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Abstract

This thesis aims to study the potential relationship between spot electricity prices and the wealth of households and companies across the Eurozone, which has not been extensively studied in the past. With the increasing importance of electricity in daily life and its role in meeting climate goals, understanding the correlation between electricity prices and wealth is crucial. The literature review shows that while there has been extensive research on the relationship between energy and GDP/industrial production, there has been no attempt to study this relationship for electricity. The thesis is divided into two parts, where the first part aims to capture the relationship between monthly electricity prices and industrial production, while the second part focuses on the relationship between monthly electricity prices and GDP. Both the industrial production and GDP show a

statistically significant correlation: the first one positive and the other negative. Lastly, we find electricity prices granger causes industrial production levels.

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1 Introduction

The aim of this thesis is to study the potential relationship between spot electricity prices and the wealth of households and companies across the Eurozone, which has not been extensively studied in the past. Given the increasing importance of electricity in daily life and its role in meeting climate goals, understanding the correlation between electricity prices and wealth is crucial.

The decision to pursue a study on this topic comes from the strong belief that, whether the outcome would be, correlation or not, it would fill a gap in the scientific world. The importance of electricity has always been growing, since its very first days.

Electricity as a vector of energy accounts for about 20% of the world's total final consumption of energy. It has a central role to many aspects of daily life and becomes more so as electricity spreads to new end-uses, such as electric vehicles

(EVs) and heat pumps. The electricity sector accounts for 59% of all the coal used globally in 2021, together with 34% of natural gas, 4% of oil, 52% of all renewables and nearly 100% of nuclear power. It also accounted for over one-third of all energy-related CO2 emissions in 2021. (IEA, 2022)

Furthermore, the call for a transaction to a more sustainable economy implies an increasing reliance on electricity. The global pressure to address climate change is straight-forward driving to the rapid electrification of numerous end-users from transport to industry, leading to a massive increase in power demand as well as the need to generate as much of it as possible from renewable sources. The result is obviously a transformation of power systems as it is nowadays. The literature has come out with the so-called Electrification of Everything (EoE). For this reason, most of the papers and studies conducted on a worldwide scale outlooks electricity as the fastest-growing source of final energy demand (IEA, 2022). The implementation of energy coming from renewable energy sources to the electricity grid can help in cutting air pollution and meet climate goals. Such a radical transformation also calls for new approaches to how the network and power grid are designed and operated. This is why now most of the investments are towards the power sector. Only a fully decarbonised electricity sector would be useful for a net zero energy system. To be consistent with the Net Zero Emissions by 2050 Scenario, which share needs to drop to 26% by 2030. The pace of deployment of low- and zero-emission sources must pick up significantly to meet this milestone. (IEA, 2022)

Since the scientific question is challenging, to gain a better understanding of the correlation, the model has been divided into two parts. The first part is aimed at capturing the relationship between monthly electricity prices and industrial production. Industrial production is thought to be a good proxy for the wealthy of enterprises. The second part has a focus on the relationship between the monthly average of electricity prices and GDP, gross domestic product as a proxy for households' wealth.

Nevertheless, that is only one side of the question. An even-more important result from this study would be the inverse relationship between the wealth, measured by the GDP or the industrial production, and the electricity prices. Which one of the variables causal the other one is crucial for many of the aspects highlighted before. Electricity prices then are obviously correlated with the demand for electricity, even if electricity is a high inelastic good, and in the state of the world we aim to be, knowing in advance the demand for electricity can improve the grid management.

Furthermore, if the correlation exists, we can try to understand also how many lags there are between an increase in prices and a change in the wealth proxies.

The sign of this correlation would be also interesting since electricity enters in the company's equation of costs as an input. We shall expect a positive correlation when companies are able to pass to customers their increase in production cost, vice versa the sign of the correlation would be negative.

The same uncertainty applies to the GDP. Electricity costs are part of the basket of goods that computes the inflation rate and higher prices mean higher profits for companies and higher taxes levied from the governments on the ground of those profits. At the same time higher prices means less savings and less income disposable for leisure activities.

Finally, we can also obtain a non-significant correlation. In the authors' opinion, this last consideration would more probably lead to a recheck of the calculus.

2 Literature review

As it has been said in the introduction, until now, there has been no tentative attempt to conduct this type of research. To have a better insight of what model we can use, we can study a wide range of researchers who analysed the relationship between energy and the GDP/ industrial production.

Electricity is just one of the commodities traded on the market. The commodity market is particularly interesting because of its mix of goods and financial assets. Ge and Tang (2020) discovered that commodity prices return can predict changes in GDP value at 1% significance level.

Surely the paramount commodity is oil: its importance has always been growing since the discovery of what products can be extracted from it. Once it has been transformed and refined, oil becomes gasoline, diesel fuel, heating oil and liquefied petroleum. The literature has devoted itself to this topic and many papers have been written about how oil shapes the economy's state.

The very first study is the one conducted by Hamilton in 1983 which concludes that an upside in oil prices is responsible for a downturn in the real GNP. Moreover, Mork, Olsen and Mysen (1994) states that “the negative correlation between oil prices and real output seems, by now, to have been accepted as an empirical fact”. Smyth and Narayan (2014) have gone through a review of what literature has published about econometrics implications for energy economies. They find a positive cointegration between energy variables and non-energy variables but there is less evidence about Granger causality. Bergmann (2019) states that his results are consistent with the literature: oil net importing countries are negatively affected by a positive jump in oil prices. His database is updated until 2016. Nonejad (2021) investigates the relationship between crude oil prices and world industrial production. He obtains poor out-of-sample results, but he argued that happens because of misspecification of control variables rather than a non-correlation between these two variables. Nonejad (2020) using the oil volatility improves the short-term prediction for GDP instead relying on the oil price. Kilian (2008) argues instead that energy prices have a little influence when it comes to studying their correlation with real GDP.

Khan et al (2020) assess that energy prices harm the US industrial production in the short run whereas in the long run the statement holds for natural gas but not for crude oil. Wen et al (2022) results show that a positive IPI (industrial production index) in the US is aligned with an extreme positive increase in prices movement in the last quarter. Moreover, the rate is not similar for positive and negative movements: a downward trend of prices has a more robust outcome. Li et al (2022) through a panel data model observes that “the US industrial electricity demand’s price responsiveness is in the mail low and diminishing over time”.

3 European regulatory frameworks

Before moving ahead with the specific model, we intend to adopt in this study we think a review of the European regulatory framework would clarify some of the facts that will be explained later.

Among the framework of law implemented on the 2019 by the EU commission known as “Clean energy package”, four of them are related with electricity issues. The new rules will bring considerable benefits for consumers, the environment, and for the economy. Only coordination between countries can achieve the challenging long-term goal of a net zero carbon emission by 2050. The legislation also underlines

EU leadership in tackling global warming.

Clean energy for all Europeans package - legislative process

	European Commission proposal	EU Inter-institutional negotiations	European Parliament adoption	Council adoption	Official Journal publication
Energy performance in buildings	30/11/2016	Political agreement	17/04/2018	14/05/2018	19/06/2018 - Directive (EU) 2018/844
Renewable energy	30/11/2016	Political agreement	13/11/2018	04/12/2018	21/12/2018 - Directive (EU) 2018/2001
Energy efficiency	30/11/2016	Political agreement	13/11/2018	04/12/2018	21/12/2018 - Directive (EU) 2018/2002
Governance of the energy union	30/11/2016	Political agreement	13/11/2018	04/12/2018	21/12/2018 - Regulation (EU) 2018/1999
Electricity regulation	30/11/2016	Political agreement	26/03/2019	22/05/2019	14/06/2019 - Regulation (EU) 2019/943
Electricity directive	30/11/2016	Political agreement	26/03/2019	22/05/2019	14/06/2019 - Directive (EU) 2019/944
Risk preparedness	30/11/2016	Political agreement	26/03/2019	22/05/2019	14/06/2019 - Regulation (EU) 2019/941
ACER	30/11/2016	Political agreement	26/03/2019	22/05/2019	14/06/2019 - Regulation (EU) 2019/942

Figure 1 - "Clean Energy Package" schedule implementation

3.1 The Electricity Directive and Electricity Regulation

The Directive on common rules for the internal market for electricity (EU) 2019/944, which replaces Electricity Directive (2009/72/EC), and the new Regulation on the internal market for electricity (EU) 2019/943, which replaces the Electricity Regulation (EC/714/2009) on January 1 2020, poses a new cap for power plants eligible to be subsidies. It also sets out rules to ensure non-discriminatory access to transmission networks and distribution systems and promotes the development of smart grids. Furthermore, the attention is drawn to the final user and its role swifts from just as a mere consumer to a prosumer.

3.2 Risk preparedness

The Regulation on risk preparedness in the electricity sector (EU) 2019/941 requires EU Member States to prepare plans for how to deal with potential future electricity crisis, and put the appropriate tools in place to prevent, prepare for and manage these situations.

The importance of this regulation needs to be strengthened because in emergency situations countries tend to focus only on themselves, exacerbating the problems and leading to a possible shutdown of electricity service in one nation. An effective management between neighbouring countries can easily solve the issues.

3.3 The Agency for the Cooperation of Energy Regulators

Acer was established under the Third energy package and it was conceived as coordinator, advisor and monitor. As the implementation of the new market rules foresee much more cross-border cooperation, the lack of regional, cross-border oversight was seen as a potential problem, with the risk of diverging decisions and unnecessary delays. Regulation (EU) 2019/942 establishing an EU Agency for the cooperation of energy regulators recasts the regulation 713/2009. ACER also has oversight on the future regional entities ("Regional Coordination Centres") where TSOs (Transmission System Operators) decide on issues related to the fragmented national actions that could negatively affect the market and consumers.

3.4 After Russia - Ukraine war

From the second half of the 2021 there has been a significant increase in the wholesale electricity prices in the euro. Experts have linked this phenomenon to shortage of LNG (liquified natural gas) due to the restart for most of the advanced economies from the covid 19 pandemic. A combination of lower gas supplies, a longer heating 2020-2021 season and unfavourable weather conditions to produce renewable energy contributed to further strains. To a lesser extent, an increased carbon price under the Emissions Trading System (ETS) also contributed to the adverse market situation.

In addition, the invasion of Ukraine by Russia and the deliberate use of Russian gas as a diplomatic weapon, the energy crisis has exacerbated even more and the prices for European citizens have reached their peak, energy prices rose for about 20% in the next five months which is thought to be related to the embargo posed on Russian supply of oil. The Commission proposed several actions and measures to address the problem, phase out the EU's dependency on Russian fossil fuels and help EU countries and citizens tackle the rising prices.

The Commission published on 8 March 2022 the 'REPowerEU: Joint EU action for more affordable, secure and sustainable energy'. It states the EU's intention to phase out its dependency on Russian fossil fuels. On the ground of the European Green Deal proposals, the plan puts forward an additional set of actions to save energy, diversify supplies and replace fossil fuels by accelerating the implementation of renewable energy. Increasing energy savings and efficiency and scaling up renewables are expected to alleviate the pressure on energy prices, while boosting the green transition in the EU.

The new Gas Storage Regulation ((EU) 2022/1032) was agreed by the co-legislators on 27 June 2022 and requires EU countries to fill gas storage facilities to 80% by 1 November and to 90% the years to follow. On 20 July 2022, the Commission proposed new rules on coordinated demand reduction measures for gas, together with the Communication "Save gas for a safe winter" (COM/2022/361). The new Regulation on coordinated demand-reduction measures for gas ((EU) 2022/1369) entered into force on 9 August after adoption on 5 August by the Council.

On 14 September 2022, the Commission proposed a new Regulation to address high energy prices and prevent European citizens and businesses from paying enormous bills. The Commission proposes to set a cap for producers to €180/MWh. Another measure is a temporary solidarity contribution. EU countries would collect excess profits made in 2022 in the oil, gas, coal and refinery sectors and use this amount of money to relieve energy consumers. The Regulation on an emergency intervention to address high energy prices (EU 2022/1854) was adopted on 6 October 2022.

