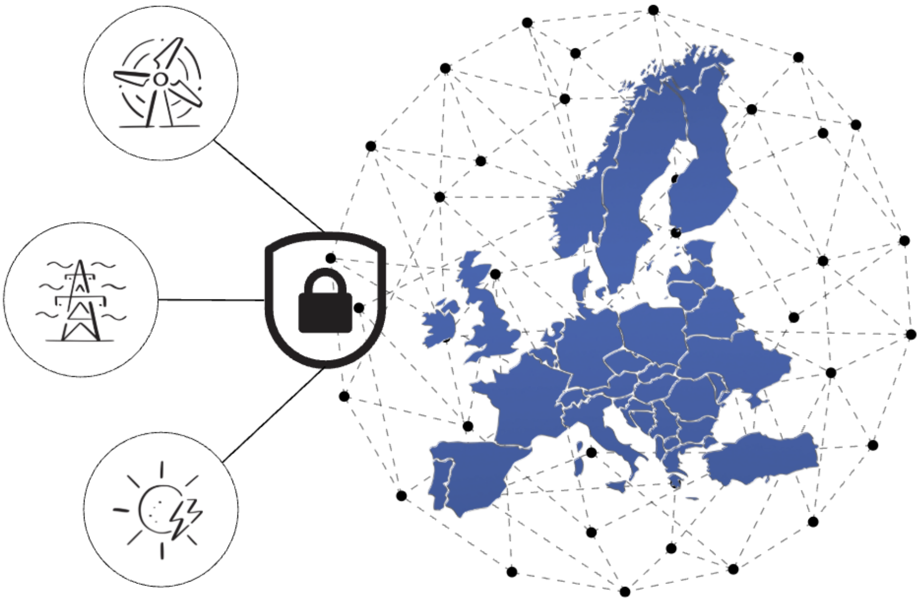

Evaluating Energy Security Strategies in the Context of Europe's 2022 Energy Crisis

An Empirical Study of the Impact of Generation Diversity, Import Dependence and Spare Capacity on Electricity Prices Across Bidding Zones

Master's Thesis in the Master's Programs in Sustainable Energy Systems and Industrial Ecology

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Abstract

In 2022, Europe experienced exceptionally high electricity prices. Diversifying the electricity mix, reducing import dependence, and increasing reserve capacity are commonly recommended strategies to enhance energy security and mitigate electricity price shocks. This thesis examines the relationship between these strategies and electricity price behavior across individual bidding zones during the 2022 European energy crisis. The results indicate that none of the strategies had a statistically significant effect on electricity prices, contrasting widely held assumptions. This outcome is likely attributable to the price-setting mechanism and extensive cross-border electricity trade, which weaken the influence of national-level strategies. Furthermore, the findings show that countries with electricity systems dominated by dispatchable renewable sources, such as hydropower, tended to experience lower electricity prices, whereas countries with a high share of gas-fired generation faced higher prices. To draw more general conclusions about the effectiveness of energy security strategies, further analysis of additional crisis periods is needed. Nonetheless, these results suggest caution in assuming that commonly recommended energy security strategies consistently improve electricity affordability, an essential dimension of energy security.

Keywords: Energy security, Diversity, Import dependence, Spare capacity, Electricity price, Energy crisis, SWI, Stirling index.

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Emanuel Carlsson & Marcus Edman, Gothenburg, June 2025

Contents

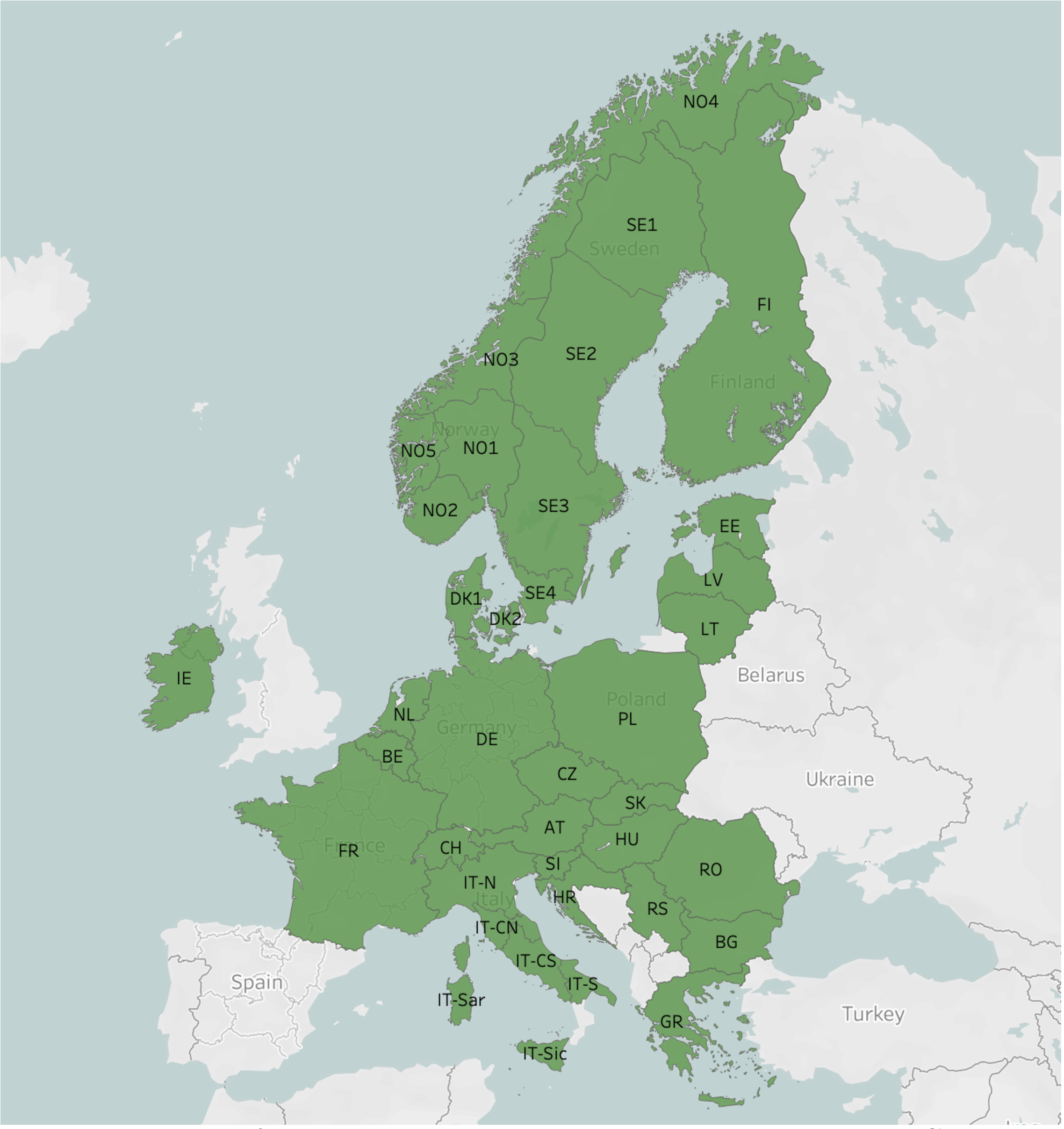

Figure 0.1: Map of the European bidding-zones included in the study. Created by the authors based on the ENTSO-E map [1].

Bidding Zone Abbreviations

AT Austria
BE Belgium
BG Bulgaria
CH Switzerland
CZ Czech Republic
DE Germany
DK1, DK2 Denmark
EE Estonia
FI Finland
FR France
GR Greece
HU Hungary
IE Ireland
IT-N Italy North
IT-CN Italy Central-North
IT-CS Italy Central-South
IT-S Italy South
IT-Sic Italy Sicily
IT-Sar Italy Sardinia
LT Lithuania
LV Latvia
NL Netherlands
NO1, NO2, NO3, NO4, NO5 Norway
PL Poland
RO Romania
RS Serbia
SE1, SE2, SE3, SE4 Sweden
SI Slovenia
SK Slovakia

1

Introduction

The security of energy supply has long been understood as a foundation for economic stability and prosperity. A wide range of economic activities are dependent on a steady flow of energy for essential functioning. Disruptions to this flow can have severe consequences for the economy and public welfare. Although the concept of energy security lacks a universally agreed-upon definition, it is widely used in both academic literature and political discourse to describe the challenges of ensuring access to reliable and affordable energy over time [2]. Some energy security literature incorporates many perspectives in its analysis [3], but the core of the concept is often condensed to the ability of an energy system to meet the energy demand at an affordable price [4][5].

Many strategies have been put forth to enhance energy security. A 2015 survey [2] identified several commonly cited approaches, including diversifying energy sources and supply chains, enhancing the resilience of energy infrastructure and improving energy efficiency. Governmental action play a key role in the deployment of these strategies through energy planning, regulation, diplomacy and distribution of information. Energy security indexes can be used to gauge energy security performance. These indexes often have a specific focus and methodology, and typically aggregate several different metrics (e.g., fuel import dependence and energy mix diversity) into a single composite measure of energy security. Example of such indexes being: "Index of U.S. Energy Security Risk" and the "International Index of Energy Security Risk". Due to the multitude of methodologies used to construct such indexes, direct comparisons can be challenging [2].

One of the most cited strategies for energy security is increasing the diversity of the energy system [6][7][5][2]. The general idea is that by diversifying assets or supply chains, one becomes less vulnerable to disruptions from one single source. In essence, it is best to avoid putting 'all eggs in one basket', as the famous proverb goes. It is not always explicit what the 'baskets' consists of. It could for example refer to fuel sources, fuel types, technology type, power generation or generation capacity. The strategy is sometimes linked to financial asset theory, where risk-minimization can be achieved by spreading risk between assets with different characteristics [7]. Other proposed strategies include reducing reliance on imports from external systems and maintaining reserve capacity to compensate for generation losses caused by supply shocks or outages [8].

This thesis investigates the extent to which general energy security strategies implemented prior to the 2022 energy crisis influenced electricity prices during the crisis. This is achieved by quantitatively assessing these pre-crisis strategies and analyzing their relationship to electricity price behavior across the European bidding zones shown in Figure 0.1.

1.1 The European Energy Crisis 2022

Already in the second half year of 2021 the natural gas prices started to rise [9]. When the Russian invasion of Ukraine happened on the 24th of February 2022, Europe entered a time with extraordinary high electricity prices. This event will in this thesis be referred to as the energy crisis of 2022. The geopolitical tensions caused by the war had major impacts on the energy imports to the EU and other European countries [10]. In 2017, 39% of the coal and natural gas and 30% of the oil imported to the EU came from Russia. In response to the Russian invasion of Ukraine, the EU adopted sanctions prohibiting the import of oil and coal from Russia [11]. The import of natural gas to Europe also decreased with around 80% from the invasion day until the end of the year [12]. The rapid abandonment of Russian energy sources caused a shortage of supply that increased both the gas and electricity prices. In August 2022, the EU gas price reached its peak of 340 €/MWh [9]. Another factor that also influenced the electricity prices in Europe during this time was technical problems with the French nuclear reactors. These problems impacted numerous reactors and reduced nuclear electricity production in France by approximately 100 TWh in 2022 [13], more than the total annual electricity generation in Belgium that same year [14]. The sabotage of the gas pipeline Nord Stream on the 26th of September 2024 did not impact the situation directly since the gas supply by the affected pipes already was cut off [12].

1.2 Aim and Research Questions

This study investigates the extent to which key energy security strategies influenced electricity prices during the 2022 energy crisis. The analysis focuses on three main strategies: diversification of generation resources, reduction of import dependence, and expansion of spare capacity. In addition, three system characteristics are included to support and deepen the analysis. These characteristics are: the share of variable renewable energy (VRE), the share of dispatchable renewable energy (DRE), and the share of natural gas. They were selected due to their perceived impact on electricity price formation.

How these strategies and system characteristics impact the electricity prices is assessed through an empirical study, where price levels and volatility are compared between a reference non-crisis year and a crisis year. This research is expected to generate insights about importance of these strategies and how to better prepare for future disruptions. The thesis hypothesis and corresponding tests can be summarized as following:

Hypothesis 1: Electricity systems with more diverse generation capacity, lower import dependence, and higher spare capacity were on average more resistant to electricity price shocks during the 2022 energy crisis.

Motivation 1: Answering this question will contribute with knowledge to the more general question if commonly cited energy security strategies actually enhances energy security.

Test 1: Identify statistical relationship between metrics reflecting the energy security strategies for European bidding-zones, and the experienced electricity price behavior.

Hypothesis 2: The share of renewable energy and the share of natural gas in the electricity mix influence electricity prices and price volatility during an energy crisis.

Motivation 2: Renewables and natural gas have distinct operational and cost characteristics that influence electricity price dynamics. During an energy crisis, these structural characteristics may amplify or mitigate price increases and price fluctuations.

Test 2: Identify statistical relationships between the share of renewables, share of gas and electricity price behavior.

1.3 Scope

The temporal boundaries of this study include the years 2019 and 2022, representing a non-crisis reference year and a crisis year, respectively. The year 2019 was selected due to its relative market stability, working as a baseline for comparison with the volatile conditions in 2022. The analysis is limited to European bidding zones where data is available in the ENTSO-E database. These zones form the basis of the comparative analysis and allow for regional variation in system characteristics and strategy approaches to be captured.

The project scope will only include electrical power generation and usage, and will thus exclude any analysis of primary fuel imports and non-electrical energy consumption in other sectors such as heating, industry and mobility. However, these excluded factors may indirectly influence electricity price as acknowledged in the introduction.

The analysis is quantitative in nature, using statistical methods to evaluate the relationship between selected energy security strategies and electricity price behavior. It does not include qualitative assessments of policy implementation or institutional factors, although such aspects are recognized as important in the broader discourse on energy security. Finally, this study is based on historical data and does not attempt to make future projections or policy recommendations beyond the empirical insights generated.

