying the exclusion of data corresponding to the Global Energy Crisis.

Secondly, figures 10b and 10e show that the total load follows a seasonal pattern with larger loads during winters. Also, the load did not change its patterns when the electricity wholesale prices increased during the Global Energy Crisis, which is in line with the very small electricity-price-demand elasticity reported in the literature.

Furthermore, it can be observed in Figure 10c that the output of the three VRE sources follows a seasonal pattern and that the output of all three sources has increased over time. Specifically, it can be seen that Onshore wind and Solar seem to be correlated negatively; this is also visible in figure 10f. From these figures, one cannot deduce a relation between VRE output and wholesale electricity prices or balancing prices.

On the smaller time horizons, all three balancing prices show daily patterns, and mFRR and FCR specifically show higher prices on weekends. This is somewhat unintuitive since the wholesale prices of electricity and the load are lower on weekends. However, the daily patterns in balancing prices do seem to correlate with the highly variable solar output.

The above-described trends, patterns, and relations hold for other countries on a high level. However, it must be noted that profiles do differ between countries. Where the data shows that Germany has a large installed solar capacity and relatively less offshore wind capacity, the opposite holds true for the Netherlands.

The limited variance in balancing prices as a result of the longer contract durations in earlier parts of the sample period is more clearly visible in the plots of the balancing prices for other countries, e.g. Czech Republic and the Netherlands.

6 Results

This section presents the results of the estimated regression models for the various combinations of included countries and balancing services. In total, 13 different models were estimated: five, five, and three for FCR, aFRR and mFRR, respectively.

The aim of these regression results is to answer this research question: "What is the effect of increasing grid-scale BESS capacity on balancing market prices in Europe?". Based on the conceptual framework, it is hypothesised that storage has a negative effect on balancing prices. This effect is expected to be more pronounced for the two shorter-term markets, FCR and aFRR, given that these markets are more suitable for batteries.

6.1 Regression results

To make the coefficient estimates more comparable across countries and variables, all variables are standardised, i.e., centred around 0 and then scaled to a standard deviation of 1.

The results are presented by balancing service in tables 7 to 9, rather than by country, because it is expected that the effect of storage capacity on the balancing prices varies across the balancing types due to their difference in nature.

The tables report standardised estimates of the time series models from Equation 1 for the respective balancing services. The models control for the seasonality of electricity demand, for price correlations between the wholesale and balancing prices and for variable renewable energy production. The models use 1-hour data over a four-year sample period from 2016 to 2019.

6.1.1 FCR

Table 7 presents the results for the five regression models estimating the effect of BESS capacity on FCR balancing prices in the five included countries. As hypothesised, increased battery capacity leads to a decrease in FCR balancing prices in most countries. Among the five models for FCR balancing prices, statistically significant coefficients for the BESS variable were found in three countries at the 1% significance level. The estimates are negative for every country except for the Czech Republic. For the Czech Republic, unexpectedly, the estimated effect is positive.

The standardized effects for countries with significant negative estimates, Germany and Hungary, are of a similar magnitude, -0.673 and -0.758, respectively. It is important to note that the positive coefficient for the Czech Republic, at 0.171, is substantially smaller than the negative coefficients for Germany and Hungary.

Table 7: Regression Results for FCR

	Country				
	BE	CZ	DE	HU	NL
BESS	−0.316	0.171***	−0.673***	−0.758***	−0.008
	(0.483)	(0.037)	(0.259)	(0.191)	(0.210)
	[−0.388]	[1.093]	[−0.028]	[−14.155]	[−0.005]
Price	−0.023	0.224***	−0.154***	0.069*	0.081**
	(0.061)	(0.028)	(0.034)	(0.041)	(0.040)
	[−0.015]	[4.270]	[−0.037]	[57.026]	[0.024]
Load	0.024	−0.080**	0.040	−0.032	0.099***
	(0.023)	(0.033)	(0.034)	(0.037)	(0.037)
	[0.262]	[−0.765]	[0.017]	[−2.387]	[0.166]
VRE	−0.055***	0.053***	−0.047	−0.005	0.031
	(0.017)	(0.017)	(0.033)	(0.021)	(0.040)
	[−0.928]	[1.691]	[−0.019]	[−2.868]	[0.286]
Constant	−0.783	−0.089	0.289	−0.009	0.444
	(0.779)	(0.103)	(0.454)	(0.415)	(0.401)
	[14.360]	[62.871]	[22.039]	[109.162]	[14.735]
Observations	35,065	35,065	35,065	35,065	35,065
R^2	0.828	0.458	0.715	0.727	0.436
Adjusted R^2	0.828	0.458	0.715	0.727	0.435
Residual Std. Error (df = 35040)	0.415	0.736	0.534	0.522	0.751
F Statistic (df = 24; 35040)	7,030.797***	1,234.833***	3,666.665***	3,897.469***	1,127.221***

Note: Significance levels are indicated as *p<0.1; **p<0.05; ***p<0.01. Because all variables are standardised, the coefficients presented in the table indicate the extent of change, measured in standard deviations, in the dependent variable for every standard deviation increase in the independent variables. Standard errors are heteroskedasticity and auto correlation-consistent (HAC) and are reported in parentheses. In addition, coefficients in their original scale have been included in brackets for easier interpretation of the actual effect sizes. The dummy variables are omitted in this table for ease of exposition.

Due to the standardization of the variables, interpreting the coefficient estimates can be less intuitive. For Germany, a one standard deviation increase in storage capacity leads to a 0.673 standard deviation decrease in the FCR balancing price. To make this clearer, I have converted the effect size back to the original scale using Equation 2, yielding the values presented in brackets in Table 7.

$$\hat{\beta}_x = \hat{\beta}_{x,st} \times \frac{\sigma_y}{\sigma_x} \tag{2}$$

Where:

- $\hat{\beta}_x$ is the coefficient on the original scale.
- $\hat{\beta}_{x,st}$ is the coefficient on the standardized scale.
- σ_y is the standard deviation of the dependent variable.

- σ_x is the standard deviation of the relevant independent variable.

For Germany, this means that a 1MW increase in BESS capacity decreases the FCR balancing prices by 0.028 €/MWh. This is reported in brackets underneath the standard deviations in Table 7. So even though standardised estimates are similar in order of magnitude, the absolute effects vary greatly across countries. This has to do with the difference in magnitude and variation in both storage capacities and balancing prices across countries.

6.1.2 aFRR

For the effect of BESS on aFRR balancing prices, as presented in Table 8, there are significant estimates for BESS in all five countries at the 1% level except for Belgium, which is significant at the 5% level. Except for Hungary, all estimates are negative.

Table 8: Regression Results for aFRR

	Country				
	BE	CZ	DE	HU	NL
BESS	-1.950^{**}	-0.055^{***}	-1.284^{***}	0.343^{***}	-0.771^{***}
	(0.839)	(0.012)	(0.119)	(0.058)	(0.116)
	[−4.323]	[−0.193]	[−0.207]	[1.221]	[−0.515]
Price	0.112^{**}	-0.010^{***}	0.013	0.016	0.246^{***}
	(0.051)	(0.003)	(0.038)	(0.024)	(0.036)
	[0.130]	[−0.102]	[0.012]	[2.475]	[0.072]
Load	−0.009	-0.013^{***}	-0.154^{***}	-0.326^{***}	0.021
	(0.033)	(0.005)	(0.034)	(0.041)	(0.031)
	[−0.178]	[−0.069]	[−0.250]	[−4.688]	[0.036]
VRE	-0.046^{***}	0.0005	0.018	0.009	0.076^{**}
	(0.017)	(0.002)	(0.025)	(0.023)	(0.038)
	[−1.422]	[0.009]	[0.027]	[1.047]	[0.690]
Constant	2.806	-1.503^{***}	1.552^{***}	0.122	1.515^{***}
	(1.872)	(0.030)	(0.264)	(0.135)	(0.268)
	[155.556]	[58.106]	[112.631]	[39.469]	[22.672]
Observations	35,065	35,065	35,065	35,065	35,065
R^2	0.616	0.989	0.552	0.266	0.664
Adjusted R^2	0.616	0.989	0.552	0.266	0.664
Residual Std. Error (df = 35040)	0.620	0.105	0.669	0.857	0.580
F Statistic (df = 24; 35040)	$2,346.509^{***}$	$132,145.200^{***}$	$1,799.727^{***}$	529.726^{***}	$2,887.122^{***}$

Note: Significance levels are indicated as *p<0.1; **p<0.05; ***p<0.01. Because all variables are standardised, the coefficients presented in the table indicate the extent of change, measured in standard deviations, in the dependent variable for every standard deviation increase in the independent variables. Standard errors are heteroskedasticity and auto correlation-consistent (HAC) and are reported in parentheses. In addition, coefficients in their original scale have been included in brackets for easier interpretation of the actual effect sizes. The dummy variables are omitted in this table for ease of exposition.