4 European Market

To attain a comprehensive understanding of the formation of electricity prices and other potential implications relevant to this paper, an examination of the European electricity market is warranted.

The market for electricity in Europe comprises various stakeholders, similar to other markets. It is segmented into four distinct stages, namely, production, dispatching, distribution, and retailing. The supply chain is a mixture of free-market and monopoly dynamics. For example, transmission and distribution are characterised by monopolies, as it would be inefficient to have more than one company operating in these stages. In this study, we shall concentrate exclusively on the wholesale market and its outcomes. In the wholesale market, producers compete to produce electricity at the lowest possible cost from diverse energy sources available in nature.

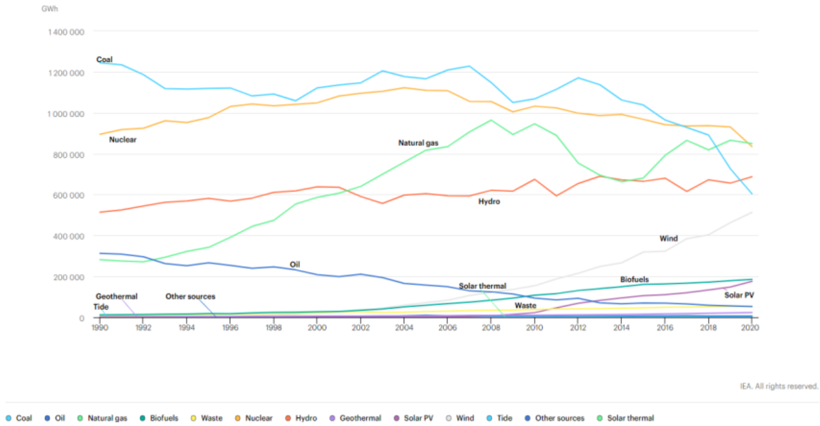


Figure 2 - Share of production of electricity per source in Europe

4.1 Spot market

In the wholesale market, producers compete to generate electricity at the lowest possible cost from various energy sources available in nature. Once the electricity is produced, and the offers, quantities, and prices are submitted along with the demand, the clearing market price is determined. National power exchanges (PXs) construct the demand and offer curve, with bidders submitting the maximum quantities they are willing to sell at the minimum price, while buyers indicate their minimum desired purchase quantity at the maximum price. The offers are then combined hourly, yielding a single hourly price at which every buyer can purchase electricity and every seller is rewarded. This price is the same for all players in the market and equals the maximum offer required to satisfy all demand.

A second important feature of the electricity market is the construction of the offer curve. Each bidder has a different cost curve, depending on the plants used to generate electricity. Plants that rely on non-renewable energy sources, such as coal and natural gas, have a higher marginal price that includes the cost of the underlying commodity and the cost of transformation. In contrast, renewables have a marginal cost of zero. The merit order curve or the offer curve, starting from the cheapest offer to the most expensive one, is constructed in this manner, leading to the phasing-out of the most expensive plants. This also incentivizes producers to rely less on non-renewable resources, as electricity generated from coal or gas-based plants is more costly than that produced from renewable sources. When renewable energy plants are installed, the marginal cost is zero, and bidders with electricity produced from renewable energy sources are more likely to offer lower prices. However, solar plants and windmills are not operational throughout the day, and thus the base load typically comes from non-renewable sources such as combined cycle and thermal plants. A general consensus on the marginal market as the most efficient one is widely accepted; in fact, it has been used by most of the European countries before being stated in law.

4.2 Long term contracts

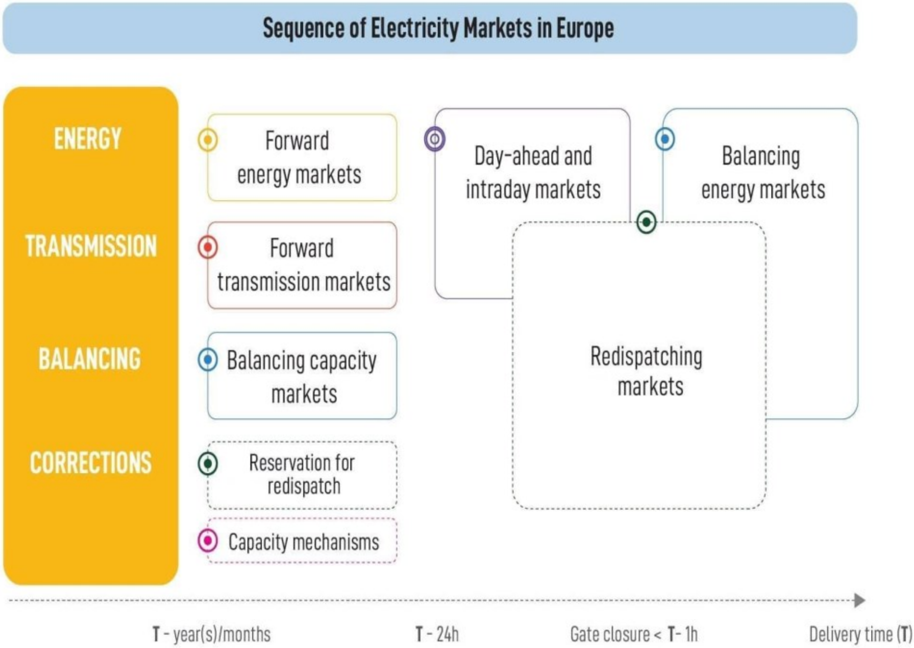
Although often considered a mere mechanism for adjusting long-term contracts, the day-ahead market plays a crucial role in the electricity market. In fact, the majority of electricity quantities are exchanged in this market, and long-term contracts are priced based on day-ahead market outcomes. To manage the volatility of the day-ahead market, market players use a range of hedging instruments, including long-term markets such as forward energy markets and forward transmission markets, as well as capacity mechanisms.

Forward energy markets cover a period from nine years up to one day before delivery. The trade is based using standardised products, or parties can make bilateral agreement over the counter (OTC) deals. The negotiated energy prices are denominated per bidding zone.

Member States can also set up capacity mechanisms if they are deemed necessary for ensuring adequate supply. Typically organised by the Transmission System Operator, capacity procurement begins approximately four years before delivery. Capacity mechanisms are temporary support measures that EU countries can introduce to remunerate power plants for medium and long-term security of electricity supply. To ensure that supply and demand are balanced in real-time and avoid any potential shortfalls in electricity service, the electricity market relies on balancing mechanisms. The transmission system operator of each country handles the real-time balance in its control area. Balancing markets consist of balancing capacity markets and balancing energy markets. In balancing capacity markets, contracted Balancing Service Providers (BSPs) receive an availability payment, and the volume of electricity exchanged is based on real-time imbalances.

The last stage available for market correction is the redispatch and it is useful when the market outcome results in generation and consumption schedules that would lead to a potential violation of operational limits (e.g., thermal limits, voltage ranges, etc.) of a certain network element within a bidding zone. It is not rare that this situation happens, as usually transmission network elements within a bidding zone are not considered when trading in wholesale markets, only the physical limits of network elements between bidding zones are considered (so-called zonal pricing). Typically, re-dispatch involves increasing or decreasing the output of a generator at the ends of a potentially

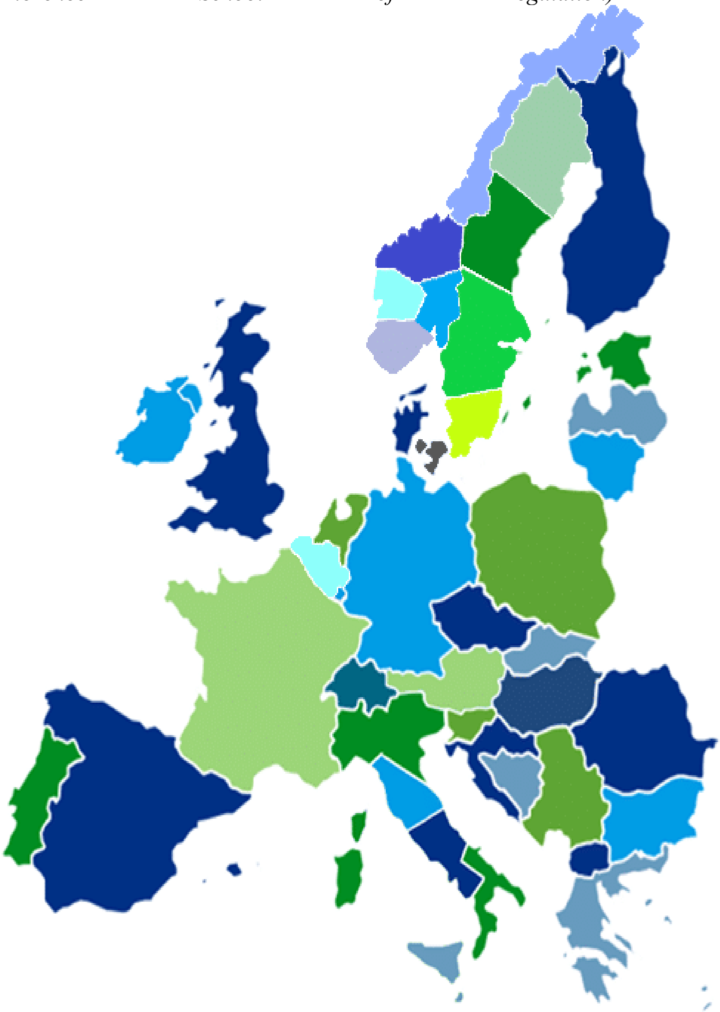
Figure 3 - The evolution of electricity markets in Europe



Leonardo Meeus, 2020. The Evolution of Electricity Markets in Europe. Book published by Edward Elgar

congested line.

Figure 4 - The bidding zone configuration in September 2020 (Florence School of regulation)



4.3 Price Coupling of Regions

Price Coupling of Regions (PCR) is the project of European Power Exchanges to develop a single price coupling solution to be used to calculate electricity prices across Europe considering obviously all the constraints of the network elements on a day-ahead basis. This goal is vital if the EU wants to achieve the target of a convergence in the European electricity market. The integrated European electricity market is expected to increase availability of electricity, efficiency, and social welfare (i.e., an equal input cost for all the European companies would benefit the consumers and accelerate the free competition between players in the same industry).

PCR is based on three main characteristics: a single algorithm, robust operation and individual power exchange accountability.

- The common algorithm gives a fair and transparent determination of day-ahead electricity prices and a net position of a bidding area across Europe. The algorithm is developed respecting the specific features of the various power markets across Europe and the electricity network constraints. It optimises the overall welfare and increases transparency.

- The PCR process is based on decentralised sharing of data, providing a robust and resilient operation.
- The PCR Matcher and Broker service enables exchange of anonymised orders and electricity network constraints among the power exchanges to calculate bidding zone prices and other reference prices and net positions of all included bidding areas.

A crucial element of the PCR project is the development of a single price coupling algorithm, which goes by the name of EUPHEMIA (Pan-European Hybrid Electricity

Market Integration Algorithm). The outcome of the algorithm would be the energy allocation, net positions and electricity prices across Europe, maximizing the overall welfare.

4.4 Electricity's properties

Electricity is a commodity, just as copper, oil and grain are. However, electricity markets differ substantially from other commodity markets. This is due to the physical characteristics of electricity:

- *Time*: large volumes of electricity cannot be stored economically (yet). Therefore, electricity has a different value over time.

- *Location*: electricity flows cannot be controlled easily and efficiently, and transmission components must be run under safe flow limits. If not, there is a risk of cascading failures and blackouts. Therefore, electricity has a different value over space.

- *Flexibility*: demand and generation must always match each other; otherwise, there is a risk of blackout. However, demand and the availability of renewable energy resources can vary sharply over time, while some power stations can only change output slowly and can take many hours to start up. Also, power stations can fail suddenly. Therefore, the ability to change the generation/consumption of electricity at short notice has a value.

The inherent characteristics of the electricity market result in prices that are more volatile and subject to greater fluctuations than other commodities or financial assets. However, the increasing awareness of the need for sustainability has led to a rise in the proportion of electricity generated from renewable sources, prompting concerns about the impact on prices.