2

Theory

This chapter will establish the theoretical foundation for the study. It includes a review of scholarly work which supports and inform the research objectives. Topics include energy security, descriptions and quantification of energy security strategies, electricity price metrics, and sources referencing electricity price formation and electricity markets.

2.1 The Electricity Market

Since the deregulation of many of the world's electricity markets in the 1990s, these markets have evolved to deliver cheaper and more reliable electricity to consumers [15]. The planning for setting electricity prices for the operation hour begins the day before, in the day-ahead market. The system operators provide forecasts regarding the upcoming day about expected load, weather conditions, and other important information. The power producers then bid in their capacity and operating costs for the next day to the electricity markets. In many European countries, power producers submit their bids to electricity markets that are integrated across borders, e.g. in the Nord Pool market [16]. The operating cost consists of a start-up cost, minimum load-cost and a cost for higher load-levels [15]. All the bids are reviewed and the generators with the lowest running cost are selected until the expected demand is met. This is called the merit order effect and is illustrated in Figure 2.1. The price is decided by the cost of producing one extra MWh. This is called the marginal cost of electricity.

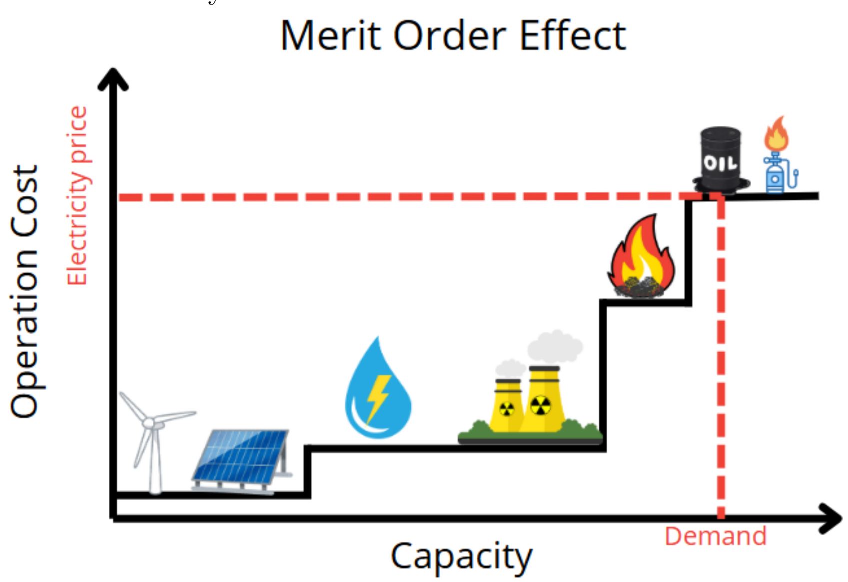

Figure 2.1: Illustration made by the authors (in Canva) depicting how electricity prices are determined through the merit-order effect.

All of Europe is divided into different bidding zones (as shown in Figure 0.1), which are geographical areas where electricity is bought and sold at a uniform price on the wholesale market [1]. In general, this division follows the national boarders with a few exceptions. The Scandinavian countries and Italy have several price zones within their countries and Northern Ireland is included in the Irish price zone. The microstates in Europe are all absorbed into neighboring countries price zones.

The grid capacity does not affect the electricity prices inside a bidding zone [17]. However, when electricity is traded in between price zones the transmission capacity is a limiting factor. If the transmission cable is congested between two prices zones, the zones have different electricity prices. This means that with unlimited capacity on the transmission cables the price would be equal everywhere. So, as the transmission capacity between two price zones increases, the price difference evens out. Historically the general direction of the electricity flows in Europe has been from north to south [18].

2.1.1 Energy Policies Affecting Electricity Prices

To address the high electricity prices during 2022, the implementation of price caps and other market regulations were explored by many countries [19] [20]. In February 2023, the European Union implemented a natural gas price cap mechanism to limit the natural gas prices to 180 €/MWh. This mechanism has never entered into force, as gas prices never reached the set cap post implementation. On the Iberian peninsula, regulatory action moved more swiftly [21]. On 15 June 2022, a price cap for gas and coal was implemented in Spain and Portugal. This was exclusively for natural gas and coal used for power generation purposes. The policy was partly financed by reducing the profit margin for plants with cheaper operating costs, such as wind, solar, hydro and nuclear. It is difficult to determine the exact effect of this policy, however it is clear that it reduced the electricity prices in both Spain and Portugal.

2.2 Energy Security

Since the beginning of the 20th century, the global primary energy consumption has increased almost fifteen fold [14]. The increased energy consumption has occurred alongside global economic growth and population expansion. Today, energy use in various forms and has become an intrinsic part of all sectors of human society. Energy security has become a concept which relates to these streams of energy flows [22]. Energy security does not have an explicit definition [2], but it is commonly cited as referring to the uninterrupted flow of energy at an affordable price [4]. Another common interpretation of energy security is that it includes the dimensions of affordability, availability, and acceptability [22]. Where affordability is about the cost of electricity. Availability is to make sure the supply cover the demand. Acceptability is about making sure the environmental and social aspects meet the requirements. Some studies measure energy security with more comprehensive indexes which are based on several aspects that are usually considered important. Diversity, import dependence and geopolitical stability are common parameters in different energy security indexes trying to capture energy security [10] [23].

The disruptions of an energy system come from many different sources [3]. For example, extreme natural events; resource depletion; political embargoes; malevolent exercise of market power; market volatility; sabotage and terrorist attacks; regulatory changes; variations of climate; technological change; failures of energy infrastructure; demand outgrowing supply. In the following three subchapters, we examine three key strategies commonly associated with energy security: diversity of generation, import independence, and spare capacity. For each strategy, we explore its theoretical foundations and discuss its potential implications for electricity price formation.

2.2.1 Diversity in Energy Systems

Diversity of generation sources has long been accepted as an important parameter for the robustness of an electricity system [22]. The underlying logic is to minimize the risk of disruptions from any single source by diversifying the portfolio of generation assets. To what extent diversity increases the energy security has been more difficult to determine. This is in part because the concept of diversity can be measured and interpreted in several different ways [24].

The concept of diversity can be broken down into three aspects: variety, balance and disparity [25]. Variety is in the context of electricity systems how many different types of power generation sources there are in the system. The balance reflects the relative contribution from the sources. Lastly, disparity is how technically different the sources are. For instance an oil plant is more similar to a coal plant than a wind farm in the sense that coal and oil plants are driven by fuel and emit CO_2. For power generation sources the disparity is a subjective measurement and is not considered in the most frequently used diversity indexes called Shannon-Wiener index (SWI) and Herfindahl-Hirschman index (HHI).

The SWI is today used for assessing diversity in many different fields [24] and originates from the field of ecology [26]. In the energy security field it has been used since 1994 [24]. The strengths of this diversity index is that it starts from zero and has declining growth for each equally large added source. This reflects a decreasing value for each added source. For example going from 1 to 2 equally large sources increases the diversity more than adding a fifth source to a system already consisting of four equally large sources. The formula for the SWI is:

$$SWI = -\sum_{i=1}^{n} S_i * \ln(S_i)$$

Where:

n : Number of generating sources
S_i : The percentage share produced by the specific source

The HHI is mostly used in economics to measure concentration of portfolios [24]. HHI was first used in ecology where it is more known as Sampson Index. The HHI starts at 1 (or 10000) for systems with no diversity and reduces as more sources is added. Therefore, a low HHI means high diversity. Similar to the SWI the HHI also gives declining effects for each added source. Using the inverse of the HHI is also common in energy studies [27]. The formula for the HHI is:

$$HHI = \sum_{i=1}^{n} S_i^2$$

Where:

n : Number of generating sources
S_i : The percentage share produced by the specific source

For SWI and HHI it is assumed that all categories are equally different, or in other words, have same disparity [28]. To capture the disparity of the electricity system the Stirling index can be used [25]. This index were developed by Stirling for energy systems in 1998. The disparity values are based on the dissimilarity between inherent technical attributes for example, fuel type, operation pattern and costs structure. The disparity value is always between 0 and 1. The value zero means identical technologies (which in that case should have been same category) while 1 means completely different technologies. Since the disparity values are subjective and can be assigned in many different ways, transparency in this process is of high importance. This can be done either by using a dendrogram or by assigning a value between 0 and 1 for each attribute considered. The disparity value is then equal to the distances between the technologies in an Euclidean space where each dimension represents an attribute considered, as shown in Equation (2.1). Finally, the disparity values are normalized to avoid increasing the impact of disparity in relation to variety and balance for each added attribute as in Equation (2.2).

$$d_{ij} = \sqrt{(\alpha_1^i - \alpha_1^j)^2 + (\alpha_2^i - \alpha_2^j)^2 + \cdots + (\alpha_n^i - \alpha_n^j)^2} \tag{2.1}$$

where:

α_1^i : is the assigned value for technology i for attribute 1

α_1^j : is the assigned value for technology j for attribute 1

$$\textit{Stirling Index} = \sum_{\substack{i,j=1 \\ i<j}}^{n} d_{ij} S_i S_j \tag{2.2}$$

Where:

n : Number of generating sources

S_i : The percentage share produced by the specific source
S_j : The percentage share produced by the other specific source
d_{ij} : The dissimilarity between the generation sources (disparity value)

In the few previous studies it has not been found that diversity reduce the electricity price. In Kenya, a diverse generation mix was actually associated with an increase in electricity prices [29]. In this case, it is important to note that a different price-setting mechanism is used in Kenya in contrast to Europe. In USA (1973-82 & 2003-12) the diversity seems to be uncorrelated to the electricity price during crisis years [7][30].

2.2.2 Import Dependence

Historically, reducing the import dependence has been the main strategy to increase the energy security and reduce risks related to geopolitics for example, embargoes or wars [3]. Diversifying the import to different fuels and importing from different nations has also been seen as a valid method to reduce the vulnerability from unexpected events. Domestic production means more control over the sources which reduces the the risk of supply disruptions, however problems can occur for domestic production as well [10]. As the affordability of solar and wind has improved, the options for countries to reduce their import dependence have expanded [24].

In the context of energy security, import dependence usually refers to relying on importing fuels such as coal, oil and gas [3]. However, import of electricity can also be of importance for the energy security. For example, Lithuania imports two thirds of their electricity, which might be problematic from an energy security perspective since electricity shortage in neighboring countries are likely to heavily increase electricity prices in Lithuania [31]. On the other end, the lack of generation in Lithuania can increase the electricity prices in neighboring countries [17]. EU countries have no legal right to limit the use of existing transmission capacity to other countries [32]. This means countries have limited abilities to keep the electricity inside their borders and are therefore affected by cross-country connections.

In Kenya from 2008-2018, the amount of imported electricity correlated positively with electricity prices [29]. In the USA, during the energy crises of the 1970s and 2000s, the net trade of electricity was found to be uncorrelated with electricity prices [30]. The formula used to calculate the import dependence metric *Proportion Export Import* (PEI) for net importers is [29]:

$$PEI = \frac{\textit{Net Import}}{\textit{Total Consumption}}$$

and for net exporting countries:

$$PEI = \frac{\textit{-Net Export}}{\textit{Total Generation}}$$

2.2.3 Spare Capacity

Spare capacity is the difference between the maximum capacity and what is actually generated [8]. This represents the available reserve capacity. The unused capacity can be used in case of unexpected events such as plant failures or fuel disruptions, where it can fill the generation gap and maintain function of the system. In the 2012 paper from Molyneaux et. al. [8], spare capacity from thermal power generators were assumed to have a max capacity factor of 90%, this includes a 10% reduction to account for maintenance and outage-related losses. Variable renewables were assumed to always operate at their available capacity, due to their low operating costs, and will therefore by definition have no spare capacity. Spare capacity usually only include generation capacity, but it could be expanded to also include transport capacities for fuels [30]. This would capture the resilience against fuel-shortages due to disruptions in the supply chain or other reasons.

The cost of spare capacity is paid by the increased investment cost of having excess capacity in the power plants [29]. Spare capacity might therefore increase the system costs, but will protect against price spikes when system is disrupted from e.g. supply shocks or unplanned outages. In a study from Kenya [29], spare capacity was found to correlate both positively and negatively with electricity prices depending on the type. Spare capacity from thermal and hydro-power correlated with increased electricity prices, and vice versa for geothermal. The formula for spare capacity is [7]:

$$\text{Spare Capacity} = \frac{\sum_{i=1}^{n} ((GW_i \cdot \text{hours}) \cdot CF_i - GWh_i)}{GDPR}$$

Where:

GW_i : Installed capacity from source i (in gigawatts)
CF_i : Maximum annual capacity factor for the source i
GWh_i : Electricity generated from source i (in gigawatt-hours)
$GDPR$: The real gross domestic product
$hours$: 8760 hours (hours in a year)

2.3 The Effect of Renewables and Gas

The share of renewables has increased in Europe over the last decades [33]. In general, this is expected to reduce the electricity prices [34]. How this increase of renewables will influence the energy security and the electricity prices during a crisis is more uncertain. There are indications that renewables could contribute to resilience. Because renewable energy sources do not require any fuel, adopting them can decrease vulnerability to fuel price shocks [24]. Renewables have not only reduced the import dependence but also increased the diversity of electricity generation in European countries since 1990.

A 2025 study [33] indicated that European countries with more decarbonized electricity generation are not in general more vulnerable to natural gas price increases. On the other hand, countries with intermittent renewables are more vulnerable, probably because the flexibility from gas plants is used to stabilize the intermittency from the variable renewables. Another 2025 study [34] uses energy system modeling to show that renewable energy deployment can protect economies from fossil fuel price shocks, even when demand and weather variability are accounted for, suggesting an overall stabilizing effect on electricity prices.

As already mentioned, the electricity price is set by the most expensive generating source, and gas has a very high operation costs [35]. This means that if gas is running it is likely to set the electricity price. This also explains how fluctuations in gas price can influence the electricity price in electricity systems relying on gas. There are studies showing, for example, that the presence of solar and wind generation in the system can help mitigate price increases following nuclear shutdowns [36]. However, this can indicate that some specific types of diversification can reduce the electricity prices rather than diversification in general.

