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The Impact of the COVID-19 Pandemic and Russia's Invasion of Ukraine on Electricity Demand: A Case Study of Southern European Countries.

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Abstract

Recent global events, particularly the COVID-19 pandemic and Russia's invasion of Ukraine, have been found to dramatically influence electricity consumption patterns, especially within European nations. In this study, the impacts of these consecutive crises on the electricity demand of selected EU countries: Bulgaria, Greece, Romania, and different regions of Italy were examined. The Ordinary Least Squares regression model was utilized to analyze hourly load data and air temperatures. The findings indicate that the 2020 COVID-19 lockdown reduced consumption uniformly across the studied regions, while the 2022 energy crisis led to varied impacts, with distinct patterns being exhibited in regions within Italy. Remarkably, resilience was shown by Bulgaria during both crises, whereas pronounced effects were experienced in Southern Italy in both periods. The importance of understanding these shifts for effective policymaking and future resilience planning is emphasized in this study. A limitation of the analysis is found in its sole use of aggregate power load data and its generalized modelling. It is suspected that clearer results could be obtained in each case if analyzed the electricity consumption data separated by sectors.

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1. Introduction

In recent years, global shock events have prompted a close examination of various sectors, revealing the vulnerabilities and resilience of systems that underpin our society. Among these, the electricity sector stands out, acting as both a barometer for economic activity and a critical service underpinning modern life. The confluence of the COVID-19 pandemic, which brought major shift in global behaviors, combined with the geopolitical aftershocks of Russia's invasion of Ukraine, has cast a spotlight on the electricity consumption patterns, especially in European countries. As electricity consumption patterns recede and flow in response to these monumental events, it becomes imperative to understand the nuances of these changes, not just for the sake of academic exploration, but for effective policymaking, economic forecasting, and strategic planning for a resilient future.
The COVID-19 pandemic, which originated as a health crisis, rapidly metamorphosed into an economic and societal challenge of unprecedented magnitude. Global electricity demand patterns were significantly altered, reflecting the disruptions in daily life and economic activity. Following closely on its heels, the energy crisis in Europe, exacerbated by Russia's aggressive geopolitical maneuvers in Ukraine, added another layer of complexity, altering the energy landscape of the continent.

This thesis dives into the interplay between these two critical events and their cumulative and individual impacts on electricity consumption in Southern European countries. Drawing from available data and contextual insights, it aims to address a pivotal question:

RQ1. How did the electricity consumption in the selected countries change due to the impacts of the COVID-19 pandemic and the energy crisis resulting from Russia's invasion of Ukraine, and were these impacts consistent across these countries?

The subsequent chapters will delve deeper into the documented effects of both crises, the theoretical frameworks, and provide empirical evidence to answer this question, aiming to offer a comprehensive understanding of a region's response to dual economic shocks. In doing so, this thesis hopes to shed light on the resilience and vulnerabilities of the electricity sector, informing both present and future strategies for regions grappling with multifaceted challenges.

2. Background

This chapter outlines the documented impacts of the COVID-19 pandemic and the subsequent energy crisis in Europe on electricity demand. Based on this information, the chapter presents an argument in favor of conducting an analysis of the effects of both these crises on electricity load, aiming to assess their influences and potential disparities in seasonal consumption shifts.

The course of COVID-19 pandemic impacts on electricity demand

In 2020, global electricity demand is anticipated to decrease by 2%, the most significant drop since the mid-20th century, due to the Covid-19 pandemic's economic impact. This decline surpasses the 0.6% drop after the 2009 financial crisis. China, accounting for 28% of global electricity use, was expected to be the only major economy with rising electricity demand, but at 2%, it was well below its 2015 average of 6.5%. Despite some recovery in many regions, most major consumers like the US, India, Europe, and others saw annual demand declines.

Wholesale electricity prices have dropped in 2020 due to lower demand, reduced fuel costs, and a rise in renewables. The IEA indicated a 28% price drop in 2020, following a 12% decline in 2019. (IEA, 2020)

The COVID-19 pandemic has significantly altered daily life globally, affecting travel, social activities, work, schooling, and business operations. These changes have reshaped electricity consumption patterns. Analyzing these shifts is crucial for two primary reasons. First, understanding the electricity system's reaction to such unprecedented disruptions helps ensure grid reliability and resilience. Fluctuations in consumption can influence the grid's operation, balancing, and forecasting. Second, studying the pandemic's effect on electricity consumption highlights the potential of governmental policies to alter deep-rooted consumption habits. Both individual decisions and state policies have influenced these consumption changes.

The immediate consequences of Russian Aggression on Ukraine in Europe

During Q4 2021, European electricity markets witnessed a remarkable spike in day-ahead prices. This surge was primarily fueled by escalating prices of commodities like gas, coal, and CO2, a rising demand spurred by economic revival, and the limited supply from traditional power plants. Prices rose dramatically by over 200%, and even doubled that in certain markets. Italy reported the steepest average at 243 €/MWh, showing a 394% leap from Q4 2020. The UK closely followed with an average of 239 €/MWh, a 355% year-on-year growth. The European Power Benchmark for the last Q4 of 2021 averaged out to 194 €/MWh, marking a 400% yearly increase. Countries including Norway, Switzerland, France, Spain, and Portugal encountered the sharpest price hikes. Norway's increase was particularly astounding at 760%. On the other hand, Poland, less reliant on gas, noted a comparatively restrained increase of 146%. To combat these soaring prices, the European Commission introduced the Energy Prices Toolbox in October 2021, with the goal of protecting consumers from the effects. In the wake of Ukraine's invasion by Russia, the Commission rolled out REPowerEU in March, setting a goal to reduce Europe's dependence on Russian energy sources by 2030. As March concluded, they also suggested measures like maintaining a gas storage level of at least 80% by November 2022 to bolster energy security and keep prices reasonable for Europeans (MOE, 2021).

While there was a 2% growth in global electricity demand in 2022, the EU saw a decline of 3% - the steepest dip among major power consumers. Such a demand drop has only been recorded twice in the 21st century: after the 2008 financial turmoil and amidst the 2020 Covid-19 restrictions. The 2022 EU consumption dip was a result of milder winter conditions, an unusually warm summer, and high electricity costs. Though climatic conditions had a pronounced role, they contributed to less than a 1% demand reduction for the year. The other 2% was shaped by factors not related to weather. One significant factor was the electricity price spike, which heavily impacted high-consuming sectors (IEA, 2023). These significant surges in electricity prices impacted not just industries but also threatened the economic stability of households, particularly the disadvantaged ones. These shifts potentially altered daily and yearly consumption patterns and raised concerns about national energy security in several European nations.

Understanding the impacts of two economic shocks on electricity consumption

Understanding the effects of COVID-19 and the subsequent energy crisis on electricity consumption is paramount, especially considering their distinct root causes. COVID-19 primarily seized economic activity, while the European energy crisis experienced an unprecedented spike in energy prices. Electricity consumption acts as a vital gauge of a region's economic health, with shifts in usage offering insights into economic vigor or slowdown. With the pandemic halting many sectors, and the energy crisis altering costs, accurate infrastructure planning becomes imperative for utilities. The need to address both decreased demand from halted activities and potential heightened demand once the economy resumes, all while avoiding inefficiencies. Unforeseen changes in demand, as witnessed during these crises, can induce price fluctuations that ripple through the entire economy, affecting both households and businesses. These fluctuations further complicate the incorporation of renewable energy sources, such as wind and solar, which thrive on stable and predictable consumption. Environmentally, any change in electricity consumption patterns, especially in regions heavily dependent on fossil fuels, directly impacts emission levels. Policymakers, equipped with knowledge on how such significant events like the pandemic and energy crises affect electricity consumption, can formulate more adaptive and resilient energy and environmental strategies. Simultaneously, energy traders and financial markets, to safeguard their investments, must navigate the electricity consumption landscape affected by these unique crises. For instance, shares of utility companies can oscillate based on the unpredictability of these events. Furthermore, industries with large electricity footprints need a deep understanding of these events to manage risks and devise forward-looking strategies. Monitoring shifts in electricity usage also helps discern evolving consumer patterns, providing insights into societal adaptations to changing economic circumstances. On a broader scale, such domestic electricity demand changes, induced by global events like COVID-19 or regional crises, can shape international energy dynamics and diplomacy. In essence, the multifaceted nature of electricity consumption interlinks with numerous aspects of the modern world. Grasping its subtleties, especially against the backdrop of significant crises with varied origins, is crucial for fostering resilience, effective planning, and holistic economic growth.

The aim of this thesis is to contribute to earlier research on the impacts of the COVID-19 pandemic on electricity consumption and other economic instabilities. It further seeks to expand this work with a study on the effects of two consecutive crises on the load demand in European countries. While the quantitative impacts of both shocks are well-documented at this juncture, understanding the varying impacts among countries and the distinct influence of each crisis on electricity demand within the same nation is more intricate but offers insightful observations. Recognizing these variations might also enable swifter responses by policymakers during subsequent economic disturbances.

Organization of the Thesis

The structure of the thesis is as follows:
Chapter 3 offers a literature review and the theoretical framework, encompassing the European electricity market, documented impacts of economic instability on load demand, and well-established associations with factors shaping electricity consumption patterns.
Chapter 4 introduces the data used in the analysis, while Chapter 5 details the methods applied to the study.
Chapter 6 outlines the results, succeeded by an in-depth discussion of the findings in Chapter 7. Chapter 8 concludes with remarks, study limitations, and recommendations for future research in this domain.

3. Theory and literature review

As highlighted in the preceding chapter, the core objective of this analysis is to measure the impacts of crises on electricity demand and compare these effects against a generated scenario that depicts power consumption during tumultuous periods, had the crises not occurred. This analysis is not anchored in any specific economic theory. Instead, it leans heavily on carefully chosen literature relevant to the specific region under examination. The theory and literature review delve into studies and reports that explore determinants of electricity consumption. Some factors, such as fluctuations in air temperature or the observance of holidays, apply a direct influence on electricity demand. Others, like shifts in electricity pricing, economic disruptions, or policies targeting market integration, impact consumption more indirectly. The broad aim of this review is to provide a solid foundation for the analysis, validate the choice of variables, and determine relationships pivotal for interpreting the results of two successive crises.

3.1 Economic instability and its impact on electricity consumption

This section focuses on providing insights into the correlation between economic instability and electricity consumption, as seen in different contexts. Study by Balabanyan et al. (2010) analyses the 2008 financial crisis's effect on the power sectors of Eastern Europe and Central Asia. Prior to the economic shock due to GFC, all the target countries, namely Armenia, the Kyrgyz Republic, Romania, Serbia, and Ukraine, were experiencing economic growth and a surge in electricity consumption, fueled by an expanding GDP. However, their deteriorating, underfunded, and outdated energy infrastructure posed a significant risk to the stability of their economies. The dramatic plunge in these countries' GDP, significantly decreased tax revenues, resulting in budget deficits and public debt. The ripple effects of this economic downturn reverberated through the energy sectors of the countries under study, deepening and prolonging the repercussions of the financial crisis itself. The economic downturn led to reduced electricity demand due to decreased industrial production. Reduced tax revenues and increased public deficits also resulted in lower electricity consumption and revenue losses for the power sector, further exacerbating the economic instability.

This study demonstrates that internal imbalances in a country's development (in this case, a lack of investments in the energy sector) can be exacerbated by a crisis. Regardless of the primary cause of the crisis, these imbalances might be further aggravated by instability in the energy sector.

Santamouris et al. (2013) conducted an in-depth exploration of the relationship between Greece's post-Global Financial Crisis economic situation and household energy consumption patterns. This study, focusing on electricity, gas, and oil consumption, discovered a surprising reduction in household energy usage during the colder winter of 2011-2012. The economic downturn, in fact, accelerated this trend. Comparisons with the winter of 2010-2011 revealed an unexpected result: even with a harsher winter, the energy consumption in 2011-2012 was 37% less than expected. This significant finding deepens the understanding of how economic factors can shift household energy consumption habits. Utilizing cluster analysis, the researchers categorized the surveyed households into two distinct groups: a lower-income group and a high-income group. The lower-income group, making up three-quarters of the study population, resided in smaller spaces and had lower income levels. Despite these constraints and the severity of the winter, this group consumed specific energy types in lesser quantities than the high-income group, an outcome that was unexpected given the more challenging conditions.

Another relevant mention here corroborating the findings of the two previous referenced papers is a study focusing on energy poverty in European countries by Halkos, and Gkampoura (2021). The study employed primary indicators such as the ability to maintain a warm home, overdue utility bills, and the presence of leaks, damp, or rot in housing. To gain a deeper understanding of energy poverty, secondary indicators were also examined. These encompassed measures like income inequality (represented by the Gini coefficient), GDP per capita, unemployment rates, urban population density, housing space, and electricity prices. These secondary indicators were essential in pinpointing potential causes of energy poverty. The study evaluated data spanning from 2004 to 2019, covering 28 European countries.

Before the onset of the global economic crisis (2004-2008), among the countries with the lowest energy poverty were Scandinavian countries and Austria, while Bulgaria, Poland, Lithuania, Latvia, Cyprus, and Portugal were found at the opposite spectrum. However, while most European countries experienced a decline in energy poverty, Slovenia, Bulgaria, and Belgium, experienced slight increases, remaining consistently high levels of energy poverty during this period.

The advent of the global economic crisis (2009-2013), energy poverty intensified in several nations. Bulgaria, despite its efforts, had the highest energy poverty in Europe, while Greece, Cyprus and Portugal faced a sharp surge, becoming one of the most affected countries. Post-crisis (2014-2019), a trend of improvement was noted across Europe. While Bulgaria still had the highest energy poverty, it did show signs of reduction. Greece, following a tumultuous period between 2014 and 2016, also showed significant improvements. By 2017, most of the countries, showcased a remarkable recovery from their previous energy poverty levels.

Delving deeper into the intricacies of energy poverty, the study unveiled that electricity prices were the foremost contributors to the issue. In particular, there was a distinct connection between elevated electricity prices and heightened levels of energy poverty, especially when it came to overdue utility bills. The economic performance of a country, as denoted by its GDP per capita, had an inverse effect on energy poverty. In contrast, higher unemployment rates bore a direct relation to households facing difficulties in maintaining warmth and efficiently handling their utility bills. Additionally, the study indicated that in countries with a greater portion of their population at risk of poverty, energy poverty issues were more pronounced, though the impact of this factor was somewhat overshadowed by the influence of electricity prices.

When it came to household dynamics, the study found that homes with a larger number of rooms per individual often struggled with heftier utility bills due to the augmented energy demands. Yet, these spacious households were less plagued by common problems like dampness or leaks. As for urbanization, city-dwelling households frequently had more outstanding utility bills and grappled with a greater number of housing-related challenges.

Despite these drawbacks, urban households typically had a better track record of keeping their homes warm, possibly attributable to the nature and placement of urban residences.

The three studies presented here clearly indicate that disadvantaged households experience more severe impacts from financial crises. It's reasonable to draw a parallel to the country level, implying that financially disadvantaged households or under-invested sectors/countries with lower GDP will likely suffer more acute effects from a crisis and grapple with its aftermath for a longer period.

3.2 The impact of COVID-19 pandemic on electricity consumption

A recent and relevant in context of this analysis paper by Buechler et al. (2022) conducting a detailed analysis of changes in electricity consumption during the COVID-19 pandemic across 58 countries, which collectively account for about 60% of the global population and 75% of electricity demand across the globe. Conducted panel regression analysis reveled a strong correlation of stringent government restrictions, higher COVID-related mortality rates with the decreased electricity consumption. Interestingly, the authors also found a strong correlation between each country's pre-pandemic sensitivity to holiday consumption reductions and their maximum change in electricity consumption during the pandemic, suggesting that the former might serve as an indicator of how responsive electricity consumption is to economic activity.

The findings suggest that there was a decrease in daily electricity consumption of 7.6% on average across the countries in April 2020. However, the reductions varied significantly among regions, with India seeing a significant average decrease of 15% from March to May, while Australia had only a minor change of 2% in the same period. Further diversity of impacts is highlighted by Southern European countries, namely Italy, France, and Spain, experiencing more substantial reductions in electricity usage, unlike their Northern European counterparts such as Sweden, Denmark, and Finland, where the decrease was less pronounced. This disparity was not unique to Europe. A similar pattern was observed across different continents. In Asia, China and India encountered significant drops in electricity consumption early into the pandemic, a stark contrast to Japan, where changes were relatively minor. In the Americas, Argentina, Brazil, and Mexico registered sharp declines, while Chile

saw only a minimal decrease. A similar scenario was observed in Africa, with South Africa experiencing a substantial reduction in contrast to other countries.
Overall results suggest, that by the autumn of 2020, electricity consumption in almost all regions had returned to levels comparable to the pre-pandemic period. However, the paper also reveals a great diversity in the impact of the pandemic on electricity consumption across countries, even within the same region.

As evidenced by the studies presented, economic instability consistently leads to a decrease in electricity consumption, regardless of the underlying causes of the economic turbulence. The magnitude and duration of this decrease, however, significantly depend on the region's economic conditions. Economically diverse countries less reliant on industries are likely to experience less severe impacts during a crisis. In contrast, countries grappling with economic dysfunction are expected to endure more substantial effects. This study will attempt to examining and interpret these disparities within and between countries.

3.3 Patterns in electricity consumption

The structure of electricity demand, or load, is largely influenced by everyday activities in households, industry, and other sectors. Factors such as holidays and temperature, which were explained in previous sections, also play a role. For instance, turning the lights on and off, heating during cold days or cooling systems during hot summers, and in the industrial sector, electricity usage increases with the rise in production and decreases or shuts down during bank holidays.
The load exhibits a minimum basic level and follows a periodic pattern across different time periods. This pattern is significantly influenced by weekly routines, seasons, weather conditions, and economic cycles. (Cretì, Fontini, 2019)

Generally, the load is lower during weekends compared to weekdays, higher during winter and summer, and lower in spring and autumn. The electricity consumption in the U.S. fluctuates predictably throughout the year, with the highest demand in summer afternoons due to air conditioning use, and less variable, dual peaks in winter mornings and evenings. Consumption is lowest in spring and autumn with minimal heating or cooling is needed. Daily usage follows residents' habits, with the least consumption at night and lower usage on weekends and holidays due to commercial offices closing. On weekdays, peak hours are generally between 7:00 a.m. and 11:00 p.m., with off-peak hours being the remaining hours. Daily consumption cycles, influenced by household activities and weather-related factors, with summer having a wider range due to air conditioning use. The demand varies regionally due to weather patterns and types of electrical equipment in use. (Hodge, 2020)

There are two critical features of power markets identified from this pattern. Firstly, there is always a minimum level of electricity in the grid, and the second being, that although the load can significantly spike above this minimum level, such instances are rare. Both of these aspects can be visualized in a single curve that shows the load distribution over a specific period. This understanding of load patterns is crucial to understanding the structure and characteristics of electricity markets. (Cretì, Fontini, 2019)

In this paper, the load data recorded are hourly, allowing for a precise counterfactual analysis that takes this specific seasonality into account. Moreover, these patterns are amplified to replicate them when modeling the alternative 'business as usual' scenario (process described in Chapter 5. Method). For the discussion in this section, and to compare the specific patterns across all four countries studied in this paper, electricity consumption plots for the months of March and April were generated from the original load dataset in Python for each country. Figure 1 below displays the electricity consumption in Northern and Southern Italy from March 1st to April 30th, 2019, and is used to highlight specific trends and differences. Electricity consumption patterns for all other countries can be found in Appendix 1.

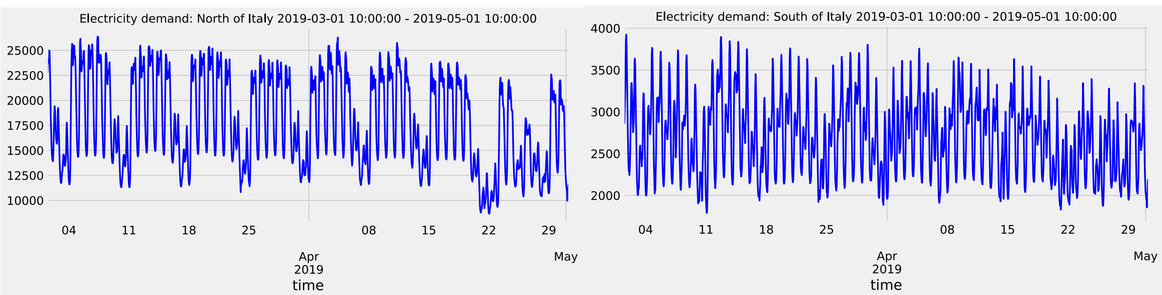

Figure 1: The weekly pattern of electricity consumption in the North and South of Italy between March 1st and April 30th, 2019.

The figure above on the left illustrates the pattern of electricity consumption in Northern Italy, a region characterized by increased industrial activity and a higher GDP (Musolino, 2018). The daily peaks from Monday to Friday are noticeably consistent and with evident two peaks within a day (morning and afternoon), signifying the regularity of the workweek.

The dips in consumption observed between these weekdays represent the weekends, where electricity usage markedly decreases and does not exhibit the two peaks visible on weekdays. Notably, consumption on Saturdays is slightly higher than on Sundays, reflecting most likely the operational hours of retail and other services that remain open on Saturdays but closed on Sundays. The month of April 2019 was deliberately chosen for this comparison due to the observance of Easter holidays on the 21st (Sunday), which showcases a distinctly different power demand pattern towards the end of the month. The figure on the right side, which shows the electricity consumption pattern in Southern Italy, displays less regularity. Demand is higher in the middle of the week and lower on Mondays and Fridays, with daily peaks indicating higher usage during the afternoons.While Sundays and holidays in south still exhibit lower demand, the distinction is less pronounced than in the Northern region. This variation can be attributed to the region's predominantly agricultural economy, smaller family-run businesses, and a significantly lower GDP compared to the North (Musolino, 2018).

Highlighting weekly cycles of electricity demand

This consistent weekly pattern, observed across all countries, serves as the foundation for creating several variables for this analysis. Given the availability of hourly recorded load data, which provides a highly accurate record of consumption changes due to external factors, and the expected pronounced and volatile effects of both crises on the load, multiple dummy variables were introduced to capture these changes. The detailed description of computing these time-dependent variables can be found in chapters 5.1 and 5.4.

The subsequent figures illustrate the monthly electricity consumption patterns for 2018 and 2019. Just as with the figures depicting weekly electricity consumption, these graphs were derived from the original load dataset using Python. The two plots presented below highlight the seasonal trends of Northern and Southern Italy for the mentioned years. Graphs for other countries can be found in Appendix 1.

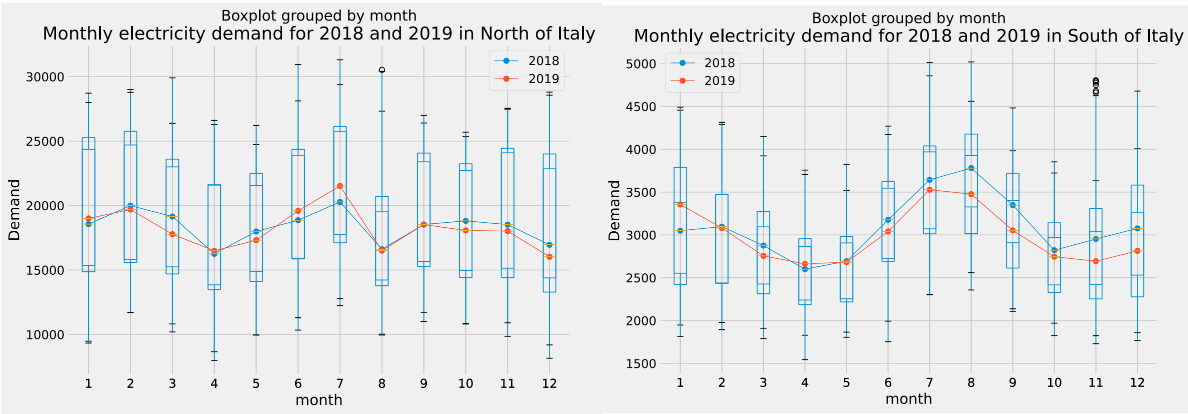

Figure 2: Comparison of the annual seasonality in the electricity consumption in 2018 and 2019 for Northern and Southern Italy.

With minor variations attributed to weather conditions (such as hotter summers and colder winters), both regions exhibit similar yearly consumption patterns. Electricity use peaks during summer and winter months because of cooling and heating requirements, respectively, and diminishes in the spring and autumn. The latter two seasons can be considered as representing baseline consumption, unaffected by air temperature. Interestingly enough, the distinctly lower demand in January 2018 can be explained by the weather conditions and irregular January. Based on Terna's data from January 2018, Italy experienced a 2.8% decline in electricity demand compared to the same month in the previous year. Factors like this year's calendar setup and temperature fluctuations played a role in this decrease. Specifically, January of this year had an additional workday (22 instead of 21) and the average temperature was 4°C higher than that of January 2017. On a regional scale, all parts of Italy saw a decline in January 2018: the North decreased by 0.8%, while the South witnessed drop of 6%. (TERNA, 2018)

The subsequent two sub-chapters will discuss the two factors foreshadowed in this section. These well-documented factors directly influence electricity consumption and are thus used in the analysis to reinforce the regular patterns of power consumption in each country studied.

3.3.1 Effect of temperature on electricity consumption

Heating and cooling degree days. Indicator code: CLIM 047 (European Environment Agency, EEA)

As space heating and cooling account for a significant portion of Europe's energy consumption, European Environment Agency provides an indicator for heating and cooling degree days aim to support Environmental policy formulation, establishing goals, and transitioning from oversight and assessment to informing decision-makers and the populace. Heating degree days (HDDs) and cooling degree days (CDDs) estimate the energy required to either heat or cool buildings based on external temperatures. The actual energy need also depends on factors like building design, insulation, heating/cooling systems, economic conditions, and user behavior. Reduced heating demand can lower Europe's energy consumption, but this can be counteracted by increased cooling needs. Heating sources vary, but cooling mainly uses electricity. Thus, changes in cooling needs can have a greater impact on costs, energy demand, and supply network capacity than equivalent changes in heating. Their calculation can vary depending on the methodology and available data. Prior to 2016, the method used only daily mean temperatures and had inconsistencies. The method used to create the current indicator was developed by the UK Met Office using daily mean, minimum, and maximum temperatures, making it more accurate for assessing climate change impacts on energy demand. This is because maximum temperatures influence cooling more, while minimum temperatures are crucial for heating. The reference temperatures for HDDs and CDDs are 15.5°C and 22°C, respectively. When aggregating HDDs and CDDs data over large regions, using population weighting is more suitable for regions with varied population densities, like Europe.