Interestingly, standardised effects of the BESS variable are substantially larger for aFRR than for FCR. It can also be noted that consistently across the five countries, BESS capacity appears to have the largest effect on the aFRR balancing prices compared to the three included control variables.

6.1.3 mFRR

Among the results for mFFR, in Table 9, only the models estimated for the Netherlands yield significant coefficients at $\alpha = 0.01$ and for Germany at $\alpha = 0.05$. For Germany, the effect is positive, while the BESS has a negative effect on the mFRR balancing price in the Netherlands.

Table 9: Regression Results for mFRR

	Country		
	BE	DE	NL
BESS	1.732	0.512**	−0.468***
	(1.055)	(0.216)	(0.178)
	[4.441]	[0.037]	[−0.227]
Price	0.099*	−0.435**	0.056
	(0.059)	(0.184)	(0.040)
	[0.133]	[−0.180]	[0.012]
Load	−0.091*	−0.144	0.040
	(0.054)	(0.105)	(0.029)
	[−2.070]	[−0.105]	[0.049]
VRE	0.133*	0.073	0.060
	(0.077)	(0.085)	(0.038)
	[4.725]	[0.050]	[0.400]
Constant	−1.825**	−0.532*	0.997***
	(0.836)	(0.318)	(0.278)
	[−67.532]	[−0.808]	[8.958]
Observations	35,065	35,065	35,065
R^2	0.316	0.267	0.630
Adjusted R^2	0.316	0.267	0.630
Residual Std. Error (df = 35040)	0.827	0.856	0.608
F Statistic (df = 24; 35040)	676.016***	532.707***	2,486.527***

Note: Significance levels are indicated as *p<0.1; **p<0.05; ***p<0.01. Because all variables are standardised, the coefficients presented in the table indicate the extent of change, measured in standard deviations, in the dependent variable for every standard deviation increase in the independent variables. Standard errors are heteroskedasticity and auto correlation-consistent (HAC) and are reported in parentheses. In addition, coefficients in their original scale have been included in brackets for easier interpretation of the actual effect sizes. The dummy variables are omitted in this table for ease of exposition.

Note that although the results clearly suggest that in the Netherlands, there is a negative effect of BESS on the mFRR balancing price, this effect is smaller for mFRR than for the shorter-term balancing service aFRR, in line with the hypotheses.

6.2 Model statistics

R-squared The R^2 is the ratio of variance in the dependent variable that is explained by the specified model. The effectiveness of the regression model in explaining variation in the dependent variable depends on various factors, including the quality of the data, the appropriateness of the model specification, the inclusion of relevant predictor variables, and the presence of other sources of variation that may not be captured by the model.

In general, it is expected to find relatively high R^2 values in the results because of the use of time series data and the consequential inclusion of many time- and date-related dummy variables. This raises the question of whether the high R^2 values are primarily due to these dummy variables or whether the independent and control variables actually explain most of the variation in the dependent variable. To investigate this, the models discussed in subsection 6.1 have been modified and run without the dummy variables. The complete regression tables of these models are presented in Appendix C.1 The resulting R^2 values are presented in Figure 11.

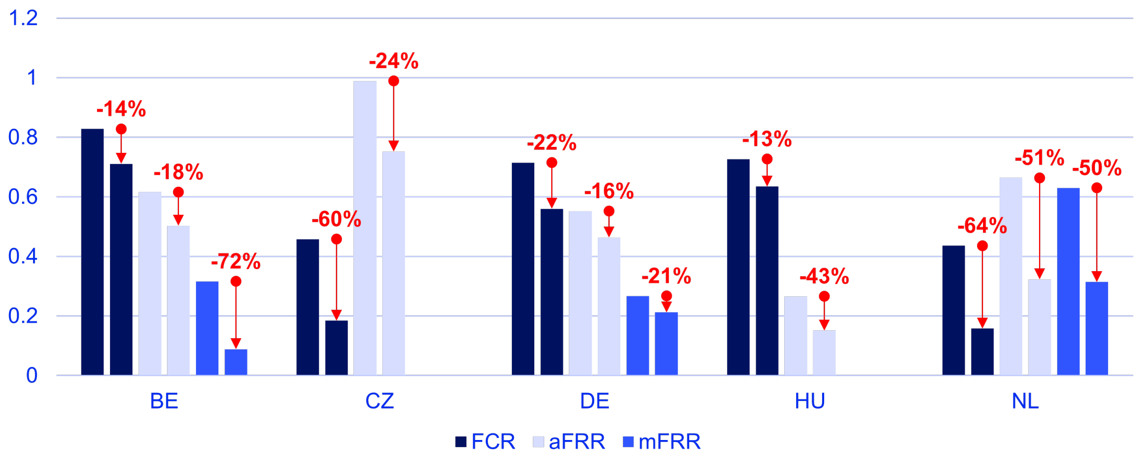


Figure 11: R^2 values with and without dummy variables.

In Figure 11, the R^2 values are presented for all 13 models with and without the dummy variables; the red percentages indicate the percentual differences between the R^2 with and without dummy variables. Figure 11 shows that, indeed, there is a notable discrepancy between the adjusted R^2 values for the models with and without dummy variables. On average, the dummy variables explain 18.3%, 17.9%, and 20.0% of the variation in the FCR, aFRR, and mFRR balancing prices, respectively. This signifies that the values presented in tables 7 to 9 do indeed, for a substantial part, result from the inclusion of time and date-related dummy variables. However, overall BESS, Price, Load, and VRE clearly explain the major part of variation.

Furthermore, Figure 11, shows that the R^2 values vary both across the balancing services and countries. For the models with dummies, on average the R^2 values for FCR and aFRR are 0.63 and 0.62, respectively. For mFRR, the R-squared values are substantially smaller, with an average of 0.40. It is possible that because of the different nature of the FCR and aFRR balancing services, the corresponding balancing prices are influenced by different factors compared to mFRR. The independent variables may actually be better predictors for the balancing market prices for FCR and aFRR compared to mFRR. This would indeed mean that the independent variables are more effective at explaining the variability in FCR and aFRR than mFRR. This is indeed in line with the hypothesis.

F-statistic The F Statistic tests the overall significance of the regression model. It assesses whether at least one of the independent variables has a non-zero coefficient, i.e., whether the independent variables, as a group, are jointly significant in explaining the variation in the dependent variable.

In all regression table results, the F statistics are all statistically significant at a high level ($p < 0.01$), indicating that the overall regression models are significant; this is as expected with relatively large sample sizes.

6.3 Robustness analysis

A robustness analysis is undertaken to validate the decisions for model specification and to contrast their effects with alternative options. In the robustness analysis, several model definition choices are changed: dummy variable definition and aggregation of different VRE sources.

In addition to the main model formula in this thesis, model 1, as defined by Equation 1, seven alternative model definitions have been defined. The seven alternative models have been estimated for all thirteen combinations of balancing services and included countries. The exact modifications of the seven alternative model equations are discussed below, followed by discussions of the statistical significance and effect sizes of BESS coefficients for the seven alternative model equations.

6.3.1 Alternative Model Equations

Whereas model 1 controls for VRE impact on the balancing price by aggregating the Solar Onshore-Wind and Offshore-Wind electricity output variables, model 2 includes these three variables separately as it might be possible that any of the three included VRE sources affect the balancing prices differently from the other two.

Models 3 through 6 include the alternative definitions for the dummy variables. Model 1 controls for potential diurnal variation by including 5 binary dummy variables for every four-hour time period, except one. Model 3, alternatively, controls for the same variation by including 23 binary dummy variables for every hour of the day, except one.

Model 4 controls for weekly variation by including 6 dummy variables for each day of the week minus one, as opposed to model 1, which included only one dummy variable for weekdays versus weekends.

Model 5 controls for yearly recurring seasonal variation by including dummy variables for 51 weeks, while model 1 only includes 11 dummy variables for the months. Here, there is no fundamental difference, only the granularity of the dummy is increased.