2.4 Price Variability

Price variability is the simple observation that prices fluctuates across time. This variability can be measured in many different ways, capturing different dynamics. A system might exhibit high hourly price fluctuations without significant daily variability. Determining the relevant type of variability requires identifying its importance from an energy security standpoint.

Hourly price variability is often seen as less relevant from a macroeconomic perspective than long periods of high prices [37]. The EU electricity market design regulation from 2024 qualifies an energy crisis as "very high average prices in wholesale electricity markets of at least two and a half times the average price during the previous 5 years, which is expected to continue for at least 6 months" [38]. In other words, only increased hourly variation with a minor change in average daily prices, would not qualify. It is instead implied that the duration and magnitude are of most importance.

Price variability in power markets is influenced by several factors, including demand fluctuations, fuel costs, and weather conditions [37]. A 2022 study investigated the impact of increasing renewable energy shares on electricity price variability in day-ahead markets [39]. It found that high renewable energy penetration can lead to lower spot prices due to extremely low operation costs, but larger shares can lead to significant price differences due to solar and wind variability. Other research has found renewable deployment can promote electricity price stability in the face of increasing gas prices. [37]. Simulations of electricity price dynamics in the EU power market found that increasing the renewable energy share could lower average electricity prices by 26 %, while price spikes may decrease by 20 %.

In the simulation study, the authors use two metrics to capture price variability [37].

The first is the standard deviation, a common measure of variance for stochastic variables. However, this metric has certain analytical limitations, as it is influenced by both the mean value and the variation. This measurement can however have certain analytical drawbacks. For one, the parameter depends on both mean value and the variation. The same absolute price fluctuations in systems with different means, will yield two very different results, making comparisons difficult. To address this issue, the authors also use percentiles. The 85th percentile (P85) represents high but relatively frequent prices, while the 95th percentile (P95) captures extremely high yet infrequent prices. According to the authors, these percentile based metrics are better suited to reflect the concerns of policymakers and the interests of consumers.

3

Method

The methodology chapter will relay the structural procedure for answering the research questions. The thesis is a quantitative empirical study. The hypothesis will be tested by the collection, manipulation and analysis of historical data. The methodology is described in the following three parts: data collection; defining key variables; statistical analysis.

3.1 Data Collection

The study will be based on electricity market data from the database of ENTSO-E [1]. All relevant data will be gathered for all available European bidding-zones. Table 3.1 summarizes the collected data and indicates the source database for each entry. All subsequent metrics and variables are derived from this data.

Data Category	Time	Sources
Electricity Prices	2022 and 2019	ENTSO-E
Load	2022 and 2019	ENTSO-E
Generation Capacity	2022 and 2019	ENTSO-E
Electricity Import	2019	ENTSO-E
Electricity generation	2019	ENTSO-E
Peak demand	2019	ENTSO-E

Table 3.1: All data collected for the calculations in the analysis. The time resolution is usually hourly, however some countries report data every 15 minutes.

The spacial boundaries can be seen in Figure 0.1 and includes all bidding-zones in Europe with available data from the ENTSO-E. Spain and Portugal are excluded from the scope due to their implementation of a market distorting policy which led to artificially low prices. To ensure consistency and comparability, this study will focus exclusively on day-ahead wholesale prices from the ENTSO-E database.

In some rare cases, the data for generation and capacities are not compatible, for instance some bidding zones have generation without corresponding installed capacity. This lack of data, for example, affects the spare capacity results for Sweden and Norway and possibly other bidding-zones. However, the study will be based on data provided by the database and, based on our assessment, these potential errors are unlikely to significantly affect the overall results.

All our data are processed in either Excel or Python. Aside from simple calculations, these tools is also used to e.g. handle missing data. When missing data occurs in a data time series, it is either set to the value of the previous hour or removed depending on how it best preserves the integrity and accuracy of the analysis. If, for example, it is a sum, the data point is set to the same value as the hour before. But when resampling hours to days in a yearly time price series, the missing hours are instead set as "Not Available", after which the resampling ignores the missing value. The average daily price is then calculated with the data points remaining, without causing a misalignment.

3.2 Definition of Key Variables

This section presents all variables used in the upcoming models, beginning with the outcome variables, followed by the independent variables. The subsequent subchapters outline the computation method together with a brief interpretation of every variable.

Variable	Description	Unit
Price Metrics		
Price Increase	Annual electricity price increase between 2019 and 2022	€/MWh
P95	Daily price level exceeded only 5% of the time	€/MWh
CV (Coefficient of Variation)	Standard deviation divided by mean	–
Explanatory Variables		
SWI (Shannon-Wiener Index)	Measures diversity of generation capacity 2022	–
Stirling Index	Measures diversity of generation 2022 while accounting for technological disparity	–
PEI (Proportion Import Export)	Proportional share of imports or exports from 2019	%
SP (Spare Capacity)	Average unused generation capacity 2019; normalized by peak-demand	MWh/h
Share VRE	Share of variable renewable generation 2019 (e.g., wind, solar)	%
Share DRE	Share of dispatchable renewable generation 2019 (e.g., hydro water reservoir, biomass)	%
Share Gas	Share of electricity generation from gas 2019	%
Control Variable		
Load	Change in load	MWh

Table 3.2: Summary of all key variables

3.2.1 Price Increase

To measure how resistant a system is to price shocks a baseline to compare with is needed. Comparisons can be made from a reference year, or a running average of a set of reference years. The change in price can then be calculated in either percentage or an absolute increase with all currencies converted to Euro. Both methods have their own advantages. Percentage change will reveal the systems resilience in a comparable manner. However, with percentage increase the past performance has very high impact. Using absolute price increase will to some extent capture both the resilience, since it is a comparison, and the affordability, since it is measured in Euros, of the system. There is also a question if the absolute price is similar in effect for all countries. Countries with lower income generally have a lower purchasing power, which could correspond to a more severe effect per Euro increase. This is true, but since only European countries are analyzed, we hereon assume that they are not drastically different and consider them to be comparable.

For this calculation, the forecasted day-ahead wholesale electricity prices were used. The electricity price in each time step were multiplied by the share of electricity consumed that hour in relation to the consumption of the year. This is usually referred to as load-weighted electricity price. The load-weighted price of the reference year were then subtracted from the load-weighted price of the crisis years, which gives the price increase. If the data is reported in another currency than Euro, the average yearly exchange rate was used to convert the electricity price to euros. The final value represents the annual price increase of a MWh electricity.

$$\text{Price Increase } = \text{Average Electricity Price}_{2022} - \text{Average Electricity Price}_{2019}$$

3.2.2 Extreme prices - P95

The 95th percentile of the daily prices (P95) was used to capture the magnitude of extreme prices. The P95 is calculated from the the annual daily price distribution, and revealed the price level which is exceeded only five percent of the days. The calculation process of P95 is similar to how the median is calculated. The median is equal to the 50th percentile.

$$P95 = P_{\lceil 0.95 \cdot n \rceil}$$

where:

- If P_t represents the electricity price on day t
- The set of daily prices $\{P_1, P_2, ..., P_n\}$ is sorted in ascending order, $P_{(1)} \leq P_{(2)} \leq \cdots \leq P_{(n)}$.
- $\lceil \cdot \rceil$ denotes the ceiling function, which rounds up to the nearest integer.

For all bidding zones, the outcome variable $P95$ is defined as:

$$\Delta P95 = P95_{2022} - P95_{2019}$$

3.2.3 Price Volatility - CV

For measuring price volatility, two key methodological choices were made. First, we calculated annual price volatility using daily resolution to avoid capturing hourly fluctuations. Since most consumers are less affected by hourly variation, we argue that daily price variance offers a more relevant perspective. Second, we normalized volatility by the annual mean price, as volatility otherwise scales with the mean. This mean-adjusted volatility, known as the coefficient of variation (CV), better supports comparison across different systems. We used the following formula:

$$CV = \frac{\sigma_{Price}}{\mu_{Price}} = \frac{Standard\ Deviation}{Mean}$$

This provided a relative measure of price volatility, making it useful for comparing volatility for bidding zones with different average electricity prices. Finally, the difference between reference year and crisis year was calculated which was the value used in the analysis.

$$\Delta CV = CV_{2022} - CV_{2019}$$

3.2.4 Diversity of Capacity - SWI

The diversity of the electricity systems was based on the installed capacities rather than the actual generation since the capacities are independent of the crisis. The installed capacity of generation is a measure of potential power output and not what is feasible to generate in energy over a year. The capacity thus needed to be adjusted in order get a sensible comparison between the generator types, for example fuel-based generation can be used almost always while intermittent renewables are limited by weather conditions. To make sure the capacities of the generation better reflects the possible electricity output, all the capacities were multiplied by a general availability factor for the specific generation source according to Table 3.3.

Generation Type	Availability Factor	Motivation	Source
Biomass	0.95	Restricted by maintenance	[40] [41]
Fossil brown coal	0.95	Restricted by maintenance	[40] [41]
Fossil coal-derived gas	0.95	Restricted by maintenance	[40] [41]
Fossil gas	0.95	Restricted by maintenance	[40] [41]
Fossil hard coal	0.95	Restricted by maintenance	[40] [41]
Fossil oil	0.95	Restricted by maintenance	[40] [41]
Fossil shale oil	0.95	Restricted by maintenance	[40] [41]
Fossil peat	0.95	Restricted by maintenance	[40] [41]
Geothermal	0.86	European average capacity factor	[42]
Pumped hydro	0.00	Net consumer of electricity	
Run of river	0.44	European average capacity factor	[42]
Hydro water reservoir	0.44	European average capacity factor	[42]
Marine	0.30	Default value	
Nuclear	0.95	Restricted by maintenance	[43]
Other	0.95	Restricted by maintenance	[40] [41]
Other renewables	0.30	Default value	
Solar	0.10	European average capacity factor	[42]
Waste	0.70	Average over plant lifetime	[44]
Wind off-shore	0.42	Global average capacity factor	[45]
Wind on-shore	0.21	European average capacity factor	[42]

Table 3.3: Values used for adjusting the capacity to reflect the possible output of electricity of the capacity mix. Default values were used if the uncertainty of the availability factor is high and the amount of data in the category were low.

This gave all biding zones an adjusted capacity for all generation types the year 2022. The values were then converted to percentages of the total share. The percentages of the capacity mix were then calculated by Shannon-Wiener formula for each bidding zone. This value represented the diversity of the capacity mix.

$$SWI = -\sum_{i=1}^{n} S_i * \ln(S_i)$$

Where:

n : Number of generating sources
S_i : The percentage share produced by the specific source

For both SWI and HHI the level of detail of the generation categories will impact the result. When labeling the categories it is important to consider which generation sources are different enough to be separate categories and which generation has such low impact that they can be included in another category or counted as "other" [28]. SWI and HHI are very similar, however the indexes put slightly different emphasis on variety and balance [24]. Because of the high similarity no analysis with HHI were conducted.

3.2.5 Diversity of Capacity - Stirling

To investigate a deeper dimension of diversity, Stirling index were also calculated. The percentage shares of the capacities of each generation types was calculated in exactly the same way as for the SWI. However, the disparity values for the generation types had to be calculated as well. The Euclidean space approach was selected to calculate the disparity values since this method is more systematic and transparent [25]. The attributes should ideally be relatively few while still being able to highlight the differences and reflect how the generation types are used in the electricity system. The attributes of dispatchability, operation cost and fuel driven were selected to represent the differences of the generation types. Dispatchability includes both the ability to chose running load and to quickly ramp up or down. Operating cost captures the relative cost of running each generation source. Being fuel driven means that buying fuel is needed which is connected to energy security in the sense that these technologies are vulnerable to price increases on fuel. This attribute is binary, 0 for no and 1 for yes, however, the category Other Renewables can in some cases include biomass and therefore was assigned the value of 0.1. Each generation type was then given a value from 0 to 1 for each attribute. These values were estimated to the best of our knowledge. The distances were calculated for all types and attributes in a Euclidean space and were finally normalized using minimum-maximum normalization.

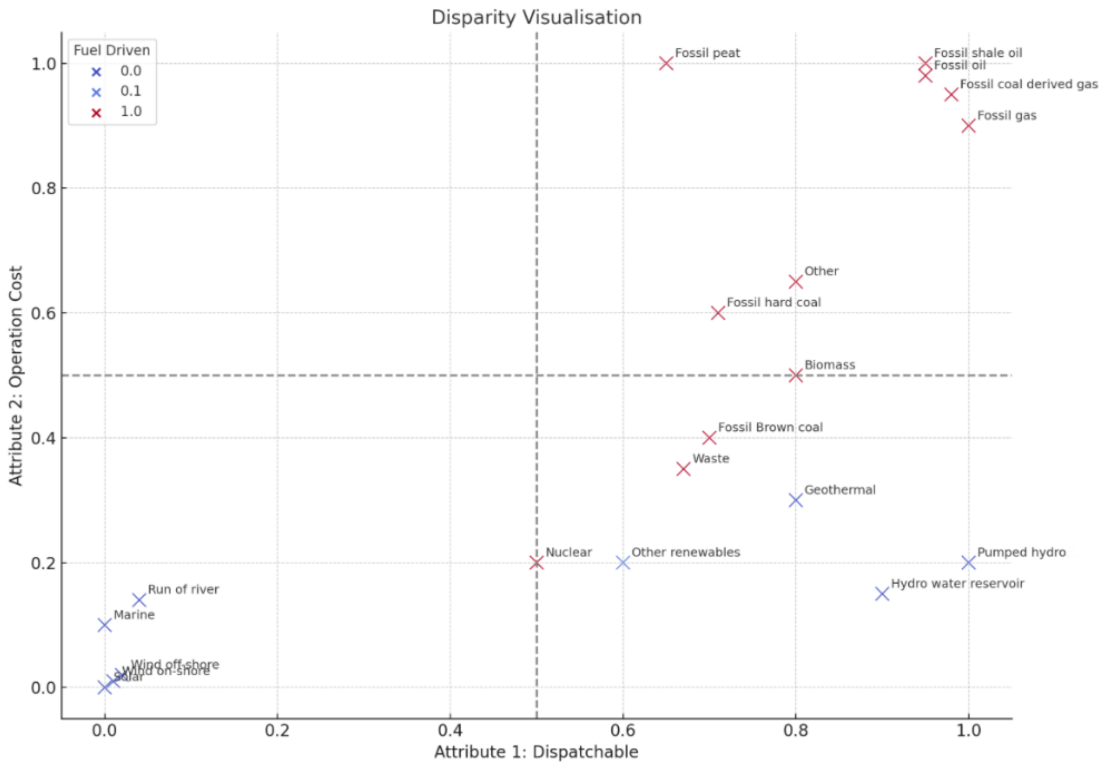

Figure 3.1: Visualization of the differences between generation types based on dispatchability, operation cost and fuel driven. The accuracy of the values are limited by our knowledge.