Heating degree days (HDDs) and cooling degree days (CDDs) are essential indicators in understanding energy demand based on external temperatures, specifically for heating and cooling needs, in Europe. These indicators have a significant effect on the electricity supply network and electricity demand patterns. Prior research, notably by Spinoni et al. (2016) and referenced by EEA due to its methodology, has demonstrated strong correlations between HDDs and CDDs across most of Europe, using an extensive independent data set.

Constructing a temperature-driven variable for electricity demand fluctuations

Considering the significant influence of certain factors on electricity consumption patterns, this study integrates these elements as independent variables for both heating and cooling temperatures, using threshold grades specified by the CLIM 047 indicator.
While this research's primary objective isn't to specifically gauge the influence of temperature on electricity load, it leverages information from the EEA and the correlation between cooling, heating needs, and electricity demand as identified by Spinoni et al. (2016). This foundational understanding facilitates the integration of air temperature data, alongside the introduction of heating and cooling dummy variables. The primary goal of this analysis is to accentuate the fluctuations in electricity demand due to air temperature, ensuring accurate predictions in alternative scenarios.

Challenges arise when correlating load data from vast areas with temperature datasets. Larger nations often experience varied climates, making it preferable to use locally-collected temperatures. The division of electricity consumption into bidding zones will be further elaborated upon in section 3.5. Given this study's focus on load fluctuations, temperature data collection points are aligned with the capitals of the countries under examination (specified in 4.3). Italy, with multiple bidding zones, aligns temperatures with weather stations corresponding to the region's capital. Meanwhile, Romania, the largest country in this study with a singular national bidding zone, uses the weather station in its capital for simplicity, despite potential regional temperature variations. Cooling and heating degree variables are introduced to capture the impact of temperature on the load, rather than to quantify these effects, thus a streamlined approach is adopted.

3.3.2 Effect of holiday on electricity consumption

Modeling public holidays in load forecasting: a German case study (Ziel, F.)

The paper examines the impact of public holidays on electricity load in Germany and their influence on regular weekday demand patterns. Using two main benchmark models, both univariate and multivariate modeling strategies are explored. These models are crafted to produce identical outcomes and pave the way for the integration of public holiday modeling techniques. Various adaptations for public holidays, such as their removal from the dataset,

designating public holidays with a Sunday dummy, or introducing independent holiday dummies, have led to the development of 32 distinct models across 8 model categories.
This study offers a detailed discussion on the influence of holidays. During these days behaviors change, influencing electricity demand, resulting in impacts on electricity prices. Public holidays, set by authorities in advance, can be predicted in energy forecasts. However, unforeseen changes in holiday scheduling by governments can disrupt these patterns. Globally, holidays often reduce work and thereby electricity demand. Yet, in tourist regions, demand might increase on holidays. Given their once-a-year occurrence, modeling the impact of public holidays on energy demand is challenging. While most energy consumption follows a weekly pattern, holidays can disrupt this, resembling weekend consumption patterns.
It's also noteworthy that holidays are generally divided into two categories: fixed-date public holidays – falling on the same date each year, like New Year’s Day (1 January) and Christmas Day (25 December) or national holidays that mark historical significance, such as Independence Day, Constitution Day, or Unity Day. The second category is a weekday public holiday. The date of these holidays varies, but they always occur on a specific weekday each year. Examples include Christian holidays like Easter and Ascension in Europe.
Analysis of German electricity load data between 2010 and 2016 reveals stable impacts from varying-date holidays like Good Friday and Easter Monday, while fixed-date holidays like Labor Day have varied effects depending on which day of the week they occur. Some holidays, such as regional public holidays, don't neatly fit into these categories, but this study concentrates only on standard public holidays in German load forecasting.
Various methods were explored, such as removing public holidays from the dataset, treating them as Sunday dummies, or introducing distinct holiday dummies. The most effective approach is the "replacing public holiday dummy", which proved to be effective in multivariate models. In this method, while adding holiday dummies, weekday dummies on holidays are set to zero. The main result and the final conclusion put forward by the author confirm that including holiday effects can potentially enhance the accuracy of holiday period forecasts by over 80%, and also decrease the error for non-holiday periods by roughly 10%.

Modeling Holiday Effects on Electricity Demand Fluctuations

Drawing on the findings of Ziel (2018) and the significance of holidays in predicting crisis impacts, as highlighted by Buechler et al. (2022), a 'Holiday' variable is employed for each year analyzed across all countries. This variable seeks to capture the effects of non-working days on electricity consumption patterns rather than precisely quantifying their impact. For this analysis, any 'Holiday' occurrence during the weekends is excluded, while its effects during weekdays are considered. Accounting for holidays specifically on weekdays captures the unique shift within the weekday pattern and ensures model consistency across time. The inclusion of this variable is vital for accurately capturing seasonal patterns within each nation, which is essential for making precise predictions of electricity load during the evaluated periods.

3.4 European electricity market and pricing

The EU's journey towards an integrated goods and services market began with the 1988 Single European Act. It soon broadened to encompass the unification of national electricity markets, aiming to elevate competition and reduce consumer prices. Milestones include the Price Transparency Directive (1990) for clearer industrial electricity and gas prices and the Electricity and Gas Transit Directives (1990 and 1991) to ease cross-border energy exchanges. The 1995 Green Paper proclaimed energy market liberalization, culminating in the Electricity Directive (ED) in 1997 and the Gas Directive in 1998. Both aimed for a cohesive EU electricity market by 2000, emphasizing improved energy infrastructure for competition and integration. Gradually, the EU transitioned from state-controlled energy to market-driven processes. The emphasis was on consumers on the retail market having ability to choose providers, fueling consumer market competition. Competitive bidding for new generation assets played a key role in initiating wholesale markets where electricity was traded as a commodity. By 2001, intense competition, particularly in Germany, led to significant price reductions for consumers, driven rather by competitive forces than by actual cost reduction. However, price disparities among nations persisted. Issues like high network tariffs and market power in generation meant consumers often faced elevated prices (Bower, 2002).

2009's Third Energy Package aimed to strengthen the internal energy market, updated later in 2019 with the Clean Energy package, which emphasized consumers participation. The Climate and Energy Package 2020 set targets for emissions and renewables. While steps towards improved market design and increased cross-border exchanges have brought industries closer in terms of electricity prices, determining the exact effect of a competitive market on prices is complex. Retail prices vary significantly across the EU. For example, two-thirds of retail electricity prices come from regulated charges, levies, and taxes, leaving a fraction for the energy commodity. While some regions, like the Baltic, show integration strides, others lag behind (Cassetta et al., 2022).

3.4.1 Price elasticity in residential and non-residential sectors and electricity consumption

The interplay between electricity prices and consumption patterns in various sectors has been a focal point in numerous studies, illustrating varying sensitivities across sectors and regions. The finding of price elasticity in a study by Azevedo et al. (2011), focused on residential electricity demand in the U.S. (data from 1990 to 2003) and the EU (from 1990 to 2004) indicated modest impacts. Their research suggested that residential electricity demand is generally price-inelastic, with price elasticity values ranging from -0.18 to -0.25 depending on the region and model used. They concluded that a mere increase in electricity prices might not be sufficient to influence electricity intensity.

Gutiérrez-Pedreroa et al. (2018) further expanded this discussion by examining the drivers of electricity intensity in the non-residential sectors of 18 EU countries. They argued that while increasing electricity prices is a commonly suggested tool to reduce electricity intensity, the effect of such price changes is limited. Non-price barriers like hidden costs, lack of awareness, and other systemic issues often play a more pivotal role in influencing electricity intensity, especially in non-energy-intensive sectors.

Research by Cialani and Mortazavi (2018) examines the electricity demand for residential and industrial users across 29 countries during Europe's electricity market liberalization from 1995 to 2015, aiming to understand the long-term effects of prices on electricity demand. The key insights reveal both sectors to be price and income inelastic, with the residential segment less reactive to price fluctuations than its industrial counterpart. A significant price surge is necessary to notably affect consumption in either sector. The observed high long-run income elasticity suggests that as European incomes rise, the acquisition of electrical devices, and consequently electricity consumption, will likely increase.

A fairly recent study by Csereklyei (2020) examined both residential and industrial electricity demand responses to short-term and long-term price and income fluctuations in the European Union from 1996 to 2016. This research demonstrated that in the long run, residential and industrial electricity consumption is sensitive to price changes, with the latter showing greater elasticity. Specifically, long-run residential price elasticity ranged from -0.53 to -0.56, while the industrial price elasticity was between -0.75 and -1.01. Contrary to two prior studies, this research indicates that while residential electricity consumption does decrease in response to price increases, industrial sectors adjust their consumption more significantly. However, short-term demand appears less responsive to such price fluctuations.

Price dynamics in explaining electricity demand

While studies on price elasticity in electricity consumption provide varied conclusions, one consistent finding is evident: mere price increments might not drastically change consumption patterns, particularly in the short-term. Other determinants, like economic shifts and income changes, often play pivotal roles. Results presented by Cialani and Mortazavi (2018), pointing towards muted reactions of the residential segment to price fluctuations, can perhaps be linked to the effects of European electricity market, particularly the prevalent fixed-price contracts among European households. Additionally, their assertion that a significant price surge can markedly affect consumption is crucial in the context of the recent energy crisis analyzed in this paper. The findings from Csereklyei's recent research (2020) seem to mirror the current economic situation, especially in light of the energy poverty discussed in section 3.1 by Halkos and Gkampoura (2021). This discussion also encompasses the recent energy crisis, as analyzed in this study, and its projected impact on electricity demand. Expecting the surging prices during 2022 having some effects on electricity demand, their inclusion in this analysis would only make sense. However, due to limited data access, ambiguous evidence from the presented studies, and the dominance of fixed-price schemes in the EU electricity market - which may result in long-term impacts rather than the short-term effects analyzed in this paper -the price variable won't be integrated into the model for this analysis.

3.4.2 Price Convergence in European Electricity Markets

Understanding the differences in price elasticity sensitivity sets the stage for discussing more specific market phenomena of the price convergence in the European Union's electricity market. Elasticity plays a role, as the responsiveness of electricity demand and supply to price changes can influence the pace and extent of price convergence across member states.
In the European electricity market, price convergence refers to the alignment of prices across regions, which signals efficient resource use and robust competition. This alignment combats

the inefficiencies that arise when regions operate in isolation. However, achieving price convergence in reality is not only complex but also incredibly challenging. Numerous studies on the harmonization of electricity prices across EU member states have yielded mixed results. Zachmann (2008) points out that the implementation of EU directives among member states has been uneven, leaving the EU's ultimate goal unfulfilled. His work reviews several studies assessing the impact of these reforms, particularly in relation to the convergence of electricity prices across European countries. Some research, like that of Armstrong and Galli (2005), suggests that European electricity prices converged between 2002 and 2004. In contrast, studies by Bower (2002) and Boisseleau (2004) document varying levels of market integration and price convergence throughout Europe.

Zachmann's focus was the integration of Europe's electricity markets between 2002 and 2006, using wholesale prices as a metric. His findings indicate that by mid-2006, a unified electricity market in continental Europe remained unachieved. Though some national electricity price differences diminished, significant discrepancies persisted. Notably, while 59% of national wholesale electricity prices converged between 2002 and 2006, this trend was mainly evident during off-peak times. Moreover, international price differences couldn't be solely attributed to cross-border transmission capacity prices. In fact, over 93% of the market pairs studied displayed significant, predictable arbitrage opportunities. However, 42% of these opportunities showed no signs of being eradicated in the near future.
A recent study by Cassetta et al. (2022), takes interest in intriguing trend in electricity prices, particularly when comparing household and non-household markets between 2008 and 2021 in EU. Despite the extensive efforts to harmonize and integrate the market, significant disparities in retail electricity prices continue to persist across Member States of the EU. This variation becomes more intriguing in light of empirical studies that introduce the concept of "club convergence." This idea assumes that instead of a single unified price, countries are gravitating towards multiple equilibrium states for end-user electricity prices.

A closer look reveals that the domestic household prices are more varied and divergent than their industrial counterparts. Such a trend is evident as nine countries within the household sector did not follow the general convergence trend and remained outliers. This raises the question of what factors or variables influence these disparities. Interestingly, the "convergence clubs", which are groups of countries with analogous price behaviors, do not adhere strictly to geographical boundaries or the established structures of wholesale markets.

Furthermore, these clubs don't consistently reflect the intrinsic structural features that characterize each nation's electricity market.

Delving deeper, it becomes apparent that factors such as public intervention in determining electricity prices, along with the inconsistent criteria set by countries to define energy components, play a substantial role in influencing price convergence. Moreover, while deregulation might be seen as a solution to these disparities, the process of relaxing regulated prices, especially for households, has been hindered. This slowdown stems from an evolved focus of energy policies prioritizing ecological concerns and ensuring supply security. As a result, there has been a significant uptick in non-contestable charges, which include taxes and network costs. These charges, not emerging from competitive markets, are often determined by governmental or regulatory bodies.

The puzzle of price convergence also gets more intricate when considering the role of socio-economic considerations, divergent national energy stances, and varying industrial policies. For instance, in a bid to boost industrial competitiveness, major industries might be granted price reliefs, which unfortunately often results in households bearing the brunt of price hikes. These increases are usually justified by the need to finance policies that champion renewable energy sources.

In conclusion, while the European Union has been committed in its attempts to integrate markets and harmonize prices, the landscape of electricity prices across member states remains varied. This variation isn't just a product of market forces but is influenced by numerous factors, ranging from policy decisions to socio-economic considerations.

As mentioned in the previous section, price effects are anticipated to influence electricity demand among countries, particularly during the 2022 energy crisis. This shock was driven by a surge in electricity prices due to sanctions on gas deliveries from Russia. However, the intricate web of price-related connections among countries, industries, and households of member states, combined with various financial stimulus packages introduced during the two analyzed periods, complicates the modeling process. Additionally, limited data access for accurately modeling these specific years and months (spanning COVID-19 and the energy crisis) means a variable capturing price convergence will not be incorporated in the analysis. Nevertheless, its potential influence will be discussed in the results section.

3.4.3 Relationship between the EU gas market and EU electricity market

A logical continuation from the discussion on price effects, stemming from price convergence in the EU electricity market and the energy crisis induced by sanctions on Russian gas, is to explore the relationship between the electricity and gas markets in Europe. Uribe et al. (2022) analyzed the influence of natural gas price fluctuations on electricity prices in 21 European countries from 2015 to 2022. Rising global electricity prices, especially in Europe during 2021-2022, have highlighted the interconnectedness of these markets. Factors like supply issues and geopolitical events, such as Russia's Ukraine invasion, have affected these prices. The relationship between electricity and natural gas is complex; the latter is used for power generation and as an electricity substitute. The study employed quantile regressions to understand electricity market scenarios based on weather and gas prices. Historically, gas prices significantly affected electricity rates, with gas power plants setting prices during peak demands. Unexpected gas price hikes directly affect consumers. Elevated electricity prices increase gas demand, raising its price. The study revealed countries like Denmark and Germany are more sensitive to gas price shocks, suggesting a need for more integrated European electricity markets. Amidst price surges, the European Commission has pushed for better pricing mechanisms. The study recommends distancing Europe's energy system from fossil fuel market unpredictability.

Ciferri et al. (2020) explored the relationship between wholesale electricity and fuel prices in Europe. They discerned convergence patterns among national electricity prices and found that integrating oil Brent prices confirmed this link. Despite varied power generation methods, national electricity markets are influenced by fuel prices. Tests showed a significant link between electricity and oil prices, indicating fuel price dynamics stabilize electricity prices. Transient shocks impact nations differently, depending on their market interconnections; for instance, Italy's price variance is significantly influenced by France and the German-Austrian market.

Despite the primary focus on the EU's electricity market, comprehending the energy crisis's effects on electricity consumption necessitates recognizing the pivotal role of the gas market. Countries' dependencies, market convergence, and resultant price impacts during the crisis were evident even in nations not reliant on gas deliveries. Moreover, understanding price elasticities across all sectors is indispensable for a holistic analysis.

3.5 Bidding zones

The role and concept of bidding zones are fundamental to this analysis, both for collecting load data and understanding the intricate relationships among member countries that lead to price convergence. This is further underscored by the term “convergence club” introduced by Cassetta et al. (2022) in section 3.4.2.
A deep understanding of the concept of bidding zones is crucial for interpreting results and formulating meaningful conclusions. As highlighted earlier, bidding zones, typically coupling similar markets, are vital for facilitating cross-border electricity trade and ensuring efficient energy flow. This mechanism directly influences price formation and dynamics. Market coupling and bidding zones are instrumental in promoting price convergence in the electricity market. By unifying these markets, cross-border electricity trade is enhanced, leading to a harmonization of prices in interconnected regions.

Bidding zones are strategically delineated based on grid constraints and physical barriers, ensuring efficient price convergence. The European Commission's Bidding Zone Review (BZR) is designed to optimize the performance of the electricity market. Specifically, Commission Regulation (EU) 2015/1222 (CACM) categorizes these zones for effective congestion management, while Regulation (EU) 2019/943 emphasizes their design around enduring transmission network congestions instead of national boundaries. This mandates Transmission System Operators (TSOs) to continually evaluate and adjust these zones, with goals of economic efficiency, enhancing cross-border trades, and maintaining electricity supply security in the EU (ENTSO-E, 2023).
Following the mandated in 2019 review, the EU's Agency for the Cooperation of Energy Regulators (ACER) decided on alternative electricity bidding zone layouts. While these zones usually align with European national boundaries, the EU model insists they center around network congestions. ACER's recent choices, influenced by 2022 consultations and TSO data, proposed different configurations for several EU countries, including multiple zones for Germany and Sweden, and earlier than 2022 for Italy. Properly designed zones, in line with long-term congestions, bring benefits like improved cross-border trading, strategic network investments, and efficient technology integration. As a result of this review, the bidding zones for Bulgaria (BG) and Greece (GR), both located in the South-East Europe (SEE) bidding zone region, as well as Romania (RO) in the Central Europe (CE) bidding zone region, remained unchanged, following the countries' borders as indicated above. (ACER,

2022). These BZN are the source of aggregate electricity load used to analyze the effects of both crises on consumption. They also dictated the choice of matching weather observations described in 3.3.1.

Figure 3: Bidding Zone Review Regions (ENTSO-E, 2023a).

In 2021, the Italian Bidding zones were adjusted, maintaining the previous division of Italy into six regions, with some local adjustments, however. Although TSOs submitted the updated BZR proposal in that year, the BZ changes from the previous process in Italy had not been implemented until they took effect in 2021. Specifically, the Central-Southern Italy zone was expanded to include the region of Umbria, which was formerly a part of the Central-Northern bidding zone. The map below, sourced from Annex 4 of the Bidding Zone Review process, depicts these changes in the bidding zones. (ENTSO-E, 2019; ACER, 2022)

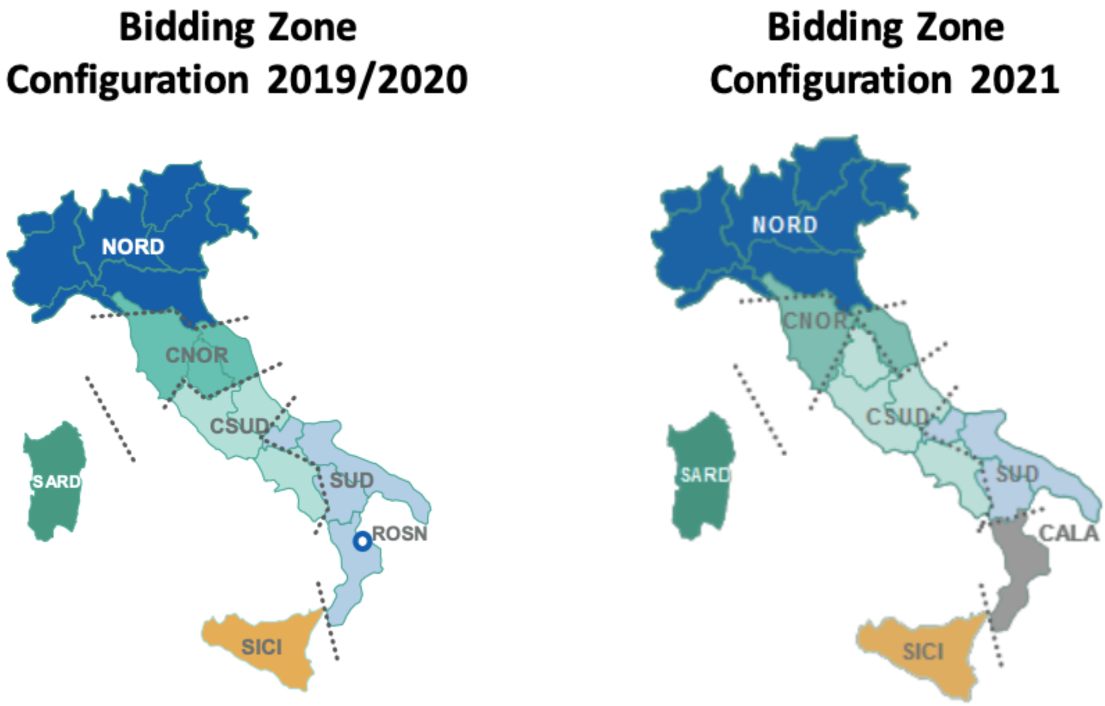

Figure 4: Configuration of Bidding Zones in Italy pre-2021 and post-2021 (ENTSO-E, 2019).

This information is vital for accurately interpreting the results from the analysis presented in this paper, as Central-Northern BZ loses one region in favor of Central-Southern BZ affecting most likely the electricity patterns estimated on the years prior 2021. This analysis, only the four regions located on the Italian peninsula are considered.

3.6 Forecasting electricity consumption

The most prevalent application of econometrics involves testing economic theories, evaluating the effects of implemented policies, and estimating economic relationships. These analyses often encompass topics such as GDP, wages, oil prices, or interest rates, where the forecasting application is widespread and versatile.

In the context of energy, the advancing electrification aimed at reducing greenhouse gas emissions, diversifying resources for electricity generation, and adapting to more extreme weather conditions has accentuated the importance of accurate load forecasting. It has become a critical issue for power utilities and national energy security. The particularly volatile nature of electricity consumption has spurred significant advancements in various load forecasting models. These models can be categorized into two main branches of classification: traditional statistical models and artificial intelligence models.

Traditional statistical models utilize historical data to identify relationships between load and exogenous variables, as well as detect trends or seasonality across time, typically defining these relationships as linear. Some widely used and tested statistical models for electrical load forecasting include Box-Jenkins ARIMA, exponential smoothing models, Kalman filtering models, Bayesian estimation models, and regression models (Hong, 2020).

The aim of this study is to examine the effects of crises on electricity load by predicting the dynamics of hourly electricity consumption, including all time-dependent trends and seasonalities, based on past data from an undisrupted economic scenario. Unlike conventional forecasting models where the precision of the forecasted load is essential, the focus here is on accurately capturing and reflecting the underlying patterns and fluctuations in electricity consumption. To achieve this objective, a Static, Multiple-Step Forecasting approach is employed, augmented with the use of dummy variables. This method allows for the recognition of any underlying trends and seasonal variations within the data, providing a nuanced view of how crises may disrupt or alter these established patterns (Wooldridge, 2016).

An important clarification regarding the nomenclature used in subsequent chapters needs to be addressed at this point. Though this section of the study is titled 'Forecasting electricity consumption,' the specific technique and methodology employed to estimate the data will henceforth be referred to as 'predicting.' This distinction is vital, as forecasting extends beyond mere prediction, involving the generation of new or unseen values for the independent variables, often associated with greater uncertainty. In contrast, this analysis estimates values of the dependent variable – electricity load – for given values of the independent variables, such as the air temperature in the context of this study. (Dunham, 2003).

Econometrics, as stated at the outset of this chapter, are grounded in and utilized to test economic theories that articulate well-established relationships between the variables under study. This foundation enables the interpretation of uncertain and unclear results arising from forecasts. In this specific investigation, where there is no ability to rely directly on economic theories related to aggregate electricity consumption or the effects of crises on load demand, and where there are no restrictive assumptions, predictive techniques will be applied (Hirchey M., 2009). Unlike more constrained models, predictive techniques are adaptable to various functions, as their estimations are grounded in historical data. This flexibility allows for an approach that aligns with the unique aspects of this study, emphasizing the importance of accurate prediction over broader forecasting.

4. Data

4.1 Selection of Countries for Analysis

As highlighted in the introduction, this analysis aims to compare two potential scenarios - one encapsulating unanticipated conditions and the other reflecting a 'business as usual' situation. Considering unique triggers and solutions under both crisis, along with restricted access to power load data and the inherent national, as well as somewhat regional, nature of electricity markets, the choice of countries for analysis was limited to Europe.

It's important to underscore that the two case scenarios analyzed impacted all selected countries within the same timeframe and season. This suggests that despite minor climate differences, each country was faced with similar challenges. Furthermore, all these countries are members of the same political and economic union, which ensures a certain degree of coordination and consistency in their responses. Therefore, the primary differences among the included countries lie in their economic discrepancies, dominant economic sectors, and energy dependencies. This analysis allows, to some extent, examine how the patterns of electricity consumption were affected by the crisis in different countries.

Anticipating opposite consumption pattern changes in service-based and industrialized economies, and with an interest in investigating countries with varying energy mix, this paper focuses its analysis on four EU member countries: Italy, Greece, Romania, and Bulgaria. The unique characteristics and energy dependencies of each of these countries will be discussed in Chapter 7.

4.2 Power Load Data Collection

The electricity load data for all four countries was collected directly from the from the website of the European Network of Transmission System Operators for Electricity (ENTSO-E). ENTSO-E is a non-profit organization representing 42 transmission system operators from 36 European countries, making its data crucial for understanding the market trends and operational patterns. The data available on the platform include market data (such as electricity prices, demand, and supply), grid data (like network topology and load flows), balancing data (use of reserves and management of frequency), renewable energy data (focusing on generation and integration), and energy consumption data. Datasets are compiled through direct measurements and reporting by transmission system operators, providing an overview of the European electricity market (ENTSO-E, 2023b).

The fetching of the Actual Total Load data was carried out through the REST API implemented in Python. This approach offers a publicly available web URL, enabling seamless access to the data sets. The endpoint, specified as 'https://web-api.tp.entsoe.eu/api', was established in the Python environment, allows the download for Entso-e Pandas Client by providing a unique API key (ENTSO-E, 2023c-2023i).