The intermittent nature of renewable sources, such as solar and wind, can limit their availability when demand is high, which is considered a significant disadvantage when compared to more reliable non-renewable sources. On the other hand, incorporating renewables into the energy mix has the potential to lower the marginal price, given their zero marginal cost. This phenomenon has been extensively studied, with research indicating that the inclusion of renewables in markets utilising a merit order dispatch system result in lower prices.

According to Ballester and Furio(2015), the impact of renewables has also the consequences of a higher frequency on jumps as well as increase in price volatility. They conducted a study in the Spanish electricity market from 2002 to 2009 and they confirm the intermittency of renewables is transferred to prices. A similar study has been conducted to the Italian market by Clò, Cataldi and Zoppoli (2014). Their conclusions are the same: an increase of 1 GWh in the hourly average of daily production from solar and wind sources has, on average, reduced wholesale electricity prices by respectively 2.3 euro/MWh and 4.2 euro/MWh. However, Italy implemented one of the most generous supporting schemes and authors find that the reduction in prices is not sufficient to compensate for money expended on the scheme. The same conclusion is drawn by Paraschiv, Erni and Pietsch (2014). They study the impact of renewables on the EEX spot market. The reduction in prices is significant however the feed-in scheme tariffs for the promotion of renewables outweighed the reduction in electricity cost.

Sensful, Ragwitz and Genoese (2008) analysed the impact of renewables on the German spot market through PowerAce Cluster System, a market simulator platform. The outcome given by the platform indicates that the financial volume of the price reduction is high.

The intrinsic properties of the electricity spot prices lead also to the impossibility to capture all their behaviour using financial econometrics variables. For instance Guthrie and Videbeck (2007) analysing the New Zealand spot market found that half hourly trading periods fall naturally into five groups corresponding to the overnight off peak, the morning peak, daytime off peak, evening peak and evening off time peak. Prices within each group are highly correlated but less correlation between distinct groups.

5 Models

The present study focuses on European countries, while some countries were not included in the analysis due to several reasons. For instance, Portugal was excluded since it has similar electricity prices as Spain, and Northern countries have a zonal pricing system that makes it challenging to compute national prices. However, Switzerland, although outside the euro area, was included in the investigation since it shares the same electricity exchange platform with France and Germany, and its economy is strongly correlated with its neighbouring countries.

To examine the relationship, analysis with pooled OLS is used for both models, with most variables being common but with different time intervals. Specifically, the industrial production model was conducted monthly, while the GDP model was conducted quarterly. Nevertheless, due to a lack of business confidence data for

Switzerland in both models, the panel is not balanced.

Furthermore, a bidirectional Granger-causality test has been conducted on both models to test if electricity prices do have a granger-causality on industrial production or gross domestic product.

5.1 Industrial production model

The relationship between production and electricity prices has been investigated using the following model:

$$indpro_{c,t} = \beta_1 logelprice_{c,t} + \beta_2 load_{c,t} + \beta_3 gas_{c,t} + \beta_4 euro50_{c,t} + \beta_5 infl_{c,t} + \beta_6 ETS_{c,t} + \beta_7 busconf_{c,t} + \theta_1 covid + \varepsilon i_{c,t}$$

The dependent variable, *indprod*, represents monthly industrial production, while the independent variables include *elprice*, which denotes monthly electricity prices, *load*, representing monthly electricity load, *gas*, indicating gas prices, *ETS*, referring to emission allowances prices, *infl*, representing the inflation rate, *euro50*, denoting the index for the fifty most capitalised firms in the Eurozone stock market, and *busconf*, representing the business confidence index. Additionally, $\theta covid$ is a binary variable that takes the value 1 for the period preceding the spread of the Covid-19 pandemic, with March 2020 serving as the reference date. Every variable is then specified according to the country (*c*) and the month (*t*). The errors εi are assumed to be independent and identically distributed (ε ~ IID(0, $\sigma_\varepsilon{}^2$)).

In light of the extensive dataset utilized in this thesis, a division of the findings into three distinct panels, namely A, B, and C, is employed for the purpose of facilitating a more streamlined presentation of the data. Panel A encompasses the entirety of the available data, whereas panel B specifically pertains to the data preceding the outbreak of the COVID-19 pandemic.

Conversely, panel C exclusively focuses on the data collected during the COVID-19 period, denoted by the dummy variable $\theta covid$ being assigned a value of zero.

In this study, we employ a linear-log model to investigate the relationship between the aforementioned variables. The use of a linear-log model is preferred for several reasons. Firstly, this type of model can manage data that are highly skewed or have a wide range of values. In particular, the electricity prices variable in our dataset exhibits an upward trend over the considered period, and extreme values occur more frequently than usual. By taking the logarithm of this variable, we can normalise its distribution and reduce the impact of extreme values. Secondly, the coefficients in a linear-log model have an interpretable elasticity interpretation, where the coefficient on the logarithmic variable represents the percentage change in the outcome variable associated with a one percent change in the predictor variable. This provides a more meaningful way to interpret the results compared to the coefficients in a standard linear model, which represent the change in the outcome variable associated with a one-unit change in the predictor variable.

5.2 Gross Domestic Product model

Here the model we adopt for GDP:

$$loggdp_{c,q} = \beta_1 logelprice_{c,q} + + \beta_2 laglogelprice_{c,q} + \beta_3 loggas_{c,q} + \beta_4 logeuro50_{c,q} + \beta_5 loginfl_{c,q} + \beta_6 logETS_{c,q} + \beta_7 logbusconf_{c,q} + \theta covid + \varepsilon i_{c,q}$$

The current study investigates the relationship between the quarterly logarithmic value of gross domestic production (*loggdp*) and several independent variables, including quarterly electricity prices *(logelprice*) and its lag ($laglogelprice$), gas price (*loggas*), emission allowances price (*logETS*), inflation rate (*loginfl*), the index for fifty most capitalised firms in the eurozone stock's market (*logeuro50*), and business confidence index (*logbusconf*). We incorporate a dummy variable, $\theta covid$, which takes the value of one for the period before the spread of the Covid-19 pandemic (with March 2020 serving as the reference date).

Every variable is then specified according to the country (*c*) and the quarter (*q*). The errors εi are assumed to be independent and identically distributed (ε ~ IID(0, ${\sigma_\varepsilon}^2$)).

To enhance comprehension of the obtained results, the findings will be systematically categorized into three panels. Panel A encompasses the entirety of the available dataset, thereby providing a comprehensive overview. Panel B extends this analysis by incorporating the lag value of logarithmic quarterly electricity prices, which allows for a more nuanced examination of the data. Lastly, Panel C exclusively considers data preceding the onset of the COVID-19 pandemic, thus affording insights into the pre-pandemic dynamics and serving as a benchmark for comparative analysis.

A log-log model is employed for several reasons. Firstly, taking the logarithm of both variables enables transformation of the data into a more normal distribution, thereby enhancing the model's robustness to outliers and minimising the impact of extreme values. Furthermore, the upward trend of GDP over the examined time span necessitates the utilisation of the logarithmic value to establish a stationary frame. Secondly, the coefficients in a log-log model represent elasticities, indicating the percentage change in the dependent variable associated with a one percent change in the independent variable. This enables a more meaningful interpretation of the results compared to coefficients in a standard linear model, which represent the change in the dependent variable associated with a one-unit change in the independent variable. Finally, a log-log model can uncover non-linear relationships between the variables, which may apply to the relationship between GDP and electricity prices.

6 Data

As done in the previous section, we first analyse the model concerning industrial production and subsequently the one regarding GDP. To gain a more comprehensive understanding of the variables' trend, we employ descriptive statistics, including correlation coefficients, stationary tests, and structural break tests.

6.1 Industrial production model

The dataset used for this model comprises 1536 observations, consisting of 96 temporal observations spanning from January 2015 to December 2022 for 16 countries, namely Austria, Estonia, Germany, Greece, Hungary, Italy, France, Slovenia, Slovakia, Latvia, Lithuania, Switzerland, Netherlands, Belgium, Spain, and Czech Republic. To ease analysis, a second dataset was developed from the original one. The new dataset consists of 96 observations (number of months) and was constructed by computing the average of the different values for each variable across all countries.

Monthly Electricity Prices

The explanatory variable used in the model is the electricity prices, which were obtained from hourly spot prices available on ENTSO-E[1]. To ensure that the independent variable had the same temporal lag as the dependent variable, the raw data were processed. Specifically, the hourly spot prices were multiplied by the hourly load and divided by the total daily load. This computation was repeated again until the final weighted monthly prices were obtained (daily prices were multiplied by the daily load and divided by the total monthly load). The resulting dataset covers the period from January 2015 to

[1] ENTSO-E is the European association for the cooperation of transmission system operators (TSOs) for electricity.

December 2022 and has a unit measure of euro/MWh. For constructing a graph, the weighted average monthly prices across the sample countries were computed. The graph indicates a significant increase in electricity prices over the last year and a half in contrast to the period from 2015 to 2018, during which prices remained low.

For this model, the hourly spot prices ρ_{h} have been multiplied by the hourly load η_{h} and then divided by the total daily load $\Sigma_{\mathrm{d}}\eta_{\mathrm{h}}$. The computation has been repeated until final weighted monthly prices ρ_{m} was calculated. [2]

[2] h stands for hourly price/load, d for daily and m for monthly.

$$\left(\frac{\Sigma d(\rho h \times \eta h)}{\Sigma d \eta_h}\right) = p_d \quad =>$$

$$\left(\frac{\Sigma m(\rho d \times \eta d)}{\Sigma m \eta_d}\right) = p_m$$

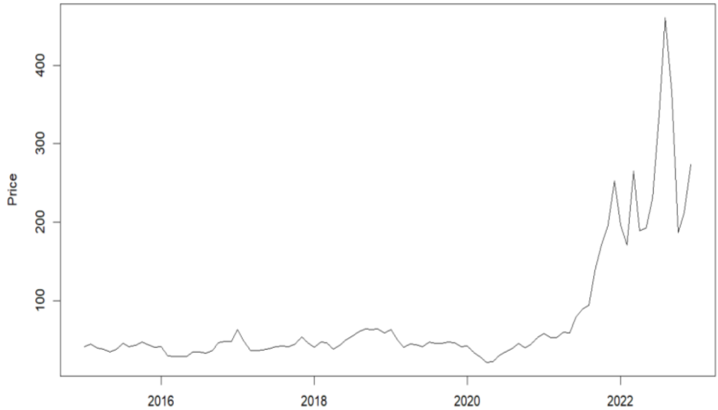


Figure 5 - Time series plot of monthly electricity prices

Industrial production

Industrial production is in this model the dependent variable and it is intended as a proxy for the wealth of enterprises. Industrial production is a monthly value, and it is a volume index for production with 2015 as reference year equals to 100. The data are available on Eurostat[3]. Data is not adjusted for seasonality nor calendar. Here is the plot of Industrial productions' levels from January 2015 to December 2022. We can see a lot of volatility in the sample: industrial production is affected surely by seasonality. It is clear also the significant drop in April 2020 when factories were shut down.

---

[3] Eurostat is the statistical office of the European Union.

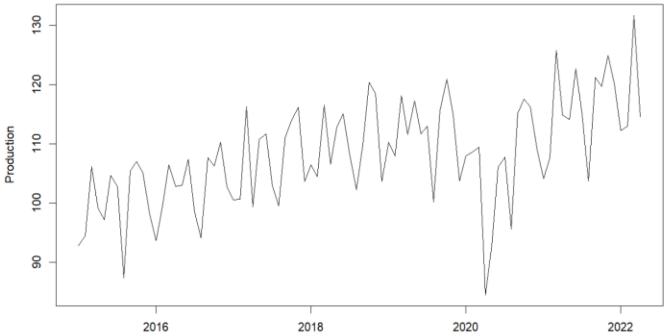
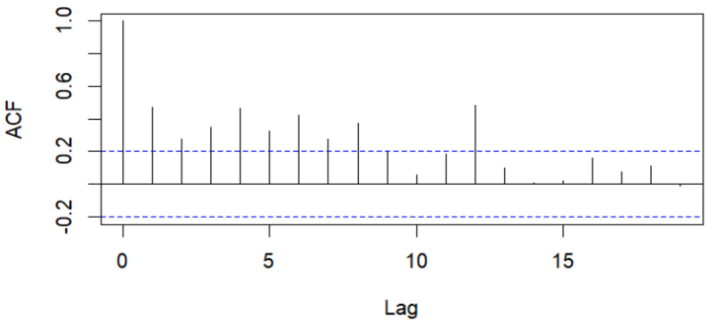


Figure 6 - Time series plot of monthly industrial production values

Stationary

If we recall the plot of industrial production, we can see there is a little upward trend until 2019, in 2020 Covid hits production and then the following two years a recovery to the past values.