The distances were calculated with this formula:

$$d_{ij} = \sqrt{(\alpha_1^i - \alpha_1^j)^2 + (\alpha_2^i - \alpha_2^j)^2 + \cdots + (\alpha_n^i - \alpha_n^j)^2}$$

Where:

α_x^i : is the value of the attribute x for option i.

The distances were then normalized to ensure a fair balance between variety balance and disparity.

Source	Biomass	Coal	Gas	Hydro	Nuclear	Solar	Wind
Biomass	0	0.08	0.26	0.62	0.25	0.81	0.80
Coal	0.08	0	0.24	0.65	0.27	0.80	0.80
Gas	0.26	0.24	0	0.74	0.50	0.98	0.98
Hydro	0.62	0.65	0.74	0	0.63	0,.54	0.53
Nuclear	0.25	0.27	0.50	0.63	0	0.67	0.66
Solar	0.81	0.80	0.98	0.54	0.67	0	0.01
Wind	0.80	0.80	0.98	0.53	0.66	0.01	0

Table 3.4: Shows some of the final normalized disparity values. Coal = Fossil hard coal, Gas = Fossil Gas, Hydro = Hydro water reservoir, Wind = Wind onshore. Full disparity matrix can be found in Appendix C.

These disparity values were then used in the Stirling formula to get the Stirling index.

$$\text{Stirling Index} = \sum_{i<j} d_{ij}(S_i \cdot S_j)$$

where:

d_{ij} : is the disparity value of technology i and j
S_i : is the percentual proportion of source i in the system.
S_j : is the percentual proportion of source j in the system.

3.2.6 Spare Capacity - SP

The spare capacity represent available unused capacity. The spare capacity was calculated from conventional fossil plants, biomass and nuclear. The spare capacity from hydro power were excluded mainly because it is difficult to estimate. Doing this in a precise way would require plant specific data regarding storage capacities and water inflow to investigate if there is water available where it is unused turbine capacity. Geothermal spare capacity was also exluded since only one bidding zone (IT-CN) had a significant share of geothermal power in the electricity mix and the capacity factor was very high anyway. For the spare capacity calculation, all data were from 2019. The formula used based on Molyneaux et. al. [7] was:

$$\text{SP} = \frac{\sum_{i=1}^{n}\left(MW_i^{\text{cap}} * \textit{Availability Factor} - \bar{MW}_i^{\text{gen}}\right)}{MW^{\text{Peak demand}}}$$

Where:

n : the n:th generation type.
MW_i^{cap} : is the installed electricity generation capacity.
$\bar{MW}_i^{\text{gen}}$: Average power generated generation type.
$MW^{\text{Peak demand}}$: the maximum power demand during the year.
Availability Factor: Adjustment to capture the maximum annual capacity, values from Table 3.3.

If the availability factor was lower than the actual output the formula gave negative spare capacity, however in these cases the spare capacity was set to zero. Using peak demand, rather than GDPR as in the original formula, has two major advantages. Firstly, the measure is directly connected to demand, and secondly using GDPR for bidding zones that are not countries are complicated.

3.2.7 Proportion Export Import - PEI

The variable PEI represents a bidding-zone's self sufficiency of electricity production. PEI is the proportion of electricity that is imported or exported, according to the following formulas.

For net importing price zones:

$$PEI = \frac{\textit{-Net Import}}{\textit{Total Consumption}}$$

and for net exporting price zones:

$$PEI = \frac{\textit{Net Export}}{\textit{Total Generation}}$$

The formula uses the net electricity trade balance, and divides it by either load (if net importer), or by generation (if net exporter). An advantage with taking net import/export values is that electricity that only flows through a bidding zone will not be accounted for. The index was calculated for all price zones using 2019 data. This was done to have it as an independent variable from the crisis year, where it will represents if a bidding-zone prior to the crisis were a net exporter or net importer.

3.2.8 Renewables, Gas and Load

Other independent parameters calculated were the share of DRE, VRE, and gas. These calculations were based on the actual generation 2019. The generation from each category was summarized and divided by the total generation.

Generation Type	DRE	VRE	Gas
Biomass	X		
Fossil coal-derived gas			X
Fossil gas			X
Geothermal	X		
Run of river		X	
Hydro water reservoir	X		
Marine		X	
Other renewables		X	
Solar		X	
Wind off-shore		X	
Wind on-shore		X	

Table 3.5: Categorization for the generation types.

The control variables for load were calculated based on day-ahead forecasts. The purpose of the control variable is to see if changes in price could be explained by changes in demand. This variable should not be seen as an independent variable since price and load stabilizes each other. One load metric for each dependent variable was calculated in exactly the same way as the dependent variable - but with demand instead of price. The control variables were:

- **Load Increase**: Increase in average daily electricity demand between 2019 and 2022 (MWh)
- **Load P95 Increase**: Increase in the 95th percentile of daily loads between 2019 and 2022 (MWh)
- **Load CV Increase**: Increase in daily load coefficient of variation between 2019 and 2022 (–)

3.3 Statistical Analysis - OLS

After defining the variables a statistical framework was needed to identify any potential relationships. One common method is Ordinary Least Squares (OLS) regression [46]. OLS estimates the extent to which independent variables (for example, diversity) influence the dependent variable (for example, electricity price) [46, p.8]. The main advantage of OLS is that it always produces the best linear approximation of the relationship between variables. A regression formula with three independent variables can be written as [46, p.13]:

$$y_i = \beta_1 + \beta_2 x_{i2} + \beta_3 x_{i3} + \beta_4 x_{i4} + \varepsilon_i$$

Where:
x_{i2-4} : The independent variable
y_i : Expected value of dependent variable
β_1 : The interception term

β_{2-4} : The coefficients of the 3 independent variables
x_{i2-4} : The independent variable
ε_i : The error term representing unobserved factors that affect the dependent variable

The coefficient of the independent variables tells what impact the specific independent variable have when the other independent variables are kept constant [46, p.13]. This is referred to as P-value. The coefficients can be used to test the null hypothesis, or in other words, the possibility that the independent variable have no impact on the dependent variable. From the model output, the most probable values of coefficients are given as well as ends of a confidence interval [46, p. 25]. If the value at both ends of the confidence interval has same sign the null hypothesis can be ruled out. This means that the impact from the independent variable on the dependent variable is statistically significant. In our models, we set a p-value threshold of 5%. This means that we accept a 5% risk of incorrectly rejecting the null hypothesis.

To measure how much the independent variables explain the variance of the dependent variable, the coefficient of determination (R^2) is used [46, p. 21]. R^2 is always a value between 0 and 1 where zero means that no variance is explained by the independent variables and 1 means that all variance is explained by the independent variables. There is no rule of thumb or such regarding wether the R^2 should be considered high or low, that fully depends on the context [46, p. 22]. When several independent variables are included adjusted R^2 is used, because this metric also has a punishment for adding more independent variables. Without this adjustment adding many random independent variables will eventually result in high explanatory power. As a consequence of this, adjusted R^2 actually can be negative however this should be interpreted as zero explanation power.

A prerequisite for trustworthy results is that there is no problematic multicollinearity between the independent variables [46, p 44-47]. If a independent variable is a linear combination of another independent variable the model can not tell which independent variable is causing the effect. To check for multicollinearity the variance inflation factor (VIF) or Pearson coefficient can be calculated. Low levels of mutual correlation is unproblematic. A reason to use multiple linear regression is that explanatory variables affecting the outcome variable are mutually correlated [46, p. 44]. By including multiple variables in the model simultaneously, it is possible to isolate the separate contribution of each variable to the outcome, while controlling for the influence of others. However, problems can arise if VIF and Pearson coefficient is too high. As a rule of thumb a VIF value lower than 5 is unproblematic while a value of 10 is certainly problematic [47]. For the Pearson coefficient a value lower than 0.5 is unproblematic while a value of 0.8 means high risk of too strong correlation. The VIF formula for a given independent variable x_{ik} (e.g., x_{i2}, x_{i3}, or x_{i4}) is given by:

$$\mathrm{VIF}(x_k) = \frac{1}{1 - R_k^2}$$

Where:
x_k: the k-th independent variables in the model
R_k^2: is the R-squared value from a separate regression where x_k is predicted using all the other independent variables

Heteroskedasticity is when the variance of the error terms correlate with the magnitude of the explanatory variable [46, p.100-102]. This can be seen when the distance between the data points and the regression line will vary across different sections of the model. If this effect is large it reduces the ability for the model to predict the confidence interval in a good way. A simple method to estimate the risk of heteroskedasticity is the Breusch-Pagan test [46, p. 109]. If the test shows high risk a solution is to weight the observations with a GLS estimator [46, p.100-102]. The estimator weights the observations so the ones closer to the regression line receives a higher impact. This new weighted model does not have an interpretation by itself but should rather be analyzed in context with the original unweighted version.

In the multi-variable OLS regression, the predictive power of all independent variables was tested against one price metric at the time. This can be complemented by bi-variate regressions, which are done to give an idea of how the variable variance spread looked. An overview of our statistical analysis is found in Table 3.6 below.

Analysis Type	**Description**	**Purpose**
Multivariable OLS Regression (Main)	One regression for each price metric using all explanatory variables simultaneously (3 regressions total)	Detect joint effects and control for covariates
Bivariate OLS Regression (Complementary)	Four separate regressions, each testing one explanatory variable against one price metric	Illustrate individual relationships, variance spread and show preformance of bidding zones

Table 3.6: Overview of regression analyses

For the upcoming OLS-regression models, we used Python and two libraries: scikit-learn [48] and statsmodels [49]. Scikit-learn provided a interface for regression modeling, and statsmodels allowed for detailed statistical analysis, including e.g. significance tests, co-linearity tests, and confidence intervals. This also provided the Breusch-Pagan test for checking heteroskedasticity and Jarque-Bera test to check the normality of the residuals.

4

Results

In this section the results of the study will be presented. The initial results consist of bivariate regression plots, where the metrics, SWI, Stirling PEI and SP are plotted against the price increase together with a fitted regression line. Thereafter, the main results of the multivariate OLS regression results are presented. The section begins with two tests for multicollinearity to ensure reliable coefficient estimates. Next, all explanatory and control variables are entered into the regression model to assess which factors have a statistically significant impact on the price metrics, and to evaluate how well the model explains their variation. This multivariate approach is essential, while reliance solely on bivariate regressions risks omitted variable bias, as excluding relevant variables can distort the estimated effects [46, p. 65]. In every model run, the input variables are presented together with a short description of the model setup. All model runs are all given a dedicated subchapter. In the first analysis, the relationship between diversity of capacity and price increase will be looked at. A summary of the two diversity metrics, SWI and Stirling Index, are shown in map-format in Figure 4.1. On the map, a higher relative number, and darker the blue, indicates high diversity bidding zones.

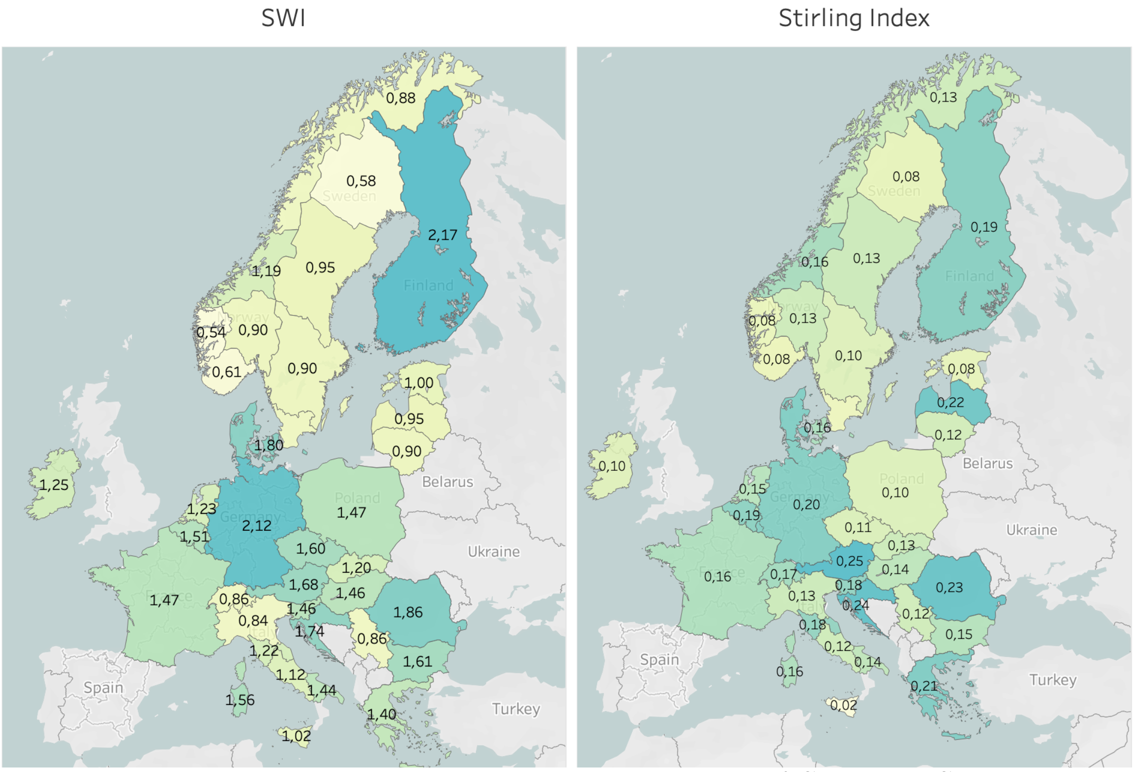

Figure 4.1: Map over bidding zones with the values of SWI and Stirling Index. The darker shades of blue indicate high diversity.