The complete documentation and guide for the RESTFUL API implementation is available on the transparency.entsoe.eu (ENTSO-E, 2023j) website and provides in depth explanation of the use case and process sequence. The data for each country was gathered according to a specific bidding zone, referred to as the BZN. This method facilitated the alignment of load data with the available temperature data, which is detailed in the following section. The BZN for each country are:

Bulgaria (BG):	BZN|BG	UTC+2
Greece (GR):	BZN|GR	UTC+2
Romania (RO):	BZN|RO	UTC+2
Italy (IT):	BZN|IT-North	UTC+1
Italy (IT):	BZN|IT-Centre-North	UTC+1
Italy (IT):	BZN|IT-Centre-South	UTC+1
Italy (IT):	BZN|IT-South	UTC+1

For each of the bidding zones the data fetched presented an hourly frequency and ranged from 2015-12-31 until 2023-02-28. All the countries are following the standard winter -

Central European Time (CET) and daylight-saving summertime - Central European Summertime (CEST): Italy of (UTC+1/UTC+2) and Greece, Bulgaria, and Romania (UTC+2/UTC+3). In the process of preparing the raw data, a separate column was generated for each country, calculating the actual hour of the day ‘hour’, and additional column ‘date’ adjusting the right date (e.g., 00:00:00+01:00). This arrangement ensured compatibility with the hourly temperature data. Due to the large size of the datasets, some sporadic missing data were encountered. To ensure the smooth execution of the linear regression prediction, these missing or 'NaN' load data points were linearly interpolated - replaced with the average of the two nearest load values. This process resulted in a new, fully populated column named 'nload'.

In the datasets of three countries, Bulgaria (BG), Greece (GR) and Central-Southern Italy (IT-Centre-South) single instances of unexpectedly low load values or registering load twice for the same hour were identified, spanning 1 to 3 hours. These anomalies posed challenges in visually analyzing and explaining the comparison between the actual load and the business-as-usual (BAU) scenario. The values discovered:

Bulgaria:	
2019-04-03 00:00:00	3303.0
2019-04-03 01:00:00	1803.0
2019-04-03 01:00:00	3512.0
Greece:	
2022-10-31 03:00:00	3595.0
2022-10-31 04:00:00	408.0
2022-10-31 05:00:00	731.0
2022-10-31 06:00:00	1478.0
2022-10-31 07:00:00	2255.0
Central-Southern Italy:	
2019-10-27 03:00:00	3375.0
2019-10-27 04:00:00	3169.0
2019-10-27 03:00:00	1334.0
2019-10-27 04:00:00	3067.0
2019-10-27 05:00:00	3061.0

These values act as outliers; however, they are unlikely to disrupt predictions given the extensive sample size during the estimation period, which outweighs the influence of these records. Consequently, no attempts have been made to correct their values to avoid external intervention. These values are duly presented, and their presence in the dataset is acknowledged.

4.3 Temperature Data Collection

To ensure the exogenous variable during analyzing changes in load patterns, the temperature data from a publicly available website of The Iowa Environmental Mesonet (IEM) were collected and later merged with the load dataset.

IEM collects an expanding archive of global automated airport weather observations, referred to as 'ASOS' or 'AWOS' sensors. These observations are transmitted as METAR data (standardized meteorological report used primarily for aviation purposes). The archive serves as a historical collection with minimal quality control. Data sources include Unidata IDD, NCEI ISD, and MADIS One Minute ASOS (IEM, 2020).

The temperature data were fetched manually from ASOS-AWOS-METAR Data Download (IEM, 2023). To align these observations with the load datasets, the air temperature data was collected for the same period between 2015-12-31 and 2023-02-28. The air temperature, recorded in degrees Celsius, was obtained at a frequency of every 30 minutes, and the measurements were noted in Coordinated Universal Time (UTC). The stations chosen for temperature data collection were strategically selected to correspond with the bidding zones for which the load data was sourced.

BZN|BG	‘LBSF’	Sofia
BZN|GR	'LGAV'	Athens
BZN|RO	'LROP'	Bucharest
BZN|IT-North	'LIMC'	Milano
BZN|IT-Centre-North	'LIRQ'	Florence
BZN|IT-Centre-South	'LIRA'	Rome
BZN|IT-South	'LIBD'	Bari

The handling of temperature datasets paralleled that of the load data. To ensure uniformity, the frequency of temperature data was adjusted to align with the hourly intervals of the load data collection. Any sporadic missing values were seamlessly omitted during this process, and further supplemented the dataset with a new column, 'ntmpc', representing these adjusted values.

4.4 Missing observations

Two data frames were merged by linking rows through the shared 'date' and 'hour' columns, aligning corresponding temperature and load data. In the new data frame, the 'date' and 'hour' columns were consolidated into the new column 'time' and setting 'time' as the new index. Such restructuring of the data simplifies manipulation and analysis, ultimately improving the efficiency of the process.

The majority of missing values in both load and temperature observations can be attributed to errors during recording the values, not the data handling.
In three datasets, specifically BG, GR, and RO, several consecutive missing values were identified within certain days. This made it impractical to use the linear interpolation method. To maintain consistency, five days in total were removed from the datasets. The affected dates are:

BG - 2017-10-04, 2017-10-05, 2018-10-28
GR - 2016-10-15
RO - 2021-08-06

The overview of missing values, total observations, and observations removed from the datasets is available in Appendix 2.

4.5 Holiday Data Collection

Holiday data for each country was manually collected from the website timeanddate.com/holidays (Time and Date AS, 2023). This source was chosen because it provided the most reliable and consistent list of holidays dating back to the year 2016 for all the countries under study.

This analysis spans of seven and a half years and includes only the holidays from the category 'Official holidays and non-working days', as any local and regional celebrations would not have any significant impact on the aggregate load.
A notable difference in dates is seen in the celebration of Easter by the Catholic and Orthodox Churches, aligned with the Gregorian calendar in Italy and the Julian calendar in Romania, Bulgaria, and Greece, respectively. Furthermore, Easter is recognized as a floating holiday. National holidays, such as independence, liberation, or constitution days, maintain fixed dates within their respective countries. Other fixed-date holidays, like New Year's Day (January 1) and Christmas Day (December 25), are observed in all four countries. Separate lists of holiday dates for each country, as well as those shared across all four countries under study, were generated in Python and are included in Appendix 3.

4.6 Software Used for Data Analysis

The primary tool used for data analysis in this study was Python, a versatile and powerful programming language that enables data analysis and output visualization. Python was accessed through Anaconda, a free and open-source distribution that simplifies managing and deployment of packages commonly used for data analysis.

Jupyter Notebook, an open-source web application, was utilized for creating and sharing documents that contain both Python code and figures, links). Jupyter Notebooks are ideal for data cleaning and transformation, numerical simulation, statistical modeling, data visualization, and machine learning. They facilitated the iterative and collaborative nature of the data analysis, allowing to integrate the code, visualizations, and narrative into a single, easily shareable document.

5. Method

This chapter provides a comprehensive explanation of the econometric methods employed to quantify the effects of the COVID-19 pandemic and the energy crisis in Europe. The models used are intentionally streamlined, incorporating only those variables that are consistent across all countries and have an indisputable influence on electricity consumption. This strategic simplification serves to highlight the differences in consumption that can likely be attributed to the impact of the crises and the unique economic circumstances of each country.

5.1 Predicting the electricity load with OLS regression model.

One of the primary challenges in shaping the empirical analysis lies in formulating the research questions and constructing the economic model. Considering that most economic factors depend on various conditions and complex interdependencies, the selection of variables to include in the model, along with the assumptions associated with these choices, becomes crucial and necessitates clear explanation. (Wooldridge, 2016)

The aim of this paper is to quantify the impact of the COVID-19 pandemic and subsequent energy crisis in the European Union on aggregate electricity consumption. The analysis will lean heavily on the well-documented relationships and dependencies between load, seasonal trends, and the correlation between electricity demand and temperature, as discussed in Chapters 3. Factors such as the economic conditions in the countries under study will be portrayed in the best way possible in the discussion part of this paper. However, due to restricted data access, these elements will not be incorporated into the model.

The data preparation and processing outlined in Chapter 4 of this paper resulted in creating a unified time-series dataset for each country. This data, organized chronologically, reveals significant trends and consumption patterns tied to specific dates and hours. Furthermore, this data includes the air temperature at specific points in time, which is essential information for this analysis.

To ensure the model encapsulates the strong associations between electricity load and factors such as temperature or specific time frames (week, year, or day), additional categorical variables such as ‘trend’, ‘Holiday’, 'week_dummy', 'hofw_dummy', 'heat_hours_dummy', and 'cool_hours_dummy' are introduced to further highlight these dependencies. These observations are computed as follows:

1. The **'trend'** values are calculated by dividing the corresponding index value by the total number of hours in a year (365.25 days * 24 hours per day). Variable captures the gradual changes over time, which will improve the analysis.

2. The **'Holiday'** variable was derived from a manually curated list of holidays for each country, spanning from 2016 to 2023. A new column, 'Holiday', was then generated

based on these specific dates. If there were overlaps between the entries marked as 'Weekend' and the new 'Holiday' column, these entries were set to 0; all other entries in the 'Holiday' column were set to 1. This approach to configuring the 'Holiday' variable follows one of the methods outlined by Ziel (2018).

3. The **'week_dummy'** variable is generated from the 'week' values restricted to a maximum of 52 to avoid including the 53rd week, which surfaces in the irregular years of 2017 and 2023. All the entries in data frame rows corresponding to the week in column are set to 1. Otherwise, the value defaults to 0.

4. In a similar manner, the **'hofw_dummy'** variable is generated from the 'hofw' column derived from converting the 'day' value to hours and adding the current 'hour'. By applying the modulus operator `%` with 168 to this value, a weekly cycle from 0 to 167 is established. Each 'hofw_dummy' column corresponds to an hour of the week, with matching rows set to 1 and non-matching set to 0.

5. The **'heat_hours_dummy'** is derived from the 'hour' and 'heat' columns. 'Heat' is calculated by subtracting 'ntmpc' from 15.5, representing the number of degrees Celsius below a comfortable indoor temperature - need for heating. Negative 'heat' values are set to zero, indicating no heating need. The variable signifies the heating required at every distinct hour of the day based on CLIM 047 indicator (EEA, 2021).

6. The **'cool_hours_dummy'** is generated similarly to 'heat_hours_dummy', but is multiplied by the 'cool' column. 'Cool' is determined by subtracting 22 from 'ntmpc', representing the cooling need to obtain the comfortable temperature in degrees Celsius. Negative 'cool' values are set to zero, indicating no cooling need. This variable is highlighting hourly cooling requirements based on CLIM 047 indicator (EEA, 2021).

After all the required dummy variables - reflecting unique trends and seasonal changes in load demand - have been constructed for each country, the model for daily electricity consumption is determined. This process is undertaken individually for each country and across three distinct time periods.

The load is estimated using an Ordinary Least Squares (OLS) regression model, which is applied to a dataset that has been split into an estimation period and a prediction period. This method is based on the commonly utilized train-test split procedure. This procedure ensures the model's ability to effectively generalize its learning to new, unseen data, thereby helping to prevent overfitting while maintaining the model's accuracy and predictive power.

The data frame for each country is individually divided into three time periods of interest. Initially, the model is estimated using data from the period between January 1, 2016, and December 31, 2018. Then, the model is used to predict data from January 1, 2019, to December 31, 2019. This evaluates the model's performance during a 'business as usual' period.

Subsequently, the model is estimated on data from January 1, 2016, to December 31, 2019, and the predicted period ranges from January 1, 2020, to December 31, 2020. This step assesses the impact of the COVID-19 pandemic on electricity consumption.

The model for daily electricity consumption for these two periods, which includes all appropriately transformed dummy variables and two subsets for each country, can be mathematically presented as follows:

$$f(nload_t) = \beta_0 + \sum_{i=1}^{52} \beta_i week_{it} + \sum_{j=1}^{168} \beta_j hofw_{jt} + \sum_{k=0}^{23} \beta_k heat\_hour_{kt} + \sum_{l=0}^{23} \beta_l cool\_hour_{lt}$$
$$+ \beta_m Holiday_t + \beta_n trend_t + e_t$$

The final model is estimated using data spanning from January 1, 2016, to December 31, 2021, and predictions are generated from January 1, 2022, to February 28, 2023.
The estimation period was selected to analyze the impact of the energy crisis in the EU. Considering potential anomalies due to the inclusion of 2020 - a year profoundly affected by the COVID-19 pandemic, and 2021 - a post-pandemic period generally viewed as a year of 'normal' consumption, a dummy variable accounting for COVID-19 effects was introduced in the model.

It's important to note that while 2021 is assumed to reflect normal consumption levels, there might still be some variations. This assumption is supported by literature review, suggesting that most countries experienced changes in load patterns in the first two to three months following the onset of the pandemic. By the second half of 2020, most consumption levels had returned to their 2019 levels. (Buechler et al., 2021). However, there are some exceptions to this general trend that the model must account for.
Just like the 'week_dummy' variable, the 'covid_dummy' variable is derived from the 'week' column, creating a distinct column for each week after the country-specific date marking the start of the nationwide COVID-19 lockdown. The binary 'covid_dummy' variable is used to differentiate between the weeks prior to the initiation of the COVID-19 restrictions in each given country and the weeks during or after the COVID-19 period. This strategy facilitates differentiation and accounts for the impact of various weeks within the COVID-19 period in the subsequent regression analysis.

The model for daily electricity consumption for this last period of analysis, which includes all five transformed dummy variables (‘week’, ‘hour_of_the_week’, ‘heat_hours’, ‘cool_hours’, and ‘covid’), can be mathematically represented as follows:

$$f(nload_t) = \beta_0 + \sum_{i=1}^{52} \beta_i week_{it} + \sum_{j=1}^{168} \beta_j hofw_{jt} + \sum_{k=0}^{23} \beta_k heat\_hour_{kt}$$

$$+ \sum_{l=0}^{23} \beta_l cool\_hour_{lt} + \sum_{m=1}^{52} \beta_m covid_{mt} + \beta_n Holiday_t + \beta_p trend_t + e_t$$

After estimating the model on the designated time periods, it is utilized to produce predicted load values for each prediction period. These predicted values are then graphed alongside the actual load data from the original data frame. This visualization allows for an easy comparison between real consumption levels and predicted consumption. Detailed results specific to each country are presented and discussed in the subsequent Chapter 7.
Additionally, the ogarithmic difference between actual and predicted load consumption - the differences between the actual and predicted values - are plotted as well (process described in subsequent Chapter 5.2), allowing a more straightforward visual evaluation of the model's performance. All the plots comparing the predicted load against the actual load are presented in Appendix 4.

Addressing Heteroskedasticity and Autocorrelation in OLS Regression with HAC Covariances: Newey-West Standard Errors

OLS model is estimated on large time series data, where the errors may be correlated across time and variance may vary significantly and any seasonality in the data is amplified with the dummy variables. To account for this autocorrelation and heteroscedasticity in the errors a Newey-West type of HAC standard errors is applied in OLS regression model.
Newey-West or HAC standard errors are types of robust standard errors to provide consistent estimates of the standard errors even when there is autocorrelation or heteroskedasticity present.
The method employs a specific weighting scheme for the autocorrelations that declines linearly with the lag length (Wooldridge, 2016).
The number of lags of residuals to be used in the construction of the autocorrelation robust standard errors is set to 168 (24 hours * 7 days = 168 hours), accounting for potential weekly patterns in the data, which could be important given the hourly frequency of the data.

The Wald test

The Wald test, a parametric statistical test frequently used in econometrics and statistical analysis, is designed to evaluate the significance of coefficients within an unrestricted regression model. This test is particularly suitable for large samples as it is asymptotic (Wooldridge, 2016). Given some inconsistencies in estimated parameters and the insignificance levels of some specific weeks or cool and heat hours within the model results, the Wald test is employed to assess the joint significance of the selected variables (excluding the 'covid_dummy' variable).

The null hypothesis (H0) within the model states that the set of parameters attributed to each of the four dummy variables is equal to zero. This hypothesis implies that the respective variable does not have any noticeable effect. If a p-value is less than the conventional statistical significance level of 0.05, it permits the rejection of the null hypothesis, indicating that the variable does indeed have a significant effect. The Wald test results for each of these four dummy variables are provided in Appendix 4.

5.2 Logarithmic difference between actual and predicted load consumption

The subsequent step in this analysis involves calculating and graphically representing the logarithmic difference between the actual and predicted load consumption. The method used to obtain this variance, while similar, is not precisely an error forecast. An error forecast typically computes the absolute difference between the logarithm of the predicted value and the logarithm of the actual value, without considering the direction of the prediction error (whether the prediction is higher or lower than the actual value). However, in this analysis, the variance is determined through a subtraction operation, thus maintaining the direction of the error:

$$load\_difference = 100 * (ln(actual\_load) - ln(predicted\_load))$$

The load difference is computed as 100 times the difference between the logarithm of the actual load and the logarithm of the predicted load. This calculation results in a percentage change, which provides an intuitive measure of the relative error in the predictions. It also allows for an easier interpretation than a raw logarithmic difference. Negative percentage changes on the plot indicate instances where the predicted load was higher than the actual, suggesting events that negatively impacted the aggregate electricity consumption. These could include a milder winter or summer, or larger fluctuations due to crises. Conversely, positive percentage changes suggest that the predicted values were lower than the actual. This could be caused by colder winters, hotter summers, or increased productivity efforts to recover GDP after an economic downturn caused by a crisis. Country specific observations are discussed in the following Chapter 7. Plots are presented in Appendix 4.

5.3 Cumulative load comparing

Considering the specific nature of the datasets used in this analysis, which consist of hourly aggregate load data for each specific country over extended periods, assessing the predictive power and accuracy of the model can be challenging. One method to facilitate this evaluation is by plotting the cumulative sum of predicted and actual loads over time. The cumulative sum at any given point in time represents the total of all prior values. This visualization allows for a more comprehensive comparison of the overall performance of the predicted total load against the actual load accrued over time.

This strategy provides an insight into the total energy load and how well the model performs over extended periods. It is an effective way to visually assess the accuracy of the model's predictions in a cumulative manner. Cumulative load plots for all three periods in each country are presented in Appendix 4.

5.4 Estimating the effects of crises.

The methods described earlier facilitated the comparison of the actual load with the predicted load, under the 'business as usual' scenario that assumes the absence of both the COVID-19 pandemic and the EU energy crisis. Interpretations from these earlier models rest exclusively on the presumed accuracy and predictive power of the models. In the next phase of the analysis, four new dummy variables are introduced. These are intended to quantify the distinct impacts of the two crises and examine their effects in isolation from other variables in the dataset.

Effects of COVID-19

To account for the impact of the COVID-19 pandemic, two new features were added to the dataset: 'covid_hours_dummy' and 'covid_week_dummy'. The first one illustrates the influence of the pandemic on hourly electricity consumption patterns, while the second variable demonstrates the pandemic's weekly impact throughout the entire year of 2020.

In both instances, a new column titled 'covid' was initially introduced to each country's data frame. If a given timestamp equals or surpasses the specified start of the COVID-19 lockdown in each respective country (dates specified in Appendix 2), the 'covid' value is set to 1. For all other times, the 'covid' value defaults to 0. Essentially, this binary variable indicates whether a given record falls within the COVID-19 period.

Subsequently, dummy variables were created for each hour of the day using the 'hour' column, which resulted in 24 unique variables, one for each hour. These were then multiplied by the 'covid' column, setting 'covid_hours_dummy' to 1 if both the specific hour and the COVID-19 period conditions were met, and to 0 otherwise. These interaction terms allow the model to estimate the COVID-19 period's impact for each hour of the day separately.

The 'covid_week_dummy' variable was created similarly, but it utilizes the 'week' column instead of the 'hour' column. Consequently, 'covid_week_dummy' values are 1 only for the weeks that coincide with the COVID-19 lockdown period.

Effects of Russian invasion in Ukraine

The impact of the Russian invasion in Ukraine and the subsequent energy crisis in the EU has been encapsulated by incorporating two additional features in the dataset: 'war_hours_dummy' and 'war_week_dummy'. These variables are presenting the crisis's impact on hourly and weekly electricity consumption trends, following a similar procedure to the creation of the Covid-19 period dummy variables.

Initially, the 'war' column was generated, attributing the value 1 to each timestamp beyond the war's initiation on 24th February 2022, a date consistent for all countries. All remaining timestamps are assigned a 'war' value of 0. This binary variable effectively determines if a specific record corresponds to the energy crisis in EU period.

Following this, dummy variables were created for each hour of the day using the 'hour' column, culminating in 24 separate variables. These variables were subsequently multiplied by the 'war' column, assigning a value of 1 to 'war_hours_dummy' if both the specific hour and crisis period conditions were met, and 0 otherwise. These interaction terms equip the model with the capacity to separately estimate the crisis's influence for each hour of the day.

The process of creating the 'war_week_dummy' variable mirrors this for hourly impacts, substituting the 'hour' column with the 'week' column. Consequently, 'war_week_dummy' values are 1 exclusively for weeks concurrent with the energy crisis period.

The Wald test

Also here, prior to the transformation and visualization of parameters, a crucial step in evaluating the impacts of the two crises is testing the significance of the parameters for each of newly created dummy variables by employing the Wald test.

The null hypothesis (H0) for each variable states that the set of parameters corresponding to each variable - which represents the crises' impacts on electricity consumption - is equal to zero. This implies that the respective variable does not exert a noticeable effect. A p-value less than 0.05 allows for the rejection of the null hypothesis, indicating a significant effect of the tested variable. The Wald test results are provided in Appendix 5.

Estimating the effects

Following the creation of all four dummy variables – two for COVID-19 period and two for energy crisis impacts, the parameters associated with each dummy were saved to a separate list. After estimating the OLS regression model as described in section 5.1, list saved in the previous step are deployed to filter the residuals from the model and include only these indexed with parameters saved to the list for each dummy variable.

The OLS regression was estimated over two periods: from January 4th, 2016 (the first Monday of the year) to May 1st, 2022 — the point until which, according to the findings of Buechler et al. (2020), the most severe effects of the COVID-19 lockdown were presumably observed — to evaluate the impact of COVID-19, and from January 4th, 2016 to February 28th, 2023 to analyze the energy crisis in the EU.

This allows for a focused investigation of the effects of both COVID-19 and the energy crisis in the EU, which was triggered by the war in Ukraine, in a controlled environment, distinct from potential influences of other variables within the data set. The parameters are subjected to transformations as described below, for their rescaling and acquisition of confidence intervals.

1. Beta parameters: The coefficients associated with each dummy variable introduced to the model are represented by these parameters. The isolated impact of the respective crisis or variable is encapsulated in these parameters. A rescaling of these values is achieved by multiplying these coefficients by 100. This transformation enables interpretation of the changes in terms of a 100-unit change in the independent variable and are later plotted to represent the Effect (%) of given crisis on weekly and hourly electricity consumption changes.
2. Standard Errors: These errors are indicators of the variability surrounding the estimate of the beta parameters. A rescaling of these values is also accomplished by multiplying them by 100, thus aligning them with the scaling of the beta parameters.

3. Confidence Interval bounds: Calculated as 1.96 times the standard error, these bounds present the parameters for a 95% confidence interval under the assumption of a normal distribution of the estimates.

The beta parameters are used to plot the effects of given crisis, where y-axis represents the 'Effect (%)' and the height of each bar indicates the magnitude of the effect (estimated beta coefficient) of the corresponding hour.

The error bars (black lines) on the plots represent the standard errors of the estimated coefficients multiplied by a z-score 1.96 to form a 95% confidence interval. This gives a range of plausible values for the true effect. If the error bar for a particular hour does not cross the 0 line on the y-axis, it suggests that the effect for that hour is statistically significantly different from zero. All the plots with the effect of each dummy variable are presented in the Appendix 5.

6. Results

In the first part of this chapter, the focus is primarily placed on the presentation of the results, the assessment of the selected methods' performance, and the clarification of possible statistical anomalies. The regression results including the significance of variables (Wald test for joint significance of dummy variables) and predictions of electricity consumption for all three periods are to be presented first, followed by an analysis of the logarithmic differences between projected and actual loads. The results of effect quantification and the Wald test are then set to be explored. The relationship between load consumption and crisis impact is to be established and explained in the following Chapter 7.

6.1 OLS regression results for predicting electricity consumption

The formulation, the time periods of the estimation and prediction subsets, and the variables included in the regression were detailed in the previous chapter. The methodology chapter also presented the steps for using cumulative load plotting to visually inspect the model's predictive power. The insights gained from this graphical validation method will be further explored in the sections that follow. However, prior to that, the numerical results of the OLS regression and the significance of the chosen formulation must be detailed. Appendix 4 contains the tables presenting the key regression results.

The number of observations for the regression in 2019 totals 26281, with the exceptions of Bulgaria (26208) and Greece (26257), where a few days were omitted due to missing load data. In 2020, there were 35041 observations, except for Bulgaria with 34968 observations and Greece with 35017 observations due to missing data. For 2022, the model included 52585 observations, except for Bulgaria (52512), Greece (52561), and Romania (52561) where few days were removed.

Considering the extended time periods analyzed and the simplicity of the regression model employed for this analysis, the resulting R-squared statistic—which hovers approximately around 90%—suggests that a satisfactory portion of the variance is explainable by the independent variables included in the model. As expected, the highest R-squared values were obtained for the estimations for the year 2019, while the lowest values were observed in 2022 across all the countries. The best performing model across all three periods was performed in Romania, where the explanatory power reached 94.2%, 93.5%, and 92.1% in 2019, 2020, and 2022, respectively. This was followed by Bulgaria, with corresponding values of 93.2%, 92.9%, and 92.5% in 2019, 2020, and 2022, respectively, and North of Italy, with 93.3%, 92.9%, and 90.9% in the same years, respectively.

The weakest results were obtained for Southern Italy, with all R-squared values below 90% and the lowest overall value recorded in the analysis of 79.1% in 2022 (compared to 85.2% in 2019 and 84.6% in 2020. All other models exhibited performances that reached 90% or more in 2019 and 2020, and approximately 88% in 2022.

Adjusted R-squared statistics tracked closely to the R-squared values, with the largest difference of 0.002 observed for Southern Italy. As the adjusted R-squared provides a more accurate measure of goodness of fit, its close proximity to the R-squared values suggests that the majority of predictors contribute significantly to the model.

F-statistics for all the models corroborate the overall statistical significance of the models, in other words, the predictors as a group add statistically significant predictive power to the model beyond what would be expected by chance.

The potential non-normal distribution of residuals in the OLS models may arise from the inherent nature of the dependent variable, in this case, electricity load data. Such data can frequently exhibit skewness or kurtosis due to varying demand at different times of the day or across different seasons.