Figure 7 - Autocorrelation function plot of monthly industrial production values



Moreover, from the ACF plot we see industrial production has many significant lags of autocorrelation.

Stationarity means that a time series has a constant mean and constant variance over time. Although not particularly important for the estimation of parameters of econometric models these features are essential for the calculation of reliable test statistics and, hence, can have a significant impact on model selection.

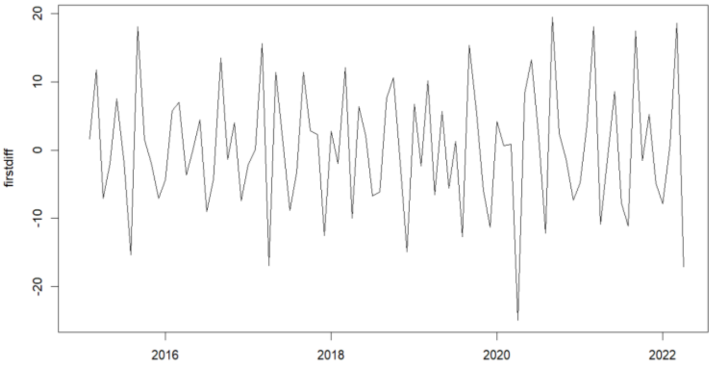


Figure 8 - Time series plot of difference between monthly industrial production and its first lag

```
###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression trend


Call:
lm(formula = z.diff ~ z.lag.1 + 1 + tt + z.diff.lag)

Residuals:
     Min       1Q   Median       3Q      Max 
-27.6163  -4.2298   0.1345   5.6059  15.2697 

Coefficients:
            Estimate Std. Error t value Pr(>|t|)    
(Intercept) 93.57507   13.34987   7.009 4.25e-10 ***
z.lag.1     -0.93379    0.13332  -7.004 4.35e-10 ***
tt           0.17732    0.03766   4.709 9.00e-06 ***
z.diff.lag   0.13012    0.10426   1.248    0.215    
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 '

Residual standard error: 7.089 on 90 degrees of freedom
Multiple R-squared:  0.4251,    Adjusted R-squared:  0.4059
F-statistic: 22.18 on 3 and 90 DF,  p-value: 7.673e-11


Value of test-statistic is: -7.0042 16.4407 24.5622 

Critical values for test statistics: 
      1pct  5pct 10pct
tau3 -4.04 -3.45 -3.15
phi2  6.50  4.88  4.16
phi3  8.73  6.49  5.47
```

We select the ’trend’ option in R code because, looking at the figure, it seems to be a positive trend over time. The appropriate number of lags, however, was selected by the test itself with the ‘Selectbics’ option.

For all the reasons outlined before an Augmented Dickey-Fuller test has been conducted on our dependent variable. Since the t-test is lower than the critical value ($-7.0042 < -4.04$) and the p-value < 0.05; we can reject null hypothesis (HO), i.e., time series does not have a unit root, meaning it is stationary. It does not have a time-dependent structure.

Correlation Among Variables

The correlogram outlined below helps us to detect perfect or imperfect multicollinearity.

	indpro	elprice	load	gas	busconf	infl	ETS	euro50
indpro	1.000	0.474	0.025	0.445	0.339	0.586	0.592	0.479
elprice	0.474	1.000	-0.092	0.960	0.132	0.860	0.826	0.439
load	0.025	-0.092	1.000	-0.155	0.231	-0.228	-0.134	0.057
gas	0.445	0.960	-0.155	1.000	0.164	0.829	0.796	0.414
busconf	0.339	0.132	0.231	0.164	1.000	-0.012	0.148	0.443
infl	0.586	0.860	-0.228	0.829	-0.012	1.000	0.926	0.475
ETS	0.592	0.826	-0.134	0.796	0.148	0.926	1.000	0.641
euro50	0.479	0.439	0.057	0.414	0.443	0.475	0.641	1.000

Figure 9 - Correlogram among industrial production model's variables

The correlation coefficient between *elprice* and *indpro* is 0.474, a positive correlation but not so high. Indpro is positively but not so strongly correlated with all the variables. Instead, the correlation between *gas* and *elprice* is very high (0.960) as we expected. Also, *infl* and *ETS* both have a high positive correlation with *elprice*. *busconf* presents low correlation coefficients with other variables and correlation between *busconf* and *infl* is the only negative coefficient of the table.

6.2 Gross Domestic Product model

The dataset for this model is made of 227 observations and only four countries are part of the sample (Italy, Germany, France and Switzerland). The reason behind this choice is that these are the biggest central European countries. For Germany, Italy and Switzerland the temporal length is similar with 2007 quarter three as starting point, instead data for France are from 2013 quarter one. Since the hourly load is not available for years before 2015, the simple average has been used. In this equation the temporal lag is quarterly, so we have four data per year. Data for electricity prices is from ENTSO-E while for GDP is downloaded from Eurostat. GDP is expressed in millions of euros and is not adjusted for seasonality nor for calendar.

Quarterly prices

The independent variable is quarterly electricity prices, which were obtained from hourly spot prices calculated by power exchanges in various European countries. First, daily prices have been computed just averaging hourly spot electricity prices, then from daily ones we obtained monthly electricity prices and finally quarterly prices. The resulting dataset covers the period from Q3 2007 to Q4 2022 and has a unit measure of euro/MWh. Here the plot of quarterly electricity prices from the third quarter of 2007 to the last quarter of 2022. Once again, we can appreciate the skyrocketing increase after the Covid-19 pandemic.

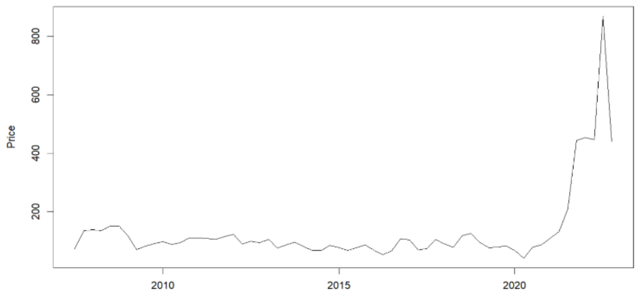


Figure 10 - Time series plot of quarterly electricity prices

Gross Domestic Products

GDP is in this model the dependent variable and it is intended as a proxy for the wealth of households. Gross domestic product is quarterly value, and it is a volume index for production. The data are available on Eurostat. Data is not adjusted for seasonality nor calendar. A clear upward trend is visible from the graph below as long as the drop consequently the spread of covid-19.

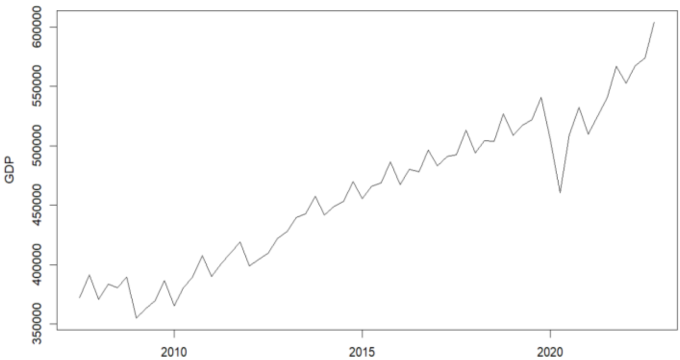


Figure 11 - Time series plot of quarterly GDP values

Stationary

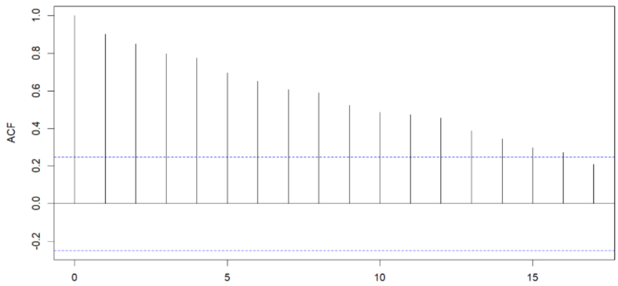


Figure 12 - Autocorrelation function plot of quarterly GDP values

Both the plot of Gross domestic production over the year and its ACF plot suggest us to check for stationary trough Augmented Dickey-Fuller test.

This is the plot of the quarterly difference between GDP and GDP_{-1}.

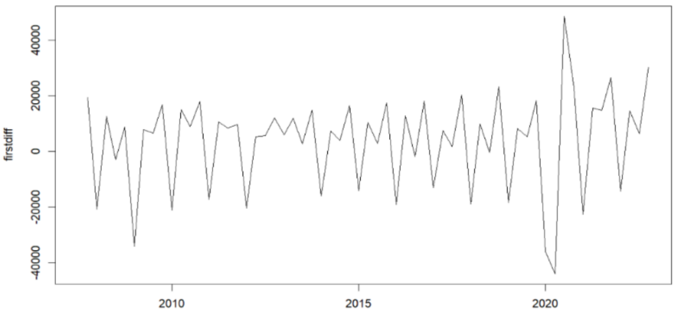


Figure 13 - Time series plot of difference between quarterly GDP values and its first lag

```
###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression trend


Call:
lm(formula = z.diff ~ z.lag.1 + 1 + tt + z.diff.lag)

Residuals:
   Min     1Q Median     3Q    Max 
-62684  -7350   2024   7943  32655 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  1.975e+05  5.328e+04   3.708 0.000481 ***
z.lag.1     -5.594e-01  1.506e-01  -3.715 0.000470 ***
tt           1.987e+03  5.090e+02   3.905 0.000256 ***
z.diff.lag  -5.333e-02  1.366e-01  -0.390 0.697716    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 14980 on 56 degrees of freedom
Multiple R-squared:  0.2977,    Adjusted R-squared:  0.2601 
F-statistic: 7.913 on 3 and 56 DF,  p-value: 0.000173


Value of test-statistic is: -3.7152 6.9881 7.7164 

Critical values for test statistics: 
      1pct  5pct 10pct
tau3 -4.04 -3.45 -3.15
phi2  6.50  4.88  4.16
phi3  8.73  6.49  5.47
```

Based on the results we get we fail to reject the null hypothesis. The p value is lower than 5% and the test is greater than the critical value: data is not stationary and there is evidence of a trend.

Correlation Among Variables

	gdp	elprice	gas	infl	busconf	euro50	ETS
gdp	1.000	0.464	0.477	0.920	0.425	0.547	0.645
elprice	0.464	1.000	0.922	0.661	0.216	0.264	0.769
gas	0.477	0.922	1.000	0.678	0.314	0.278	0.782
infl	0.920	0.661	0.678	1.000	0.356	0.427	0.788
busconf	0.425	0.216	0.314	0.356	1.000	0.622	0.267
euro50	0.547	0.264	0.278	0.427	0.622	1.000	0.431
ETS	0.645	0.769	0.782	0.788	0.267	0.431	1.000

Figure 14 - Correlogram among GDP model's variables

The correlation coefficient between Gross Domestic Product and electricity prices is positive but not so high: once one variable increases the other one will follow the increase but not with the same magnitude. GDP is highly correlated with inflation, even though for a large part of the sample we did not observe significant inflation in these countries the correlation is still positive. In this model, as the one before, electricity prices are highly correlated with Gas price. All the signs of the table are positive.

6.3 Control Variables

To validate the robustness of the correlation derived from ordinary least squares (OLS) analysis, additional control variables have been incorporated into both models to mitigate the potential influence of omitted variables. The selection of control variables was determined by a combination of empirical and subjective criteria. For consistency with the time frame of the dependent variable, the control variables in the initial model were measured monthly, as opposed to quarterly measurements in the GDP model.