4.1 Price Increase vs Diversity of Capacity

In Figure 4.2, we plot the bidding-zones annual price increase against the diversity of capacity, measured using the adjusted capacity via the SWI-method. The price increased in all bidding zones included in the study except for NO4, the northernmost part of Norway. In general, the northern part of Europe experienced lower prices compared to the southern part. Finland has, according to the SWI metric, the most diverse capacity mix with a value of 2.17, while NO5 has the least with a value of 0.54 To set these values in context, the Finnish capacity mix has nearly the same value as a mix with nine equally large sources, while the capacity mix in NO5 is worse/less diverse than a mix with two equally large sources.

Bidding-zones with a high diversity on average experienced a larger increase in price. This relationship is however relatively weak, implying that diversity may have some explanatory power, but is not statistically significant which is evident by the 95% confidence interval. By looking at the indicated confidence interval, it is clear that the regression does not rule out either a positive or a negative correlation between the variables at the given confidence level. One can also note that the standard error is larger for bidding-zones with lower diversity. Through the R-squared value in the legend, we can see that the SWI can explain 9% of the price increase.

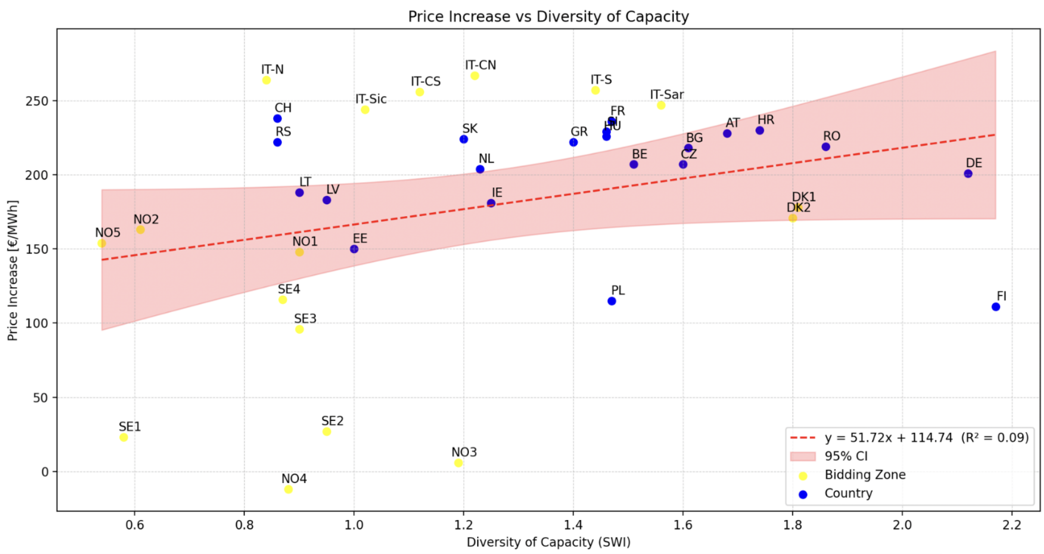

Figure 4.2: Regression model results showing the relationship between diversity of capacity measured in SWI and price increase in euro per MWh.

In Figure 4.3, the diversity of capacity, using the Stirling index, is plotted against price increase. The results show similar overall pattern, although the regression with Stirling index is slightly less correlated with price, as indicated by the lower R-squared. With this measurement, Austria has the most diverse capacity mix and Italy-Sicily by far the least diverse. Both the SWI and Stirling index plot includes many data points which have a large standard error in relation to the regression line.

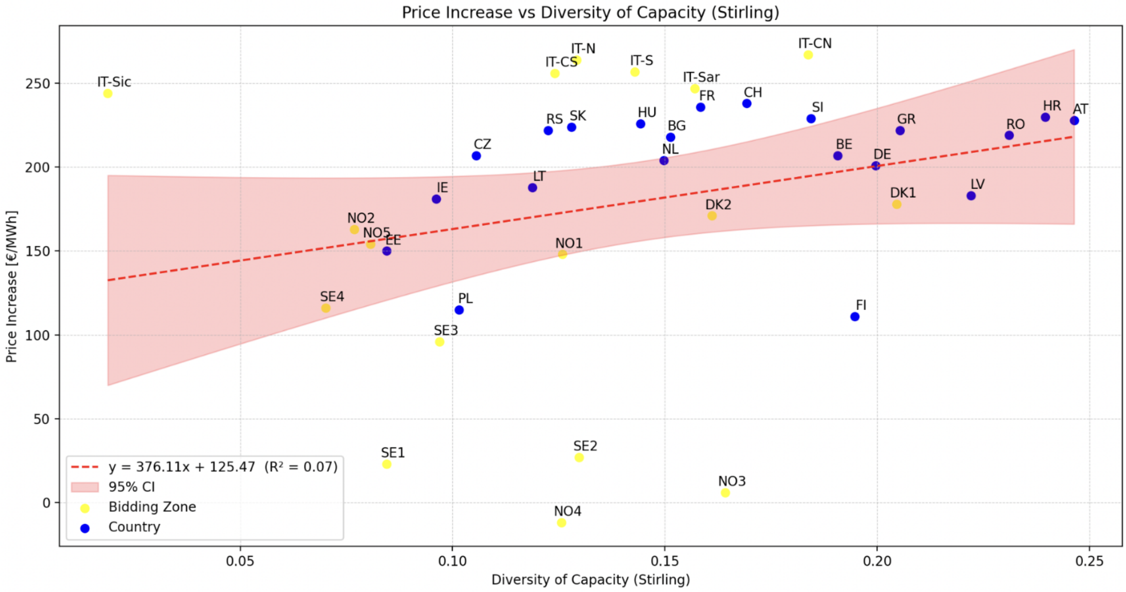

Figure 4.3: Regression model results showing the relationship between diversity of capacity measured using the Stirling Index and price increase in euro per MWh.

4.2 Price Increase vs Import Dependence

In Figure 4.4, the PEI variable is plotted against price increase. The regression shows that countries that were more import dependent experienced slightly higher electricity price increase on average. However the correlation is very weak, where PEI metric could only explain 2 percent of the price increase. Lithuania is the most import dependent price zone while Italy-South exports the largest share of their generation, both at around 80%. Except for Lithuania, most countries are concentrated around zero, where the electricity trade balance is close to zero.

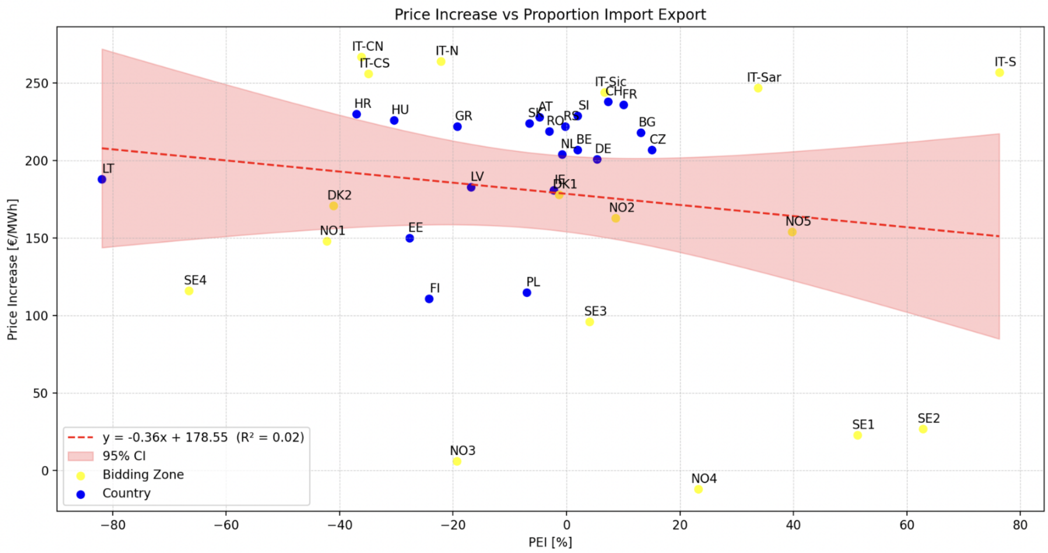

Figure 4.4: Regression model results showing the relationship between proportion export import and price increase.

4.3 Price Increase vs Spare Capacity

When plotting the spare capacity against price increase, it can be seen that countries with higher SP had a higher price increase on average. The variable can in this case explain 11 percent of the price increase. The confidence interval is again too wide to rule out either a positive or negative correlation. The bidding-zones of northern Sweden and Northern Norway (SE1, SE2, NO4, NO3) all have close to zero spare capacity and a low or negative price increase. When looking at the countries, indicated by the blue color, an opposite trend can be inferred, where high SP correlates with a lower price increase. This will be discussed later in the sensitivity analysis.

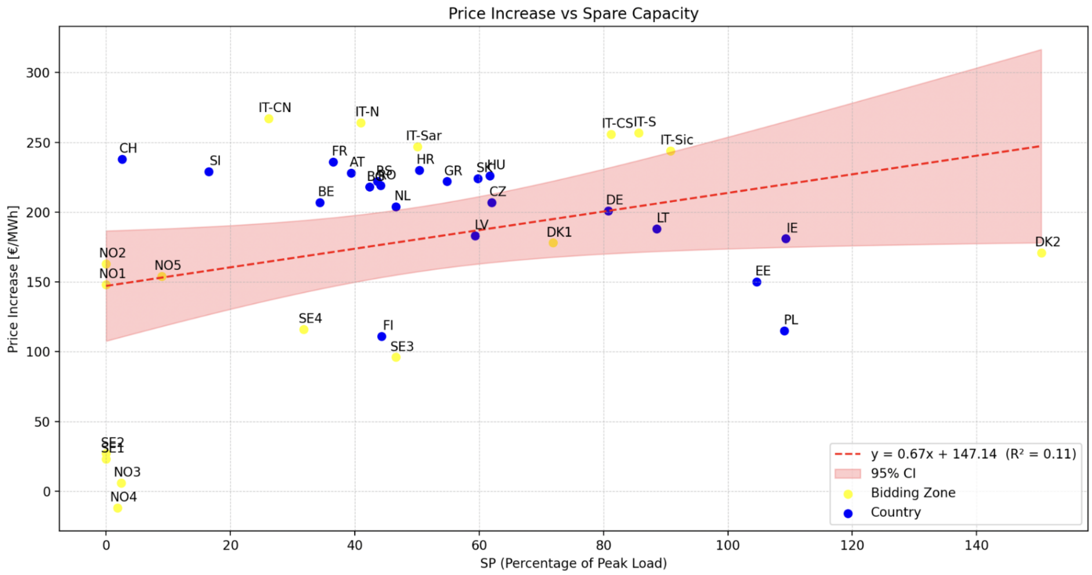

Figure 4.5: Regression model results showing the relationship between spare capacity and price increase.

4.4 Multi-Variable Analysis

In this subchapter, all the independent variables are added to analyze their impact on the electricity price metrics. The results are estimated using a linear regression model, using the OLS method. The independent variables are all normalized to standard scores (z-scores) which are based on the mean and standard deviation of each distribution. Since the variables are normalized, the values indicate the effect of an increase of one standard deviation has on the outcome variable. Before the analysis, a multicollinearity analysis was conducted.

4.4.1 Multicollinearity Analysis

As discussed in the theory chapter, it is important to check all explanatory variables for unwanted multicollinearity. It is no issue that the independent variables are correlated, but if they are correlated to a high degree there can be analytical problems [46, p. 44]. We here show the Pearson coefficient matrix in Table 4.6 and the VIF analysis in Figure 4.7.