Testing the joint significance of dummy variables with Wald test

Dummy variables were created to highlight and quantify the impact of temperature on electricity consumption (as represented by the heat_hours_dummy and cool_hours_dummy variables), fluctuations in hourly and weekly load demand (captured by the week_dummy and hofw_dummy variables), and any abnormal effects on load patterns following the COVID-19 lockdown (accounted for by the covid_dummy variable in the 2022 analysis). The significance results from OLS regression of most of these variables is substantial, though some exceptions exist and vary by the years and countries tested. A small number of significance levels for week_dummy and hofw_dummy exhibited statistical insignificance, likely owing to unique country-specific patterns linked to sectoral and household activities. Likewise, heat_hours_dummy, and more prominently cool_hours_dummy, demonstrated statistical insignificance during the late evening and early night hours. This is likely due to decreased or absent heating and cooling needs during these hours. Given these sporadic occurrences, the joint significance of each dummy variable was evaluated to confirm whether they collectively have a significant influence on the dependent variable in a regression analysis. The Wald test substantiated the significance of all four dummy variables across each period and all countries. These results can be found in Appendix 4.

Holiday variable

The 'Holiday' variable, exhibits high significance levels and all negative coefficients across the regression results for each individual country and every tested period. Notably, there is a variance in the magnitude of the coefficients among the countries, with the highest absolute values being exhibited in Northern Italy and the lowest in Bulgaria and Southern Italy. Greece, Romania, Central-Northern and Central-Southern Italy are displaying comparable values of the 'Holiday' coefficients.

Changes in Holiday coefficients from 2019 to 2022

	BG	GR	RO	IT NORD	IT CNOR	IT CSUD	IT SUD
2019	-299	-626	-748	-4678	-710	-780	-364
2020	-301	-650	-751	-4448	-685	-740	-351
2022	-326	-624	-755	-4203	-627	-692	-329

% change of Holiday coefficient between two periods							
% change from 19 to 20	-0,54	-3,87	-0,337	4,91	3,52	5,13	3,81
% change from 19 to 22	-8,7	0,3	-0,9	10,2	11,7	11,4	9,8
% change from 20 to 22	-8,1	4,0	-0,5	5,5	8,5	6,6	6,2

Table 1: Changes in 'Holiday' coefficients from 2019 to 2022

The estimated coefficients are, as expected, negative, confirming the assumption that holidays generally lead to a reduction in electricity consumption, holding all other factors constant. In a linear regression model, the coefficient on a binary variable such as 'Holiday' signifies the average change in the dependent variable (in this case, electricity load in MW) when the binary variable switches from 0 to 1, holding other factors unchanged.

For example, the coefficient of -299 for Bulgaria in 2019 (the lowest value of coefficient) suggests that the electricity load in Bulgaria was, on average, 299 MW lower on holidays compared to non-holidays in that year. Similarly, in Northern Italy in 2019, the electricity consumption decreased by 4678 MW (the highest absolute value of coefficient) on holidays compared to non-holidays, assuming all other factors are held constant.

Interpreting changes in these coefficients between time periods is somewhat more complex. For instance, the 'Holiday' coefficient for Bulgaria changed from -299 in 2019 to -326 in 2022, translating to an 8.7% increase in the magnitude of the negative effect of holidays on electricity load. On the other hand, a positive change of 11.7% from 2019 to 2022 in Central-Northern Italy may indicate a reduction in the negative impact of holidays on electricity consumption.

The interpretation of these changes is partially dependent on the model's accuracy and assumptions. However, it's worth noting that the coefficients may not entirely encapsulate the variability of holidays' impacts on electricity load. This variability might be subjected to influences from other factors not accounted for in the model, such as economic fluctuations, demographic shifts, or policy implementations. The causes and implications of these coefficient changes will be delved into in the subsequent sections of this paper.

Trend variable

Considered as a continuous representation of time, 'trend' captures linear time effects - any consistent pattern resulting in the increase or decrease in the electricity load present over time, in other words any unobserved factors that are changing over time and that may influence the dependent variable.

In this context, the 'trend' coefficient is understood as the average change in electricity load over time, holding all other factors constant. The changes in these coefficients across different periods can reflect how the long-term trajectory of electricity load is evolving. A positive coefficient suggests that, on average, electricity load is increasing over time, whereas a negative value indicates a decreasing trend. The coefficients for 'trend' display somewhat substantial fluctuation in between the three years under study, with both positive and negative values present. This underscores the nuanced impacts these factors can exert on electricity load, contingent on specific circumstances or conditions. The magnitude of these coefficients also differs. Similar to the 'Holiday' coefficients, the lowest absolute values of 'trend' coefficients are observed in Bulgaria, while the highest are found in North of Italy.

Changes in trend coefficients from 2019 to 2022

	BG	GR	RO	IT NORD	IT CNOR	IT CSUD	IT SUD
2019	40	63	152	516	65	-41	166
2020	-2	45	87	293	30	-11	88
2022	6	53	80	302	-10	32	29

% change of trend coefficient between two periods

% change from 19 to 20	-103,80	-28,62	-42,707	-43,18	-53,40	72,44	-47,23
% change from 19 to 22	-85,6	-15,9	-47,8	-41,4	-114,8	176,8	-82,4
% change from 20 to 22	480,0	17,8	-8,8	3,1	-131,8	378,8	-66,6

Table 2: Changes in 'trend' coefficients from 2019 to 2022

All results, with the exception of the coefficients for Bulgaria in 2020 and 2022, Central-Northern Italy in 2022, and Central-Southern Italy in 2020, are statistically significant at the

0.05 level. In this context, statistical significance is a marker of confidence that the observed relationship between the independent variable ('trend') and the dependent variable (electricity load in MW) is not just a result of random variation.

The 'trend' coefficient for Bulgaria being statistically significant in 2019 but not in 2020 and 2022 suggests a meaningful and consistent association between time and electricity load for that year, which is less clear in the subsequent years. This suggests that during 2019, shifts in the 'trend' variable likely corresponded to changes in electricity load. However, in 2020 and 2022, the observed relationship could be attributed more to random fluctuations rather than a genuine, systematic effect.

On the other hand, the statistical significance of 'trend' for Greece, Romania, Northern Italy, and Southern Italy across all three years indicates a consistent and reliable relationship between time and electricity load in these regions. This suggests systematic annual changes in electricity load in these countries, as reflected by the 'trend' variable.

Yet, the statistical significance (or lack thereof) of the 'trend' doesn't diminish the importance of observing the magnitude of change across the three periods. Notably, these changes are most pronounced in Bulgaria, suggesting substantial fluctuations in electricity load due to crisis events, which are not systemic changes.

Investigating these changes in the 'trend' can provide vital insights for our research questions. Understanding the underlying causes for such shifts in the 'trend' variable could help elucidate how the relationship between electricity load, temperature, and the effects of crises evolves over time.

6.2 Regression results from estimating the effects of crises

As detailed in Chapter 6, the models used for quantification are largely analogous to those utilized in the electricity consumption regression. Consequently, the majority of the results closely mirror those outlined in the previous section. Only key observations will be highlighted here, given that the interpretation, magnitudes of results, and their significance for each country bear a striking resemblance to the results previously presented. Detailed results are available in Appendix 5.

The OLS regression models employed to estimate the impacts of both crises yield similar statistical results to those discussed in section 7.1. The models showcase the lowest R-squared values for Southern Italy, while Bulgaria and Romania exhibit the best model performance across all four variables.
The adjusted R-squared statistics closely align with the R-squared values, further attesting to the significant contributions of the majority of predictors to the model.
Lastly, the F-statistics confirm the overall statistical significance of the models.

The results of the Wald test, employed to determine the joint significance of the dummy variables capturing the hourly and weekly effects of both crises ('covid_hours_dummy', 'covid_week_dummy', 'war_hours_dummy', and 'war_week_dummy'), affirm the significance of all four dummy variables across each period and for every country. Detailed results are provided in Appendix 5.

6.3 Visual comparison of predicted and actual electricity loads: assessing the impact of crises

The specification and estimation method used to develop the model, based on past electricity load values for predicting 'normal' load values in years impacted by crisis, are detailed in Chapter 6. This section will visually assess and compare these predictions among different countries and periods. The graphical representations of predictions and logarithmic differences will focus on the two countries with the most reliable models, namely Romania and Northern Italy, along with the least accurate model represented by Southern Italy. This comparison will highlight variations between different countries and regions within the same country. Although only selected cases will be discussed in this section, other noteworthy observations from other countries under study may also be included. The comprehensive set of figures and graphs for all countries will be provided in Appendix 5, as a country-specific analysis will not be conducted here.

Counterfactual validation of the model performance

The challenge in assessing the impacts of a crisis arises from creating a counterfactual scenario, where no anomalies are present, and generating a dataset that represents this scenario. The intention is to then compare this data to the actual data collected during the

shock event. While the model used for generating these predictions has been statistically demonstrated to have strong predictive power, the nature of electricity load data - characterized by large variances, long time frames, seasonal trends, and hourly frequency - means that the statistical predictive power represents the sum of all these factors taken together. Consequently, econometric best practice recommends visually assessing such data types in addition to relying on purely statistical methods. The OLS model specified for the purposes of this analysis leans heavily on seasonal trends in electricity consumption. Thus, a visual inspection is performed not only to verify but also to demonstrate the model's capacity to accurately capture and predict these trends.
The term 'counterfactual validation' refers to the process of comparing model-generated predictions for the year 2019 with the actual load data from that same year - a year absent of any anomalies. The three figures below depict the predicted load values alongside the actual load data for a given country. In some instances, the inherent characteristics of the load make the visualization too complex, thus a plot of the cumulative differences between the predicted and actual data is provided to better clarify how closely the predictions align with the actual load. Moreover, graphs representing the logarithmic difference between the actual and predicted load consumption are provided in Appendix 4. These graphs reveal both the variance and direction of the prediction error. Majority of graph for 2019 displays slightly lower actual load than predictions. This could be due to the model's predictive power diminishing over time, or other external factors like temperature. One possible explanation for this difference might be the unusually warm winter of 2019-20, which was apparently the second-warmest recorded globally in over a century (Hansen, 2020). The fact that predictions for 2019 in Greece were perfectly aligned with actual load, and even slightly exceeded predictions in Central-Southern Italy, leads to the assumption that the negligible differences in the remaining countries and regions studied are the result of abnormal temperatures, rather than a weak model.

The models for Romania and Northern Italy, which performed the best, are tracking the actual load quite accurately with their predictions. The predicted values are slightly higher than the lowest actual load values and closely follow the highest actual load values. There is an exception during July and August in Northern Italy, where the actual load values exceed the predicted ones. This discrepancy could be the result of higher temperatures during the summer, or another external factor. It's worth noting that towards the end of the year, the predicted values appear to exceed the actual load values in both countries. This observation is supported by the cumulative difference plot, which shows a more pronounced divergence of the two lines towards the year's end.

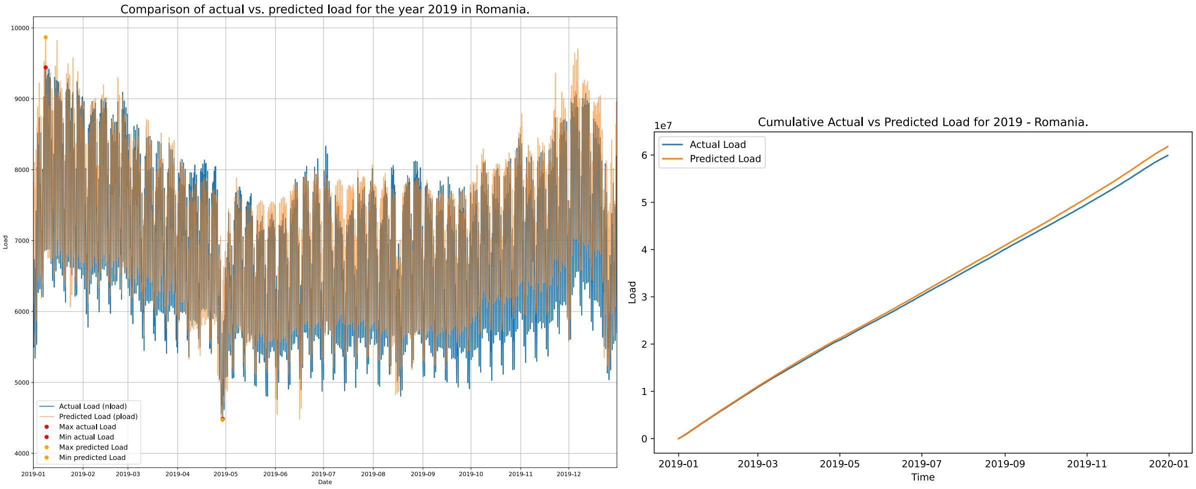

Figure 5: Comparison of the actual and predicted load in Romania for 2019.

Interestingly, the visual performance of the models for the remaining countries follows a similar pattern to that of Romania and Northern Italy, (all oscillating between 91%-93% predictive accuracy). Despite a slightly lower predictive power of 90%, Greece's model stands out as its cumulative prediction plot perfectly mirrors the actual load curve throughout the entire year of 2019.

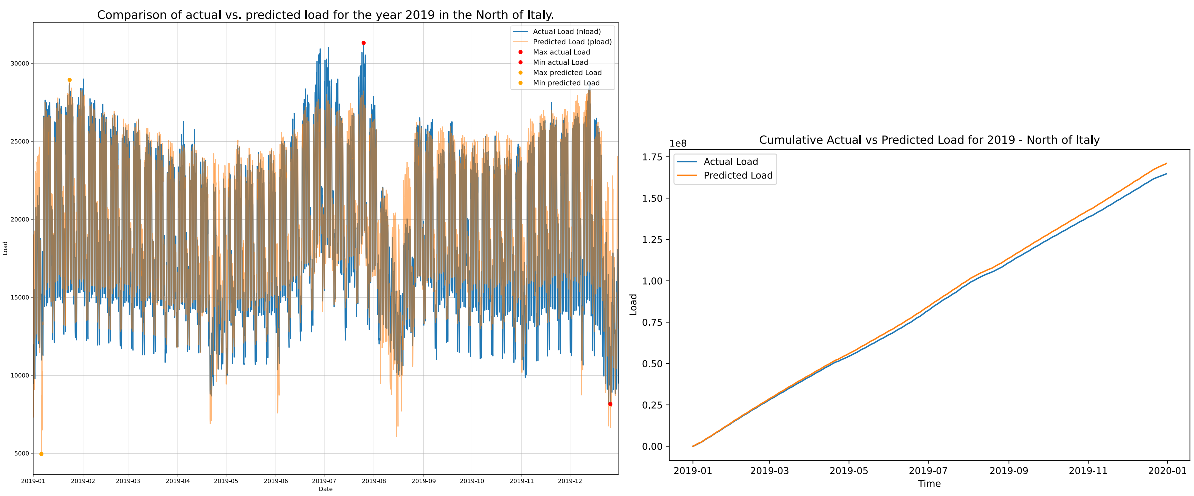

Figure 6: Comparison of the actual and predicted load in the North of Italy for 2019

The predictions for the load in Southern Italy follow a similar trend to the previous two models up until April 2019. This includes higher predicted values than the actual lowest load levels and predicted values closely tracking the highest actual load levels. However, after April, the predicted load values are consistently higher than the actual load values, with a significant divergence apparent by the end of the year, particularly in September/October. This observation is confirmed by the cumulative load plot.

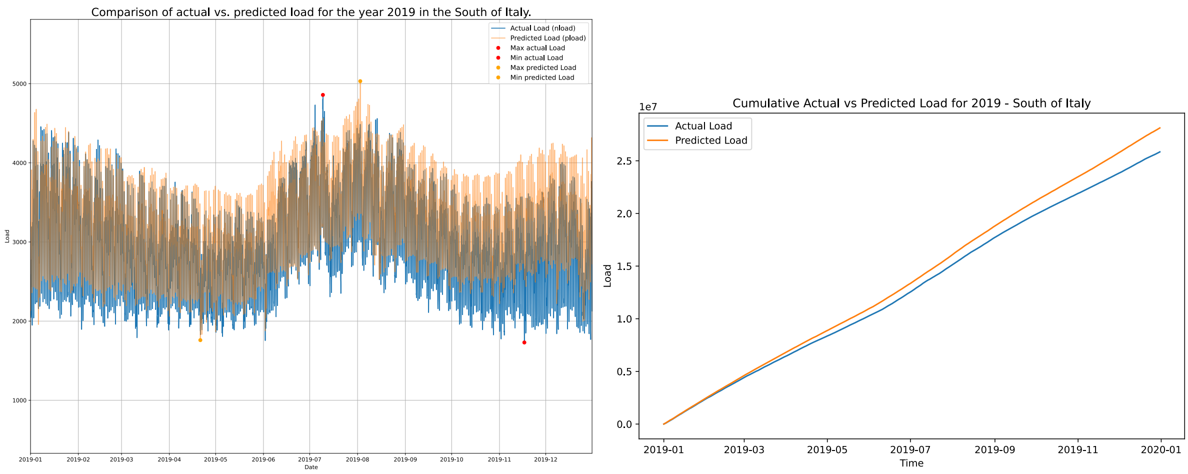

Figure 7: Comparison of the actual and predicted load in the South of Italy for 2019

The model for predicting electricity load in 2019 exhibits the poorest performance in Southern Italy. This is apparent both in statistical results and in the clear visual disconnect between the two plots.

Counterfactual analysis of COVID-19 impacts on electricity load

After assessing the plots and concluding that the models perform satisfactorily in the studied countries for 2019, the evaluation of the impacts of COVID-19 can be discussed.
The predicted load in Romania follows a similar pattern to the actual load, oscillating between 9000 and 8000 MW, until mid-March. At this point, the actual load drops abruptly, reaching its lowest value of approximately 6500 MW in mid-April. After this dip, the actual load seems to recover, and by August or September 2020, it aligns with the predicted values. The cumulative plot clearly shows a gradual divergence between the two curves starting from March 2020, with the gap widening until September 2020.

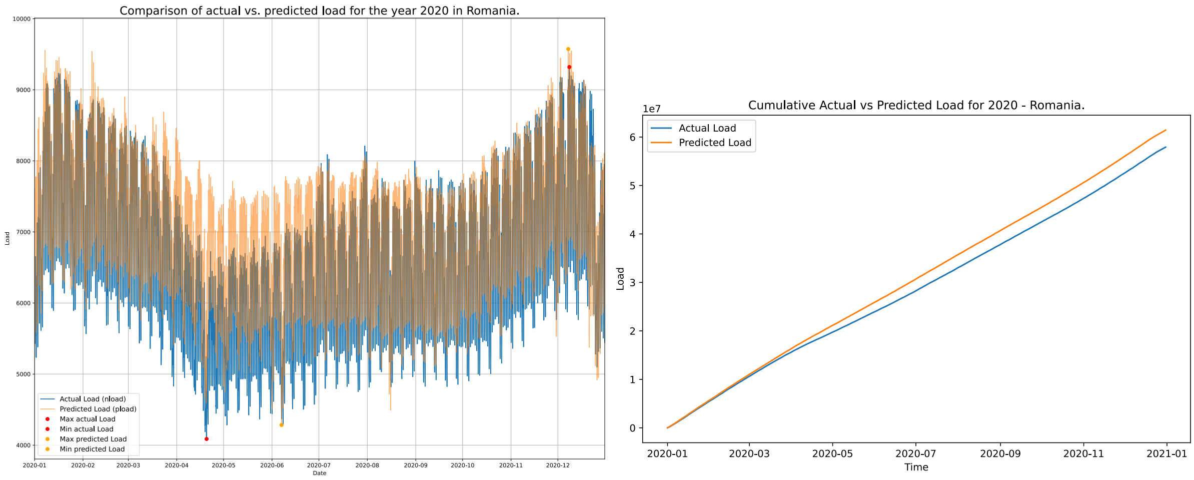

Figure 8: Comparison of the actual and predicted load in Romania for 2020

The impact observed in Northern Italy unfolds similarly to what was described for Romania. Both the predicted and actual load values oscillate between 26000 and 28000 MW. Once again, the actual load demand experiences an abrupt drop mid-March, reaching its lowest value of 16500 MW in April. The decline in consumption in Northern Italy appears to be more severe and sharper, but the recovery is also quicker, aligning with predicted load values by mid-July. The disconnect between the two curves on the cumulative difference plot further corroborates the statement of a more severe and sharper drop in load.

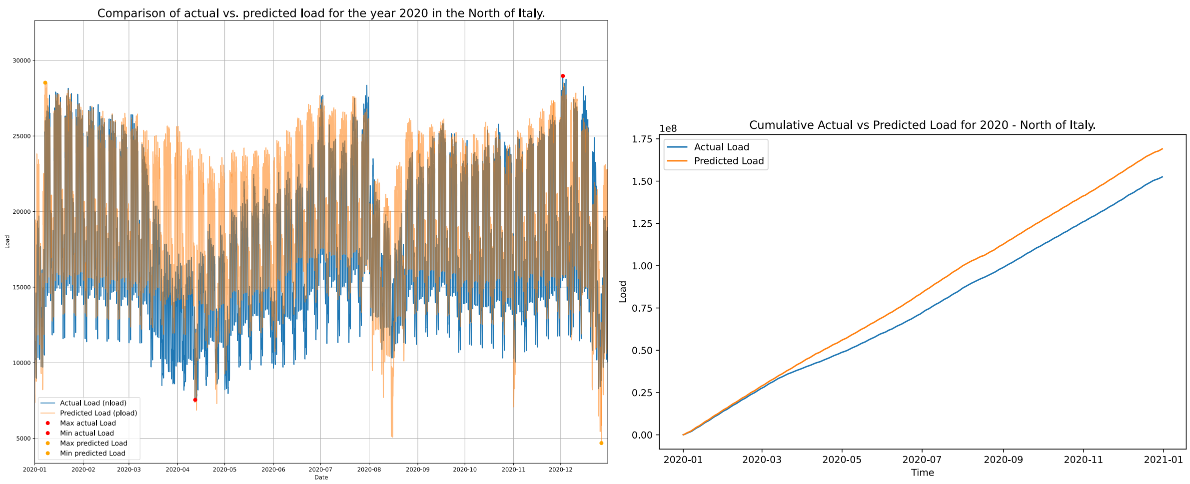

Figure 9: Comparison of the actual and predicted load in the North of Italy for 2020

The impact of COVID-19 and the subsequent pandemic lockdown observed in Southern Italy is less abrupt. Both the predicted and actual load follow the same pattern throughout the year, though the actual demand consistently displays lower values. The impacts of the pandemic seem more drawn out over the entirety of the year, with no clear recovery point in electricity consumption. A brief period between July and September shows predicted and actual load aligning. However, for the remaining months, the predicted load values are consistently higher than the actual demand. The cumulative plots show a divergence starting right at the beginning of the year, which continues to widen up until the end of 2020. This corroborates the lack of a sudden decrease in load demand and the absence of a recovery phase.

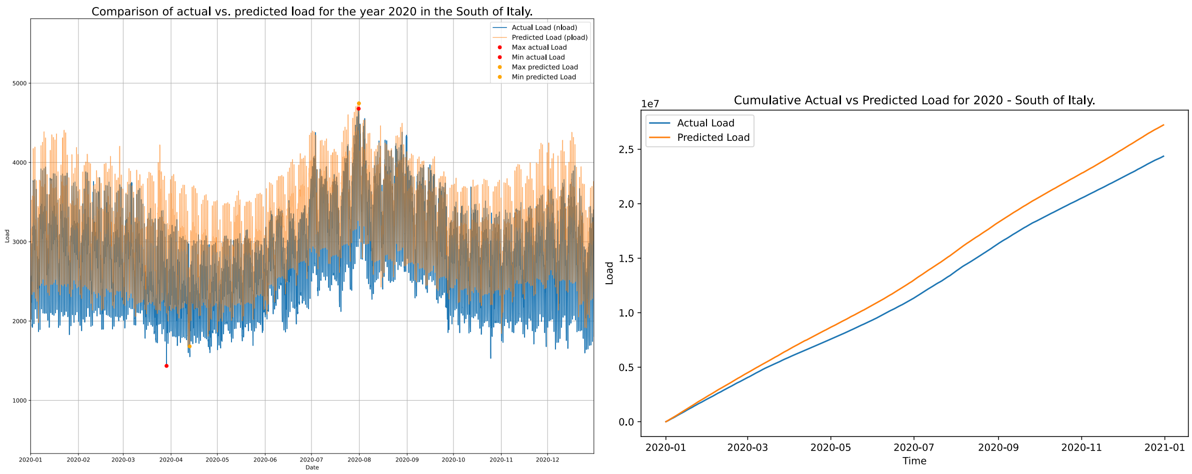

Figure 10: Comparison of the actual and predicted load in the South of Italy for 2020

While the impacts of the pandemic in Central-Northern and Central-Southern Italy follow the pattern described for Romania and Northern Italy – characterized by a sharp decrease and subsequent recovery of actual load – the pattern of actual load observed in Greece appears to display more similarities with the situation described in Southern Italy. This includes the alignment of both predicted and actual load from July to September. The differences between the actual and predicted load in Greece are smaller, and the actual load at the beginning of the year closely follows the predicted load before diverging mid-March.
In Bulgaria, the actual load closely mirrors the predicted load, with a mild decrease in actual demand from May to September.

Counterfactual analysis of energy crisis impacts on electricity load

Lastly, the energy crisis in the EU appears to have more varied range of impacts across the studied countries, as the severity of this crisis is intrinsically linked to the energy security and independence of each individual nation.

In Romania, the actual load initially follows the predicted levels of electricity consumption until May 2022, when a gap between the two curves gradually widens throughout the rest of the period. This observation is corroborated by the cumulative difference plot.

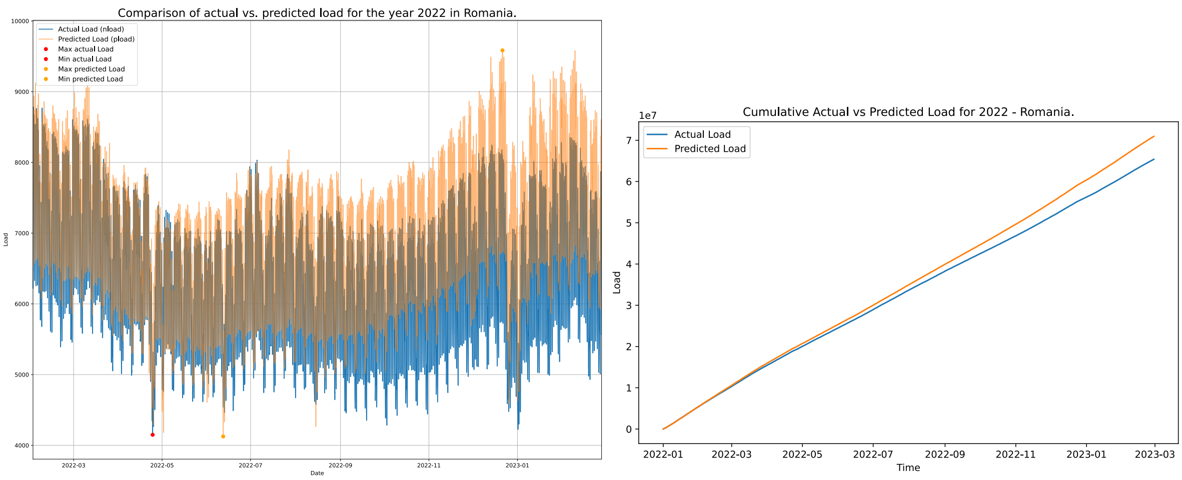

Figure 11: Comparison of the actual and predicted load in Romania for 2022

Meanwhile, the cumulative difference plot for Northern Italy exhibits both curves following each other almost perfectly, with a negligible gap observed between the two curves from May to July and at the beginning of 2023, suggesting no clear signs of decreased electricity consumption due to the crisis. The plot illustrating the load curves shows the actual load slightly exceeding the highest values of predicted load from January to August 2022. Afterwards, the actual electricity consumption values slightly decrease, falling marginally lower than predicted values during the cooler months from September 2022 to January 2023. These values then seem to realign with the predictions in February 2023.