Load

Electricity load refers to the amount of electricity consumed. The term "load" is used to describe the demand for electricity that is placed on the electrical grid. Below we have plotted the monthly electricity load from January 2015 to December 2022. We can appreciate the seasonality of the load: during winter times the demand is higher (heating), during spring or autumn it is minimised with a little peak during summer (cooling). We can also observe the big drop in March 2020 due to the shutdown of factories due to Covid-19. Data is downloaded from ENTSO - E and is expressed in MWh.

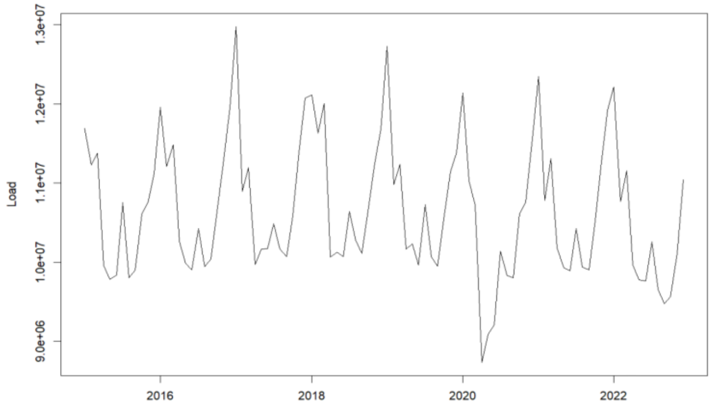
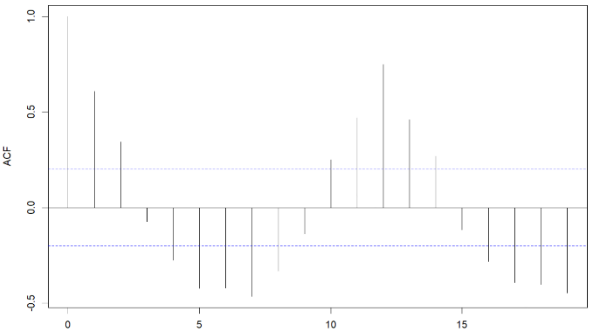


Figure 15 - Time series plot of monthly load

Figure 16 - Autocorrelation function plot of monthly load



Ets

ETS is the acronym for emission trading scheme. The EU ETS is one of the weapons the EU's countries have implemented to combat climate change and reduce greenhouse gas emissions cost-effectively. ETS provides a cap dictating the amount of greenhouse gas a firm can emit. Under this principle maximum kilos of gas are setted to be emitted in the atmosphere and all the willing participants must trade in the market to buy the right to pollute. EU Allowances for emissions were allocated for free when this scheme was conceived, and subsequently were traded. Firms must monitor and report their CO2 emissions, ensuring they possess enough rights to the authorities to cover their emissions. If emission exceeds their allowances, they must buy in the market this right. Vice versa, if an installation was able to reduce its emissions, it can sell its leftovers. Daskalikis, Psychoyios and Markellos (2009) investigates the behaviour of ETS prices: “a horse race amongst popular continuous time processes showed that spot prices are better approximated by a Geometric Brownian motion augmented by jumps". This mechanism allows the system to find the most cost-effective ways of reducing emissions without significant government intervention. Year by year the total number of allowances are reduced from 2021 by a 2.2% rate, accelerating the trend on the previous period 1.74%. The reduction rate was set in accordance with the 2030 target of at least 40% cuts in EU greenhouse gas emissions.

Yet, some critics have been moved to EU ETS. When this scheme was initially conceived in 2005, permissions were allocated for free rewarding enterprises with a possible source of revenue. Secondly, the member states over allocated allowances and caused the price fall, significantly reducing the impact ETS should have had. According to Bublitz et al (2017) the main factor in the reduction in electricity prices between 2011 and 2015 is due not to the increase of renewables but to a drop in coal and carbon emissions prices.

A study conducted by Borghesi, Cainelli, Mazzanti (2015) investigates the link between EU ETS and the push for environmental innovation through a survey among the Italian manufacturing industry. They find a negative correlation between policy stringency and innovation, but they argue that happens because policy was discussed time ahead before its implementation. Furthermore, the costs for ETS are considered when corporate decisions are made (Hoffmann, 2007).

The plot shows the price's trend of allowances since 2015. Data was collected from Bloomberg L.P.[4], and it is expressed in euros.

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[4] Bloomberg L.P. provides financial software tools and enterprise applications such as analytics and equity trading platform, data services, and news to financial companies and organizations.

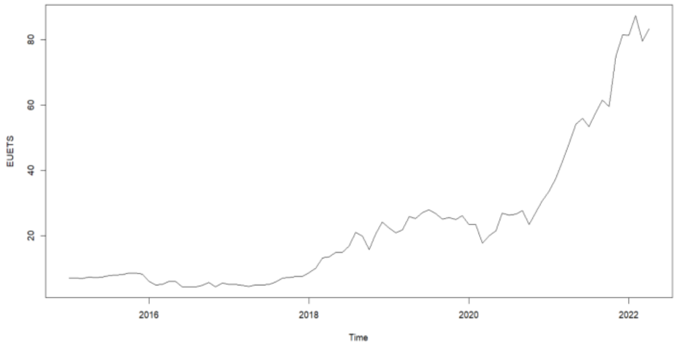
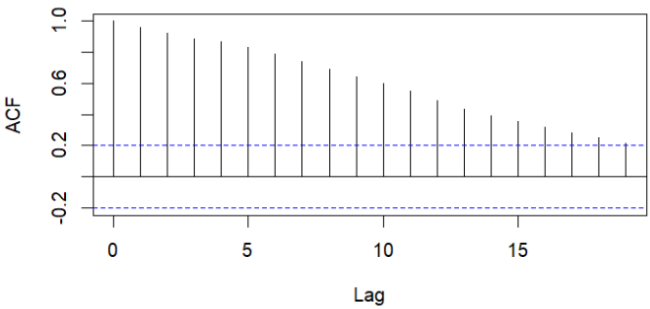


Figure 17 - Time series plot of monthly EU ETS

Figure 18 - Autocorrelation function plot of monthly EU ETS



Business confidence

Business confidence is a monthly index available on Eurostat. We considered it appropriate for this study because we intend to use it as a measure of expectation. An increase in business confidence would probably lead to a subsequent increase in employment, strengthening the production for industries and the income for workers. Vice versa, if there is the perception of a downside of the economy, employees are more likely to lay off their workers, diminishing the investment and the production, the outcome would be a shrink in industrial production and a less or negative GDP growth in the following years.

The data is available from Eurostat and each country has its own monthly observation. It is a balanced unadjusted dataset (i.e., neither seasonally adjusted nor calendar adjusted data). The drop in April 2020 is clear.

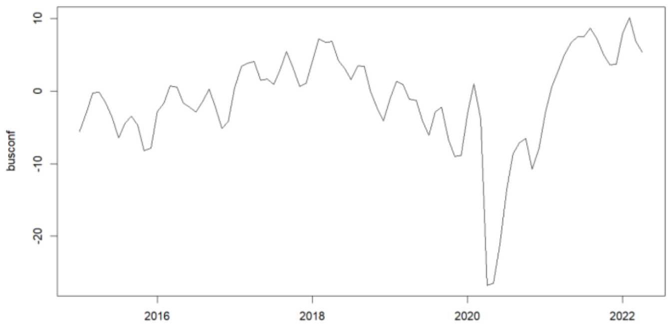
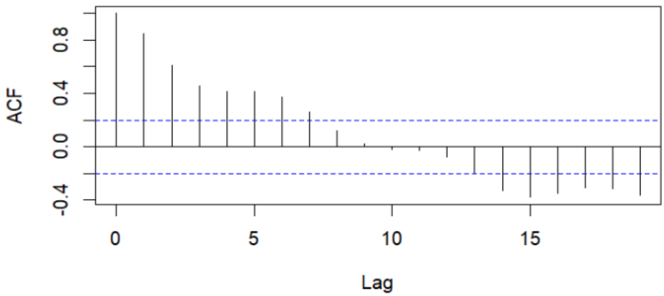


Figure 19 - Time series plot of monthly business confidence values

Figure 20 - Autocorrelation function plot of monthly business confidence values

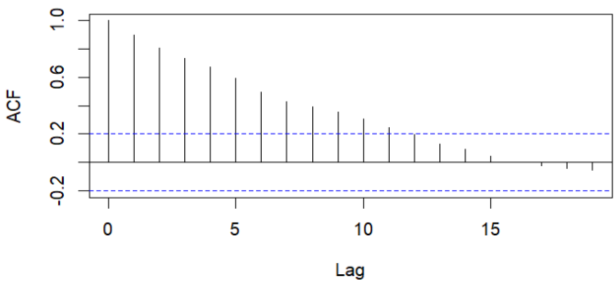


Gas price

Electricity powers our houses and our businesses but it is not unfortunately available in nature. Electricity is instead a vector to transport energy. There are obviously many sources for electricity but the one which account for 20% of the electricity production in the EU(IEA) is gas and it's the primary electricity's source and future prices on the electricity market are mainly driven by gas and coal prices (Mosquera-Lopez and Nursimulu, 2019). The most innovative and recent plants can transform 7.36 cubic feet of natural gas into 1 kWh (US *Electric Power Annual*, November 2022).

We know there are other sources which still influence electricity prices, i.e. coal or renewables. We decided to incorporate only gas because the first one is gradually phasing out due to legislation requirements. Secondly, the basket of renewables is priced at zero marginal cost thus reducing the spot price but since their rate in the production is not constant over the time (seasonality and daily) we prefer not to include them.

The plot shows the trend of 1 month's future TTF price. Title Transfer Facility is a virtual hub for gas trading based in the Netherlands and it serves as a benchmark for all the European gas companies, for that reason all countries have the same value in respect to the date. The unit measure is euro per megawatt hour. Data is from Bloomberg L.P.. There has been a huge increase in its price following the recovery from Covid-19 pandemic.



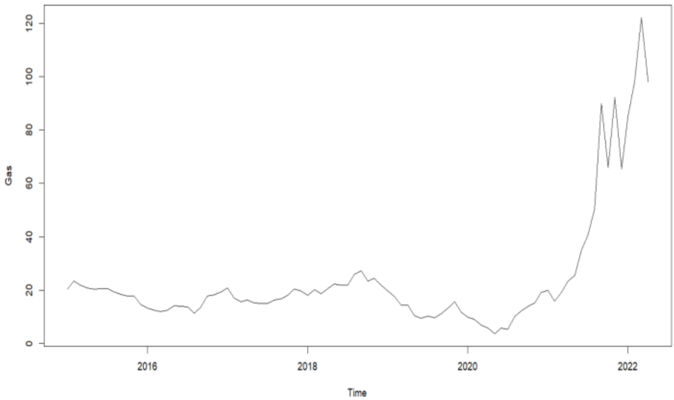


Figure 21 - Time series plot of monthly gas price

Figure 22 - Autocorrelation function plot of monthly gas price

Euro 50 Stoxx

We also include in the regression the average monthly stock's value for the fifty most capitalised European companies. Data is from Bloomberg L.P.. The EURO STOXX 50 is a stock index of Eurozone stocks designed by STOXX, an index provider owned by Deutsche Börse Group. The index is composed of 50 stocks from 11 countries in the Eurozone. EURO STOXX 50 represents Eurozone blue-chip companies considered as leaders in their respective sectors. It is made up of fifty of the largest and most liquid stocks. The index futures and options on the EURO STOXX 50, traded on Eurex, are among the most liquid products in Europe and the world. (Wikipedia)

By now it should be clear the correlation between oil prices and macroeconomic variables. But if such correlation exists and financial markets are efficient, a correlation between oil prices and performance of the stock market should exist too, as each market quickly reacts to all the available data. Jones and Kaul (1992) found an effect of oil prices on the total real stock returns, including a lag effect for a period between 1947 to 1991. On the other hand, Huang (1996) through a vector autoregressive approach examined the relationship between oil futures and stock returns, controlling for seasonality and interest rates. He found no significant correlation except in the case of some oil companies.