Figure 4.6: Heatmap showing the Pearson Correlation Coefficient for all variables

The Pearson correlation coefficients for each variable pair is shown in the form of a heat map. A positive or negative correlation is indicated by the color scheme, where darker blue indicates a negative correlation, and darker red indicates a strong positive correlation. The variables are perfectly correlated with themselves as shown by the matrix main diagonal. The variable pairs with the highest correlations are SP and Share DRE (-0.59), and SWI and Share DRE (-0.50)

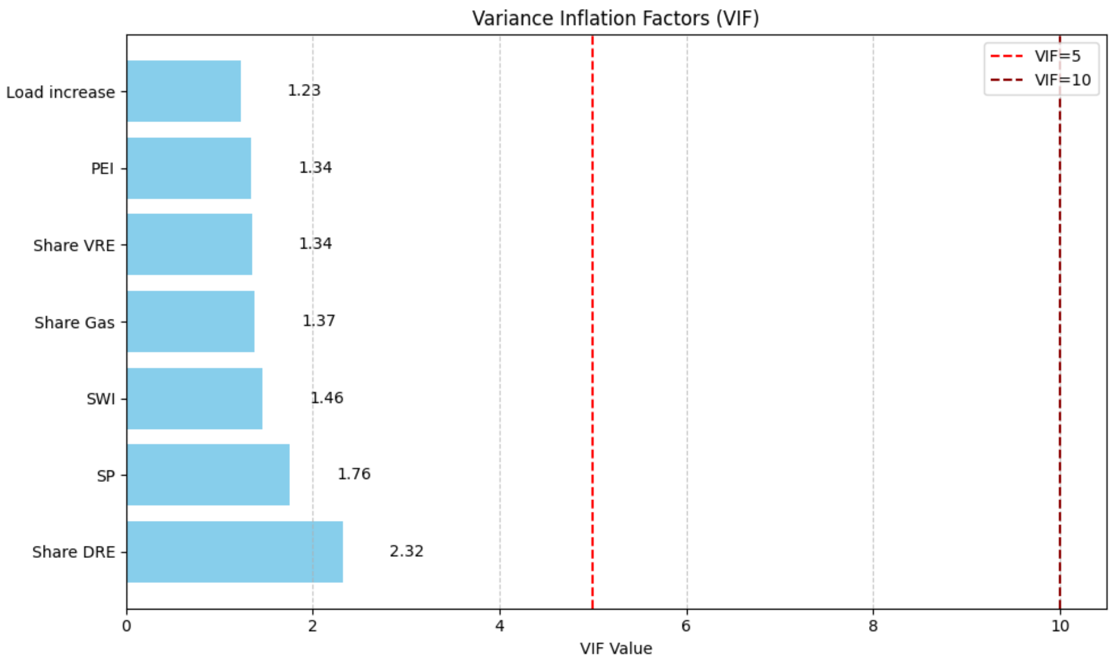

Figure 4.7: Results from the VIF-analysis

From the VIF analysis results we can see that all our variables are below the indicative values of problematic multicollinearity, with all values falling in the range of modestly correlated (1-5). We can therefore proceed with the multi-variable OLS regression analysis, without issues of the unreliable regression estimates from multicollinearity.

4.4.2 Regression of Price Increase

In this analysis, all independent variables are tested against price increases. The model results are summarized in Table 4.1. The model explains 44% of the observed increases in electricity price, as indicated by the adjusted R-squared metric. None of the three strategies, diversity, spare capacity, or PEI, showed any significant correlation with the price increases. However, the share of DRE, and the share of gas showed a significant effect. Having a large share of DRE is correlated with a weaker price increase. The DRE coefficient reflects an average negative price increase of 1.51 €/MWh for each percentage of DRE. Share Gas has a positive correlation with price. The gas coefficient reflects an average price increase of 1.30 €/MWh for each percentage of share gas.

Dependent variable: Price Increase				
Independent Variable	**Coefficient**	**P-value**	**Std. Error**	**95% CI**
Intercept	180.11	0.000	8.92	[161.89, 198.32]
SWI	1.40	0.898	10.77	[-20.60, 23.40]
PEI	1.62	0.877	10.34	[-19.49, 22.72]
SP	-10.85	0.366	11.82	[-34.99, 13.28]
Share VRE	1.26	0.904	10.34	[-19.86, 22.37]
Share DRE	**-45.01**	**0.002**	**13.57**	**[-72.73, -17.29]**
Share Gas	**22.72**	**0.038**	**10.45**	**[1.36, 44.07]**
Load Increase	1.69	0.865	9.87	[-18.46, 21.85]
Model Fit Statistics				
Adjusted R-squared		0.44		
Probability (F-statistic)		<0.001		
No. Observations:		38		

Table 4.1: OLS Regression Results for price increase

4.4.3 Regression of P95

When explaining the variation in the increase of P95 prices (Table 4.2), only share DRE was significant. Bidding zones with larger share of DRE did on average experience a lower increase in P95 prices. The normalized coefficient shows the best estimate to be -66.43, but the confidence interval is rather wide, indicating the uncertainty of the magnitude. The coefficient means each percentage share DRE reduces the P95 with -2.23 €/MWh. In total the model can explain 28% of the P95 increase variation.

Dependent variable: P95 Increase				
Independent Variable	**Coefficient**	**P-value**	**Std. Error**	**95% CI**
Intercept	396.96	0.000	15.41	[365.49, 428.43]
SWI	-7.14	0.703	18.57	[-45.08, 30.79]
PEI	-8.35	0.632	17.28	[-43.65, 26.94]
SP	-16.64	0.451	21.80	[-61.17, 27.88]
Share VRE	13.75	0.435	17.37	[-21.73, 49.22]
Share DRE	**-66.43**	**0.009**	**23.81**	**[-115.05, -17.81]**
Share Gas	15.16	0.408	18.07	[-21.74, 52.05]
Load P95 increase	-1.96	0.911	17.33	[-37.35, 33.44]
Model Fit Statistics				
Adjusted R-squared		0.28		
Probability (F-statistic)		0.015		
No. Observations		38		

Table 4.2: OLS regression results for P95

4.4.4 Regression of CV

The regression model results of CV are presented in Table 4.3. In this model, two of the predictors were statistically significant at the .05 level. These were the share of DRE and the control variable, CV load increase. Share DRE is shown to have a positive correlation, and vice versa for the control variable. The larger the share of DRE, the larger is the expected increase of the CV. The control variable is not independent in this case, so it is difficult to say which variable impacts who, this is later covered in the discussion chapter. The three metrics SWI, PEI, and SP did once again show no significance at this confidence level. The same were true for share VRE and share gas. In total, the predictors in this analysis explained 49% of the CV increase.

Dependent variable: CV Increase				
Explanatory Variable	**Coefficient**	**P-value**	**Std. Error**	**95% CI**
Intercept	0.36	0.000	0.03	[0.28, 0.43]
SWI	0.00	0.970	0.04	[-0.08, 0.09]
PEI	0.02	0.653	0.04	[-0.06, 0.10]
SP	0.01	0.893	0.05	[-0.09, 0.10]
Share VRE	0.05	0.187	0.04	[-0.03, 0.14]
Share DRE	**0.18**	**0.002**	**0.05**	**[0.08, 0.29]**
Share Gas	-0.02	0.646	0.04	[-0.10, 0.06]
Load CV Increase	**-0.08**	**0.043**	**0.04**	**[-0.17, -0.00]**
Model Fit Statistics				
Adjusted R-squared		0.49		
Probability (F-statistic)		<0.001		
No. Observations		38		

Table 4.3: OLS regression results for CV

4.5 Robustness Analysis

To assess whether the models meet the assumptions of an OLS regression, both the Breusch–Pagan test and a normality test for the residuals were conducted. The Breusch-Pagan test indicates that the risk of heteroskedasticity is high in all models. The heteroskedasticity corrected models have wider confidence intervals. The result from these models can be found in Table 4.4. The statistical significance is lost for share DRE, in the P95 model for load CV. According to the Jarque-Bera test all residuals seems to be normally distributed which is desired. A value below 0.05 would indicates non-normal distribution.

P-value Results from robustness check

Independent Variable	Price increase	P95 increase	CV increase
SWI	0.919	0.691	0.971
PEI	0.912	0.637	0.685
SP	0.471	0.610	0.856
Share VRE	0.905	0.466	0.192
Share DRE	**0.038**	0.095	**0.046**
Share Gas	**0.025**	0.307	0.549
Load	0.909	0.921	0.054
Adjusted R-squared	0.297	0.278	0.486
Jarque-Bera test	0.595	0.214	0.591

Table 4.4: Shows the P-values for the heteroskedasticity corrected model runs. **Bold** indicate that the variable is still significant while red indicates lost significance.

4.6 Sensitivity Analysis

Outliers might strongly affect the result [46, p.48-49]. From the bivariate regressions it is apparent that hydro dominated bidding zones of northern Sweden and northern Norway lie far from the regression line, potentially affecting it to a large degree. As a way to see if the results are stable for different subsets of all bidding zones, a multivariate regression is performed with price increase as the outcome variable - this time with the mentioned outliers removed. The results of this multi-variable OLS analysis is found in Table 4.5.

Dependent variable: Price increase				
Independent Variable	**Coefficient**	**P-value**	**Std. Error**	**95% CI**
Intercept	200.00	0.000	6.68	[186.27, 213.73]
SWI	3.999	0.619	7.95	[-12.35, 20.34]
PEI	10.31	0.200	7.83	[-5.79, 26.41]
SP	-13.31	0.104	7.89	[-29.53, 2.91]
Share VRE	2.92	0.717	7.96	[-13.44, 19.28]
Share DRE	-8.18	0.366	8.90	[-26.48, 10.11]
Share Gas	**24.99**	**0.003**	**7.50**	**[9.56, 40.41]**
Load Increase	-0.94	0.902	7.56	[-16.47, 14.59]
Model Fit Statistics				
Adjusted R-squared		0.297		
Probability (F-statistic)		0.0192		
No. Observations:		34		

Table 4.5: OLS Regression Results for price increase without: NO3, NO4, SE1, and SE2

When removing the bidding zones that are not actual countries from the spare capacity regression, the relation between SP and price increase changes direction to negative and becomes significant according to the confidence interval. This can be seen in Figure 4.8.

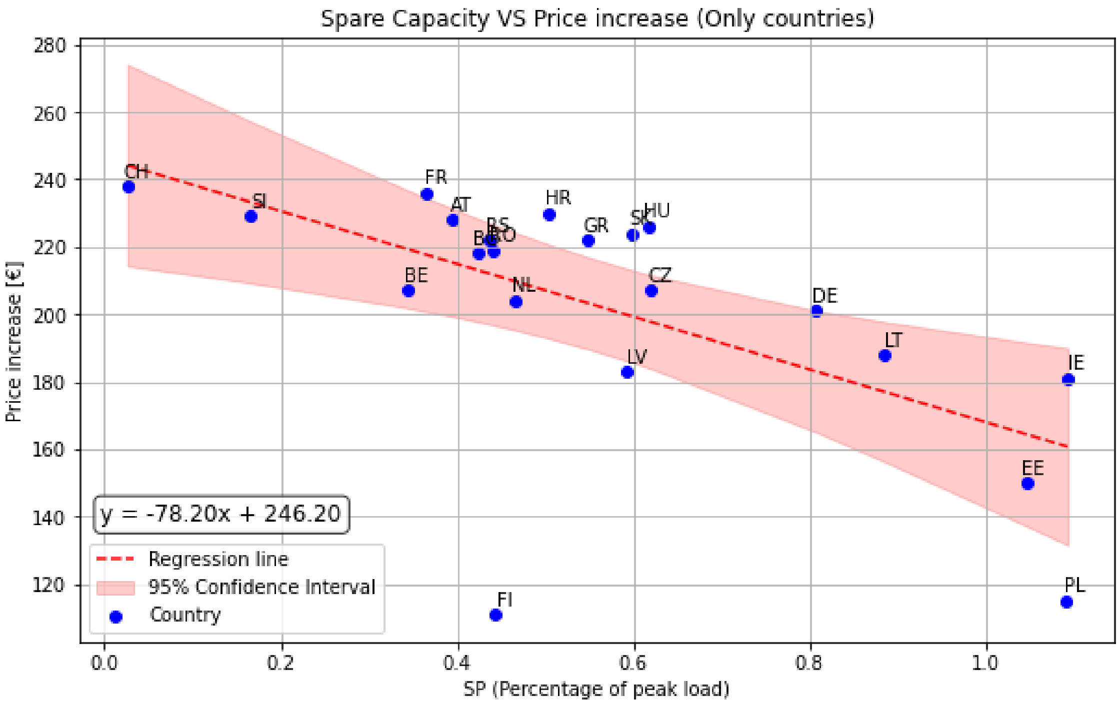

Figure 4.8: Spare capacity after removing country-divided bidding zones

5
Discussion

In this section, the results from the previous chapter will be discussed and analyzed. First, the results from the bi-variate regressions are examined. Second, the variable selection will be reviewed. Third, the multi-variable OLS regressions are evaluated. Fourth, the results will be put in relation to previous studies and research. Fifth, a reflection on the methodology choices and what limitations could be noted. Finally, the discussion is summarized with the main points highlighted.

5.1 Interpretation of Bivariate Relationships

The large differences in price increase depending on bidding-zone latitude indicate that geographical location matters. The price convergence between bidding zones are also noticeable, neighboring price zones in general has similar price increase. This shows that bidding-zones that experience high prices also affects neighboring countries. However Poland seems to be an outlier in this regard. This can stem from the fact that Poland has low transmission capacity in relation to its size compared to other countries in Europe [1]. The northern part of Sweden and Norway experienced by far the lowest price increase. These regions all have in common that they are hydro-power dominated, while also being relatively isolated from Central Europe. The bidding zone NO4 even had a negative price increase. However looking at CV and P95 (see appendix A) it is possible to conclude that they also experienced effects from the energy crisis with unusual high prices for shorter time periods.

The energy systems in the study are differently composed which is shown by the variance of the SWI metric. The diversity of Germany and Finland are high, while many other bidding-zones are lower. When comparing the SWI-values to Stirling values there is a clear difference in which bidding zones are considered diverse and not. For example, with Stirling index there are six bidding zones that are more diverse than Finland and Germany, also Latvia goes from a rather low diversity in SWI to a relatively high diversity with Stirling index, while Italy-Sicily almost lost all diversity with the Stirling metric. This shows that what is regarded as diverse or not is sensitive to the type of measurement used. This large difference in the two diversity metrics is reinforced by the multitude of generation type categories. For SWI, having 19 different generation categories as present on the ENTSO-E database, is not optimal since some are very similar. Two reasons behind the methodological choice is that few countries report data for several similar countries and keeping same categories makes it possible to compare the SWI and Stirling index in a fair way. Having many categories for Stirling is less of a problem since the similarities are accounted for.

The Stirling index also has the potential to capture interesting effects during a crisis since similar sources might be affected in a similar way during crisis. For example in a dry year run-off river will be affected similarly as hydro water reservoir, or if a price shock in gas occurs, the demand for alternative fuels will rise, likely leading to price increases of fuels similar to gas. Using Stirling index when analyzing a crisis therefore serves an important purpose. The Stirling index were also tested for the multi-variable OLS models (see appendix B), however the results were similar to the one using SWI.