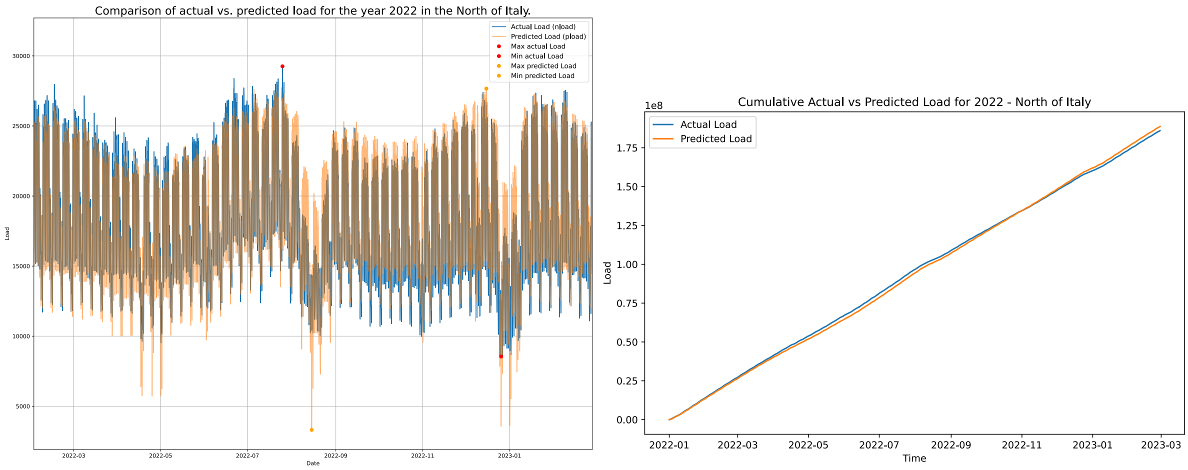

Figure 12: Comparison of the actual and predicted load in the North of Italy for 2022

As Northern Italy barely shows any signs of decreased electricity demand due to the energy crisis, the impacts of the same shock in Southern Italy are severe. The actual load remains below the predicted load levels from the beginning of 2022, with a singular exception in July, and the gap between the predictions and actual consumption level gradually widens from August 2022 until January 2023. The cumulative difference plot confirms this pattern, displaying a widening disconnect between both curves from the start of 2022 and amplifying this gap even more from August/September 2022.

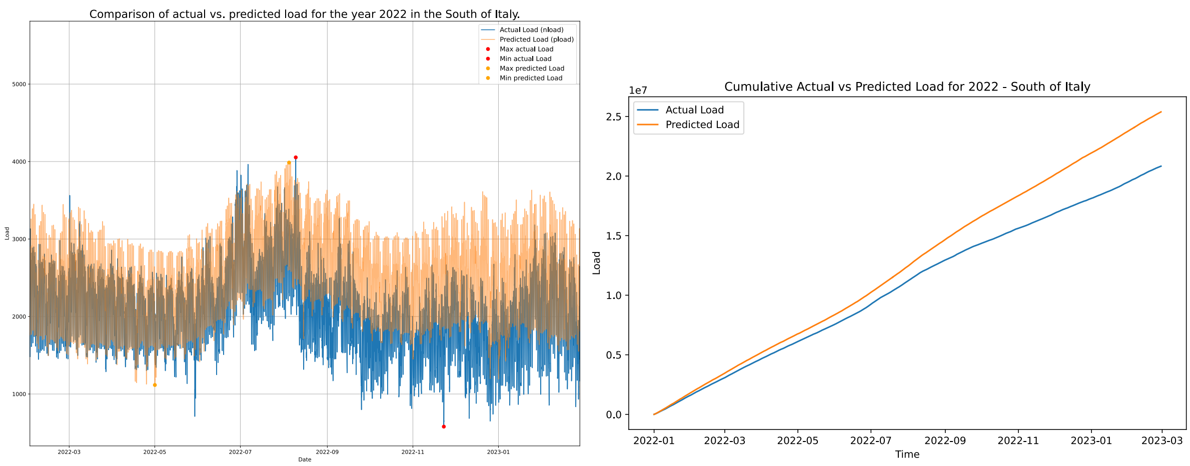

Figure 13: Comparison of the actual and predicted load in the South of Italy for 2022

Bulgaria and Central-Northern Italy appear to be experiencing the energy crisis in a similar way to Northern Italy, with only marginal differences between the predicted and actual levels of electricity consumption. Greece, on the other hand, is exhibiting a pattern of decreased electricity consumption similar to that observed in Romania, though to a lesser degree. In contrast, Central-Southern Italy, unlike any of the other studied countries or regions, is displaying higher actual electricity consumption levels than those predicted.

6.4 Comperative analysis of crises effects

The analyses of the predicted and actual electricity load in the previous sections provided an overall assessment of the severity of the crises and identified general trends, similarities, and differences among the studied countries. This section will delve deeper into the changes in electricity load on an hourly and weekly basis, providing crucial insights for further discussion of the research questions.

Bulgaria and Romania emerged as the countries with the best overall model performances for estimating crisis effects (Chapter 6.2), while the R-squared results for Northern Italy placed it in the mid-range of performance, with predictive power ranging between 90.5% and 91.9%. The regression results for Southern Italy were the weakest. Despite the slightly lower performance of models for Northern Italy, this section will present and describe plots for the same three countries. This approach not only facilitates easier referencing to patterns observed in previous sections, but also provides consistency in the comparative analysis. While any noteworthy observations from other countries will be highlighted here, additional plots will be available in Appendix 5 for further reference.

First, the effects of COVID-19 on weekly electricity consumption will be discussed. The blue bars on the plots represent beta parameters and indicate changes in electricity consumption due to the pandemic, assuming all other variables in the model remain constant. While Romania and Northern Italy show a gradual negative effect up until week 10 (beginning of March 2020), followed by a sharp increase in negative impact between weeks 10 and 20 and a subsequent gradual decrease, the effects in Southern Italy oscillate between -35% and -15% throughout the entire year. The most significant impacts in Southern Italy occurred at the beginning of the year.
Generally, the effects on all weeks are negative, with the exception of week 32 in Northern Italy. Similar effects on the consumption patterns can be observed in Greece – where load demand is negatively affected (except weeks 30-32), and in Central-Northern Italy, which

mirrors the effects in Southern Italy most closely. In Bulgaria, the impacts are milder than in other countries, and except for weeks 10-15 where the effects are positive, the remaining weeks experience negative effects. Effects on pattern in Central-Southern Italy, however, significantly deviates from the trend observed in the rest of the studied countries. Here, weeks 10-30 are negatively affected, reaching the lowest point around week 20. However, for the remainder of the year, the load consumption during most weeks is positively affected.

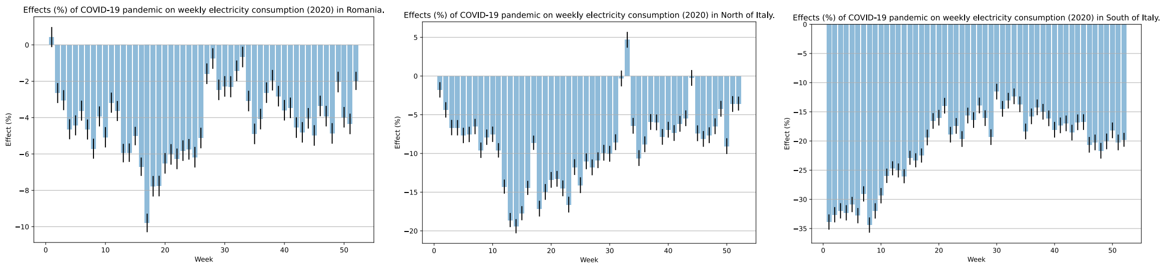

Figure 14: Effects (%) of COVID-19 pandemic on weekly electricity consumption (2020) in Romania, North and South of Italy

The plots illustrating the effects of COVID-19 on hourly electricity consumption reveal the magnitude and direction of the impact, as compared to consumption levels during periods unaffected by the crisis. Clearly, COVID-19 had substantial and negative effects on load consumption in all three countries discussed, though the magnitude of these effects varied. In Northern Italy, the effects were relatively even across all 24 hours, ranging between a -8% and -10% change. In Romania and Southern Italy, the effects were less pronounced during the day (8AM to 7PM), oscillating between -2% and -4% in Romania, and -15% and -19% in Southern Italy. The effects during the nighttime hours for both countries were more significant than those during the day, with the lowest values reaching -5.5% in Romania and -25% in Southern Italy.

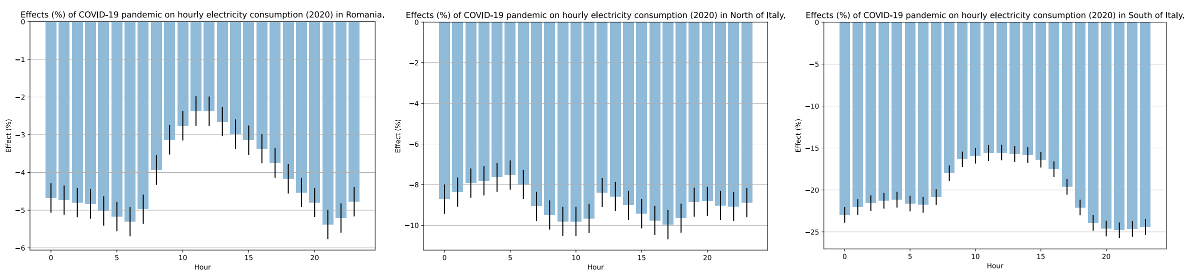

Figure 15: Effects (%) of COVID-19 pandemic on hourly electricity consumption (2020) in Romania, North and South of Italy

Central-Northern Italy's hourly effects of COVID-19 closely mirrored those observed in the Northern part of the country in pattern, but with a higher magnitude of effects ranging between -15% to -19%. Effects in Greece were comparable to those observed in Romania, with magnitude ranging between -4% and -7.5%. The impact on electricity load in Bulgaria was most pronounced during nighttime hours, reaching between -3% to -5%, and during the late afternoon/evening hours (-2.5% to -4%). During daytime, however, the effects were ranging between -2% and less than -1%.
Unlike any other country described in this section, Central-Southern Italy displays majority positive hourly effects on electricity consumption. Hours between midnight and 6AM show positive effects reaching as high as 2%, while the daytime hours from 11AM to 8PM show marginal positive effects. The only hours with minor negative effects are between 7AM to 10AM and 9PM to 11PM.

Among the effects of the energy crisis on the studied countries, tow distinguish predominant patterns can be observed. While they differ in magnitude, they align in direction across the 52 weeks, with Central-Southern Italy being the notable outlier.
Upon analysing the plots presented below, it is observed that Romania and Southern Italy experience a similar direction of effects from the shock. Except for one week of positive effects for each country, both generally exhibit negative impacts. The effects are most pronounced during the colder winter weeks at the beginning and end of the year and hot summer weeks, with magnitudes reaching -17% for Romania and -40% for Southern Italy. During the warmer spring and summer weeks, these effects decrease, falling to around -2.5% in Romania and approximately -8% in Southern Italy.
However, North Italy exhibits positive effects during the spring and summer months (from week 10 in March until week 30 in August), and negative effects for the rest of the year. The magnitude of these effects reaches an absolute value of 10% in both directions. The effects in Bulgaria are very similar to those in North Italy, both in direction and magnitude.
Greece and Central-Northern Italy experience the highest negative effects during the colder weeks, reaching approximately -15% in both countries. During the spring and summer weeks, these countries display a mix of positive and negative effects, with the maximum absolute value reaching 5%. However, the overall pattern of effects resembles these described for Bulgaria and North of Italy.

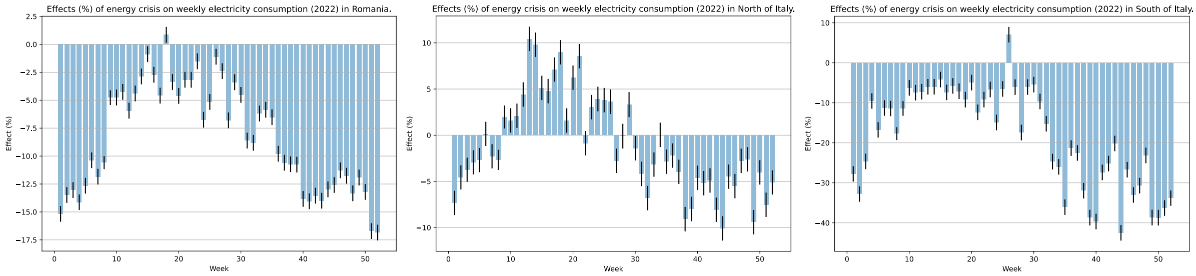

Figure 16: Effects (%) of energy crisis on weekly electricity consumption (2022) in Romania, North and South of Italy

The outlier, mentioned at the beginning of this section, is Central-Southern Italy, which predominantly experiences positive effects on weekly electricity consumption – with the negligible exceptions of two weeks. The increase in consumption, indicated by positive effects, reaches its highest magnitudes between weeks 10 and 30 (ranging from 5% to 15%). For the remaining weeks, the increase averages around 5% to 10%.

The hourly effects of the energy crisis in Romania indicate a uniform 8% to 10% decrease in electricity consumption for each of the 24 hours, suggesting a significant impact on the country's hourly consumption pattern. Southern Italy exhibits even more pronounced impacts from this crisis, with daily consumption (between 8 AM and 6 PM) reduced by 14% to 19%, and overnight consumption (during the remaining hours) reduced by 20% to 25%. Northern Italy, however, reveals a modest decrease in consumption during the daytime (from 8 AM to 11 PM) by 1% to 3%. Interestingly, the crisis seems to increase consumption after midnight until 8 AM by approximately 1%. Despite significant differences in the magnitude of effects, Greece and Bulgaria display a similar pattern in the impacts of the crisis to one described in North of Italy, with the lowest effects observed during hours between 10 and 15, and the least effects from midnight to 9 AM.

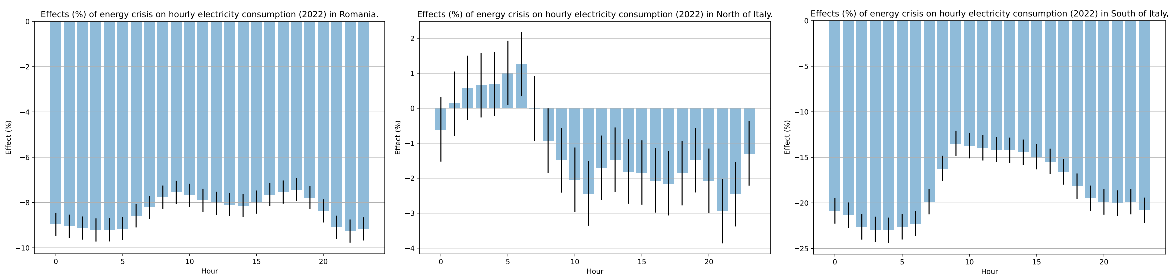

Figure 17: Effects (%) of energy crisis on hourly electricity consumption (2022) in Romania, North and South of Italy

Central-Northern and Central-Southern Italy, despite being neighboring regions within the same country, exhibit drastically different patterns of energy crisis impacts on hourly electricity consumption. The Southern region of Central Italy shows exclusively positive effects, with the highest increase, 8% to 12%, occurring between midnight and 8 AM, and a slightly smaller increase of 4% to 8% during the remaining hours.

The hourly electricity consumption in the Central-Northern region is affected negatively throughout the 24 hours. The effects of the crisis, represented by the bars on the chart, create a perfect bell-shaped curve between midnight and 11 PM, with the most severe effects reaching a decrease of -7% at both ends. However, there are negligible negative impacts from 8 AM to 2 PM, which corresponds to the peak of the bell curve.

7. Discussion

7.1 Discussion of the research question

RQ1. How did the electricity consumption in the selected countries change due to the impacts of the COVID-19 pandemic and the energy crisis resulting from Russia's invasion of Ukraine, and were these impacts consistent across these countries?

Assuming that the models presented in this paper have strong prognostic power and that the predictions of load consumption they generated are accurate, it's appropriate to state that the lockdown due to the COVID-19 pandemic had negative effects on electricity consumption for the second quarter of 2020 in all the countries studied, including four regions in Italy. Cumulative differences between predicted and actual values support this conclusion, with the smallest reduction observed in Bulgaria. Aside from Central-Southern Italy, the hourly effects of the lockdown on electricity consumption were also predominantly negative, although the patterns and magnitudes varied among regions and time of day. The weekly effects of COVID-19 were mostly negative as well. Central-Southern Italy was an exception, displaying a mix of both positive and negative effects on a weekly basis.

The mixed results observed in Central-Southern Italy during the COVID-19 lockdown are likely due to region-specific characteristics rather than the addition of another region to the bidding zone, as outlined in chapter 3.5. ACER (2022) confirms that this expansion occurred in 2021.

Though there are some similarities in the impacts on electricity load throughout 2020, the energy crisis in 2022 presents a more diverse pattern of fluctuations. During this crisis year, Bulgaria and Northern Italy did not see any significant decrease in electricity consumption overall, in comparison with predictions as evident from the cumulative load plots and comparing the actual load with predicted demand. The weekly effects of crisis in case of both countries are present in the second half of the year. Hourly effects display minor however persistent reduction during peak hours in North of Italy and predominantly marginal positive effects in Bulgaria. Negligible negative effects observed in Bulgaria are present between 10 and 15.

Central-Southern Italy experienced a significant increase in load consumption, presumably due to expended bidding zone. Conversely, Greece, Central-Northern Italy, Romania, and Southern Italy all saw declines in load. The reductions were more modest in Greece and Central-Northern Italy, while they were more pronounced in Romania and Southern Italy. For the countries where electricity demand was negatively affected, this decrease was observed throughout the year.

This pattern is especially questionable in context of Centra-Northern Italy considering the adjustment to the bidding zone, which resulted in the exclusion of one region in 2021 (ACER, 2022). Weekly patterns for this areal present predominantly negative effects towards the end of the year (weeks 35-52), and the hourly effects seem to most pronounced during off-peak consumption hours.

Not only do impacts of each crisis separately vary for each of the countries under investigation, but as shown on the example of Italy, impacts vary significantly within the same country's' regions.

To concisely answer the research question, electricity consumption in the selected countries experienced decreases due to the impacts of the COVID-19 pandemic and the energy crisis resulting from Russia's invasion of Ukraine. However, these impacts varied across countries.

7.2 What factors might explain observed differences in the impacts of these crises on electricity consumption among the studied countries?

The effects of the crises varied across the studied countries, and several key factors can be attributed to these variations. First, the underlying causes of the two crises were different. The crisis known as COVID-19 stemmed from a health emergency that led to nationwide lockdowns worldwide, halting the majority of economic activities. On the other hand, the energy crisis caused a significant spike in energy prices due to sanctions imposed on Russia, which restricted gas (and crude oil) deliveries to Europe. The severity of the outcomes of these shocks depended on a set of country-specific characteristics. Economic structure, particularly the dominance of industrial and manufacturing sectors, can lead to greater fluctuations in electricity demand during economic shocks compared to service, tourism or residential sectors. Additionally, the effectiveness of government responses to the COVID-19 pandemic or energy crises, such as income support, financial assistance, and economic stimulus packages, can significantly influence electricity consumption. While responses were fairly uniform across the European Union, variations did exist. Lastly, countries more reliant on Russian gas for electricity generation are likely to be more impacted by the energy crisis stemming from Russia's invasion of Ukraine (Uribe et al., 2022).

Italy's North-South divide

Before delving into the differences between the countries under study, it's essential to explore the divide within Italy itself, which may provide insights for further conclusions. As outlined in several previous chapters, Italy has been divided into four regions for this analysis, mainly due to the availability of multiple bidding zones, but also the well-known North-South socio-economic divide within the country.

The disparity between the Central-Northern and Southern regions (Mezzogiorno) of Italy, exemplified by the Southern GDP per capita falling to near 50% of the Central-Northern GDP per capita, began to manifest in the 1950s. Since that time, the gap has remained fairly consistent, ranging between 55% and 60% up to the present day. Additional disparities are seen in areas such as labor productivity, with Southern Italy trailing Central-Northern Italy by 20%, and the employment rate, where the difference between the two regions is about 30%.

However, it's important to recognize that Central-Northern Italy and the Mezzogiorno are not monolithic or homogeneous regions. Within Central-Northern Italy, the industrial triangle of Turin, Milan, and Genova initially drove economic growth, later shifting towards the "Third Italy" region, characterized by the "industrial district model" (Musolino, 2018). These areas correspond respectively to what is referred to in the analysis as Northern Italy (Milan) and Central-Northern Italy (Florence).

On the contrary, the spatial patterns in the economy of the Mezzogiorno have remained relatively stable. Regions like Abruzzo, Molise, Sardinia, and Basilicata have shown higher levels of development, while Calabria, Campania, and Sicily have lagged behind (Musolino, 2018). In this analysis, the Central-Southern region, centered around Rome, aligns mainly with Lazio, Abruzzo, and Campania (with addition of Umbria from 2021), while the South of Italy represented by Bari (Apulia, Molise) corresponds to the second group of regions.

Evidently, industries are primarily located in the central-northern region of the country, with small and medium-sized businesses being more widespread nationally compared to large industrial entities. (Xiong, 2022). Agriculture, accounting for roughly one-sixth of Italian GDP, is mainly concentrated in the central and southern regions but is dominated by smaller, family-based operations, unlike the agricultural companies in the northern part. Finally, tourism being the fastest-growing and most economically profitable industry in Italy, also prevails in the Central-Northern and Central-Southern regions, with Rome, Florence, Milan, and Venice being the most-visited tourist destinations. It's worth noting that this highly developed tourism industry has significantly contributed to reducing the budget deficit and unemployment by increasing jobs in the service sector (Xiong, 2022).

Understanding the divide within the country and the localization of crucial sectors helps explain the impacts of the two crises and the evident differences between the regions. The lockdown due to the COVID-19 pandemic, set for the entire country on March 12, 2020 (week 11), involved a stay-at-home order, restricted domestic and international travel, and the closing of all offices, businesses, retail activities (except for food and basic necessities), institutions, schools, and universities (WHO COVID-19 Dashboard, 2020). This instantly stalled the majority of economic activities and significantly decreased electricity consumption in the predominantly developed and industrialized regions. This is highly evident in all four cumulative difference plots, which display a decrease in consumption. The effects of COVID-19 on weekly consumption are also mainly negative (with the lowest weekly values around week 11) in Northern Italy and both central regions. However, the effects in the Southern region, which is less industrial and predominantly agricultural, followed a different pattern, although impacts were still negative. These might be explained less by the abrupt consequences of the lockdown itself and more by the long-term economic hardships for small and medium operations arising from the crisis. However, due to a lack of clear evidence in this study, this is just speculative.

The majority of restrictions due to the pandemic were lifted on May 18th (week 21), and from this time stamp, the plot presenting the actual and predicted load, as well as the weekly effects plots, shows that the negative impacts begin to decrease. Although the recovery is gradual, by mid-July to August, the load for all four regions aligns with predicted values. While the other three regions continue to follow the predicted load (with minor deviations) in the second half of the year, Southern Italy's consumption decreases mid-September and remains well below the predicted level through the end of the year. The hourly effects of COVID-19 on electricity consumption are uniformly negative For Southern Italy, the decrease ranged from 15% to 25%. For Central-Northern Italy, it was between 15% and 19%, while for Northern Italy, it was from 7% to 10%. In all three regions, the coefficients for 'trend' decreased by 40-50%, indicating a decrease in electricity demand. Meanwhile, the coefficients for 'Holiday' (all 4 regions) decreased by 3.5-5%, suggesting a less pronounced effect of non-working days on load consumption within the week. This can likely be attributed to the stay-at-home orders during the lockdown.

The weekly and hourly effects observed for the Central-Southern region differ significantly from the other three regions. This cannot be explained in new configuration of the bidding zone as this took effect in 2021. Additionally, in this context, the 'trend' variable for the year was not found to be significant. This undermines the previously established relationship between load and time in this region, which was based on past data.

Since only aggregate data is available for this region, it's challenging to state confidently what might be the reason for this difference. However, some speculation can be proposed based on background information. For instance, the regions corresponding to the Southern-Central part of Italy in this analysis include Lazio, which has the 2nd highest GDP in the country (11.3% of the Italian national GDP). Given the region's lack of heavy industry and its specialization in manufacturing and high-tech, knowledge-intensive sectors - combined with its high potential for remote working as indicated by the OECD (2020) - it is understandable why this region saw negative impacts on electricity consumption only between weeks 10 and 30. In contrast, the rest of the country experienced uniform negative effects across all 52 weeks. Interestingly, predominantly positive effects were observed on hourly consumption.

In 2021, the industrial sector was the largest consumer of electricity in Italy, using approximately 135.75 terawatt-hours. Conversely, the agricultural sector accounted for the smallest electricity consumption that year, with a total of 6.7 terawatt-hours. The same year, natural gas served as the leading source of electricity production in Italy, comprising more than 48% of the country's total electricity mix, as well as the consumption of natural gas was one of the highest among European countries. Consequently, Italy was severely impacted by the cessation of exports from Russia (primary exporter of over 29 billion cubic meters). (STATISTA, 2022) In this scenario, specific effects are expected in regions with energy-intensive sectors and in those with higher levels of poverty and unemployment. Conversely, regions without these characteristics may experience relatively low impacts.