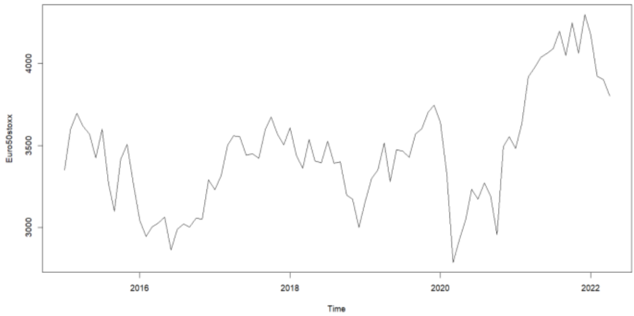
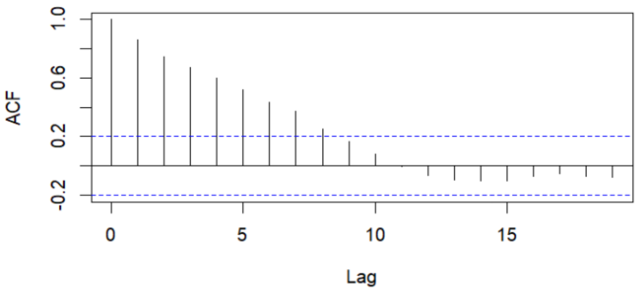


Figure 23 - Time series plot of monthly Euro50 index

Figure 24 - Autocorrelation function plot of monthly Euro50 index



Inflation

Inflation is also added among control variables to assess if the increase or decrease of the industrial production or gross domestic product is following merely an inflationary trend. Data is downloaded from Eurostat and each country has its own observations. Inflation is an index with a value of 100 in 2015 and it is all-items HICP. The graph shows the monthly inflation for countries in the first model and the average.

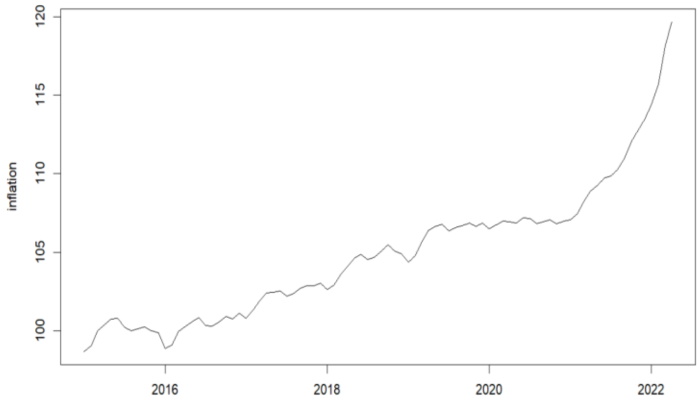
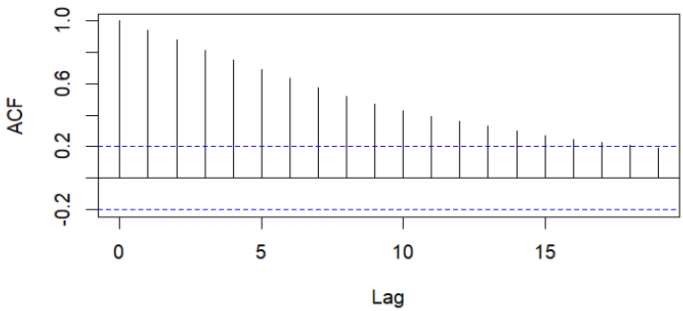


Figure 25 - Time series plot of monthly inflation rate

Figure 26 - Autocorrelation function plot of monthly inflation rate



7 Results

Finally in this section we present the results for the panel analysis for both models. Results are strong enough to state there is statically significant correlation between electricity prices and production, either industrial or national.

7.1 Industrial production model

The findings of our study indicate that the results for Panel A, which includes all the data, are statistically significant at a 1% level for all variables except the intercept. Specifically, the logarithmic value of electricity prices and linear values of load, gas, inflation, business confidence, ETS, and euro50 are all significant. Of particular interest is the positive sign for electricity prices, which, as a linear-log model, suggests that a 1% increase in electricity prices corresponds to an 0.1371 increase in *indpro*.

Our study also confirms our prior expectations that gas prices and emission allowance prices are negative factors that have a negative impact on industrial production. Conversely, inflation, business confidence, and euro50 are factors that have a positive impact on industrial production. These findings align with a recent conference held by the European Central Bank, which suggest that high inflation rates have led to most of the social welfare being absorbed by firms. As stated by Fabio Panetta, Member of the Executive Board of the ECB "Opportunistic behaviour by firms could also delay the fall in core inflation". Furthermore, he added that in some industries, profits are increasing strongly, and retail prices are rising rapidly, although wholesale prices have been decreasing for some time. This suggests that some producers have been exploiting the uncertainty created by high and volatile inflation and supply-demand mismatches. (Nelson, 2022)

Even though both industrial and electricity prices have different break dates, we have taken March 2020 as our reference point due to the outbreak of Covid-19. We have split the panel into two sections using a dummy variable, and both results are statistically significant. Additionally, the impact of *logelprice* on *indpro* during the period after April 2020 is larger in absolute value compared to the previous observation.

Table 1 - Industrial production model results

INDUSTRIAL PRODUCTION MODEL

	Panel A	Panel B	Panel C
Date	01/2015-12/2022	01/2015-03/2020	04/2020-12/2022
logelprice	13.719***	13.484***	17.841***
	(2.518)	(3.041)	(4.792)
load	-0.00000***	-0.00000***	-0.00000***
	(0.00000)	(0.00000)	(0.00000)
gas	-0.100***	-0.070	-0.054**
	(0.015)	(0.076)	(0.024)
ETS	-0.061**	-0.166***	-0.150**
	(0.029)	(0.059)	(0.071)
euro50	0.003**	0.00004	0.006**
	(0.001)	(0.001)	(0.003)
infl	0.782***	1.722***	0.439***
	(0.063)	(0.142)	(0.089)
busconf	0.261***	0.199***	0.244***
	(0.035)	(0.041)	(0.066)
Constant	-0.756	-88.231***	24.985*
	(8.633)	(15.308)	(14.096)
Observations	1,440	945	495
R2	0.374	0.319	0.474
Adjusted R2	0.371	0.314	0.466
Residual Std. Error	10.529 (df = 1432)	8.171 (df = 937)	12.575 (df = 487)
F Statistic	122.081*** (df = 7; 1432)	62.774*** (df = 7; 937)	62.604*** (df = 7; 487)

The Granger Causality test is a statistical method employed to assess the predictive relationship between two time series variables. In this context, the term "Granger-causes" signifies that possessing knowledge of the lagged values of time series x provides valuable insights into forecasting the future values of time series y. A significance level, denoted as α, is commonly set at 0.05, and if the computed p-value falls below this threshold, it indicates statistical significance. Consequently, rejecting the null hypothesis becomes plausible, allowing us to assert that time series x effectively Granger-causes time series y. In the present scenario, the p-value being more than 0.05 does not permits us to reject the null hypothesis and affirm that the knowledge of *indpro* is indeed not advantageous in predicting forthcoming electricity prices.

We had not a precise guess of what the best order in the Granger model should be, so we preferred not to specify it in the R code and let the software to use 1.

```
Granger causality test

Model 1: logelprice ~ Lags(logelprice, 1:1) + Lags(indpro, 1:1)
Model 2: logelprice ~ Lags(logelprice, 1:1)
  Res.Df Df      F Pr(>F)
1   1532
2   1533 -1 2.3301 0.1271
```

It's possible that there is a case of reverse causation happening. That is, it's possible that the *logelprice* is causing the industrial production levels to change. To rule out this possibility, we need to perform the Granger-Causality test in reverse.

The p-value of the test is far less than 0.05, we reject the null hypothesis. Thus, we can conclude that knowing the electricity prices is useful for predicting the future industrial production levels.

```
Granger causality test

Model 1: indpro ~ Lags(indpro, 1:1) + Lags(logelprice, 1:1)
Model 2: indpro ~ Lags(indpro, 1:1)
  Res.Df Df      F    Pr(>F)
1   1532
2   1533 -1 19.959 8.492e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

7.2 Gross Domestic Product

Regarding the GDP model, our findings reveal highly significant statistical results for all variables at a 1% confidence interval. The first panel, Panel A, encompasses all observations from Q3 2007 to Q4 2022. The logarithm of the electricity price and business confidence exhibit negative coefficients, whereas gas, ETS, Euro50, and inflation exhibit positive coefficients, all exerting a significant impact on the dependent variable. Specifically, in the log-log specification, the coefficient β1 (-0.437) represents the elasticity of Y with respect to X, indicating that a 1% change in electricity price is associated with a -0.437% change in GDP. A decrease in business confidence leads to a reduction in gross domestic production, while an increase in gas price, emission allowances price, Euro50 index, and inflation lead to a positive increase in GDP.

Panel B, we additionally include the first lag of *loggdp*, as previous sections have shown that

GDP suffers from trend, and its past values can aid in explaining future values. Our assumption is validated, with *lagloggdp* proving to be statistically significant at the 1% level. The only change observed from Panel A is a change in sign for ETS, which turns out to be negative this tim

In the last panel, Panel C, we solely consider the period before the spread of the Covid-19 pandemic (before March 2020). The results remain significant, and we also observe an increase in the R-squared. This time, the beta coefficient for inflation is negative, potentially due to the low inflationary economy experienced between 2007 and 2020. Furthermore, we do not run the model for the period after Q1 2020 as data is insufficient, with only 44 observations available.

Table 2 - GDP model results

GDP MODEL

	Panel A	Panel B	Panel C
Date	2007y3q-2022y4q	2007y3q-2022y4q	2007y3q-2020y1q
logelprice	-0.437***	-0.353***	-0.537***
	(0.120)	(0.112)	(0.138)
lagloggdp		0.147***	0.127***
		(0.024)	(0.024)
loggas	0.350***	0.318***	0.208
	(0.112)	(0.104)	(0.147)
logETS	0.046	-0.015	0.033
	(0.037)	(0.035)	(0.040)
logeuro50	0.797**	0.991***	1.206***
	(0.316)	(0.294)	(0.347)
loginfl	1.253	0.590	-3.355**
	(1.102)	(1.025)	(1.291)
logbusconf	-1.582***	-1.491***	-1.323**
	(0.526)	(0.487)	(0.559)
Constant	3.792*	3.390*	10.748***
	(1.950)	(1.805)	(2.322)
Observations	226	226	182
R2	0.116	0.247	0.297
Adjusted R2	0.092	0.223	0.269
Residual Std. Error	0.281 (df = 219)	0.260 (df = 218)	0.255 (df = 174)
F Statistic	4.798*** (df = 6; 219)	10.213*** (df = 7; 218)	10.515*** (df = 7; 174)

Next, we'll use the granger test function to run a Granger-Causality test to examine if the values of gross domestic product predict the values of *elprice* in the future. Here again we prefer not to specify the order for the model. We fail to reject the null hypothesis of the test because the p-value is 0.841 (>0.05) and infer that knowing the values of *loggdp* is not valuable for forecasting the future values of electricity prices.

```
Granger causality test

Model 1: logelprice ~ Lags(logelprice, 1:1) + Lags(loggdp, 1:1)
Model 2: logelprice ~ Lags(logelprice, 1:1)
  Res.Df Df      F Pr(>F)
1    222
2    223 -1 0.0403  0.841
```

We also perform the other way around to check if electricity prices are a good predictor for GDP values. Again, we fail to reject the null hypothesis, that is *logelprice* does not granger-causes gross domestic product.