While model 1 controls for potential unobserved effects over the years by adding 3 dummy variables for 2016, 2017, and 2018, model 6 omits these dummy variables.

Models 7 and 8, have alternative functional forms. Model 7 allows for any non-linear effects where the effects of the explanatory and control variables can increase or decrease at an increasing rate. This is done by including quadratic terms in the model formula.

Model 8 examines whether the effect of BESS on the balancing price varies depending on the levels of Load, Price and VRE. This is done by including interaction terms, i.e. the product of two BESS and another variable.

6.3.2 Statistical Significance

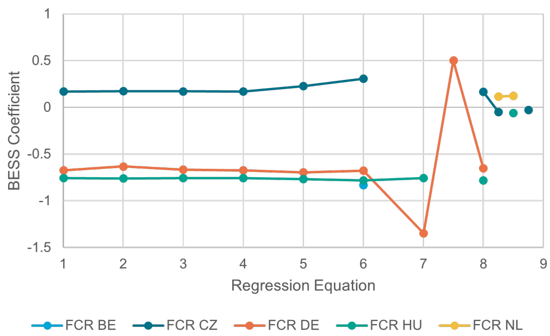
In addition to the BESS coefficients for each model, models 7 and 8 provide multiple coefficient estimates related to BESS due to their functional form. Model 7 includes both a linear and quadratic BESS coefficient, and model 8 includes three interaction coefficients for BESS with Price, Load, and VRE.

Figures 12a, 12b, and 12c show plots of the coefficients of the BESS variable for the eight different models that are statistically significant for FCR, aFRR, and mFRR respectively. The additional coefficient related to model 7 is plotted at 7.5 and the interaction coefficients for BESS with Price, Load, and VRE from model 8 are plotted at 8.25, 8.5, and 8.75 respectively.

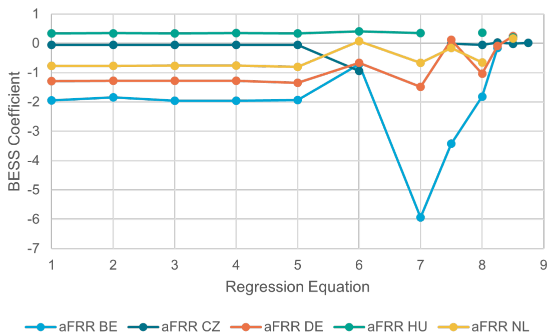
Appendix C.2 presents tables with the values of all coefficients, including the associated p-values and further model statistics for all 8 alternative model equations.

From Figure 12a, it becomes clear that only model 6 yields significant results for the effect of BESS on the FCR balancing price in Belgium. Moreover, BESS had no significant coefficient for the FCR balancing price in any of the eight model equations for the Netherlands except for the interaction coefficients with price and load. And these are positive.

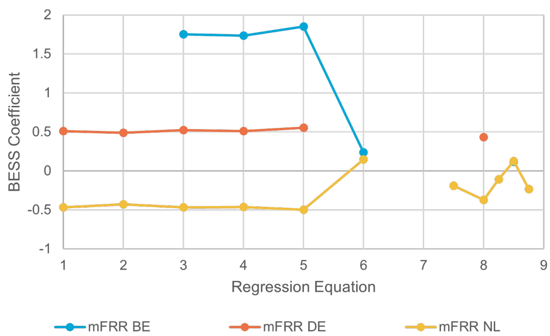
For the aFRR balancing prices, all models 1 to 6 showed statistically significant results at a 5% level, except for when the Czech coefficient was tried to be estimated with model equation 3.



(a) FCR



(b) aFRR



(c) mFRR

Figure 12: BESS coefficient plots for eight different models.

Figure 12c shows that for the mFRR prices model three did not yield significant results for BESS in any of the three countries. Moreover, this plot shows that models 5, 6, 7, and 8 did yield significant results for Belgium, as opposed to the other regression equations, including the main model.

6.3.3 Effect Size

Aside from the sporadic deviations in the significance of the BESS coefficients across the alternative model equations, the three plots in Figure 12 show that, in general, the direction and magnitude of the effects are stable across the eight alternative model equations.

Some combinations of balancing services and countries for model 6 and 7 form an exception on this general image. For Germany, interestingly, when the quadratic term is added to the model equation (model 7), the linear coefficient becomes larger (more negative) compared to the results from the other models, and the quadratic coefficient is significant and positive. For aFRR, a similar, but different, trend is visible for Belgium in the results; the linear effect of BESS on aFRR balancing prices is much larger than the other models suggest. However, where the quadratic coefficient for BESS was positive for the German FCR prices, it is negative for the Belgian aFRR prices.

From the data for aFRR in Figure 12b it appears that the results are not robust to the exclusion of the year dummy variable (model 6). For Belgium, Germany and the Netherlands, the negative coefficients from models 1-5 were substantially smaller (more negative) than for model 6, i.e. model 6 estimates a *higher* coefficient. Conversely, model 6 estimated that BESS had a negative effect in the Czech Republic, while models 1-5 estimated that there was no effect, i.e. model 6 here estimates a *lower* coefficient.

The same ambiguous consequence of excluding the year dummy is observed for the estimated effects of BESS on the mFRR prices. This is indicated by the opposite 'reaction' of the results for the Netherlands and Belgium in Figure 12c.

Moreover, the change in the BESS coefficient is also inconsistent for Belgium across the different balancing services. The exclusion of the year dummy caused the coefficient for BESS in Belgium to increase slightly for the aFRR prices but decrease substantially for the mFRR prices.

The substantial but ambiguous consequence of excluding the year dummy variable (model 6) suggests that there are year-specific effects influencing the dependent variable that are not captured by the other predictors in the model, Price, Load, and VRE. This could hint at the existence of unobserved factors that affect the outcome variable. This would, in turn, mean that omitted variable bias was created by excluding the year dummy. In that case, the effects of these unobserved factors would have been different for the Czech Republic than for Belgium, Germany and the Netherlands, hence the different result from excluding the year dummy.

In short: based on this analysis it is evident that the changes in results from excluding the year dummy variable do not indicate non-robustness; rather, they demonstrate the appropriateness of including the year dummy.

The results from model 8 suggest that this model yields coefficient estimates similar to those of models 1-5 for the specific effect of BESS separately. However, the interaction effects are generally close to zero, indicating the absence of a significant interaction effect.

Overall, the findings discussed in subsection 6.1 are robust across various model specifications.

6.4 Discussion

This section integrates the results discussed in the preceding subsections, providing some further analysis. This discussion encompasses elaborations on the presented results and limitations of the research.

6.4.1 Elaboration

BESS The analysis indicated that a total of three significant coefficients out of all thirteen models are positive.

The two largest significant positive coefficients for BESS were found in the mFRR market in Germany and the aFRR market in Hungary. In these countries, the shorter-term markets—both aFRR and FCR for Germany, and FCR for Hungary—exhibit negative coefficients of a substantially larger magnitude than the positive coefficients. These results align with the findings presented by Rangarajan et al. (2023).

The observed increases in these longer-term markets might suggest that fossil-fuel balancing market participants, unable to compete in high-frequency balancing markets, are attempting to recover costs. This hypothesis warrants further investigation in future research.

The third significant positive coefficient is for the Czech Republic. It is not immediately clear why this is the case. One potential reason could be that BESS facilities in the Czech Republic simply did not participate in the balancing services as much as in other countries.

Furthermore, it is worth mentioning that, Germany, the country where there had been the most BESS installed capacity, both in absolute and relative terms, Germany, has presented the results that most resembled those of Rangarajan et al. (2023). This resemblance shows as significant results for all three balancing services and relatively large negative coefficients for BESS in the two shorter-term markets and a positive coefficient in the longest-term market in this study. It is difficult to compare the BESS coefficients for the Australian balancing markets with those found for Germany at a more detailed level because Rangarajan et al. (2023) did not present standardised coefficients, nor is it possible to track down the standard error of their BESS variable.

Control Variables To meaningfully discuss the coefficients of the control variables, it is essential to consider the DAG shown in Figure 7. This thesis examines the direct effect of BESS on balancing prices, necessitating control for electricity prices, which act as a mediator in the causal path between BESS and the balancing price, and load and VRE which act as confounders on the paths opened as a result of controlling for electricity prices.