A difficult part of the Stirling Index is to capture the disparity in an accurate way. In our case, the number of attributes were limited to three to make it easy to visualize and understand. To set these attribution values is a complex task since they ideally should represent the average value for the European plants of the specific type. For example, the category of fossil gas consists of both simple cycles and combined cycles plants which has different characteristics. However, if the categories are many and some are very similar to each other, estimating the disparity is very likely to improve the diversity metric even if the attribution values are not exact.

An expected outcome from import dependence is that importing bidding zones would have higher price increases than exporting bidding zones, since the price differentials determines if a bidding zone is importing or not. However, this effect seems negligible when looking at the regressions graph's confidence interval. Also importing electricity counteracts these price differences. With the exception of Lithuania, the countries are more concentrated around a net trade balance of zero compared to the countries divided into bidding zones. The reason might be that it is considered safer, from a geopolitical perspective, to rely on other regions within the same country rather than on foreign countries - and this shapes how the system is planned and built.

Net importers of electricity are also better protected compared to importers of fuel due to the electricity market mechanisms and EU regulations [17]. Exporting countries have no legal possibility to keep the domestic electricity within their borders - if transmission capacity is available to export the electricity. In contrast, countries exporting fuels can choose both the price level and who they want to sell to. Two parameters that in some circumstances changes quickly. This can of course impact the operation cost for electricity generation that requires fuel which might have an effect on the electricity price as well.

Among the bidding zones with high spare capacity, those with a large share of fossil-based generation are most prevalent. Plants with high capacity coupled with low electrical energy output provide high spare capacity. These are plants with rather cheap investment cost but high operation cost for example gas plants. This effect can be seen for Ireland and Denmark, which are regions with a lot of wind power and complimenting gas that can regulate the wind variations [50]. Among the bidding zones with less spare capacity the hydro-dominated systems can be found. In reality, hydropower can also provide some spare capacity; however, to what extent is difficult to determine. Since the operation cost of hydro is low and the water supply is limited, it is reasonable to assume that the spare capacity of hydro is relatively low compared to fossil power in general, and especially gas.

For the price metrics, we have chosen three measures: annual average price, P95 of prices, and the coefficient of variation (CV). Each of these captures an important dimension of price behavior. The average price reflects overall cost levels, the P95 captures extreme price events, and the CV provides insight into price volatility. Together, they offer a more comprehensive understanding of system affordability and resilience. In our analysis we have treated them as separate but complementary outcome variables.

5.2 Interpretation of Multivariate Models

The main findings of the multi-variable regression analysis are discussed here. First, reasons behind the non-significant results for the variables SWI, PEI, and SP. Then the remaining variables (share VRE, DRE, Gas) to derive insights from the statistical relationships found. In Table 5.1, the results of all three analysis are summarized for ease of reference.

Note: **Bold** indicates statistically significant coefficients at p <.05.
`ns` indicates not significant. `'-'` indicates not applicable for the specific regression.

Variable	Price Increase	P95 Increase	CV Increase
SWI (Diversity Index)	ns	ns	ns
PEI (Import Dependence)	ns	ns	ns
SP (Spare Capacity)	ns	ns	ns
Share VRE	ns	ns	ns
Share DRE	**-45.01**	**ns**	**0.18**
Share Gas	**22.72**	ns	ns
Load Increase	ns	–	–
Load P95 Increase	–	ns	–
Load CV Increase	–	–	ns
Adjusted $\mathbf{R^2}$	0.44	0.28	0.49

Table 5.1: OLS Regression Results Summary. The significance is from the robust model where it is heteroskedasticity corrected.

5.2.1 SWI, PEI, SP

The original hypothesis is that bidding zones which scored high on the metrics SWI, PEI, and SP, would be more resistant to disturbances of the energy system, which would be indicated by more stable prices during the crisis. However, no statistical relationship was found. Consequently, the effectiveness of these strategies to support price stabilization during times of crisis must be called into question. The analysis does not support the notion that implementing these strategies in advance of a crisis leads to reduced vulnerability to price shocks. The reason for the lack of obvious effect could have many reasons, we have chosen to highlight two possible reasons.

Price Setting Mechanism
The wholesale electricity price in all bidding zones is set by the most expensive generator needed to meet demand [51]. This could lead to cases where e.g. a diverse energy system had a lower overall cost of production, where generation is moved to the cheapest available options during the crisis, but the electricity prices could be the same if the most expensive generator could not be fully substituted. Diversity without enough spare capacity to completely rule the expensive generator out, would not impact electricity prices. If this were true, it could still be beneficial with diversity from an efficiency and system cost perspective, but would not be captured by the electricity prices. In a similar sense, having spare capacity could lead to a lower system cost - but not reduce the price of electricity.

Price Convergence
Trade across bidding-zones leads to a convergence of price between said zones, where electricity flows from cheaper to more expensive zones through the electricity transmission grid. This is not an issue from an economic perspective, and is explicitly sought after from the EU, citing increased efficiency, increased competition, and affordability for customers [51]. However, since trade makes the price differences between bidding zones smaller, so does the potential effects of strategies in a given zone. If Zone A has a diverse and low-cost electricity supply, part of its production will be exported to zones with more expensive generation, constrained only by the available electricity trade capacity. This increase in demand could drive up the price for the cheap zone, removing parts of the potential benefit. Discussion on the appropriateness of this system is better left outside this thesis, but it is likely this makes it more difficult to see potential effects from strategy differences across bidding zones, when looking only at the wholesale electricity price.

5.2.2 Share of Renewables, Gas and Demand

The predictors which showed to be significant at the .05 level were share of DRE and share of gas, whereas share of VRE and the load control variables' were not. Bidding zones which had a high proportion of DRE did on average experience a lower price increase and a larger than average daily price variability increase. The dispatchability seems to hold the value, where the possibility to plan the production could be used to mitigate higher price levels. There seems, however, to be a trade-off between the effect of price mitigation and daily price variability. The fact that share of DRE is associated with a larger CV increase is surprising, as one can imagine that dispatchable energy sources supports more stable prices. One reason could be that bidding zones with a large share of DRE tends to have substantially lower and more stable average prices. This is especially the case for the northernmost bidding zones of Sweden and Norway, which almost fully rely on dispatchable hydro-power. When high crisis prices from neighboring zones, which prices operate on a higher average level, reaches an otherwise stable and low price zone, the annual variance becomes greatly affected. These outlier days also tend to give a positively skewed price distribution. Data which have a skewed distribution inflates the standard deviation to the point where it is no longer a good measure of variability [52]. In other words, the variance metric of CV, which is based on standard deviation and mean, might not be a good representation for some bidding zones. In appendix D, we have a side by side comparison of Poland and NO3's price distribution functions to show this skewness.

Variable renewable energy share did not show significance for any of the price metrics, indicating that zones high in VRE were neither better nor worse off with regard to price performance. Somewhat surprising is that VRE share did not have a significant impact on increase of CV. However, the increase of CV is relative to the level 2019. We do not measure how increase of VRE impacts variability, only how the share of VRE 2019 potentially impacts price behavior during the crisis. It is nonetheless interesting results that the bidding zones scoring high on the metric were not more sensitive to the CV increase. A Nature 2025 paper looked at the relationship between share of VRE and vulnerability to gas price shocks [37]. They found a slight positive relationship between VRE generation and vulnerability, which was statistically significant. This is not in line with our results, which could motivate further research on the matter. Notably, the Nature study specifically looks at the period between April and October 2021, and uses another type of linear regression (MM-estimation), which could explain some of the difference.

Natural gas has a special role in the energy systems, namely it is often used as a peak generator, i.e it is used to effectively supply electricity when demand or production varies. We found a positive relationship between the share of gas and the sensitivity to price increases during the crises. The significance was only present against the annual average price. Since the crisis in many ways were dominated by a breakdown of the European natural gas supply, this might be obvious. But since only the most expensive generator sets the price, it could be that the fraction is less important than the fact that it is present in the system. Using time with gas on margin as an explanatory variable was also tested; however it was close to binary variable in the sense that many countries either had gas in their system almost all time or almost never. The aforementioned Nature 2025 paper found similar results regarding the share of gas and vulnerability to gas price shocks [33], which is in line with the findings of this thesis.

5.3 Relation to Previous Research

We have looked at two studies which empirically investigates the relationship between energy security metrics of diversity, proportion export import, and spare capacity versus price performance. In a study from Kenya [29], the analysis indicated a significant predictive power of all variables on electricity prices. Diversity and electricity imports were both positively correlated with price, meaning scoring higher in diversity, and larger share of electricity imports, correlated with increased prices.

Of note is that the study looks at the variables development over time, with diversity calculated from actual generation at each time step. A reason for the positive correlation between diversity and electricity prices could be explained if generators are deployed in order from cheapest to most expensive. High diversity would thus mean that more expensive sources are present in the electricity mix which would be reflected by higher prices. Similarly, the correlation between high imports and high prices likely reflects the fact that imports occur when domestic generation is insufficient or costly. The study does not evaluate whether countries with a higher long-term dependence on imports face higher prices, but rather shows that in moments of import, prices tend to be high. The spare capacity was differentiated for the generation types of hydro, geothermal and thermal. Thermal and hydro spare capacities were associated with high electricity prices, and geothermal with low.

Molyneaux et. al. [30] have done a cross-sectional regression analysis comparing the resilience indicators for two historical periods (1973–82 and 2003–12) in the USA. The study found the following statistically significant predictors of electricity prices: spare capacity and electricity imports reduces electricity prices, while diversity increases electricity prices. As in the Kenya study, the analysis examines how the predictors co-vary with the electricity price, meaning the variables are not necessarily independent. Therefore, diversity observed during the crisis could reflect adaptive responses, not just inherent system structure. This makes the diversity, spare capacity and import dependence potentially endogenous, i.e., affected by the outcome variable (electricity price) or by the same shock affecting price.

When comparing our results with those of the other studies, it is important to note the differences in e.g. geographical scope, crisis focus, price setting mechanism, and time perspective. Both of the empirical studies mentioned in this subchapter looks at the variables co-variance over time, capturing long-term structural associations with price performance, while our study defines the predictors (or system structures) before the crisis. A cross-sectional regression analysis could be done on the European energy crisis of 2022 to potentially validate the results of the previous studies.

5.4 Methodological Reflection and Limitations

In general terms - the more data points in OLS regression, the more robust the results. In this case, all bidding zones with available and comparable data were included, which in total added up to 38 data points. This is enough to draw some conclusions, but the analysis would likely benefit from having more data points. Another weakness connected to the number of data points is that the reference data is based on only one year. This is due to the fact that 2020 was an outlier stemming from the COVID-19 pandemic, and the electricity prices started to increase to abnormal levels in late 2021. The reason for excluding data from earlier years is that some portions of the data were missing or incomparable. For example, Germany and Austria were one price zone in the beginning of 2018, and Croatia has no electricity price data from 2018. However, the electricity prices from 2019 and earlier have been relatively stable in Europe, meaning that 2019 electricity prices in general reflects the pre-crisis prices well.

It is also important to remember that only one energy crisis is investigated, and the energy strategy metrics might impact the prices in another way in next energy crisis. This crisis affected several generation sources, but mainly the one from natural gas.

This heavily impacted the electricity prices due to how the price setting mechanism works. A crisis affecting sources with cheaper operating cost, for example, a dry year, or technical problems with nuclear, would affect the electricity prices in a different way. In this type of crisis, the energy strategies might be more useful for mitigating price increases.

5.5 Comparing Countries and Bidding Zones

In this study, both actual countries and bidding zone within countries are included because both types of price zones follow identical market rules. This is an advantage because it increases the sample size with more data points to the statistical analysis. However, comparing countries with country-divided bidding zones affects the results. For example, there are six Italian data points, while Germany has one despite being a larger country. The results are therefore more influenced by Italy than Germany. While one might argue that this approach is unfair, it is also problematic to compare countries that differ significantly in size. It is possible to artificially merge price zones into a single country, but doing so would have reduced the number of observations from 38 to 25. It would also require an estimation of the electricity price instead of using the exact data.

Another property for the countries divided into several bidding zones is that the diversity of capacity is likely to decrease. The general trend is that smaller bidding zones have lower diversity, but the difference is smaller than one could imagine. For example, France and Slovenia have the same SWI and Latvia has a higher Stirling index than Germany.

When removing the bidding zones that is not actual countries, spare capacity seems to be correlated with a significant price mitigating effect, as is visually confirmed by Figure 4.8. This drastic shift can from a statistical point of view be explained by many factors. Firstly, 17 data points are removed, which is 45% of the data points. Secondly, a majority of the removed points were outliers in either price increases or spare capacity. This is partly because the hydro-zones have no or very low SP. So for actual counties, spare capacity supports the affordability, but not for other bidding zones. The exact reason behind this is uncertain, but it is reasonable to assume that system planners often consider relying on backup capacity within the country, rather than strictly within the bidding zone, to be sufficiently reliable. In other words, countries tend to plan centrally to have spare capacities, while this might not occur inside country-divided bidding zones. However, this does not explain why a price-mitigating affect is only observed among the actual countries. Further research into the effect of spare capacity on electricity price formation is therefore advisable.

When removing only the low-price, hydro-dominated bidding zones of NO3, NO4 SE1 and SE2, share DRE lost its significance on price (see Table 4.5). This highlights the sensitivity of the results, as the effect is not stable across the whole sample. The results as a whole, however, do indicate that hydro-water reservoir capacity was valuable for mitigating price increases.