Evidently, Italy has taken multiple steps since the latter half of 2021 to mitigate soaring energy prices. These began with legislative decrees in 2021 and continued with various decrees in 2022, aimed at reducing or nullifying specific tariffs in the electricity and natural gas sectors for both household and non-household users. Additionally, the VAT on gas for civil and industrial uses was temporarily cut to 5% for October-December 2021, later extended through December 2022. The government also expanded energy bonuses to aid more consumers, increasing their value for economically disadvantaged households and providing tax credits for non-domestic electricity and gas purchases. Despite these efforts, the electricity prices for non-household consumers reached second highest level in Europe in the second half of 2022 (€0.3372 per KWh). (Eurostat, 2023)

Despite their dominant industrial sectors, the Northern and Central-Northern regions have shown negligible decreases in electricity consumption, perhaps due to various steps taken by the government, as indicated in the cumulative difference plots. However, altered patterns in hourly and weekly effects might be the result of production shifts to avoid consumption peaks or other implemented solutions. Without insight into consumption by sector, it's unclear whether industries, the residential sector, or minor adjustments in both caused the shifts in consumption. Although there was no significant overall reduction in consumption, there were some seasonal (mostly during cold months) and hourly negative effects. While the Northern region displayed positive effects on night hours (from 00:00 to 07:00 AM) and negative effects throughout the daytime, indicating some reductions in consumption during the daily pattern (especially during the autumn/winter weeks), the Central-Northern part of Italy showed hourly effects that were shaped like a bell curve. The hourly effect showed the most significant negative effects during the nighttime, specifically between 9 PM and 1 AM, with negligible effects (meaning nearly no difference) during the usual morning peaks from 8 AM until 4 PM.

The 'trend' variable for Central-Northern Italy was insignificant during this period, suggesting a deviation from the systemic relationship between time and load. This deviation might be attributed to the reduced areal of the bidding zone.

The Central-Southern region experienced an increase in electricity consumption. This unexpected result might be attributed to a combination of several factors: an expanded area of the bidding zone, a robust regional economy, a post-lockdown boom in the manufacturing sector, and the absence of industries that traditionally drive peak electricity prices higher. However, due to lack of sector-specific consumption patterns, these conclusions are purely speculative.

In contrast, the Southern part of Italy decreased its consumption significantly, possibly due to its lower GDP, resulting in higher poverty rates, and higher unemployment. This explanation aligns with the findings of Halkos and Gkampoura (2021), who noted more pronounced effects of crises among disadvantaged households.

The background and characteristics of the individual regions outlined here might help explain certain effects to some extent. However, the lack of clear evidence drawn from the data prevents drawing any firm conclusions. Further study with more suitable data would enable a better understanding of the underlying factors for these regional differences.

Differences among remaining countries: Bulgaria, Greece, and Romania

The results for the three remaining countries share some similarities with the Italian regions analyzed above. During the COVID-19 pandemic, the most vulnerable were economies relying on the physical presence of workers, as measures introduced to combat the virus included the closing of non-essential businesses and a ban on gatherings of people. Some sectors managed to quickly organize remote working conditions, while industries requiring manual and on-site work had to pause operations. Additionally, the energy crisis, caused by a surge in gas prices in the EU and primarily attributed to Russia's deliberate reduction of gas supplies, has affected the wholesale price of electricity in the EU's internal market.

The high energy prices persisted throughout the colder, autumn and winter months since replacing Russian gas with other suppliers is not an instant process. In this context, in addition to understanding the dominant sectors in the economy, the dominant resources used to produce electricity, heating systems and dependency of the country on Russian gas are crucial. EU countries have adopted an emergency regulation, effective from December 1, 2022, to March 31, 2023, to help citizens and businesses most impacted by the energy crisis. (Council of the EU, 2023).

Starting with Bulgaria, which, according to the background statistics presented here, has the best set of features to avoid severe consequences of the crisis and reduction in electricity consumption. The share of agriculture in the country's GDP in 2021 was 4.37 percent, while the services sector contributed 62.27 percent. The industry's share in GDP was approximately 20.85 percent (O'Neill, 2023a). Additionally, the residential sector is the largest consumer of electricity in the country, accounting for 38% of the total in 2020, followed by industry (32%) and services (24%) (ENERDATA, 2023a). Paired with very small reliance on Russian gas for electricity production (5.75%), due to its domestic coal (42.29%) and nuclear (32.54%) energy sources, the economy should not experience significant impacts (OECD, 2023; EMBER, 2023).

Indeed, the cumulative difference plots show negligible reduction in electricity consumption during 2020, and the actual load values are placed over the predicted load. Looking only at these plots, the effects resemble those observed in Central-Southern Italy, although the larger manufacturing sector might have contributed to more substantial reductions in the Italian region during COVID-19. Predominantly negative weekly and hourly effects of COVID-19, and on the contrary, mainly positive weekly and hourly effects in 2022, seem to corroborate the resilient profile of the Bulgarian economy. The 'trend' variable was found to be not significant for both analyzed periods, indicating that none of the observed effects were related to the systemic seasonality (i.e., the relationship between load and time) that was observed in past data. Overall, Bulgaria displayed the least impacts of both crises across all the studied countries and regions. This result is somewhat unexpected, especially keeping in mind the study by Balabanyan et al. (2010) examining the effect of GFC on the power sectors in Eastern Europe. Without more specific data it is difficult to speculate about the reasons, but perhaps, Bulgaria has not yet fully recovered from 2009 shock and thus the load demand was already low, or the opposite – has recovered and managed to build more robust economy. The reasons and factors for these effects might be more than these proposed.

Romania and Greece exhibit somewhat similar impacts of both crises as indicated by the cumulative difference plots, however Romania's electricity load reduction being more significant during 2022, which might be caused by different domestic characteristics of both countries.

During 2021 in Romania, the service sector contributed the largest portion to the gross domestic product at 58.2%, followed by industry at approximately 27.78%, and agriculture at 4.35% (O'Neill, 2023b). However, it is industry that consumes most of the generated electricity, accounting for 42% of the total consumption in 2021, with households using 28% and the biggest contributor to the GDP – services, only 18% (ENERDATA, 2023b). Unlike other countries in the EU, Romania relies much less on Russian gas, producing close to 90% of its required fossil fuel locally through state producer Romgaz, oil and gas group OMV Petrom, and Black Sea Oil & Gas (Reuters, 2022). These statistics suggest a reduction in load due to the lockdown. However, at first glance, the energy crisis shouldn't have caused significant impacts on Romanian electricity consumption.

Impact of COVID-19 was evident only during the lockdown (beginning on 24.03.2020), with decreased consumption during that period and a prompt recovery starting in August of the same year. The weekly and hourly effects of both crises were distinctly negative, with the lowest values in 2020 occurring during the lockdown weeks (14-25) and in 2022, clearly lowest at the beginning and end of the year – presumably during the cold months.

The energy crisis, however, appears to have impacted consumption in the country beginning in June 2020, with a gradual reduction throughout the rest of the year and continuing until February 2023. The Romanian Government introduced a support scheme in November 2021 that capped electricity and natural gas prices for consumers, with the state compensating the difference to suppliers. This cap varied based on consumer type and energy consumption and was largely lifted for non-households by September 2022. Despite these efforts and increased independence from Russian gas, Romania's electricity prices for non-household consumers in the second half of 2022 were the highest among EU member countries, at €0.3573 per KWh. (Eurostat, 2023) Such a spike in price is most likely attributed to Romania's integration into the European electricity and gas market, resulting in prompt price convergence amidst the crisis. Such a high prices crippled most likely domestic industry consuming majority of the electricity (42%) as well as affected the to some extent electricity demand among households (28%). The effects of high prices could be linked to the findings from study by from Csereklyei's (2020), suggesting that high surges of electricity prices can reduce electricity in higher degree, or results presented by Halkos and Gkampoura (2021) indicating the role of energy poverty. The impacts observed in Romania are nevertheless surprising. Without access to demand data divided by sectors and the exact electricity prices for households and industries, one can only speculate about the likely reasons for the reduction in consumption. However, this scenario seems plausible.

The service sector in Greece is the main contributor to the GDP in 2021, accounting for 68.15%, followed by the industry at 15.31%, and agriculture contributing 3.87% (O'Neill, 2023c). Notably, the biggest sector in the economy is also the largest consumer of electricity, with the services and households using 36% and 32% respectively, and the industry using 24%. The country's electricity sector consumes approximately 65% of the total gas, while the industry (including non-energy uses) uses about 15%, and buildings consume around 12%. (ENERDATA, 2023c) For years prior the 2022 crisis, Greece has relied on gas from Russia for about 40% of its total needs. (Koutantou, 2022)

Service sector (presumably reliable on tourism) in Greece would suffer consequences of lockdown and reduced mobility due to COVID-19 also after the domestic restrictions were lifted, as international traveling was limited beyond the time period affected by national restrictions. Indeed, after a noticeable decrease in actual load due to the lockdown, which began on March 23, 2020, consumption recovered in July. However, it fell slightly behind predictions in the fourth quarter of the year. The effects of this crisis are not severe, as the dominant sector is not very power-intensive. The weekly and hourly effects on consumption were predominantly negative during 2020 period.

In 2022, consumption started to fall slightly below predictions from mid-September onwards, a trend that suggests high prices may have impacted electricity consumption, presumably in both - households as indicates in research by Santamouris et al. (2013) examining the effects of GFC and service sector. This conclusion is supported by the largest negative effects on hourly consumption observed between 8 AM and 4 PM, and predominantly during weeks at the beginning and towards the end of the year, when air temperatures were lower.

8. Concluding remarks and recommendations

8.1. Summary of findings

The method employed in this thesis aimed to quantify the impacts of the COVID-19 pandemic and the energy crisis in Europe on the aggregated electricity load for Bulgaria, Greece, Romania, and Italy, which was further segmented into four regions: Northern, Central-Northern, Central-Southern, and Southern. The dataset, comprising hourly records of observed load and air temperatures, was analyzed using the Ordinary Least Squares regression model. This model was augmented with time-specific parameters and variables that encapsulated the effects of both crises. Additionally, predictions for alternative scenarios without the crises were generated, facilitating a comparison and assessment of the shock effects. The impacts of both the COVID-19 pandemic and the energy crisis were estimated on a yearly, weekly, and hourly basis. The selected assessment method was validated for each country using data from 2019, which is viewed as a year devoid of disruptions affecting electricity consumption.

The research question addressed in this thesis pertains to two consecutive crises: the COVID-19 pandemic in 2020 and the energy crisis Europe experienced in 2022 and early 2023. The research question can be bifurcated into two subparts.

First, the impacts of both shocks on electricity load demand are assessed for selected EU member countries. Second, these effects are compared to identify evident similarities and differences between them. As evident from the analysis, the COVID-19 lockdown led to reduced electricity consumption in Q2 2020 for all studied countries, including four Italian regions. These effects varied in magnitude and the slope of impacts. The smallest drop was observed in Bulgaria. Central-Southern Italy stood out, with varied weekly impacts possibly due to regional factors, rather than changes in the regional configuration of the bidding zone introduced from 2021.

The energy crisis of 2022 showed mixed patterns. While Bulgaria and Northern Italy maintained stable consumption, Central-Southern Italy saw an increase, possibly due to a bidding zone expansion. However, Greece, Central-Northern Italy, Romania, and Southern Italy faced reductions, with the most notable declines in Romania and Southern Italy. The significant reductions observed in Romania are quite unexpected taking into considerations country's conditions.T he decline in Central-Northern Italy can be possibly partially triggered by a bidding zone adjustment in 2021. Furthermore, crisis impacts differed within regions of the same country, as seen in Italy. In summary, both the COVID-19 pandemic and the subsequent energy crisis affected electricity consumption, but the impacts differed among countries in magnitude and duration.

In essence, the dual crises of the COVID-19 pandemic and the energy crunch in the EU presented a complex tableau of challenges and responses. While each nation had its unique economic dynamics, Bulgaria stood out for its resilience throughout both shocks, whereas the south of Italy grappled with more pronounced impacts in both periods.

8.2. Limitations of the study and suggestions for further research

Based on the methodology employed and the data available for this analysis, the primary findings encapsulate the changes in electricity consumption patterns during the periods of both crises. Despite engaging in extensive discussion about the possible impacts of factors observed in the background, no claims can be put forward about the relationships between them and the load demand due to lack of unequivocal evidence.

8.3. Recommendations and suggestions for further research

Examining the impacts of both COVID-19 and energy crisis in EU on electricity consumption would benefit from extending the timescale, inclusion the sector specific load demand as well as several variables quantifying the background factors specific for each shock.

The analysis of impacts in 2020 would benefits from augmenting parameters encapsulating the severity of restrictions introduced by governments, rate of mortality, changes affecting mobility, the financial aids provided by state and changes in GDP. Extending the studied time period to include the year 2021, could also reveal some long-term effects of lockdown, as some countries did not recover immediately after lifting the lockdown restrictions, as well as some sectors were affected by increased demand and reduced supply, causing potentially some changes in consumption that could be attributed to impacts of COVID-19. Separating the residential electricity consumption from the non-residential could also reveal interesting changes in time-specific demand patterns.

Similarly, highlighting the effects of energy crisis would be possible with additional indicators encapsulating the background changes during this period. Integrating electricity or gas prices data into the model would prove the tangible impacts of this crisis on electricity consumption. Providing a detailed load demand breakdown across sectors would make it possible to identify the principal drivers of observed reductions. Quantifying the governmental financial support for both households and industries could help assessing their effectiveness. Given that this study was initiated in March 2023, broadening the timeframe to account for long-term impacts of energy crisis could reveal further insights into the enduring implications of this shock.

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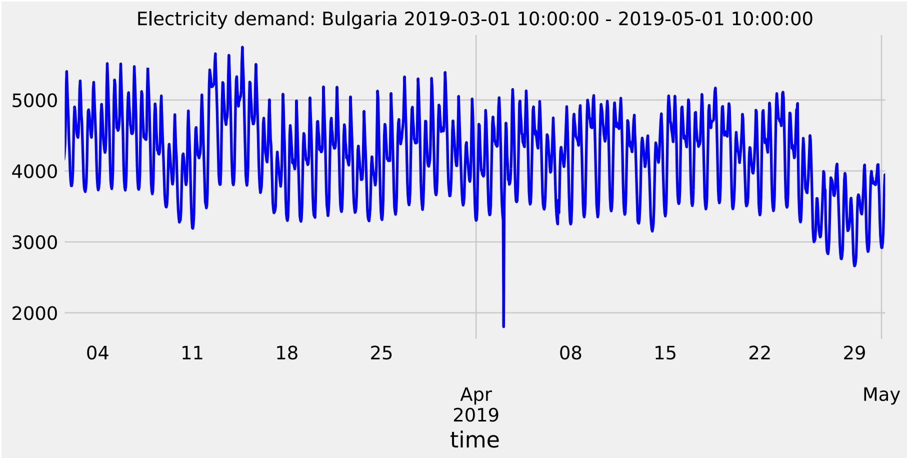
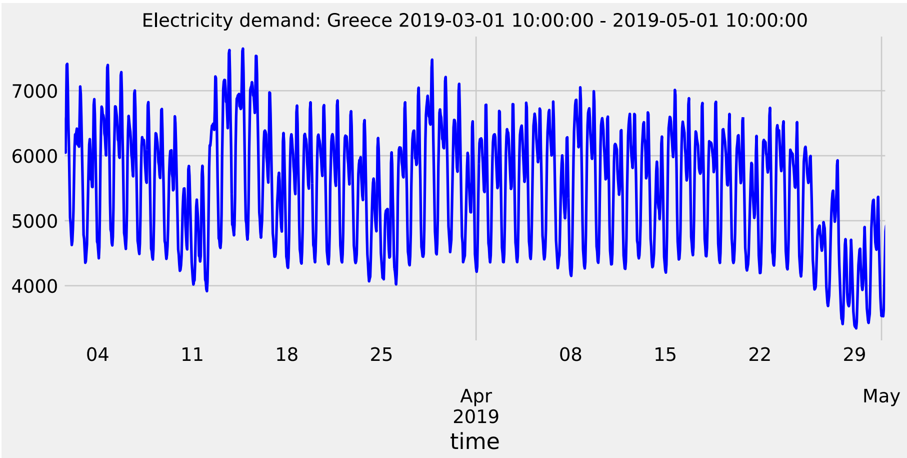
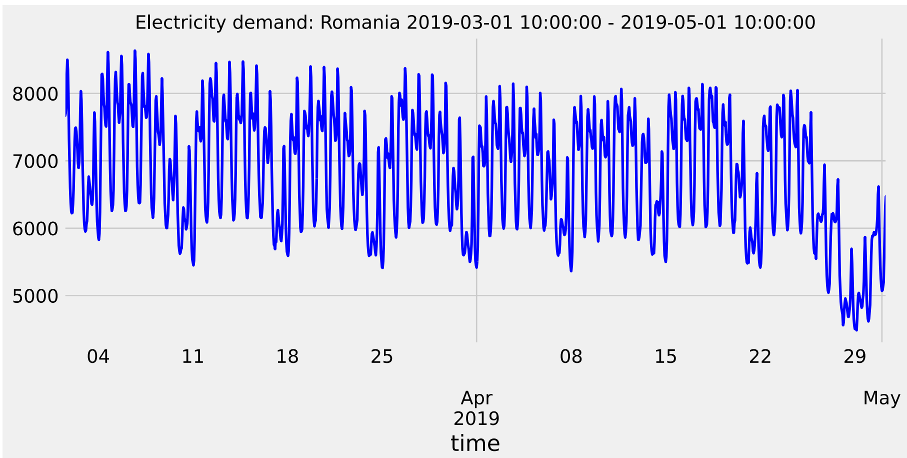
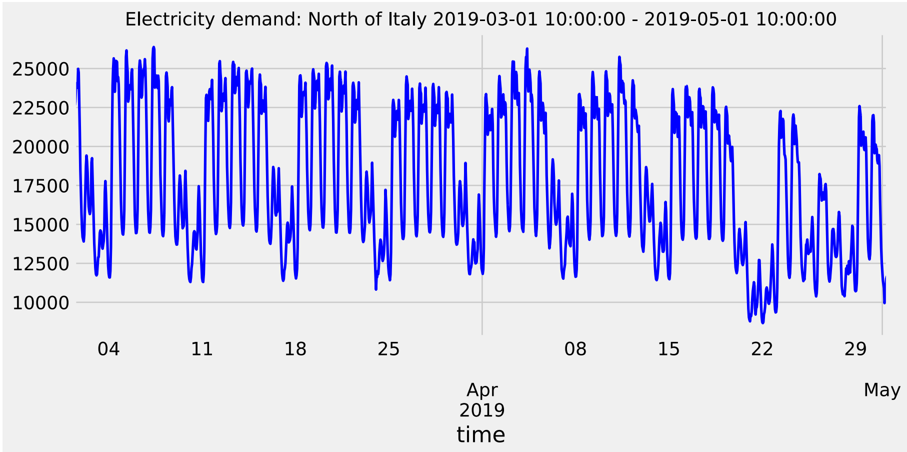
Appendices

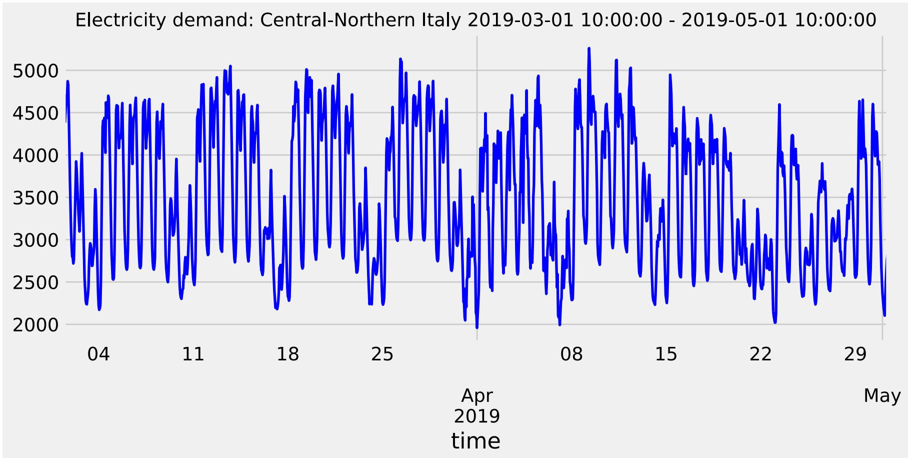
Appendix 1 – Seasonal trends in electricity demand

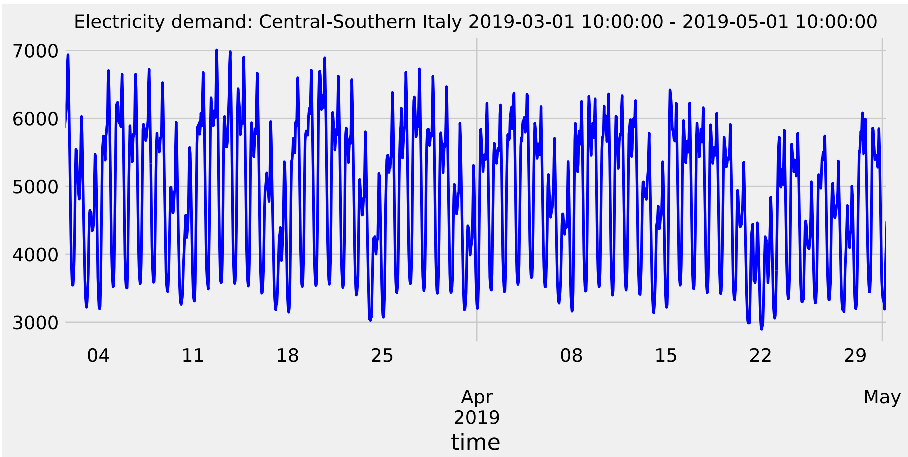







Electricity demand: North of Italy 2019-03-01 10:00:00 - 2019-05-01 10:00:00
25000
22500
20000
17500
15000
12500
10000
04
11
18
25
08
15
22
29
Apr
2019
May
time


Electricity demand: Central-Northern Italy 2019-03-01 10:00:00 - 2019-05-01 10:00:00
5000
4500
4000
3500
3000
2500
2000
04
11
18
25
08
15
22
29
Apr
2019
May
time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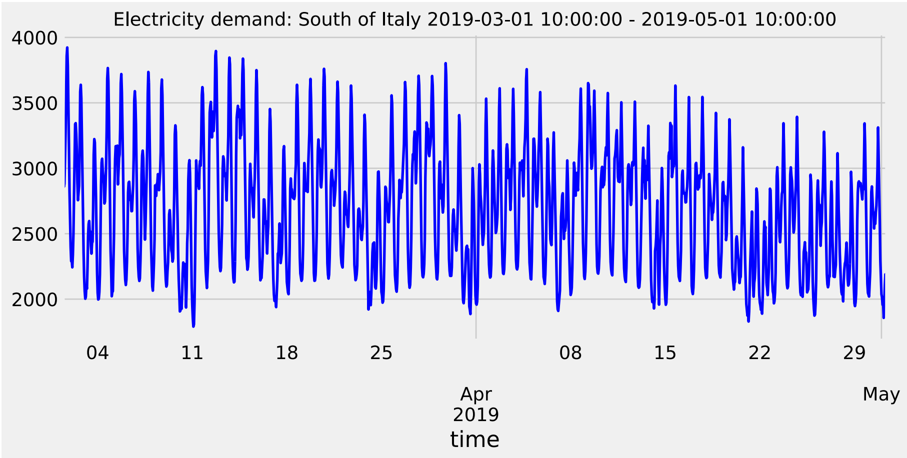
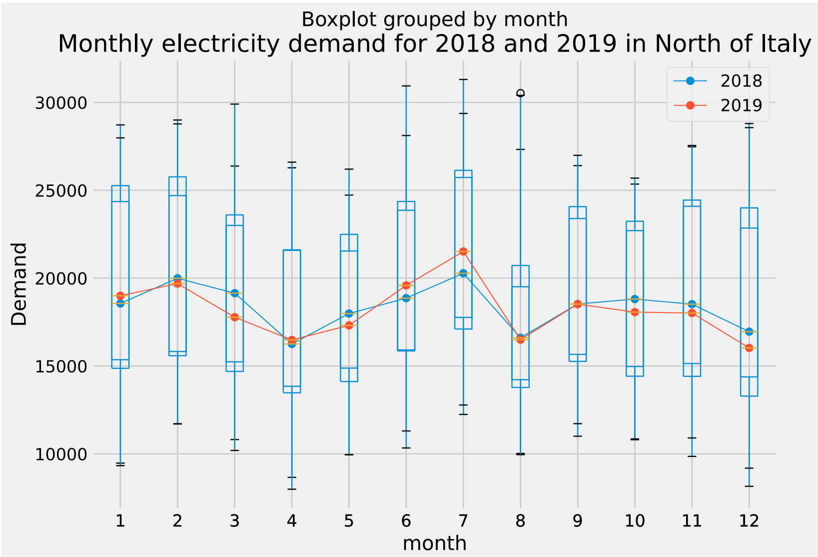
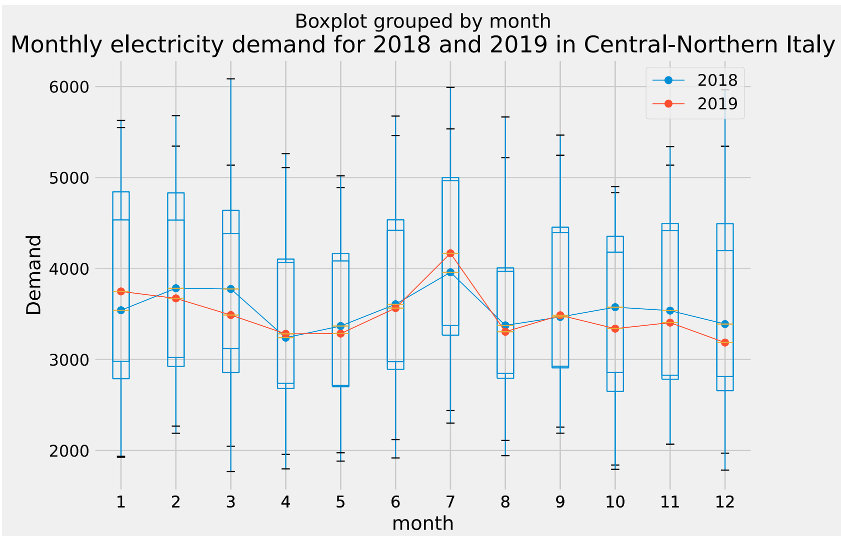
7000
6000
5000
4000
3000
04
11
18
25
08
15
22
29
Apr
2019
May
time


Electricity demand: South of Italy 2019-03-01 10:00:00 - 2019-05-01 10:00:00
4000
3500
3000
2500
2000
04
11
18
25
Apr
2019
08
15
22
29
May
time


Boxplot grouped by month
Monthly electricity demand for 2018 and 2019 in North of Italy
2018
2019
Demand
30000
25000
20000
15000
10000
1
2
3
4
5
6
7
8
9
10
11
12
month