However, if the focus shifts to estimating the effect of electricity prices on balancing prices, the causal paths change. In this scenario, controlling for other covariates or BESS might introduce bias by opening any of these alternative paths. For electricity price, all other causal paths are confounding, meaning that the model in Equation 1 correctly estimates its effect by controlling for BESS, load, and VRE, as the confounders.

From tables 7 to 9 it can be concluded that the electricity price has a significant effect on the balancing price in eight of the thirteen models. In the Netherlands, there is a positive relationship between the electricity price and the balancing price in all three balancing markets. Furthermore, there are positive significant coefficients for the Czech Republic and Belgium in the FCR and aFRR markets, respectively. These positive effects are as hypothesised. In Germany, however, the models find negative significant coefficients in the FCR and mFRR markets. It could be that the larger levels of installed BESS capacity seen in Germany reverse the effect of the electricity price on the balancing prices. This cannot be concluded from the presented data; a more in-depth analysis of the interaction between the electricity price and installed BESS capacity is needed to back such claims up.

From the perspective of estimating the effect of Load and VRE on the balancing prices, these variables have similar roles in the DAG as BESS. This means that the model only estimates their direct effects on balancing price, similar to BESS. This is due to the model controlling for the mediating role of electricity price in their respective impacts on balancing price, similar to BESS. However, in the case of BESS this limitation to the direct effect is on purpose, whereas for load and VRE, it is merely a consequence of the model definition. This is called the table 2 fallacy (Westreich & Greenland, 2013).

For both load and VRE, this means that the coefficients presented in tables 7 to 9 represent the direct effect on balancing prices, by impacting the minimum amount of reserved balancing capacity, i.e. these coefficient do not include the indirect effect of load and VRE affecting the electricity price and consequently impacting the balancing price.

For the load, tables 7 to 9 provide only five out of 13 significant coefficients, of these four are negative. This is inconsistent with what was hypothesised in subsection 4.3. One possible explanation is that during periods of higher loads, fewer balancing reserves are actually required. This could be because larger loads tend to average out deviations, bringing them closer to the expected values. The same reasoning could be argued for the VRE output, for wich there are positive and negative coefficients estimated.

6.4.2 Limitations

The research faced several limitations, primarily related to data availability and variability. The stepwise increase in BESS capacity resulted in limited variation for this variable, which could affect the reliability of the findings. Additionally, due to longer contract durations earlier on in the sample period, the balancing prices remained constant for extended durations, presenting a similar challenge to the BESS data.

Moreover, the reduction of the sample period from 2016-2022 to 2016-2019 due to the unavailability of data for the main variable, BESS, limits the validity of this research. This shorter timeframe restricts the ability to capture long-term trends and patterns, especially given that the years 2020-2023 have seen a substantial increase in installed BESS capacity compared to previous years. Additionally, the later years of the sample period showed more variation in balancing prices due to European market harmonisation and the consequent reduction in contract durations. These limitations could be easily addressed in future research if the databases containing BESS facility data are updated.

The model examining the FCR prices in Belgium demonstrated a very good fit, with a high R-squared value of 0.828. However, none of the three predictors, BESS, Price, and Load, were significant at the 10% level, indicating potential issues of overfitting or multicollinearity (Wooldridge, 2012). During the robustness analysis, rerunning the model without the year dummy—suspected of showing multicollinearity with variables such as BESS—revealed a significant coefficient for BESS. This further indicates the presence of multicollinearity or overfitting. Future research could explore this issue using techniques such as ridge regressions and Monte Carlo simulations to mitigate these problems and provide more robust conclusions.

Potential model improvements for future research include investigating specific variable combinations, such as the ratio of load and VRE, or functional forms that might yield more significant coefficients.

Lastly, it is important to note that the effects estimated on historical data may not necessarily hold in the future, as the energy landscape evolves. The uncertainty associated with the balancing price, influenced by the substantial planned increase in VRE over the next decade, further complicates the predictive accuracy of the model.

7 Conclusion

This study aimed to assess the effect of BESS on European electricity balancing markets. The context for this research is the increasing integration of VRE sources, such as wind and solar, which present challenges for grid stability and balancing costs due to their intermittent and non-dispatchable nature. As the EU targets 42.5% of its energy from renewables by 2030, understanding the role of BESS in mitigating the associated balancing challenges becomes crucial. Specifically, in this thesis, it is empirically studied how increasing BESS capacity can impact the prices that TSOs pay for reserve balancing capacity.

The empirical approach involved analyzing historical time-series data from five European countries: Germany, Belgium, the Netherlands, Hungary , and the Czech Republic. Following an assessment of data availability, the sample period was determined to span from 2016 to 2019. The focus throughout this thesis has been on the three types of European balancing services: FCR, aFRR, and mFRR. Multivariate regression models were employed to investigate the impact of increasing BESS capacity on the prices in these balancing markets.

Previously limited amounts of theoretical research had been conducted on the interplay of BESS capacity and balancing market prices. The significance of this research lies in extending previous empirical studies on the effect of BESS on balancing market prices in Australia, conducted by Rangarajan et al. (2023), to the European market. This study demonstrated that increased BESS capacity significantly reduced overall balancing costs. Extending this research to the European context broadens the scope of the understanding and addresses the geographical nuances that shape energy transition dynamics in Europe.

To answer the question of how increasing BESS capacity can impact the balancing market prices, the conceptual framework in this thesis shows that increased BESS capacity *directly* impacts balancing market prices through two primary mechanisms. First, BESS often have lower marginal costs than conventional balancing assets, leading to a horizontal shift in the merit order and, consequently, reduced balancing prices. Second, the entry of BESS into the market increases competition among BSPs, prompting existing players to lower their bid prices. Additionally, it is assumed that BESS has an *indirect effect* by its impact on wholesale electricity prices, which are known to be causally related to balancing prices. However, as the direction and magnitude of BESS's effect on the wholesale prices of electricity depend on the shape of the merit order in the relevant country, it has been chosen to limit the study of the direct effect of BESS on the balancing prices specifically. To isolate the direct effect of BESS on balancing prices, the models controlled for three key variables: total load, electricity wholesale prices, and VRE generation.

With regards to the multivariate regression analysis, it involved conducting 13 independent regression analyses for each country and each balancing service type. The regression models were specified to account for potential diurnal and seasonal variations by including dummy variables for different times of the day, days of the week, and months of the year. Furthermore, dummy variables have been added for the years to capture any unobserved factors that have affected the balancing price over the years. Additionally, HAC standard errors have been used in assessing the model results to address potential violations of the assumptions of homoscedasticity and independence among observations.

The data for the analysis was sourced primarily from the ENTSO-E transparency platform and a specific EU database on BESS capacity. The balancing market prices, total load, VRE generation, and electricity wholesale prices were obtained in various data forms, primarily day-ahead forecasts used by TSOs to determine the required minimum reserved balancing capacity. This choice aligns with the practical realities of how balancing markets operate and ensures that the control variables accurately reflect the conditions under which balancing prices are determined.

The results indicate that increased BESS capacity significantly reduces balancing prices, particularly in the FCR and aFRR markets. This reduction is attributable to the lower marginal costs of BESS compared to conventional balancing assets and increased competition among BSPs, leading to more competitive pricing. Specifically, the results show a notable decrease in balancing prices with each additional megawatt of installed BESS capacity, validating the initial hypothesis. For instance, in the FCR market, an additional megawatt of BESS capacity led to a reduction in balancing prices by a specific amount, highlighting the cost-effectiveness of BESS in providing grid stability.

The study also delved into the robustness of these findings through various model specifications. A robustness analysis was conducted by estimating different variations of the main model for most combinations of country and balancing market type; this consistently showed the negative impact of BESS on balancing prices held across different model configurations. This further strengthens the validity of the results and underscores the reliability of the methodological approach.

Conclusively, this research provides substantial empirical evidence of the positive impact of BESS on reducing balancing market prices in the European context. By extending the findings from previous studies in Australia to Europe, this thesis offers valuable insights that can inform policy decisions and strategic investments in BESS. The methodological approach, which includes controlling for critical variables and ensuring robust model specifications, enhances the credibility of the findings and contributes to a deeper understanding of the role of BESS in future energy systems. This research underscores the significant potential of BESS to offer cost-effective, CO2-neutral solutions for grid stability, aligning with broader climate policy goals and the ongoing energy transition. By addressing the outlined policy and research implications, stakeholders can better harness the benefits of BESS, contributing to a more cost-efficient, resilient, and sustainable energy system.