6

Conclusion

The strategies of diversity, spare capacity, and trade independence are frequently cited as beneficial towards energy security. The analysis showed that countries scoring high on metrics related to these strategies did not on average perform better (or worse) with regard to the tested price metrics. Diversity can be measured in different ways, each with its own advantages and drawbacks. Transparency in this process is valuable when selecting categories and possible weighting, regardless of the method used. However, in our findings, where the two methods (SWI and Stirling) were used, diversity did not increase the system's resistance to price shocks. One should therefore be cautious in claiming that diversity actually increases energy security, where electricity price affordability is an essential part. The role of import dependence showed no significant effect on the measured electricity price behavior. Possible explanations include large transmission capacities between bidding zones, which lead to price convergence, and regulations preventing exporters from setting the electricity prices. Importers of electricity are in this case better protected compared to importers of fuels such as coal, oil, and gas. Regarding spare capacity, the analysis would benefit from developing a method to accurately estimate the spare capacity of hydro-water reservoir plants. While the overall analysis showed no effect for bidding zones in general, a price-reducing effect of spare capacity was observed in countries composed of a single bidding zone. These conflicting results warrant further investigation to understand the underlying causes.

Increasing the share of dispatchable renewable energy proved to be an effective strategy for mitigating price increases during the 2022 energy crisis. However, a higher share of DRE also appeared to correlate with greater price volatility. This is likely due to temporary price effects transmitted from neighboring zones. In contrast, an increase in variable renewable energy share did not show any significant impact on either price level or volatility. Bidding zones with higher share of gas experienced higher electricity prices. This was expected due to the high gas prices and the marginal cost price-setting mechanism. Finally, it is important to remember that analyzing several different energy crises is necessary to draw general conclusions on how to increase the energy security.

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A

Summary of Variables

Bidding zone	Delta price	Delta Procentile 95%	CV Increase	SWI	Stirling	SP	PEI	Share VRE	Share DRE	Share Gas	Load increase	Load P95 increase	Load CV increase
FI	111	358.8	0.46	2.17	0.1947	0.443	-0.243	0.288	0.099	0.075	0.956	-1071	-0.012
FR	236	488.7	0.18	1.47	0.1584	0.365	0.101	0.162	0.032	0.073	0.950	-1665	0.008
DE	201	458.4	0.25	2.12	0.1996	0.808	0.054	0.353	0.081	0.110	1.008	838	-0.002
GR	222	423.4	0.21	1.40	0.2053	0.548	-0.192	0.233	0.073	0.429	0.948	-345	0.010
HU	226	462.1	0.19	1.46	0.1443	0.617	-0.304	0.036	0.036	0.387	1.003	163	0.018
SE3	96	349.8	0.57	0.90	0.0969	0.466	0.041	0.125	0.101	0.000	0.975	-374	-0.002
LT	188	445.7	0.36	0.90	0.1188	0.885	-0.819	0.626	0.137	0.135	1.003	34	0.017
SE4	116	396.6	0.54	0.87	0.0701	0.318	-0.665	0.661	0.128	0.000	0.944	-149	0.009
CH	238	460.2	0.17	0.86	0.1693	0.026	0.073	0.061	0.296	0.000	1.034	147	-0.013
SK	224	474.9	0.22	1.20	0.1279	0.598	-0.065	0.183	0.041	0.098	0.942	-110	0.020
BE	207	437.8	0.14	1.51	0.1907	0.343	0.020	0.135	0.027	0.271	0.968	-289	-0.002
BG	218	422.8	0.10	1.61	0.1513	0.423	0.131	0.085	0.047	0.051	1.012	98	0.017
SE2	27	193.8	0.96	0.95	0.1298	0.000	0.628	0.259	0.722	0.000	0.950	-211	-0.009
HR	230	459.8	0.18	1.74	0.2396	0.503	-0.370	0.311	0.363	0.191	1.013	66	0.014
CZ	207	453.9	0.25	1.60	0.1056	0.620	0.151	0.077	0.038	0.086	0.983	-225	0.003
EE	150	393.4	0.32	1.00	0.0845	1.046	-0.277	0.132	0.095	0.083	0.946	-28	0.001
IE	181	358.1	0.23	1.25	0.0961	1.093	-0.023	0.451	0.000	0.370	1.031	12	-0.017
LV	183	436.3	0.35	0.95	0.2221	0.593	-0.168	0.353	0.097	0.449	0.935	-36	0.016
SE1	23	186.7	1.01	0.58	0.0845	0.000	0.513	0.195	0.799	0.000	1.060	45	-0.022
PL	115	166.0	0.09	1.47	0.1015	1.091	-0.070	0.110	0.015	0.077	1.030	849	-0.001
RS	222	457.1	0.17	0.86	0.1225	0.437	-0.003	0.266	0.023	0.001	0.872	-723	0.019
SI	229	462.7	0.18	1.46	0.1844	0.165	0.020	0.313	0.006	0.024	0.947	-61	0.023
IT-CN	267	509.4	0.24	1.22	0.1838	0.261	-0.361	0.336	0.040	0.532	0.792	-867	0.009
IT-CS	256	487.0	0.25	1.12	0.1241	0.812	-0.349	0.314	0.028	0.414	1.103	737	0.004
IT-N	264	510.0	0.22	0.84	0.1292	0.410	-0.221	0.279	0.065	0.480	0.966	-858	-0.007
IT-Sar	247	462.9	0.22	1.56	0.1570	0.501	0.338	0.220	0.047	0.329	0.986	67	0.030
IT-Sic	244	427.2	0.15	1.02	0.0188	0.907	0.067	0.334	0.012	0.552	0.961	47	0.015
IT-S	257	477.4	0.23	1.44	0.1429	0.856	0.763	0.414	0.072	0.341	0.695	-844	0.044
NO1	148	388.1	0.34	0.90	0.1259	0.000	-0.423	0.382	0.606	0.010	0.921	-479	0.003
NO2	163	421.7	0.37	0.61	0.0768	0.000	0.087	0.097	0.901	0.001	1.021	222	-0.007
NO3	6	134.5	1.30	1.19	0.1642	0.024	-0.194	0.138	0.841	0.015	1.010	-55	-0.021
NO4	-12	26.6	1.27	0.88	0.1256	0.018	0.232	0.053	0.880	0.067	0.936	-258	-0.027
NO5	154	386.7	0.34	0.54	0.0807	0.089	0.398	0.013	0.959	0.028	1.087	260	-0.003
NL	204	434.8	0.28	1.23	0.1497	0.466	-0.008	0.062	0.000	0.411	0.993	-1746	-0.055
AT	228	465.8	0.23	1.68	0.2464	0.394	-0.047	0.650	0.125	0.183	1.001	10	0.000
DK1	178	447.6	0.35	1.81	0.2046	0.719	-0.014	0.641	0.071	0.102	1.043	209	0.010
DK2	171	444.3	0.41	1.80	0.1611	1.504	-0.411	0.461	0.282	0.063	0.994	59	0.023
RO	219	313.4	0.16	1.86	0.2310	0.442	-0.031	0.314	0.099	0.159	0.939	-313	0.010

Figure A.1: Table of all with values of the variables used for all bidding zones

B

Multivariable OLS with Stirling

Dependent variable: Price Increase

Independent Variable	**Coefficient**	**P-value**	**Std. Error**	**95% CI**
Intercept	180.11	0.000	8.84	[162.05, 198.17]
Stirling	6.99	0.0475	9.66	[-12.74, 26.71]
PEI	1.96	0.848	10.14	[-18.75, 22.67]
SP	-8.01	0.514	12.12	[-34.76, 16.74]
Share VRE	-0.24	0.981	10.44	[-21.57, 21.07]
Share DRE	**-43.23**	**0.002**	**12.80**	**[-69.37, -17.09]**
Share Gas	**22.08**	**0.038**	**10.18**	**[1.29, 44.88]**
Load Increase	1.63	0.869	9.77	[-18.32, 21.58]
		Model Fit Statistics		
Adjusted R-squared			0.45	
Probability (F-statistic)			<0.001	
No. Observations:			38	

Table B.1: OLS Regression Results with Stirling Index

C

Full Disparity Matrix

Generation Type	Biomass	ossil Brown coa	sil coal derived	Fossil gas	Fossil hard coal	Fossil oil	Fossil shale oil	Fossil peat	Geothermal	Pumped hydro
Biomass	0	0.551	0.405	0.381	0.496	0.430	0.454	0.580	0.514	0.535
Fossil Brown coal	0.551	0	0.406	0.462	0.114	0.429	0.381	0.304	0.724	0.787
Fossil coal derived ga	0.405	0.406	0	0.106	0.308	0.060	0.070	0.278	0.685	0.710
Fossil gas	0.381	0.462	0.106	0	0.375	0.085	0.172	0.362	0.678	0.678
Fossil hard coal	0.496	0.114	0.308	0.375	0	0.332	0.277	0.207	0.700	0.765
Fossil oil	0.430	0.429	0.060	0.085	0.332	0	0.101	0.286	0.708	0.724
Fossil shale oil	0.454	0.381	0.070	0.172	0.277	0.101	0	0.219	0.713	0.750
Fossil peat	0.580	0.304	0.278	0.362	0.207	0.286	0.219	0	0.790	0.860
Geothermal	0.514	0.724	0.685	0.678	0.700	0.708	0.713	0.790	0	0.187
Pumped hydro	0.535	0.787	0.710	0.678	0.765	0.724	0.750	0.860	0.187	0
Run of river	0.656	0.844	0.864	0.843	0.830	0.868	0.891	0.909	0.415	0.480
Hydro water reservoir	0.531	0.765	0.719	0.695	0.748	0.736	0.756	0.850	0.134	0.075
Marine	0.691	0.895	0.901	0.869	0.882	0.900	0.932	0.957	0.481	0.511
Nuclear	0.346	0.521	0.604	0.629	0.508	0.643	0.618	0.643	0.560	0.658
Other	0.360	0.266	0.178	0.209	0.187	0.196	0.192	0.267	0.634	0.668
Other renewables	0.499	0.764	0.710	0.674	0.742	0.717	0.750	0.830	0.234	0.212
Solar	0.721	0.927	0.937	0.900	0.919	0.934	0.971	1.000	0.521	0.530
Waste	0.159	0.427	0.408	0.405	0.392	0.436	0.441	0.516	0.513	0.560
Wind off-shore	0.692	0.888	0.910	0.880	0.880	0.911	0.941	0.964	0.470	0.502
Wind on-shore	0.703	0.901	0.920	0.888	0.893	0.920	0.952	0.977	0.488	0.512

Generation Type	Run of river	dro water reserv	Marine	Nuclear	Other	)ther renewable:	Solar	Waste	Wind off-shore	Wind on-shore
Biomass	0.656	0.531	0.691	0.346	0.360	0.499	0.721	0.159	0.692	0.703
Fossil Brown coal	0.844	0.765	0.895	0.521	0.266	0.764	0.927	0.427	0.888	0.901
Fossil coal derived ga	0.864	0.719	0.901	0.604	0.178	0.710	0.937	0.408	0.910	0.920
Fossil gas	0.843	0.695	0.869	0.629	0.209	0.674	0.900	0.405	0.880	0.888
Fossil hard coal	0.830	0.748	0.882	0.508	0.187	0.742	0.919	0.392	0.880	0.893
Fossil oil	0.868	0.736	0.900	0.643	0.196	0.717	0.934	0.436	0.911	0.920
Fossil shale oil	0.891	0.756	0.932	0.618	0.192	0.750	0.971	0.441	0.941	0.952
Fossil peat	0.909	0.850	0.957	0.643	0.267	0.830	1.000	0.516	0.964	0.977
Geothermal	0.415	0.134	0.481	0.560	0.634	0.234	0.521	0.513	0.470	0.488
Pumped hydro	0.480	0.075	0.511	0.658	0.668	0.212	0.530	0.560	0.502	0.512
Run of river	0	0.432	0.104	0.651	0.771	0.290	0.166	0.625	0.096	0.120
Hydro water reservoir	0.432	0	0.474	0.615	0.664	0.188	0.497	0.540	0.461	0.473
Marine	0.104	0.474	0	0.717	0.809	0.311	0.071	0.669	0.048	0.045
Nuclear	0.651	0.615	0.717	0	0.495	0.602	0.754	0.250	0.702	0.720
Other	0.771	0.664	0.809	0.495	0	0.643	0.842	0.299	0.812	0.823
Other renewables	0.290	0.188	0.311	0.602	0.643	0	0.334	0.508	0.308	0.317
Solar	0.166	0.497	0.071	0.754	0.842	0.334	0	0.700	0.076	0.050
Waste	0.625	0.540	0.669	0.250	0.299	0.508	0.700	0	0.664	0.677
Wind off-shore	0.096	0.461	0.048	0.702	0.812	0.308	0.076	0.664	0	0.026
Wind on-shore	0.120	0.473	0.045	0.720	0.823	0.317	0.050	0.677	0.026	0

Figure C.1: Shows the disparity value between all generation types.

D

Electricity Price Density Distributions, NO3 and Poland

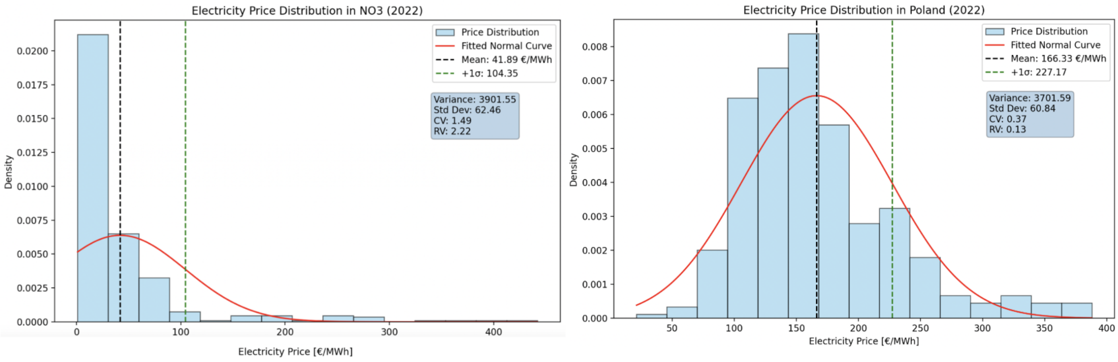

Figure D.1: Electricity Price Distribution of the 2022 price time series of NO3 and Poland.

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