```
Granger causality test

Model 1: loggdp ~ Lags(loggdp, 1:1) + Lags(logelprice, 1:1)
Model 2: loggdp ~ Lags(loggdp, 1:1)
  Res.Df Df      F Pr(>F)
1    222
2    223 -1 0.5983 0.4401
```

8 Conclusions

The objective of this thesis is to investigate the potential correlation between electricity prices and industrial production or gross domestic product across sixteen European countries. The paper is divided into two distinct models, with industrial production and GDP serving as the respective dependent variables. Initially, a basic ordinary least squares (OLS) regression is performed for both models. The results reveal a robust correlation at a 99% confidence interval between industrial production and GDP with electricity prices. Furthermore, the coefficients exhibit positive signs in both models, indicating that an increase in electricity prices incentivizes firms to produce more output, leading to a rise in national GDP.

As such, we take control variables into account and transform the models into linear-log and log-log specifications. The models are then rerun, incorporating gas prices, inflation rates, business confidence, Euro50 index, and emission allowances prices. The findings highlight significant statistical evidence of a relationship between electricity prices and production, whether industrial or national, with control variables proving to be significant as well. Specifically, an increase in electricity prices corresponds with a rise in industrial production as firms seem capable of passing on the increased input cost to customers, thus increasing their wealth. Conversely, when electricity prices rise, gross national production decreases, indicating a reduction in households' wealth.

The contrasting behaviours observed can be attributed to divergent considerations regarding arguments between companies and households. Firstly, it is postulated that the discrepancy arises due to disparate weightings assigned to various factors. Specifically, a positive correlation between industrial production and electricity prices suggests that companies possess the ability to pass on augmented input costs to end consumers. Secondly, in instances where companies encounter elevated monthly prices relative to preceding periods, concerns regarding an impending inflationary trajectory prompt them to augment production in order to pre-emptively mitigate the risk of incurring even higher input expenses. This line of reasoning assumes precedence over apprehensions pertaining to a potential recession and the subsequent decline in revenue, thus underscoring its paramount significance.

Conversely, an increase in electricity prices is found to be associated with a decline in GDP. Bianco, Manca, and Nardini (2009) assert that there exists a low elasticity of electricity consumption with respect to prices, which is supported by the graphical representation on page 71. Despite fluctuations in prices observed over the course of the study, the overall grid load appears to remain relatively constant. As the consumption quota remains unchanged over time, but costs exhibit variations, households respond to higher electricity prices by reducing their expenditure on other items. Consequently, this reduction in household consumption leads to a contraction in GDP.

When it comes to evaluating the causal relationship between variables, we can affirm that electricity prices granger causes industrial production levels, but the opposite does not hold. On the other hand, for the GDP model neither electricity prices nor gross domestic product granger causes the other variable.

It is worth noting that there exists significant heterogeneity within the sample. The sixteen countries considered are highly diverse in terms of their global goods and services provision, total gas consumption sources, financial sector importance, among other factors. Given this diversity, the consistency of the results is quite remarkable.

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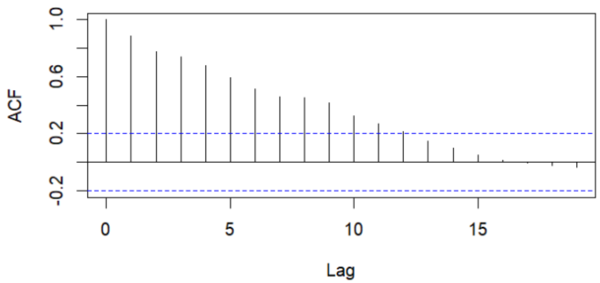
11 Appendix

In the appendix section, we have included a comprehensive compilation of tests that are deemed essential for assessing the validity of the model, yet do not possess a sufficient level of significance to warrant inclusion in the main body of the report.

Industrial Production model

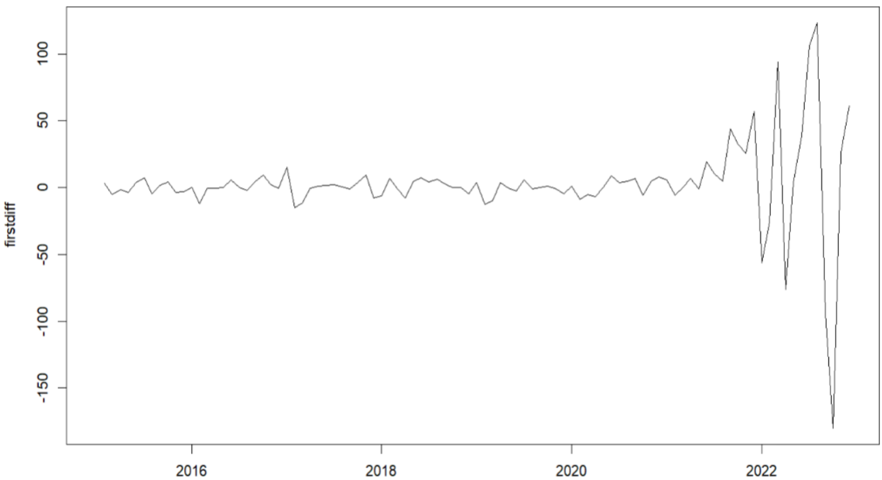
Figure 27 - Autocorrelation plot of monthly electricity prices



Monthly Electricity prices

Electricity prices have a high significant autocorrelation until twelve lags.

Figure 28 - Time series plot of difference between monthly electricity prices and its first lag



```
###############################################
# Augmented Dickey-Fuller Test Unit Root Test #
###############################################

Test regression trend


Call:
lm(formula = z.diff ~ z.lag.1 + 1 + tt + z.diff.lag)

Residuals:
     Min       1Q   Median       3Q      Max
-135.662  -10.197   -1.137    5.308  125.033

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -4.47421    6.75870  -0.662  0.50967
z.lag.1     -0.15477    0.05511  -2.808  0.00611 **
tt           0.37827    0.15598   2.425  0.01730 *
z.diff.lag   0.19416    0.10560   1.839  0.06927 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 31.86 on 90 degrees of freedom
Multiple R-squared:  0.1003,    Adjusted R-squared:  0.0703
F-statistic: 3.344 on 3 and 90 DF,  p-value: 0.02266


Value of test-statistic is: -2.8082 3.0191 4.3026

Critical values for test statistics:
      1pct  5pct 10pct
tau3 -4.04 -3.45 -3.15
phi2  6.50  4.88  4.16
phi3  8.73  6.49  5.47
```

Based on the results we get; we fail to reject the null hypothesis. The p value is lower than 5% and the test is greater than the critical value: there is evidence of a trend in the series.

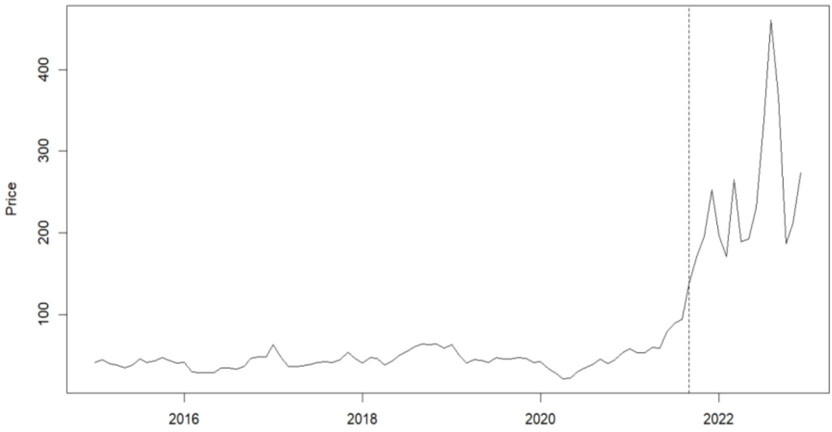


Figure 29 - Structural break plot for monthly electricity prices

A structural break test has been conducted on the price's time series and the result we get is a break in September 2021.

Industrial production

This is the scatter plot of electricity prices and Industrial production. The blue line highlights the correlation coefficient.

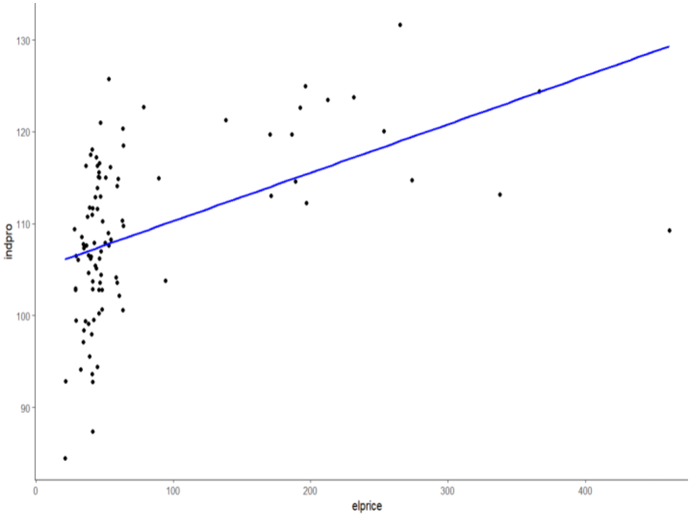


Figure 30 - Scatter plot between electricity prices and industrial production

A first OLS model on the Industrial production only with *elprice* as variable has outlined these results: both the coefficients are statistically significant at 1% confidence level. The intercept is different from zero and the Beta is positive. This means that European firms tend to increase their production when there is an increase in their monthly electrical expenditure. Even if it is only a 5% increase, it is significant that the sign is positive.

Table 3 - Industrial production OLS

Results

	Dependent variable:
	indpro
elprice	0.053***
	(0.010)
Constant	105.015***
	(1.133)
Observations	96
R2	0.225
Adjusted R2	0.217
Residual Std. Error	7.989 (df = 94)
F Statistic	27.265*** (df = 1; 94)
Note:	*p<0.1; **p<0.05; ***p<0.01

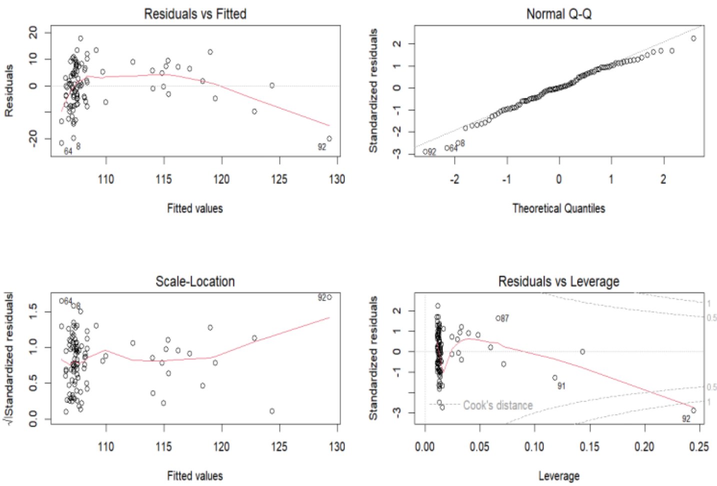


Figure 31 - Plot of residuals' model between electricity prices and industrial production

Homoscedasticity