7.1 Societal Implications

This thesis has a number of implications which can be assessed from various stakeholder perspectives.

TSO The current trend of increasing grid-scale batteries is likely to result in lower balancing market prices. This trend presents a dual impact: while lower prices benefit TSOs by reducing operational costs, they also need to adapt to the changing market dynamics to maintain grid stability. Knowing the results as presented, TSOs should consider stimulating BESS adoption through favourable regulations to leverage the benefits of lower balancing market prices and enhanced grid stability.

This can be achieved through incentives for private investments or public funding initiatives aimed at accelerating the deployment of BESS. Policymakers could also consider revising market rules to better facilitate the participation of BESS in the balancing markets, ensuring they can at least compete on a level playing field with conventional balancing assets. This could involve adjusting prequalification requirements and bid procedures to better accommodate the technical characteristics of BESS.

BESS Operators and Future Investors For BESS investors, the results are somewhat negative. As balancing market prices decrease due to the increased capacity of BESS, the revenue generated from these markets will likely diminish. This cannibalization effect necessitates careful market monitoring and strategic planning to remain competitive. BESS operators must remain vigilant about competition and market price developments, adapting their strategies to maintain profitability in a changing market landscape.

Conventional Power Plant Operators The increase in BESS capacity negatively affects short-term balancing market prices, making it less profitable for conventional power plants to participate in these markets. These operators may need to transition away from short-term balancing markets and focus on the mFRR market, where the impact of BESS is anticipated to be smaller, this is likely already the case in Germany.

Society Society stands to benefit from these developments. TSOs employ a causer-pays approach to allocate costs resulting from imbalances to the responsible parties. However, this only affects the costs incurred for the activated balancing energy and not the reserved capacity. As the price for reserved capacity decreases with increasing BESS, the overall costs passed on to consumers will likely decrease, leading to lower electricity bills.

7.2 Academic Implications

Although this study provides valuable insights into the impact of BESS on balancing markets, it also opens up several avenues for future research. Firstly, while this research studied five European countries as independent time series data, future research could study similar data as panel data. This could help identify causal relationships more accurately and control for unobserved heterogeneity, among others. Furthermore, future studies could expand the geographical scope to include more countries or regions, within or outside Europe, with different market structures and levels of BESS integration. This would help to validate the generalizability of the findings and provide a more comprehensive understanding of the role of BESS in diverse energy systems.

Additionally, future research could delve deeper into the interaction between BESS and other grid assets. For instance, investigating how BESS can complement or compete with other forms of flexible resources, such as demand response, would provide a more holistic view of their potential contributions to grid stability.

Moreover, while this study primarily considered the economic aspects of BESS integration, future research could explore the technical and operational challenges associated with scaling up BESS deployments. This could include examining issues related to battery degradation, optimal dispatch strategies, and integrating BESS with emerging technologies like electric vehicles and smart grids.

Finally, as the regulatory landscape for energy storage continues to evolve, future studies should keep track of policy changes and their impacts on the market dynamics of BESS. Longitudinal analyses that account for regulatory developments would provide valuable insights into how policy interventions can shape the adoption and effectiveness of BESS in balancing markets.

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Appendices

A Data

A.1 Data availability

Table 10: Data availability per variable per EU country

Country	Code	mFRR [€/MW/	aFRR [€/MW/	FCR [€/MW/	Day ahead price [€/MWh	Total load day ahead [MWh]	Storage, installed capacity [MW]	VRE generation [MWh]	Eligib
Albania	AL								No
Austria	AT	x	x	x	x	x	x	x	Yes
Belgium	BE	x	x	x	x	x	x	x	Yes
Bosnia and Herz.	BA					x		x	No
Bulgaria	BG					x		x	No
Czech Republic	CZ	x	x	x	x	x	x	x	Yes
Denmark	DK	x			x	x	x	x	No
Finland	FI	x	x	x	x	x	x	x	Yes
France	FR					x	x	x	No
Germany	DE	x	x	x	x	x	x	x	Yes
Greece	GR	x	x	x	x	x	x	x	Yes
Hungary	HU	x	x	x	x	x	x	x	Yes
Italy	IT				x	x	x	x	No
Latvia	LV				x	x			No
Lithuania	LT				x	x	x	x	No
Luxembourg	LU					x		x	No
Netherlands	NL	x	x	x	x	x	x	x	Yes
Norway	NO	x	x		x	x	x	x	No
Poland	PL				x	x	x	x	No
Portugal	PT		x		x	x	x	x	No
Romania	RO				x	x	x	x	No
Serbia	RS	x	x	x	x	x			No
Slovakia	SK	x	x	x		x	x	x	No
Slovenia	SI	x	x	x	x	x	x	x	

A.2 Contract durations over various periods

Table 11: Different periods of data in Belgium characterized by (contract duration, ISP length).

Period	FCR	aFRR	mFRR
01/01/2016 – 12/07/2018	Weekly, Week	Daily, 1h	Daily, 1h
12/07/2018 – 01/07/2019	Weekly, Week	Daily, 15min	Daily, 15min
01/07/2019 – 31/12/2022	Daily, 15min	Daily, 15min	Daily, 15min

Table 12: Different periods of data in the Czech Republic characterized by (contract duration, ISP length).

Period	FCR	aFRR
01/01/2016 – 31/12/2022	Daily, 1h	Daily, 1h

Table 13: Different periods of data in Germany characterized by (contract duration, ISP length).

Period	FCR	aFRR	mFRR
01/01/2016 – 12/07/2018	Weekly, Week	Daily, 1h	Daily, 1h
12/07/2018 – 01/07/2019	Weekly, Week	Daily, 15min	Daily, 15min
01/07/2019 – 31/12/2022	Daily, 15min	Daily, 15min	Daily, 15min

Table 14: Different periods of data in Hungary characterized by (contract duration, ISP length).

Period	FCR	aFRR
01/01/2016 – 01/08/2020	Long term, 15min	Weekly, 15min
01/08/2020 – 31/12/2022	Monthly, 15min	Daily, 15min

Table 15: Different periods of data in the Netherlands characterized by (contract duration, ISP length).

Period	FCR	aFRR	mFRR
01/01/2016 – 01/01/2018	Weekly, Week	Monthly, Month	Monthly, Month
01/01/2018 - 01/07/2019	Weekly, Week	Weekly, Week	Monthly, Month
01/07/2019 - 01/01/2020	Daily, 15min	Weekly, Week	Monthly, Month
01/01/2020 - 01/07/2020	Daily, 15min	Weekly, 15min	Monthly, 15min
01/07/2020 - 31/08/2020	Daily, 15min	Weekly, 15min	Weekly, 15min
31/08/2020 -31/12/2022	Daily, 15min	Daily, 15min	Daily, 15min

A.3 Additional summary statistics

	Sd	Mean	min	q1	median	q3	max
FCR	14.76	23.03	1.00	6.88	25.40	32.92	83.92
aFRR	26.64	40.14	1.48	16.20	40.80	52.40	175.48
mFRR	30.82	23.31	7.32	11.78	15.06	17.64	186.88
BESS	12.02	9.99	0.00	0.00	7.00	11.40	30.80
Price	22.93	43.95	-500.00	31.00	40.17	52.58	696.02
Load	1.36	9.84	6.61	8.76	9.88	10.86	13.38
VRE	0.87	1.01	0.00	0.35	0.82	1.40	6.29

Table 16: Summary Statistics - BE

	Sd	Mean	min	q1	median	q3	max
FCR	12.46	67.17	42.87	55.36	66.18	74.38	122.56
aFRR	6.85	67.42	55.54	65.58	71.14	73.60	80.86
mFRR	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BESS	1.95	1.64	0.00	0.00	1.00	3.00	7.00
Price	0.65	1.54	-2.00	1.14	1.48	1.90	5.64
Load	1.30	7.48	4.33	6.46	7.46	8.37	11.07
VRE	0.39	0.32	0.00	0.05	0.13	0.46	1.78

Table 17: Summary Statistics - CZ

	Sd	Mean	min	q1	median	q3	max
FCR	4.02	11.89	4.16	7.73	11.80	14.32	28.18
aFRR	15.37	16.31	0.00	3.52	13.14	25.18	353.24
mFRR	6.90	2.28	0.00	0.00	0.34	1.87	168.30
BESS	95.15	287.50	137.90	190.90	273.40	378.40	425.40
Price	16.69	36.39	-130.09	27.51	35.53	45.23	163.52
Load	9.47	55.18	33.36	47.37	55.06	63.27	75.91
VRE	10.15	21.28	2.44	13.14	19.51	28.24	59.05