```
        studentized Breusch-Pagan test

data:  model
BP = 1.6146, df = 1, p-value = 0.2038
```

Above it is shown the output of the Breusch-Pagan test. The interpretation of the Breusch-Pagan test for heteroscedasticity is simple. Because the test statistic (BP) is small and the *p*-

value is not significant (i.e., >0.05), we do not reject the null hypothesis. Therefore, we assume that the residuals are homoscedastic. We can also get the same conclusion if we check the upper and lower left plots of the residuals.

Structural Break

To conclude our analysis on industrial production we check for structural breaks. The second type of nonstationary we consider is that the coefficients of the model might not be constant over the full sample. Clearly, it is a problem for forecasting if the model describing the historical data differs from the current model. This is an issue of external validity.

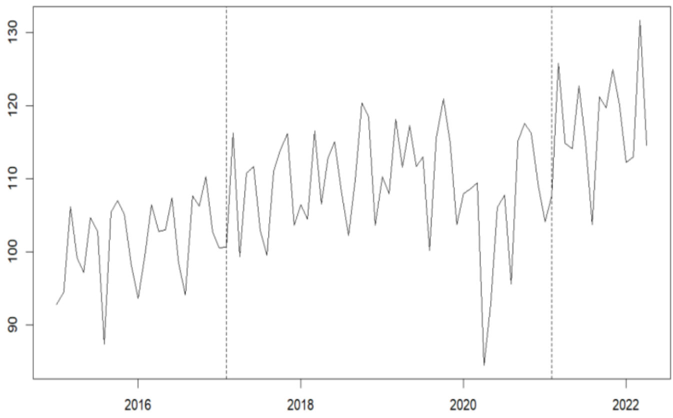


Figure 32 - Structural break plot for monthly industrial production values

The plot above is the industrial production observations over time and the two dotted lines highlight when structural breaks happen. The first one in February 2017 and the second in February 2021.

Gross domestic product model

Quarterly electricity prices

Structural Break

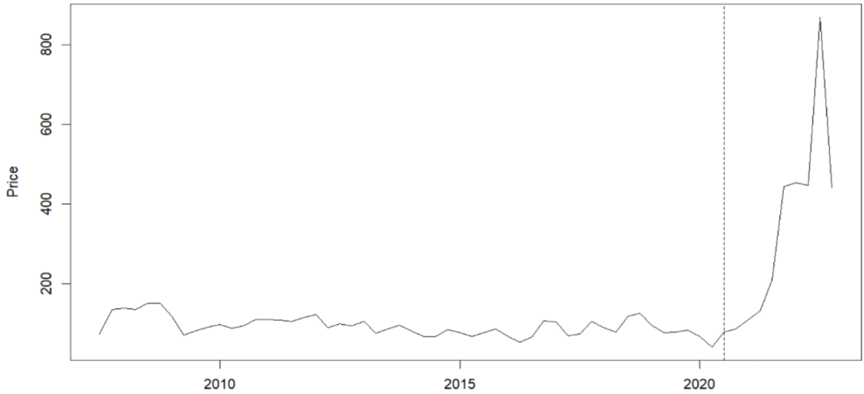


Figure 33 - Structural break plot for quarterly electricity prices

We observe a break date happening in March 2020.

Gross domestic product

This is the scatter plot of price and GDP. With the blue line we visualise the correlation coefficient and its steady positive trend. From the plot it is also clear the four clusters of GDP values for each country.

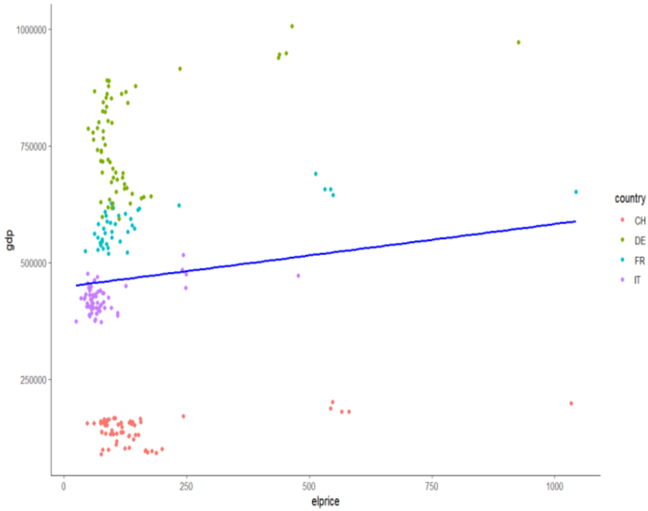


Figure 34 - Scatter plot between electricity prices and GDP

A simple OLS has been conducted on GDP regressed on electricity prices. Both the intercept and the beta coefficient are significant from zero at 1% confidence level. It is also true that the model explains only 20% of the values, not high enough to stop the regression here.

Table 4 - GDP OLS

Results

	Dependent variable:
	gdp
elprice	221.760***
	(54.648)
Constant	430,185.800***
	(10,128.110)
Observations	62
R2	0.215
Adjusted R2	0.202
Residual Std. Error	56,225.370 (df = 60)
F Statistic	16.467*** (df = 1; 60)
Note:	*p<0.1; **p<0.05; ***p<0.01

Homoscedasticity

We reject the null hypothesis, there is no evidence of heteroskedasticity in the residuals of the model.

```
        studentized Breusch-Pagan test

data:  model
BP = 0.00096443, df = 1, p-value = 0.9752
```

Structural Breaks

According to the test performed on R there have been five structural breaks over time: third quarter of 2010, first quarter in 2013, second quarter of 2015, third quarter of 2017 and third quarter of 2020.

```
        Optimal (m+1)-segment partition:

Call:
breakpoints.formula(formula = GDP ~ 1)

Breakpoints at observation number:

m = 1          29
m = 2       23    41
m = 3       21 33    53
m = 4    13 23    37 53
m = 5    13 23 32 41 53

Corresponding to breakdates:

m = 1                    2014(3)
m = 2            2013(1)         2017(3)
m = 3            2012(3) 2015(3)         2020(3)
m = 4    2010(3) 2013(1)         2016(3) 2020(3)
m = 5    2010(3) 2013(1) 2015(2) 2017(3) 2020(3)
```

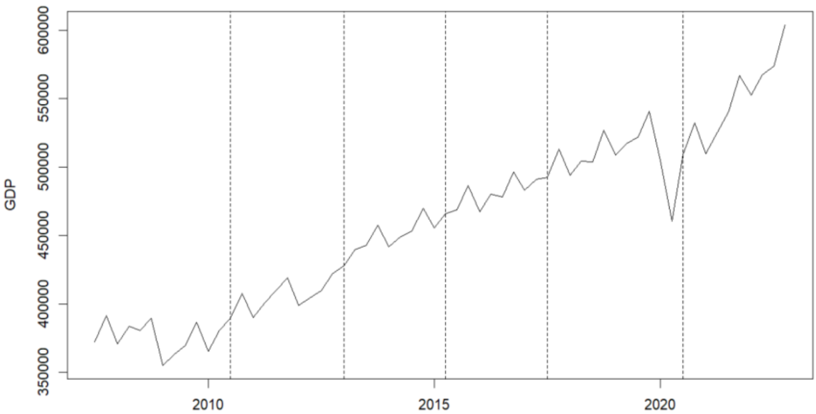


Figure 35 - Structural break plot for quarterly GDP values

R code

```
library(readxl)
datagdp<- read_excel("Gdp.xlsx", sheet = "Sheet1")
dataindpro<- read_excel("industrial production.xlsx",
sheet = "Sheet1")

dataindpro$Date<-format(dataindpro$Date,
format="%m/%Y")

#packages

library(ggplot2)
library(dplyr)
library(knitr)
library(fBasics)
library(lmtest)
library(fUnitRoots)
library(strucchange)
library(zoo)
library(tseries)
library(urca)
library(stargazer)

AT=subset(data,Country=="AT")
BE=subset(data,Country=="BE")
CZ=subset(data,Country=="CZ")
CH=subset(data,country=="CH")
DE=subset(data,country=="DE")
ES=subset(data,Country=="ES")
FR=subset(data,country=="FR")
IT=subset(data,country=="IT")
LT=subset(data,Country=="LT")
LV=subset(data,Country=="LV")
NL=subset(data,Country=="NL")
```

```
SK=subset(data,Country=="SK")
SI=subset(data,Country=="SI")
HR=subset(data,Country=="HR")
EE=subset(data,Country=="EE")
GR=subset(data,Country=="GR")

#INDPRO MODEL

INDPRO<- ts(dataindpro$indpro, start = c(2015,1),end =
c(2022,4), frequency = 12)
plot(INDPRO)
dataindpro$diff=dataindpro$indpro-
lag(dataindpro$indpro, n=1)
firstdiff=ts(dataindpro$diff,start = c(2015,1),end =
c(2022,4), frequency = 12)
plot(firstdiff)
acf(dataindpro$indpro)
x=ur.df(dataindpro$indpro,type = c("trend"),selectlags
="BIC")
summary(x)
bp.rice <- breakpoints(INDPRO ~ 1)
summary(bp.rice)
plot(INDPRO)
lines(bp.rice)

Cost<- ts(dataindpro$elprice, start = c(2015,1),end =
c(2022,4), frequency = 12)
plot(Cost)
dataindpro$diff=dataindpro$elprice-
lag(dataindpro$elprice, n=1)
firstdiff=ts(dataindpro$diff,start = c(2015,1),end =
c(2022,4), frequency = 12)
plot(firstdiff)
acf(dataindpro$elprice)
```

```
x=ur.df(dataindpro$elprice,type = c("trend"),selectlags
="BIC")
summary(x)
bp.rice <- breakpoints(Cost ~ 1)
summary(bp.rice)
plot(Cost)
lines(bp.rice)

dataindpro %>% select("indpro","elprice","load",
"gas","busconf","infl","ETS","euro50") %>% cor(use =
"complete") %>% kable(digits = 3)

plotindpro <- ggplot(dataindpro, aes(elprice,indpro)) +
geom_point() + geom_smooth(method="lm", se=FALSE,
color="blue") + theme_classic()
plot(plotindpro)

lm(formula = indpro ~ elprice, data = dataindpro)

plot(model$df.residual)
bptest(model)

lm(formula = indpro ~ logelprice + load + gas + infl +
busconf + euro50 + ETS, data = dataindpro)

grangertest(logelprice ~ indpro, data = dataindpro)
grangertest(indpro ~ logelprice, data = dataindpro)

#GDPMODEL

GDP<- ts(datagdp$gdp, start = c(2007,3),end = c(2022,4),
frequency = 4)
plot(GDP)
datagdp$diff=datagdp$gdp-lag(datagdp$gdp, n=1)
```

```
firstdiff=ts(datagdp$diff,start = c(2007,3),end =
c(2022,4), frequency = 4)
plot(firstdiff)
acf(datagdp$gdp)
x=ur.df(datagdp$gdp,type = c("trend"),selectlags ="BIC")
summary(x)
bp.rice <- breakpoints(GDP ~ 1)
summary(bp.rice)
plot(GDP)
lines(bp.rice)

Cost<- ts(datagdp$elprice, start = c(2007,3),end =
c(2022,4), frequency = 4)
plot(Cost)
datagdp$diff=datagdp$elprice-lag(datagdp$elprice, n=1)
firstdiff=ts(datagdp$diff,start = c(2007,3),end =
c(2022,4), frequency = 4)
plot(firstdiff)
acf(datagdp$elprice)
x=ur.df(datagdp$elprice,type = c("trend"),selectlags
="BIC")
summary(x)
bp.rice <- breakpoints(Cost ~ 1)
summary(bp.rice)
plot(Cost)
lines(bp.rice)

datagdp %>%
select("gdp","elprice","gas","infl","busconf","euro50","E
TS") %>% cor(use="complete") %>% kable(digits = 3)

plotgdp <- ggplot(datagdp, aes(elprice,gdp,
color=country)) + geom_point() +
geom_smooth(method="lm", se=FALSE, color="blue") +
theme_classic()
```

```
plot(plotgdp)

lm(formula = gdp ~ elprice, data = datagdp)

plot(model$df.residual)
bptest(model)

lm(formula = loggdp ~ logelprice + lagloggdp + loggas +
loginfl + logbusconf + logeuro50 + logETS, data =
datagdp)


grangertest(logelprice ~ loggdp, data = datagdp)
grangertest(loggdp ~ logelprice, data = datagdp)


#CONTROL VARIABLES
Gas<- ts(data$gas, start = c(2015,1),end = c(2022,4),
frequency = 12)
plot(Gas)
acf(dataindpro$gas)

busconf<- ts(data$busconf, start = c(2015,1),end =
c(2022,4), frequency = 12)
plot(busconf)
acf(dataindpro$busconf)

Euro50stoxx<- ts(data$euro50, start = c(2015,1),end =
c(2022,4), frequency = 12)
plot(Euro50stoxx)
acf(dataindpro$euro50)

inflation<- ts(data$infl, start = c(2015,1),end = c(2022,4),
frequency = 12)
plot(inflation)
```

```
acf(dataindpro$infl)

EUETS<- ts(data$ETS, start = c(2015,1),end = c(2022,4),
frequency = 12)
plot(EUETS)
acf(dataindpro$ETS)
```