Table 18: Summary Statistics - DE

	Sd	Mean	min	q1	median	q3	max
FCR	53.06	77.78	0.00	22.10	95.30	111.78	164.47
aFRR	10.12	19.07	0.00	11.46	17.72	22.98	100.71
mFRR	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BESS	2.84	2.04	0.00	0.00	0.00	6.00	6.00
Price	0.06	0.15	-0.08	0.11	0.14	0.18	0.96
Load	0.70	4.71	2.83	4.17	4.79	5.23	6.49
VRE	0.09	0.08	0.00	0.01	0.05	0.12	0.77

Table 19: Summary Statistics - HU

	Sd	Mean	min	q1	median	q3	max
FCR	4.33	16.06	6.24	12.87	15.44	19.07	41.60
aFRR	4.31	12.16	7.28	9.51	10.20	13.10	22.48
mFRR	3.13	3.74	0.47	0.50	2.23	6.68	9.25
BESS	6.45	15.14	0.00	10.00	14.00	18.00	28.00
Price	14.67	41.31	-9.02	31.25	38.90	49.07	175.00
Load	2.56	13.07	6.22	11.09	12.86	15.00	21.48
VRE	0.47	0.53	0.00	0.15	0.39	0.81	2.36

Table 20: Summary Statistics - NL

A.4 Additional Data Descriptives

B Code

B.1 Python Script for ENTSO-E API

Listing 1: Python script using the ENTSO-E API client

```python
import pandas as pd
from entsoe import EntsoePandasClient
from datetime import timedelta

# A function is defined to avoid repetitive code
def query_and_process_data(client, country_code, start, end, MarketAgreements, folder, multiplication_factors):
    # One query to the ENTSO-E API through the client can only contain a limited amount of data. To avoid data loss, the query for a longer period is split up into sub-periods of 9 days.
    delta = timedelta(days=9)
    dates = [start - delta] + [start_temp for start_temp in pd.date_range(start, end, freq=delta)] + [end]
    # An empty data frame frames_complete_markets is created to store the data for a complete market agreement type.
    frames_complete_markets = []

    for MarketAgreement in MarketAgreements:
        # An empty data frame frames_periods is created to store the data of all queried data for a sub-period in the current market agreement.
        frames_periods = []

        for i in range(1, len(dates)): # Iterate through the startdates of the subperiods
            start_sub = dates[i - 1]
            end_sub = dates[i]
            start_sub_string = start_sub.strftime('%Y-%m-%d')
            end_sub_string = end_sub.strftime('%Y-%m-%d')

            try:
                # Here the actual query is done to the API, it is saved as a pandas data frame
                data_1_period = client.query_contracted_reserve_prices(country_code,start=start_sub,end=end_sub,type_marketagreement_type=MarketAgreement)
                # Remove the timezone from the data frame
                data_1_period.index = data_1_period.index.tz_convert(None)
                data_1_period.columns = data_1_period.columns.to_flat_index().str.join('_')
                frames_periods.append(data_1_period) #save this sub-periods in the relevant data frame
                print(f"The sub-period {start_sub_string} - {end_sub_string} for {country_code} for {MarketAgreement}
                        was queried successfully  {start_sub_string} and {end_sub_string} for country {country_code} for market {MarketAgreement}")
            except Exception as e:
                print(f"{MarketAgreement} is not available in {country_code} between {start_sub_string} and {end_sub_string}: {str(e)}")

        if len(frames_periods) > 0:
            one_complete_market = pd.concat(frames_periods, axis=0)
            frames_complete_markets.append(one_complete_market)
```

```python
            print(f"The complete data for {MarketAgreement} in {country_code} was saved in frames_complete_markets")
        else:
            print(f"There was no data for {MarketAgreement} in {country_code}")

    if len(frames_complete_markets) > 0: # First, we check whether any data was created for the markets for this country
        # We save the complete markets in one data frame for the current country
        one_complete_country = pd.concat(frames_complete_markets, axis=1)
        # Some of the balancing prices for some balancing services are provided on an hourly, daily, and weekly basis. To convert this to quarter hourly the values are multiplied with the approriate factors
        one_complete_country = one_complete_country * multiplication_factors
        # Because of differences in data sample frequency there might be empty spots for a variable with lower sample frequency, this can be filled with the above value
        one_complete_country.fillna(method='ffill', inplace=True)
        one_complete_country = one_complete_country[~one_complete_country.index.duplicated(keep='first')]
        # Rows with duplicate indices are removed
        one_complete_country = one_complete_country.resample('15T').ffill()
        # The complete dataset is resampled to a 15 minute interval
        one_complete_country = one_complete_country.iloc[one_complete_country.index.get_loc(start):]
        # The resulting dataframe is saved in the correct folder.
        file_name = f"{country_code}_{start.strftime('%Y%m%d')}_{end.strftime('%Y%m%d')}_balancing_prices.csv"
        one_complete_country.to_csv(f"{folder}/{file_name}")
        print(f"The complete data for {country_code} was concatenated into a new DataFrame called: one_complete_country")
    else:
        print(f"There was no data available at all for {country_code} for the given period")


# Define the client key for the API
client = EntsoePandasClient(api_key="af334ee0-4add-4d6e-ba82-437741082bba")

# Market agreement codes:
# Code     | Meaning
# -------------------
# A01      | Daily
# A02      | Weekly
# A03      | Monthly
# A04      | Yearly
# A05      | Total
# A06      | Long term
# A07      | Intraday
# A13      | Hourly (Type_MarketAgreement.Type only)

# Define the country code
country_code = "DE_LU"
folder = 'balancing_prices'

# Since the length of ISP's and the contract duration changed twice in germany, the download and data modification steps script is split up in
```

```
    three parts, one for each period.

# First Period
start1 = pd.Timestamp('201601010000', tz='UTC')
end1 = pd.Timestamp('201807112359', tz='UTC')
MarketAgreements1 = ["A01", "A02"]
multiplication_factors = [1/4, 1/4, 1/4, 1/4, 1/4/24/7]
query_and_process_data(client, country_code, start1, end1, MarketAgreements1
    , folder1, multiplication_factors)

# Second Period
start2 = pd.Timestamp('201807120000', tz='UTC')
end2 = pd.Timestamp('201906302359', tz='UTC')
MarketAgreements2 = ["A01", "A02"]
multiplication_factors2 = [1, 1, 1, 1, 1/4/24/7]
query_and_process_data(client, country_code, start2, end2, MarketAgreements2
    , folder2, multiplication_factors)

# Third Period
start3 = pd.Timestamp('201907010000', tz='UTC')
end3 = pd.Timestamp('202301010100', tz='UTC')
MarketAgreements3 = ["A01"]
multiplication_factors3 = [1, 1, 1, 1, 1]
query_and_process_data(client, country_code, start3, end3, MarketAgreements3
    , folder3, multiplication_factors)
```

B.2 R code

Listing 2: Your R code caption

```
library(readxl)
library(stargazer)
library(sandwich)

# List of countries
countries <- c("BE", "CZ", "DE", "HU", "NL")
country_names <- c("Belgium", "Czech Republic", "Germany", "Hungary", "Netherlands")

# Create an empty list to store data frames
data_list <- list()

# Load data for each country
for (country in countries) {
  print(country)
  data <- read_excel(paste0("/Users/gillisvanmarwijkkooy/OneDrive - Delft University of Technology/master thesis/schroeder/data/complete/",country,".xlsx"))
  data_list[[country]] <- data
}

excluded_variables <- c("Weekday", "January", "February", "March", "April", "May", "June", "July", "August", "September", "October", "November")

##########################################################################
##########################################################################


# Fit and analyze models for each country
for (i in seq_along(countries)) {
  # Print subsection header
  cat(paste0("\\subsection{", country_names[i], "}\\label{sec:results_", tolower(countries[i]), "}\n"))

  # Get the data for the current country
  data <- data_list[[countries[i]]]

  # Fit linear regression models
  afrr_model <- lm(aFRR ~ Weekday + January + February + March + April + May + June + July + August + September + October + November + Storage + Price + Load + Total_renewables, data = data)
  afrr_log_model <- lm(aFRR ~ Weekday + January + February + March + April + May + June + July + August + September + October + November + Storage_log + Price + Load + Total_renewables, data = data)

  fcr_model <- lm(FCR ~ Weekday + January + February + March + April + May + June + July + August + September + October + November + Storage + Price + Load + Total_renewables, data = data)
  fcr_log_model <- lm(FCR ~ Weekday + January + February + March + April + May + June + July + August + September + October + November + Storage_log + Price + Load + Total_renewables, data = data)

  # Compute Newey-West standard errors for th afrr and fcr models
```

```
  afrr_hac_se <- NeweyWest(afrr_model)
  afrr_log_hac_se <- NeweyWest(afrr_log_model)

  fcr_hac_se <- NeweyWest(fcr_model)
  fcr_log_hac_se <- NeweyWest(fcr_log_model)

  # Check if mfrr variable exists in the data
  if ("mFRR" %in% colnames(data)) {
    # Fit linear regression models
    mfrr_model <- lm(mFRR ~ Weekday + January + February + March + April + May + June + July + August + September + October + November + Storage + Price + Load + Total_renewables, data = data)
    mfrr_log_model <- lm(mFRR ~ Weekday + January + February + March + April + May + June + July + August + September + October + November + Storage_log + Price + Load + Total_renewables, data = data)

    # Compute Newey-West standard errors for th mfrr models
    mfrr_log_hac_se <- NeweyWest(mfrr_log_model)
    mfrr_hac_se <- NeweyWest(mfrr_model)



    # Print regression results for each country with mfrr
    stargazer(
      afrr_model, fcr_model, mfrr_model,
      title = paste0("Regression results for ",countries[i], "."),
      align = TRUE,
      omit = excluded_variables
    )
    # Print regression results for each country with HAC standard errors
    stargazer(
      afrr_model, fcr_model, mfrr_model,
      title = paste0("Regression Results for ",countries[i], " with HAC standard errors"),
      align = TRUE,
      omit = excluded_variables,
      se = list(afrr_hac_se, fcr_hac_se, mfrr_hac_se)  # Include HAC standard errors
    )
    stargazer(
      afrr_log_model, fcr_log_model, mfrr_log_model,
      title = paste0("Regression Results for ",countries[i], " with HAC standard errors"),
      align = TRUE,
      omit = excluded_variables,
      se = list(afrr_log_hac_se, fcr_log_hac_se, mfrr_log_hac_se)  # Include HAC standard errors
    )


    ##### For the countries without mfrr:
  } else {
    # Print regression results for each country
    stargazer(
      afrr_model, fcr_model,
      title = paste0("Regression Results for ",countries[i], ". Two models (mfrr variable not present)"),
      align = TRUE,
```

```
      omit = excluded_variables
    )
    # Print regression results for each country with HAC standard errors
    stargazer(
      afrr_model, fcr_model,
      title = paste0("Regression Results for ",countries[i], ". Two models, both with HAC se (mfrr variable not present)"),
      align = TRUE,
      omit = excluded_variables,
      se = list(afrr_hac_se, fcr_hac_se)  # Include HAC standard errors
    )
    stargazer(
      afrr_log_model, fcr_log_model,
      title = paste0("Regression Results for ",countries[i], ". Compare afrr and fcr both with log, both with HAC se"),
      align = TRUE,
      omit = excluded_variables,
      se = list(afrr_log_hac_se, fcr_log_hac_se)  # Include HAC standard errors
    )
  }
}
```

C Results

C.1 Regression Tables Without Dummies

Table 21: Regression Results for FCR, Without Dummie Variables

	Country				
	BE	CZ	DE	HU	NL
BESS	-0.828^{***}	0.213^{***}	-0.689^{***}	-0.775^{***}	-0.201^{**}
	(0.036)	(0.025)	(0.049)	(0.053)	(0.079)
Price	-0.130^{***}	0.354^{***}	-0.174^{***}	-0.099^{***}	0.304^{***}
	(0.047)	(0.033)	(0.035)	(0.038)	(0.036)
Load	0.141^{***}	-0.322^{***}	0.127^{***}	0.100^{***}	0.069
	(0.023)	(0.034)	(0.026)	(0.032)	(0.042)
VRE	0.004	0.166^{***}	-0.057^{*}	-0.019	0.197^{***}
	(0.017)	(0.021)	(0.032)	(0.021)	(0.044)
Constant	0.000	-0.000	0.000	-0.000	0.000
	(0.053)	(0.034)	(0.052)	(0.070)	(0.047)
Observations	35,065	35,065	35,065	35,065	35,065
R^2	0.711	0.184	0.560	0.635	0.158
Adjusted R^2	0.711	0.184	0.560	0.635	0.158
Residual Std. Error (df = 35060)	0.537	0.904	0.663	0.604	0.917
F Statistic (df = 4; 35060)	$21{,}603.680^{***}$	$1{,}973.291^{***}$	$11{,}170.650^{***}$	$15{,}272.030^{***}$	$1{,}649.657^{***}$

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 22: Regression Results for aFRR, Without Dummie Variables

	Country				
	BE	CZ	DE	HU	NL
BESS	-0.683^{***}	-0.866^{***}	-0.648^{***}	0.382^{***}	-0.035
	(0.038)	(0.152)	(0.031)	(0.052)	(0.032)
Price	0.174^{***}	0.010	-0.037	-0.104^{***}	0.591^{***}
	(0.043)	(0.040)	(0.046)	(0.036)	(0.034)
Load	-0.012	-0.050	-0.127^{***}	-0.069^{*}	-0.254^{***}
	(0.024)	(0.042)	(0.036)	(0.035)	(0.030)
VRE	0.024	-0.018	-0.037	0.013	0.225^{***}
	(0.017)	(0.018)	(0.030)	(0.024)	(0.036)
Constant	0.000	0.000	0.000	-0.000	0.000
	(0.053)	(0.101)	(0.025)	(0.047)	(0.031)
Observations	35,065	35,065	35,065	35,065	35,065
R^2	0.503	0.752	0.463	0.151	0.323
Adjusted R^2	0.503	0.752	0.463	0.151	0.323
Residual Std. Error (df = 35060)	0.705	0.498	0.733	0.921	0.823
F Statistic (df = 4; 35060)	$8{,}888.151^{***}$	$26{,}572.820^{***}$	$7{,}570.339^{***}$	$1{,}559.148^{***}$	$4{,}186.011^{***}$

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 23: Regression Results for mFRR, Without Dummie Variables

	Country		
	BE	DE	NL
BESS	0.253*	0.044	0.106**
	(0.137)	(0.044)	(0.047)
Price	0.073	−0.441***	0.470***
	(0.063)	(0.136)	(0.025)
Load	0.125***	−0.030	−0.144***
	(0.042)	(0.065)	(0.024)
VRE	0.053	0.037	0.245***
	(0.033)	(0.053)	(0.036)
Constant	−0.000	−0.000	−0.000
	(0.140)	(0.030)	(0.032)
Observations	35,065	35,065	35,065
R^2	0.088	0.212	0.314
Adjusted R^2	0.087	0.212	0.314
Residual Std. Error (df = 35060)	0.955	0.888	0.828
F Statistic (df = 4; 35060)	841.188***	2,362.064***	4,013.635***
Note:	*p<0.1; **p<0.05; ***p<0.01		

C.2 Robustness analysis

Table 24: Robustness analysis results for Belgium

	Model #	Estimate	Std. Error	t value	Pr(>|t|)	R squared	F statistic	Residual SE
FCR	1	-0.316	0.483	-0.655	0.513	0.828	7030.8	0.415
	2	-0.190	0.669	-0.284	0.776	0.826	6410.2	0.417
	3	-0.259	0.447	-0.581	0.561	0.833	6458.1	0.409
	4	-0.325	0.448	-0.725	0.469	0.828	4019.8	0.415
	5	-0.317	0.466	-0.681	0.496	0.828	5821.9	0.415
	6	-0.264	0.345	-0.765	0.444	0.841	2891.8	0.399
	7	-0.831	0.032	-25.986	0.000	0.770	5580.2	0.480
	8	-1.004	0.648	-1.549	0.121	0.831	6139.8	0.412
aFRR	1	-1.950	0.839	-2.325	0.020	0.616	2346.5	0.620
	2	-1.845	0.787	-2.344	0.019	0.617	2171.7	0.619
	3	-1.817	0.652	-2.789	0.005	0.630	2208.7	0.609
	4	-1.956	0.874	-2.239	0.025	0.617	1341.8	0.619
	5	-1.953	0.777	-2.514	0.012	0.617	1949.0	0.619
	6	-1.931	0.716	-2.697	0.007	0.652	1024.3	0.591
	7	-0.708	0.058	-12.303	0.000	0.599	2494.5	0.633
	8	-5.934	2.475	-2.397	0.017	0.698	2892.8	0.550
mFRR	1	1.732	1.055	1.641	0.101	0.316	676.0	0.827
	2	1.389	1.010	1.375	0.169	0.304	588.6	0.835
	3	1.601	0.984	1.626	0.104	0.363	740.2	0.798
	4	1.753	0.987	1.776	0.076	0.317	387.8	0.827
	5	1.733	1.007	1.721	0.085	0.317	560.7	0.827
	6	1.853	0.985	1.882	0.060	0.313	249.5	0.829
	7	0.236	0.122	1.928	0.054	0.269	612.9	0.855
	8	3.343	3.952	0.846	0.398	0.332	622.3	0.818

Table 25: Robustness analysis results for the Czech Republic

	Model #	Estimate	Std. Error	t value	Pr(>|t|)	R squared	F statistic	Residual SE
FCR	1	0.171	0.037	4.651	0.000	0.458	1234.8	0.736
	2	0.172	0.037	4.712	0.000	0.460	1196.3	0.735
	3	0.165	0.031	5.359	0.000	0.460	1104.4	0.735
	4	0.171	0.036	4.710	0.000	0.473	749.2	0.726
	5	0.171	0.036	4.752	0.000	0.459	1024.4	0.736
	6	0.228	0.032	7.059	0.000	0.500	546.4	0.708
	7	0.305	0.021	14.644	0.000	0.385	1046.3	0.784
	8	0.115	0.117	0.981	0.327	0.464	1082.6	0.733
aFRR	1	-0.055	0.012	-4.476	0.000	0.989	132145.2	0.105
	2	-0.055	0.011	-5.169	0.000	0.989	127264.6	0.104
	3	-0.053	0.011	-4.769	0.000	0.990	122385.9	0.102
	4	-0.055	0.013	-4.123	0.000	0.989	75521.7	0.105
	5	-0.055	0.013	-4.086	0.000	0.989	110410.1	0.104
	6	-0.056	0.011	-5.047	0.000	0.990	53440.8	0.101
	7	-0.940	0.136	-6.887	0.000	0.827	7973.2	0.416
	8	-0.009	0.016	-0.550	0.583	0.989	114437.0	0.104

Table 26: Robustness analysis results for Germany

	Model #	Estimate	Std. Error	t value	Pr(>|t|)	R squared	F statistic	Residual SE
FCR	1	-0.673	0.259	-2.594	0.009	0.715	3666.7	0.534
	2	-0.632	0.231	-2.743	0.006	0.716	3396.9	0.533
	3	-0.652	0.286	-2.279	0.023	0.716	3278.9	0.533
	4	-0.667	0.318	-2.096	0.036	0.716	2099.7	0.533
	5	-0.674	0.279	-2.419	0.016	0.715	3035.8	0.534
	6	-0.696	0.290	-2.402	0.016	0.736	1527.7	0.514
	7	-0.676	0.056	-12.044	0.000	0.661	3259.8	0.582
	8	-1.347	0.433	-3.111	0.002	0.737	3514.4	0.513
aFRR	1	-1.284	0.119	-10.779	0.000	0.552	1799.7	0.669
	2	-1.277	0.109	-11.742	0.000	0.555	1678.9	0.668
	3	-1.035	0.120	-8.609	0.000	0.596	1914.4	0.636
	4	-1.280	0.108	-11.808	0.000	0.555	1041.6	0.667
	5	-1.282	0.120	-10.653	0.000	0.553	1493.3	0.669
	6	-1.350	0.121	-11.156	0.000	0.585	771.6	0.645
	7	-0.667	0.025	-26.743	0.000	0.531	1888.6	0.685
	8	-1.488	0.151	-9.869	0.000	0.557	1570.5	0.666
mFRR	1	0.512	0.216	2.374	0.018	0.267	532.7	0.856
	2	0.490	0.249	1.969	0.049	0.273	505.3	0.853
	3	0.431	0.202	2.133	0.033	0.284	514.6	0.847
	4	0.523	0.222	2.353	0.019	0.272	311.8	0.854
	5	0.512	0.216	2.367	0.018	0.270	446.9	0.855
	6	0.553	0.209	2.642	0.008	0.298	232.1	0.839
	7	0.026	0.044	0.591	0.555	0.260	587.5	0.860
	8	0.104	0.144	0.724	0.469	0.400	834.9	0.775

Table 27: Robustness analysis results for Hungary

	Model #	Estimate	Std. Error	t value	Pr(>|t|)	R squared	F statistic	Residual SE
FCR	1	-0.758	0.191	-3.976	0.000	0.727	3897.1	0.522
	2	-0.759	0.195	-3.885	0.000	0.727	3741.3	0.522
	3	-0.783	0.170	-4.597	0.000	0.730	3514.4	0.519
	4	-0.758	0.193	-3.937	0.000	0.728	2226.2	0.522
	5	-0.758	0.177	-4.281	0.000	0.728	3229.4	0.522
	6	-0.766	0.129	-5.938	0.000	0.731	1489.7	0.519
	7	-0.780	0.083	-9.389	0.000	0.662	3266.6	0.582
	8	-0.755	0.180	-4.193	0.000	0.729	3486.5	0.521
aFRR	1	0.343	0.058	5.878	0.000	0.266	529.7	0.857
	2	0.344	0.059	5.846	0.000	0.266	508.5	0.857
	3	0.363	0.058	6.214	0.000	0.296	545.8	0.839
	4	0.341	0.077	4.459	0.000	0.273	312.8	0.853
	5	0.351	0.072	4.879	0.000	0.316	558.9	0.827
	6	0.342	0.057	5.994	0.000	0.286	218.9	0.846
	7	0.410	0.056	7.270	0.000	0.257	576.8	0.862
	8	0.352	0.054	6.523	0.000	0.272	483.9	0.854

Table 28: Robustness analysis results for the Netherlands

	Model #	Estimate	Std. Error	t value	Pr(>|t|)	R squared	F statistic	Residual SE
FCR	1	-0.008	0.210	-0.036	0.972	0.436	1127.2	0.751
	2	-0.015	0.189	-0.080	0.937	0.448	1093.4	0.743
	3	0.113	0.188	0.602	0.547	0.466	1134.4	0.731
	4	-0.002	0.263	-0.009	0.993	0.437	648.2	0.751
	5	0.000	0.156	0.000	1.000	0.439	946.0	0.749
	6	-0.025	0.230	-0.109	0.913	0.485	514.6	0.718
	7	-0.095	0.068	-1.401	0.161	0.346	883.3	0.809
	8	-0.030	0.138	-0.216	0.829	0.456	1050.0	0.738
aFRR	1	-0.771	0.116	-6.618	0.000	0.664	2887.1	0.580
	2	-0.765	0.131	-5.846	0.000	0.668	2705.5	0.577
	3	-0.649	0.112	-5.785	0.000	0.686	2834.1	0.561
	4	-0.764	0.146	-5.242	0.000	0.667	1670.7	0.577
	5	-0.761	0.101	-7.551	0.000	0.669	2439.6	0.576
	6	-0.806	0.106	-7.624	0.000	0.667	1097.0	0.577
	7	0.072	0.035	2.070	0.038	0.428	1249.1	0.756
	8	-0.669	0.120	-5.557	0.000	0.703	2962.3	0.545
mFRR	1	-0.468	0.178	-2.627	0.009	0.630	2486.5	0.608
	2	-0.430	0.106	-4.075	0.000	0.659	2606.9	0.584
	3	-0.374	0.116	-3.218	0.001	0.675	2697.0	0.570
	4	-0.465	0.229	-2.034	0.042	0.630	1422.8	0.608
	5	-0.464	0.152	-3.046	0.002	0.631	2064.3	0.608
	6	-0.497	0.186	-2.675	0.007	0.633	941.3	0.607
	7	0.145	0.038	3.801	0.000	0.376	1004.3	0.790
	8	-0.323	0.234	-1.380	0.168	0.678	2639.6	0.567