Boxplot grouped by month
Monthly electricity demand for 2018 and 2019 in Central-Northern Italy
2018
2019
Demand
6000
5000
4000
3000
2000
1
2
3
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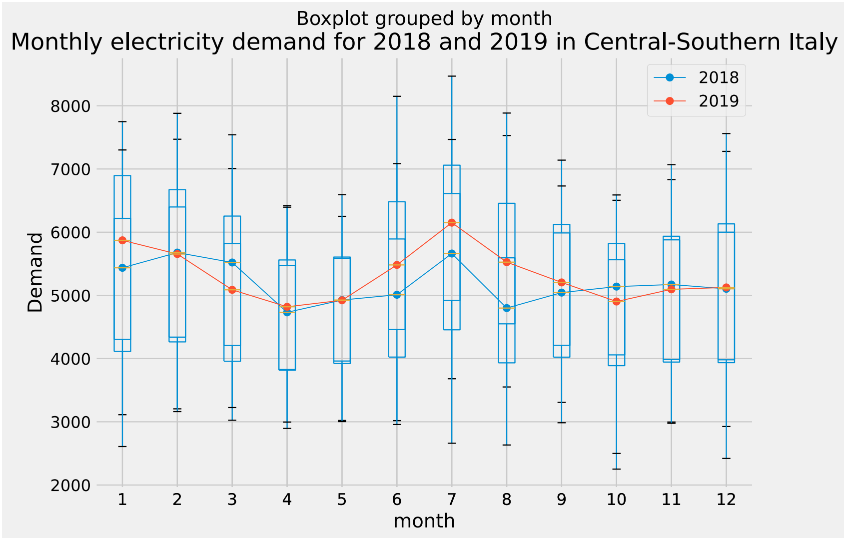
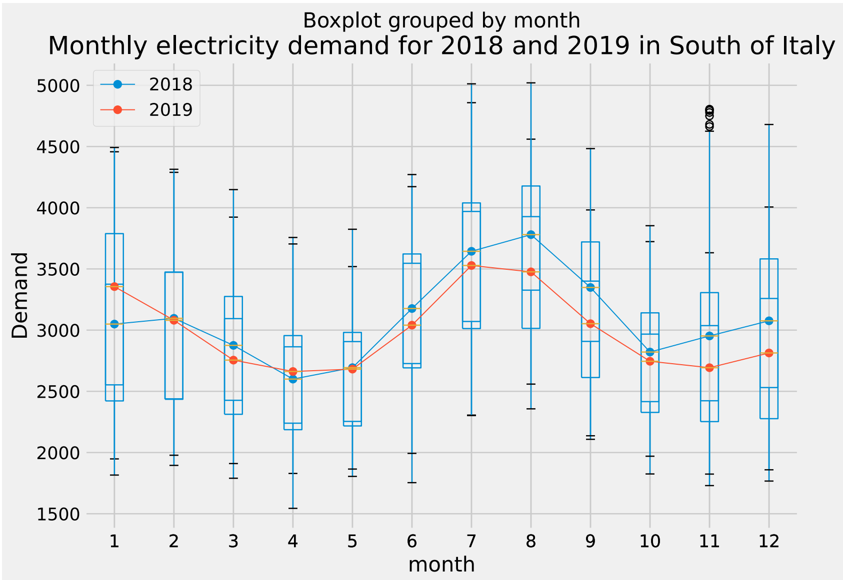
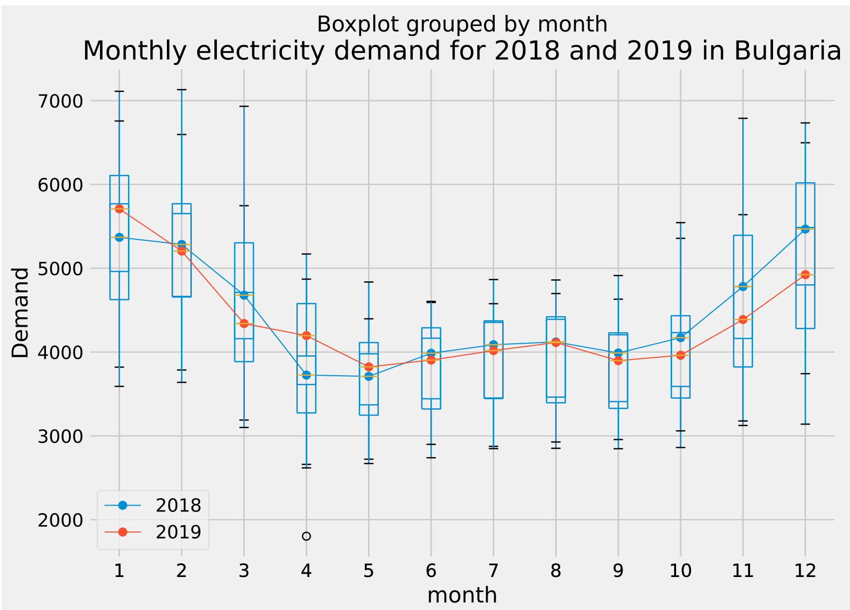
5
6
7
8
9
10
11
12
month


Boxplot grouped by month
Monthly electricity demand for 2018 and 2019 in Central-Southern Italy
2018
2019
Demand
month


Boxplot grouped by month
Monthly electricity demand for 2018 and 2019 in South of Italy
2018
2019
Demand
month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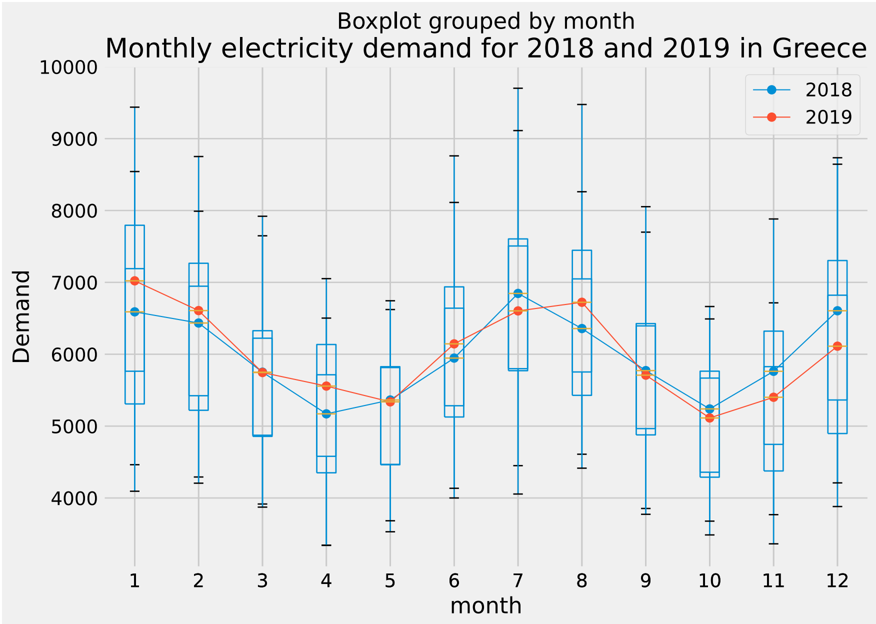
Monthly electricity demand for 2018 and 2019 in Bulgaria
2018
2019
Demand
month


Boxplot grouped by month
Monthly electricity demand for 2018 and 2019 in Greece
2018
2019
Demand
month
10000
9000
8000
7000
6000
5000
4000
1
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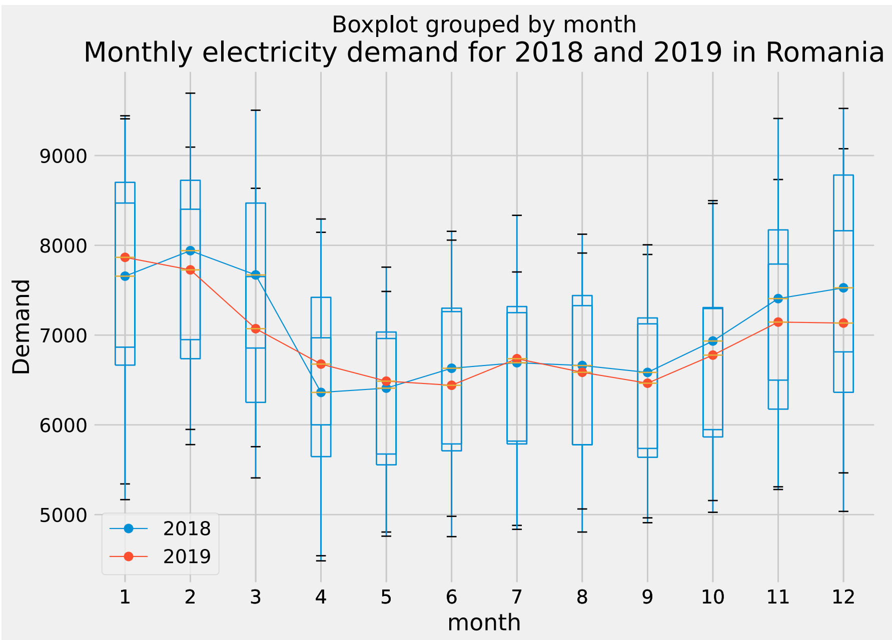
8
9
10
11
12


Boxplot grouped by month
Monthly electricity demand for 2018 and 2019 in Romania
2018
2019
Demand
month
9000
8000
7000
6000
5000
1
2
3
4
5
6
7
8
9
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11
12

Appendix 2 – Count of missing data and the dates of nationwide lockdown enforcement.

Bulgaria	Total obs	62761	Total obs removed	73	Removed dates	04/10/2017	05/10/2017	28/10/2018
	Missing temp	24	Missing temp %	0,04				
	Missing load	62	Missing load %	0,10				
Greece	Total obs	62761	Total obs removed	24	Removed dates	15/10/2016		
	Missing temp	147	Missing temp %	0,23				
	Missing load	41	Missing load %	0,07				
Romania	Total obs	62761	Total obs removed	24	Removed dates	06/08/2021		
	Missing temp	25	Missing temp %	0,04				
	Missing load	132	Missing load %	0,21				
North of Italy	Total obs	62761	Total obs removed	0	x			
	Missing temp	204	Missing temp %	0,33				
	Missing load	0	Missing load %	0				
Central-North of Italy	Total obs	62761	Total obs removed	0	x			
	Missing temp	306	Missing temp %	0,49				
	Missing load	0	Missing load %	0				
Central-South of Italy	Total obs	6271	Total obs removed	0	x			
	Missing temp	853	Missing temp %	13,60				
	Missing load	0	Missing load %	0				
South of Italy	Total obs	62761	Total obs removed	0	x			
	Missing temp	465	Missing temp %	0,74				
	Missing load	0	Missing load %	0				

Lockdown dates:

Bulgaria:	20.03.2020
Greece:	23.03.2020
Italy:	12.03.2020
Romania:	24.03.2020

Dates based on Hale et al. (2021). A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker).

Appendix 3 – Holiday dates used in analysis collected from Time and Date AS. (2023).

Shared holidays table					
Date	**Italy**	**Greece**	**Bulgaria**	**Romania**	**Holiday**
2016-01-01	Yes	Yes	Yes	Yes	New Year's Day
2016-12-25	Yes	Yes	Yes	Yes	Christmas Day
2016-12-26	Yes	Yes	Yes	Yes	Second day of Christmas
2017-01-01	Yes	Yes	Yes	Yes	New Year's Day
2017-04-17	Yes	Yes	Yes	Yes	Easter Monday
2017-05-01	Yes	Yes	Yes	Yes	Labor Day
2017-12-25	Yes	Yes	Yes	Yes	Christmas Day
2017-12-26	Yes	Yes	Yes	Yes	Second day of Christmas
2018-01-01	Yes	Yes	Yes	Yes	New Year's Day
2018-05-01	Yes	Yes	Yes	Yes	Labor Day
2018-12-25	Yes	Yes	Yes	Yes	Christmas Day
2018-12-26	Yes	Yes	Yes	Yes	Second day of Christmas
2019-01-01	Yes	Yes	Yes	Yes	New Year's Day
2019-05-01	Yes	Yes	Yes	Yes	Labor Day
2019-12-25	Yes	Yes	Yes	Yes	Christmas Day
2019-12-26	Yes	Yes	Yes	Yes	Second day of Christmas
2020-01-01	Yes	Yes	Yes	Yes	New Year's Day
2020-05-01	Yes	Yes	Yes	Yes	Labor Day
2020-12-25	Yes	Yes	Yes	Yes	Christmas Day
2020-12-26	Yes	Yes	Yes	Yes	Second day of Christmas
2021-01-01	Yes	Yes	Yes	Yes	New Year's Day
2021-05-01	Yes	Yes	Yes	Yes	Labor Day
2021-12-25	Yes	Yes	Yes	Yes	Christmas Day
2021-12-26	Yes	Yes	Yes	Yes	Second day of Christmas
2022-01-01	Yes	Yes	Yes	Yes	New Year's Day
2022-04-25	Yes	Yes	Yes	Yes	Easter Monday
2022-05-01	Yes	Yes	Yes	Yes	Labor Day
2022-12-25	Yes	Yes	Yes	Yes	Christmas Day
2022-12-26	Yes	Yes	Yes	Yes	Second day of Christmas
2023-01-01	Yes	Yes	Yes	Yes	New Year's Day

National holidays and non-working days in Bulgaria

		Date	Date	Date	Date	Date	Date	Date	Date
Year		2016	2017	2018	2019	2020	2021	2022	2023
Month	Day								
Jan	1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Jan	2	No	Yes	No	No	No	No	No	Yes
Jan	3	No	No	No	No	No	No	Yes	No
Mar	3	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mar	4	No	No	No	Yes	No	No	No	
Mar	5	No	No	Yes	No	No	No	No	
Apr	6	No	No	Yes	No	No	No	No	
Apr	7	No	No	Yes	No	No	No	No	
Apr	8	No	No	Yes	No	No	No	No	
Apr	9	No	No	Yes	No	No	No	No	
Apr	14	No	Yes	No	No	No	No	No	
Apr	15	No	Yes	No	No	No	No	No	
Apr	16	No	Yes	No	No	No	No	No	
Apr	17	No	Yes	No	No	Yes	No	No	
Apr	18	No	No	No	No	Yes	No	No	
Apr	19	No	No	No	No	Yes	No	No	
Apr	20	No	No	No	No	Yes	No	No	
Apr	22	No	No	No	No	No	No	Yes	
Apr	23	No	No	No	No	No	No	Yes	
Apr	24	No	No	No	No	No	No	Yes	
Apr	25	No	No	No	No	No	No	Yes	
Apr	26	No	No	No	Yes	No	No	No	
Apr	27	No	No	No	Yes	No	No	No	
Apr	28	No	No	No	Yes	No	No	No	
Apr	29	Yes	No	No	Yes	No	No	No	
Apr	30	Yes	No	No	No	No	Yes	No	
May	1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
May	2	Yes	No	No	No	No	Yes	Yes	
May	3	No	No	No	No	No	Yes	No	
May	4	No	No	No	No	No	Yes	No	
May	6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
May	7	No	No	Yes	No	No	No	No	
May	8	No	Yes	No	No	No	No	No	
May	24	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
May	25	No	No	No	No	Yes	No	No	
Sep	6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Sep	7	No	No	No	No	Yes	No	No	
Sep	22	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Sep	23	No	No	No	Yes	No	No	No	
Sep	24	No	No	Yes	No	No	No	No	
Nov	1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Dec	24	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Dec	25	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Dec	26	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Dec	27	No	Yes	No	No	No	No	Yes	
Dec	28	No	No	No	No	Yes	Yes	Yes	

National holidays and non-working days in Greece

		Date	Date	Date	Date	Date	Date	Date	Date
Year		2016	2017	2018	2019	2020	2021	2022	2023
Month	Day								
Jan	1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Jan	6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Feb	19	No	No	Yes	No	No	No	No	No
Feb	27	No	Yes	No	No	No	No	No	Yes
Mar	2	No	No	No	No	Yes	No	No	
Mar	7	No	No	No	No	No	No	Yes	
Mar	11	No	No	No	Yes	No	No	No	
Mar	14	Yes	No	No	No	No	No	No	
Mar	15	No	No	No	No	No	Yes	No	
Mar	25	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Apr	6	No	No	Yes	No	No	No	No	
Apr	8	No	No	Yes	No	No	No	No	
Apr	9	No	No	Yes	No	No	No	No	
Apr	14	No	Yes	No	No	No	No	No	
Apr	17	No	Yes	No	No	Yes	No	No	
Apr	19	No	No	No	No	Yes	No	No	
Apr	20	No	No	No	No	Yes	No	No	
Apr	22	No	No	No	No	No	No	Yes	
Apr	24	No	No	No	No	No	No	Yes	
Apr	25	No	No	No	No	No	No	Yes	
Apr	26	No	No	No	Yes	No	No	No	
Apr	28	No	No	No	Yes	No	No	No	
Apr	29	Yes	No	No	Yes	No	No	No	
Apr	30	No	No	No	No	No	Yes	No	
May	1	No	Yes	Yes	Yes	Yes	Yes	Yes	
May	2	Yes	No	No	No	No	Yes	No	
May	3	Yes	No	No	No	No	Yes	No	
May	27	No	No	Yes	No	No	No	No	
May	28	No	No	Yes	No	No	No	No	
Jun	5	No	Yes	No	No	No	No	No	
Jun	7	No	No	No	No	Yes	No	No	
Jun	8	No	No	No	No	Yes	No	No	
Jun	12	No	No	No	No	No	No	Yes	
Jun	13	No	No	No	No	No	No	Yes	
Jun	16	No	No	No	Yes	No	No	No	
Jun	17	No	No	No	Yes	No	No	No	
Jun	20	Yes	No	No	No	No	Yes	No	
Jun	21	No	No	No	No	No	Yes	No	
Aug	15	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Oct	28	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Dec	25	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Dec	26	Yes	Yes	Yes	Yes	Yes	Yes	Yes	

National holidays and non-working days in Romania

		Date	Date	Date	Date	Date	Date	Date	Date
Year		2016	2017	2018	2019	2020	2021	2022	2023
Month	Day								
Jan	1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Jan	2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Jan	24	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Apr	6	No	No	Yes	No	No	No	No	
Apr	8	No	No	Yes	No	No	No	No	
Apr	9	No	No	Yes	No	No	No	No	
Apr	14	No	No	No	No	No	No	No	
Apr	16	No	Yes	No	No	No	No	No	
Apr	17	No	Yes	No	No	Yes	No	No	
Apr	19	No	No	No	No	Yes	No	No	
Apr	20	No	No	No	No	Yes	No	No	
Apr	22	No	No	No	No	No	No	Yes	
Apr	24	No	No	No	No	No	No	Yes	
Apr	25	No	No	No	No	No	No	Yes	
Apr	26	No	No	No	Yes	No	No	No	
Apr	28	No	No	No	Yes	No	No	No	
Apr	29	No	No	No	Yes	No	No	No	
Apr	30	No	No	No	Yes	No	Yes	No	
May	1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
May	2	Yes	No	No	No	No	Yes	No	
May	3	No	No	No	No	No	Yes	No	
May	27	No	No	Yes	No	No	No	No	
May	28	No	No	Yes	No	No	No	No	
Jun	1	No	Yes	Yes	Yes	Yes	Yes	Yes	
Jun	2	No	Yes	No	No	No	No	No	
Jun	4	No	Yes	No	No	No	No	No	
Jun	5	No	Yes	No	No	No	No	No	
Jun	7	No	No	No	No	Yes	No	No	
Jun	8	No	No	No	No	Yes	No	No	
Jun	12	No	No	No	No	No	No	Yes	
Jun	13	No	No	No	No	No	No	Yes	
Jun	16	No	No	No	Yes	No	No	No	
Jun	17	No	No	No	Yes	No	No	No	
Jun	19	Yes	No	No	No	No	No	No	
Jun	20	Yes	No	No	No	No	Yes	No	
Jun	21	No	No	No	No	No	Yes	No	
Aug	15	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Aug	16	No	No	No	Yes	No	No	No	
Nov	30	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Dec	1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Dec	2	Yes	No	No	No	No	No	Yes	
Dec	24	Yes	No	No	No	No	No	No	
Dec	25	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Dec	26	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Dec	31	Yes	No	No	No	No	No	No	

National holidays and non-working days in Italy

		Date	Date	Date	Date	Date	Date	Date	Date
Year		2016	2017	2018	2019	2020	2021	2022	2023
Month	Day								
Jan	1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Jan	6	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mar	27	Yes	No	No	No	No	No	No	
Mar	28	Yes	No	No	No	No	No	No	
Apr	1	No	No	Yes	No	No	No	No	
Apr	2	No	No	Yes	No	No	No	No	
Apr	4	No	No	No	No	No	Yes	No	
Apr	5	No	No	No	No	No	Yes	No	
Apr	9	No	No	No	No	No	No	No	
Apr	12	No	No	No	No	Yes	No	No	
Apr	13	No	No	No	No	Yes	No	No	
Apr	16	No	Yes	No	No	No	No	No	
Apr	17	No	Yes	No	No	No	No	Yes	
Apr	18	No	No	No	No	No	No	Yes	
Apr	21	No	No	No	Yes	No	No	No	
Apr	22	No	No	No	Yes	No	No	No	
Apr	25	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
May	1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Jun	2	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Aug	15	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Nov	1	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Dec	8	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Dec	25	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Dec	26	Yes	Yes	Yes	Yes	Yes	Yes	Yes	

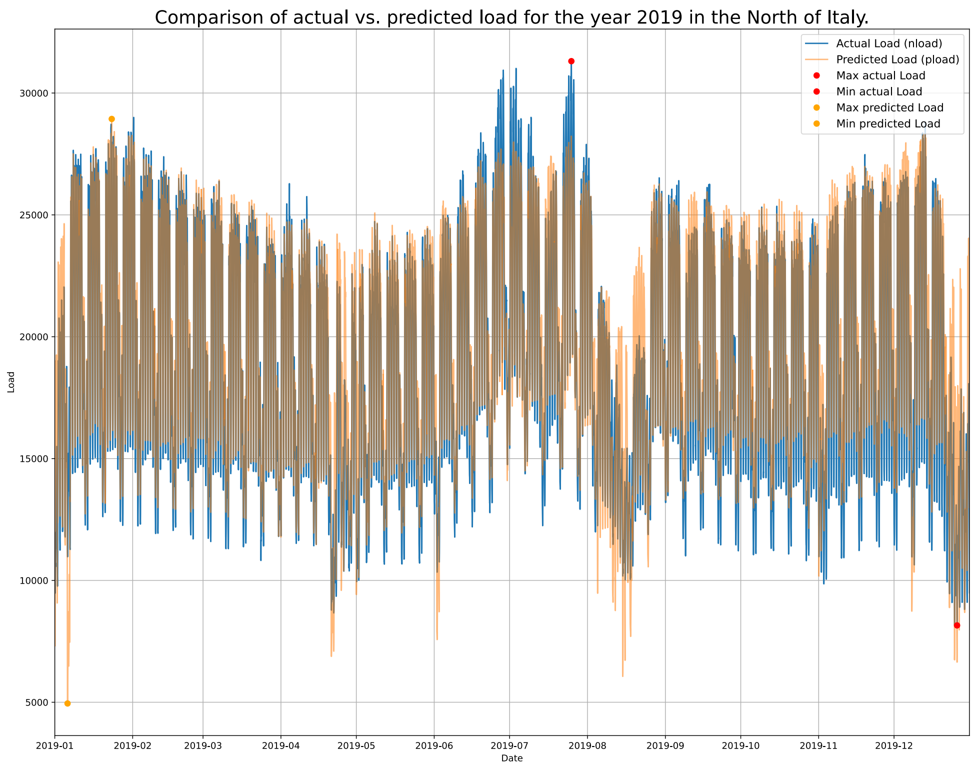
Appendix 4 – OLS Regression Analysis and Load Comparison for Actual vs Predicted Electricity Consumption

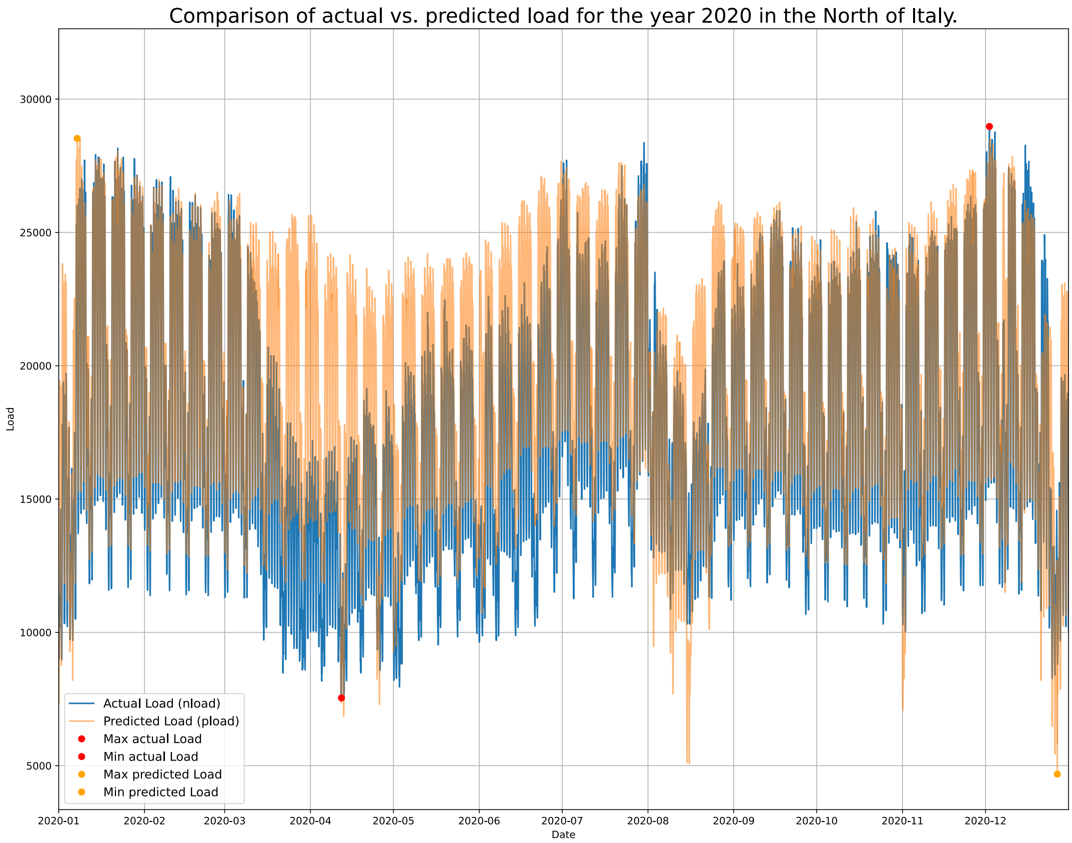
OLS Regression Results: Predicting Electricity Load in North of Italy using HAC Covariances:

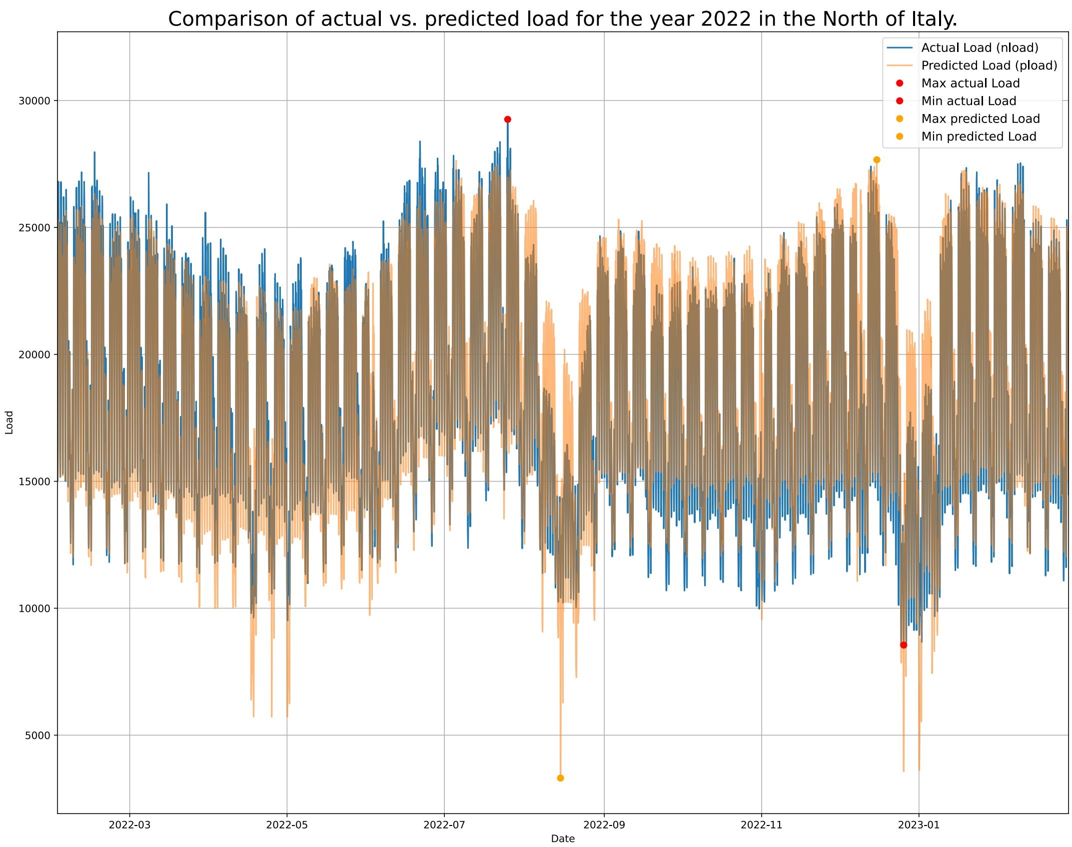
NORTH OF ITALY	2019	2020	2022
No. Observations:	26281	35041	52585
R-squared	0.933	0.929	0.909
Adj. R-squared	0.932	0.929	0.908
F-statistic and Prob (F-statistic)	1139.0 (0.00)	974.1 (0.00)	882.9 (0.00)

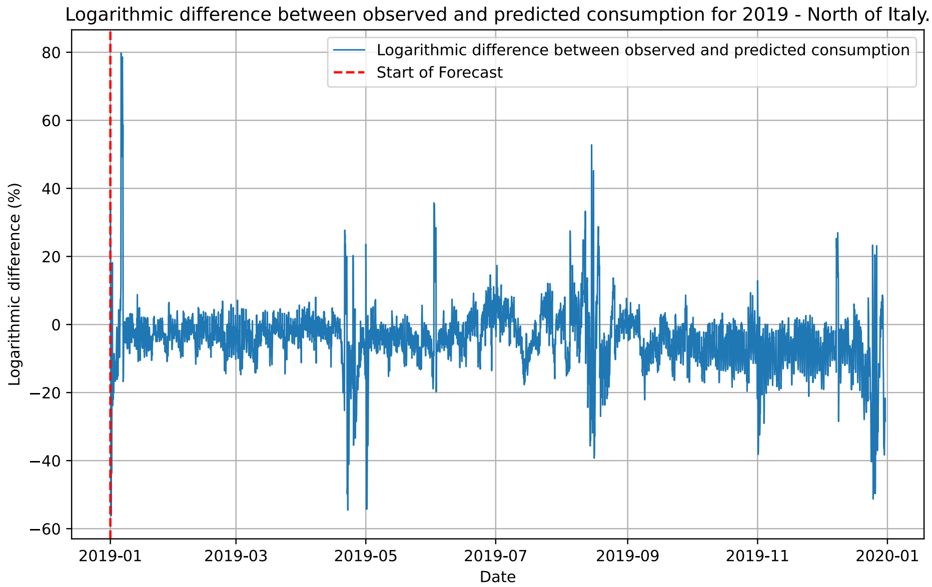
Wald Test for Joint Significance of Dummy Variables - North of Italy

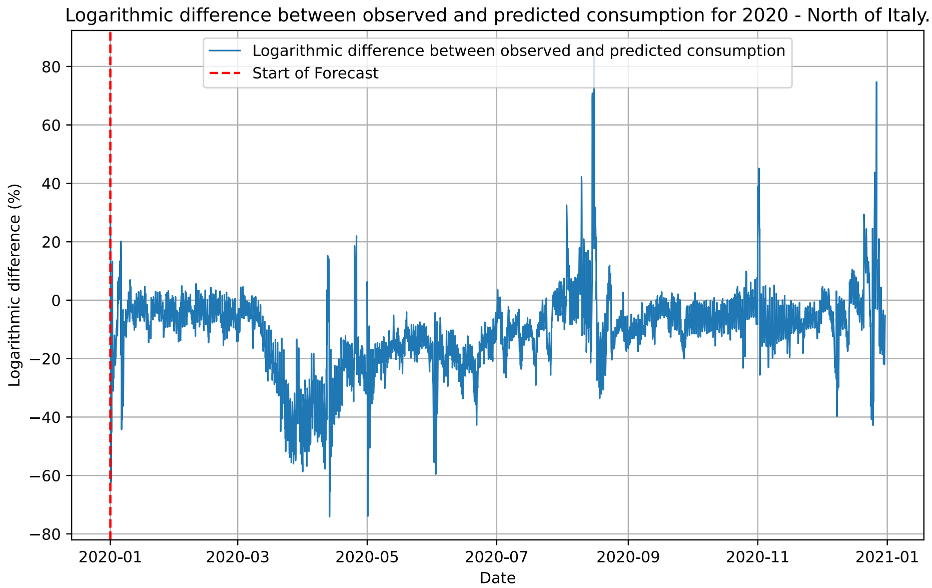
	2019 chi2	2019 p-value	2020 chi2	2020 p-value	2022 chi2	2022 p-value
cool_dummy	21.47 (df: 24)	1.18e-92	31.01 (df: 24)	5.10e-140	28.84 (df: 24)	8.95e-130
heat_dummy	45.52 (df: 24)	8.72e-211	48.97 (df: 24)	5.45e-229	63.29 (df: 24)	6.40e-302
week_dummy	27.09 (df: 51)	1.81e-248	30.18 (df: 51)	5.73e-282	20.42 (df: 51)	9.47e-183
hofw_dummy	235.34 (df: 167)	0.000e+00	232.70 (df: 167)	0.000e+00	208.09 (df: 167)	0.000e+00

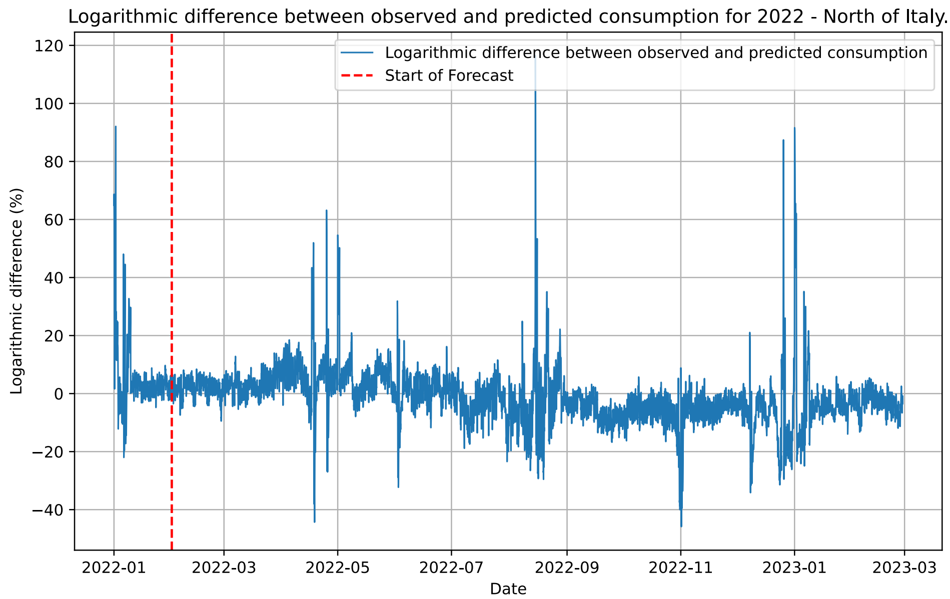



Comparison of actual vs. predicted load for the year 2020 in the North of Italy.
Load
Date
30000
25000
20000
15000
10000
5000
2020-01
2020-02
2020-03
2020-04
2020-05
2020-06
2020-07
2020-08
2020-09
2020-10
2020-11
2020-12
Actual Load (nload)
Predicted Load (pload)
Max actual Load
Min actual Load
Max predicted Load
Min predicted Load


Comparison of actual vs. predicted load for the year 2022 in the North of Italy.
Load
Date
30000
25000
20000
15000
10000
5000
2022-03
2022-05
2022-07
2022-09
2022-11
2023-01
Actual Load (nload)
Predicted Load (pload)
Max actual Load
Min actual Load
Max predicted Load
Min predicted Load


Logarithmic difference between observed and predicted consumption for 2019 - North of Italy.
Logarithmic difference between observed and predicted consumption
Start of Forecast
Logarithmic difference (%)
Date


Logarithmic difference between observed and predicted consumption for 2020 - North of Italy.
Logarithmic difference between observed and predicted consumption
Start of Forecast
Logarithmic difference (%)
Date


Logarithmic difference between observed and predicted consumption for 2022 - North of Italy.
Logarithmic difference between observed and predicted consumption
Start of Forecast
Logarithmic difference (%)
Date

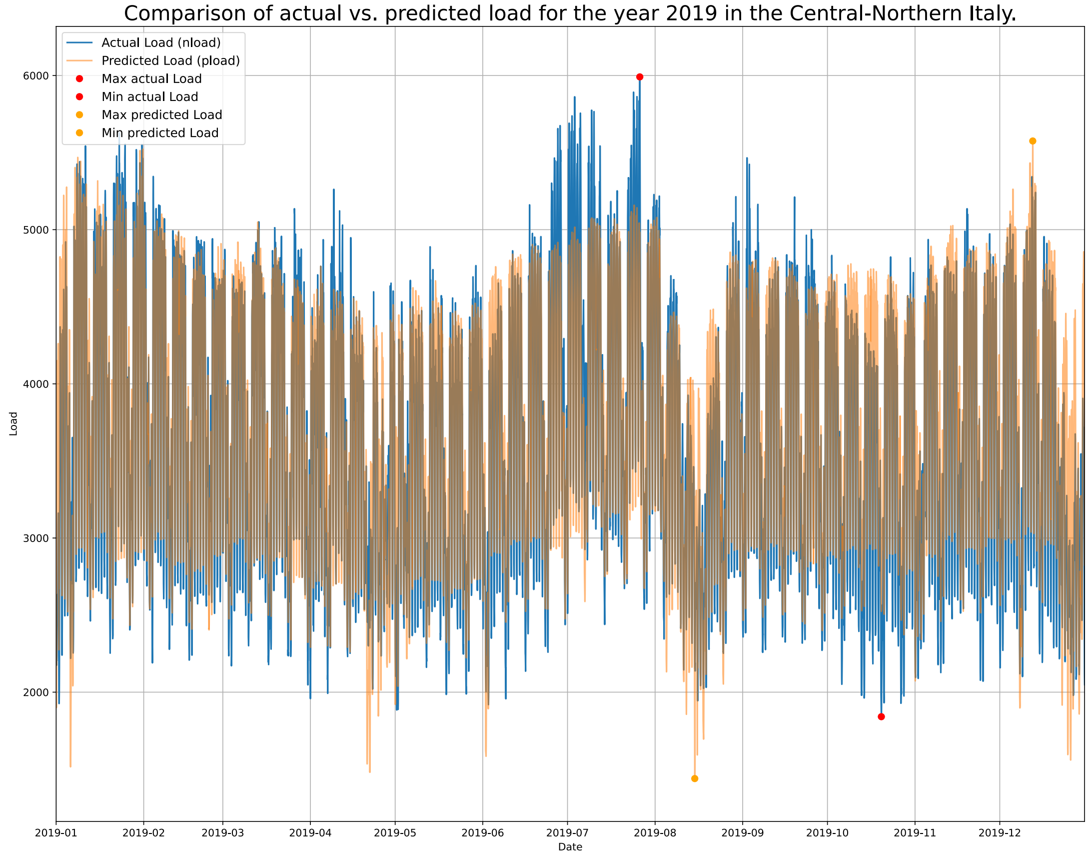
OLS Regression Results: Predicting Electricity Load in Central -Northern Italy using HAC Covariances:

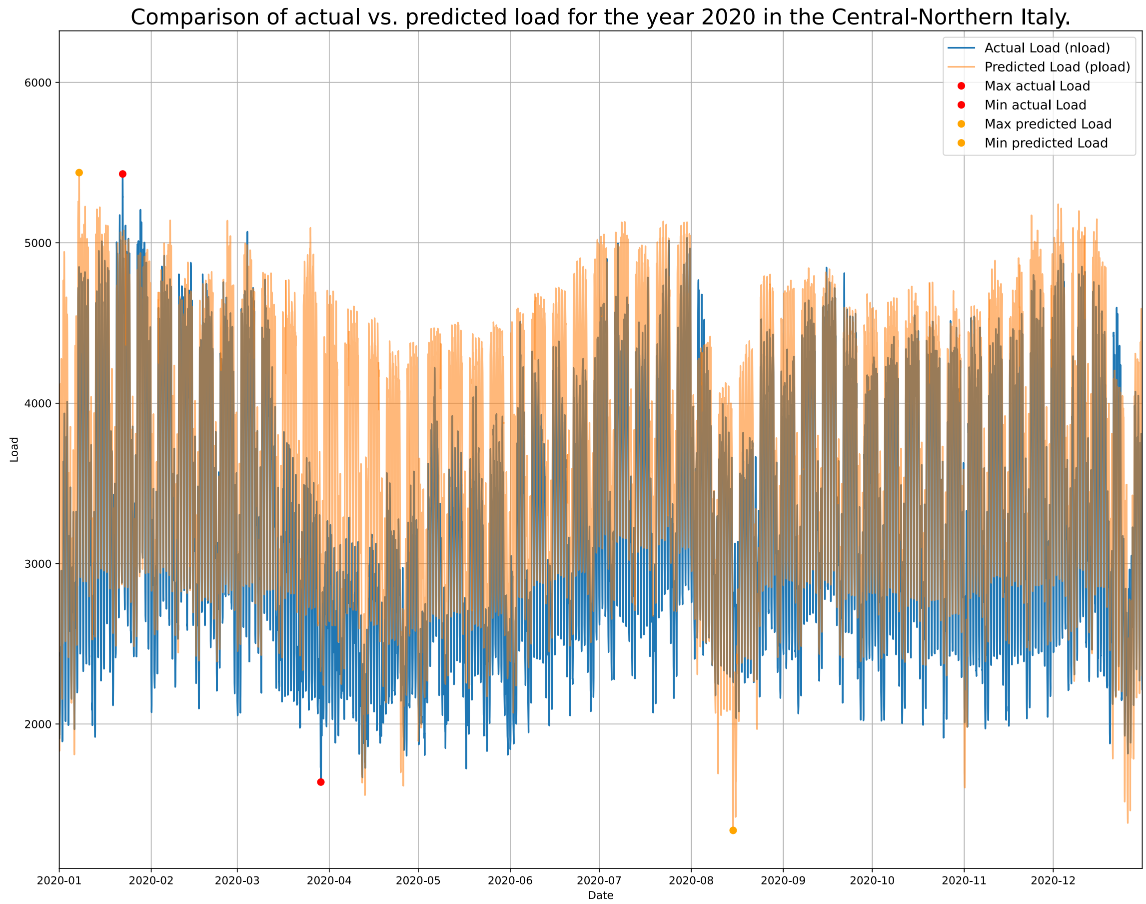
CENTRAL-NORTHERN ITALY	2019	2020	2022
No. Observations:	26281	35041	52585
R-squared	0.910	0.905	0.887
Adj. R-squared	0.909	0.904	0.887
F-statistic and Prob (F-statistic)	1079.0 (0.00)	853.0 (0.00)	319.1 (0.00)

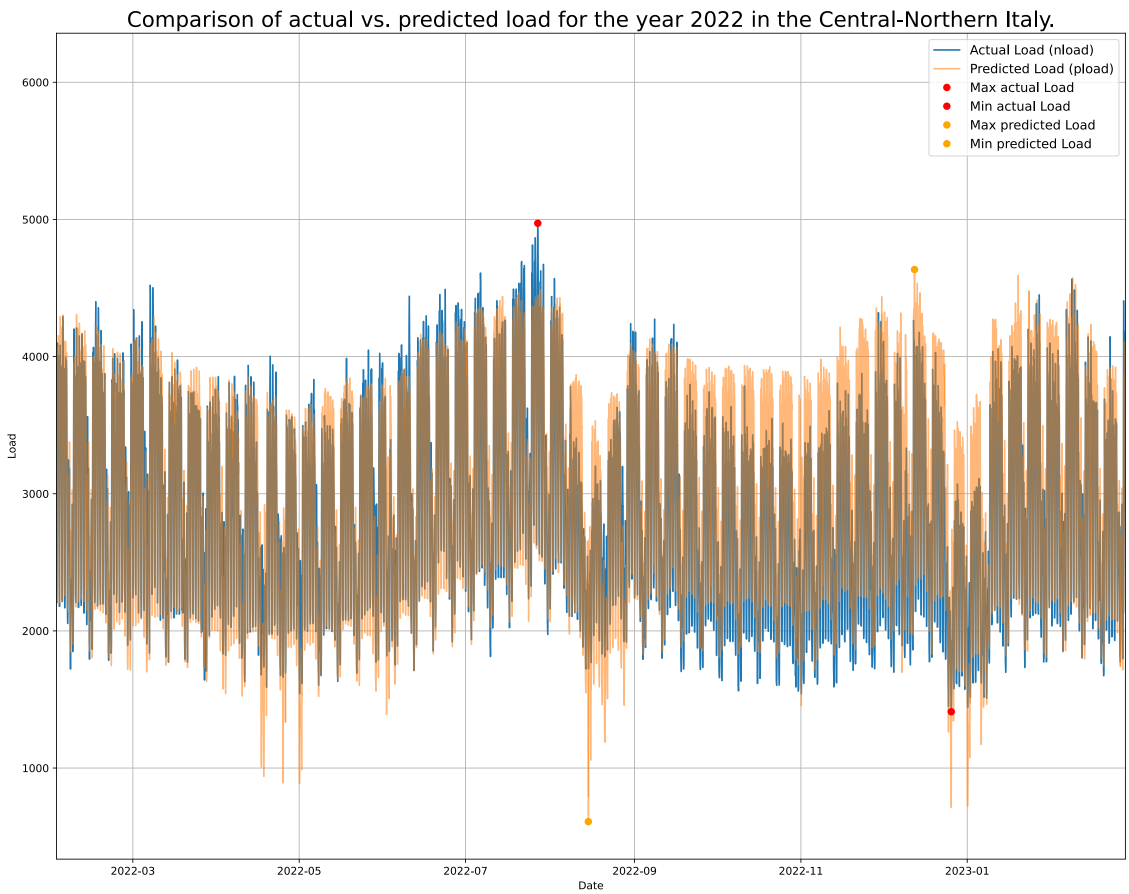
Wald Test for Joint Significance of Dummy Variables - Central-Northern Italy

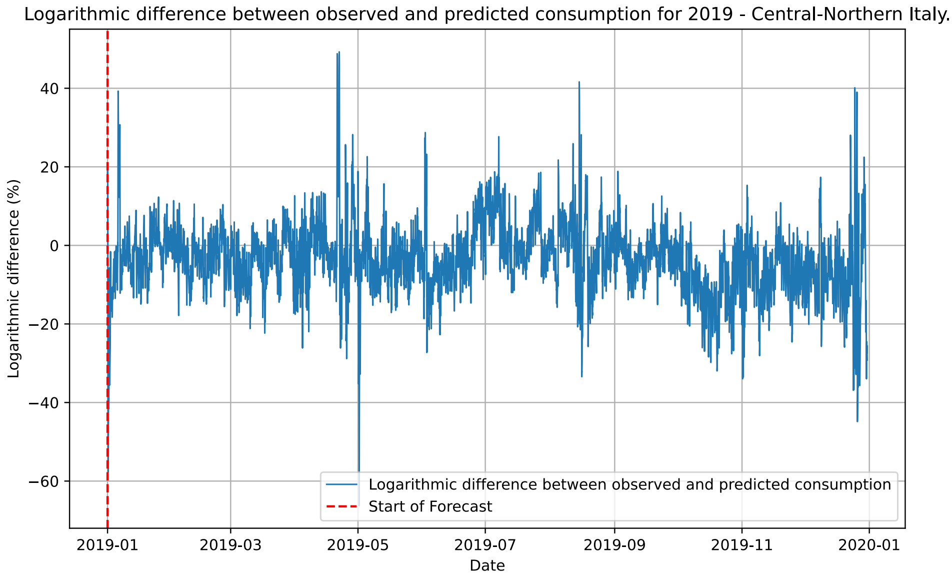
	2019 chi2	2019 p-value	2020 chi2	2020 p-value	2022 chi2	2022 p-value
cool_dummy	14.32 (df: 24)	6.79e-58	17.50 (df: 24)	1.76e-73	17.34 (df: 24)	7.30e-73
heat_dummy	25.61 (df: 24)	5.56e-113	31.33 (df: 24)	1.33e-141	30.86 (df: 24)	8.09e-140
week_dummy	12.43 (df: 51)	3.35e-100	14.49 (df: 51)	3.03e-121	9.68 (df: 51)	2.32e-73
hofw_dummy	201.57 (df: 167)	0.000e+00	187.61 (df: 167)	0.000e+00	109.12 (df: 167)	0.000e+00

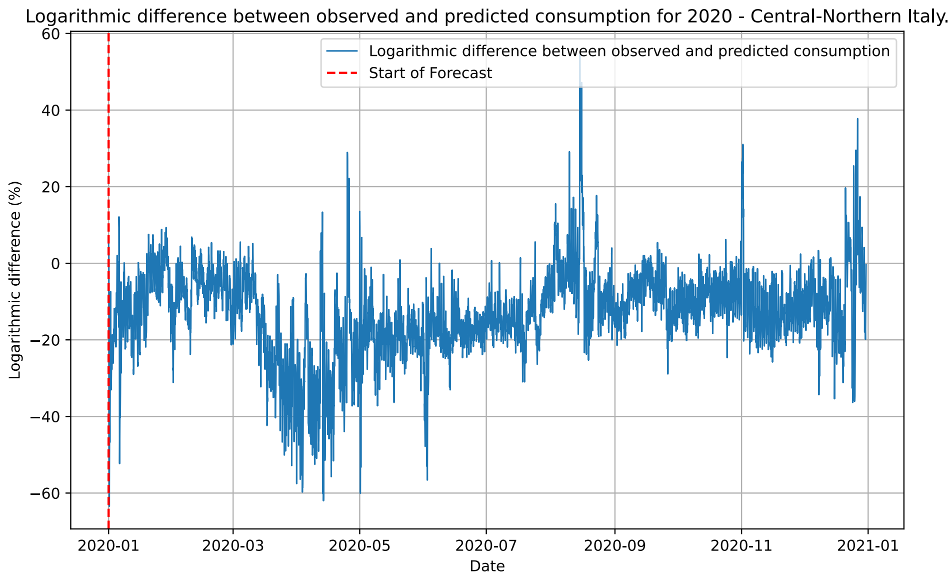
Comparison of actual vs. predicted load for the year 2019 in the Central-Northern Italy.

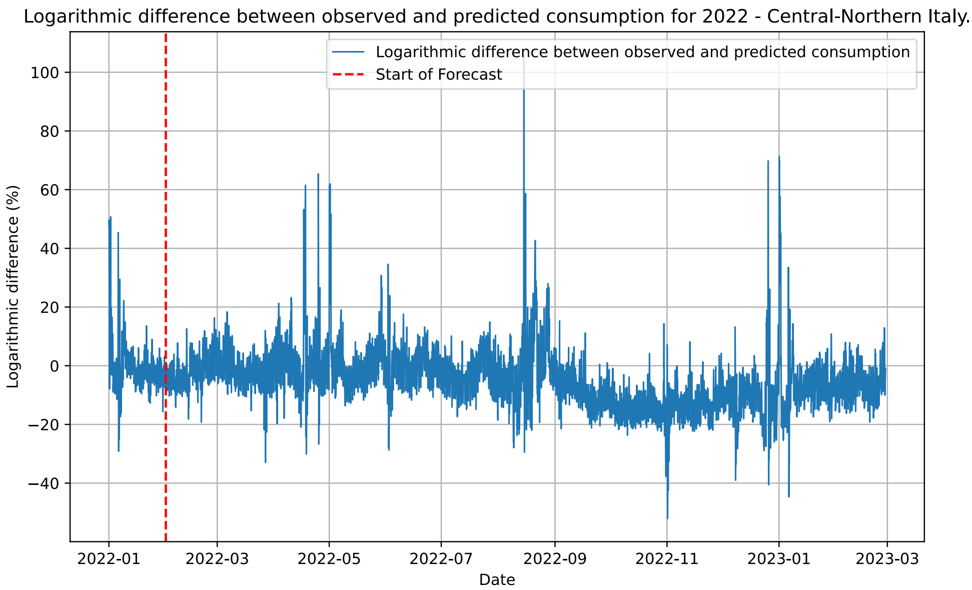



Comparison of actual vs. predicted load for the year 2020 in the Central-Northern Italy.
Actual Load (nload)
Predicted Load (pload)
Max actual Load
Min actual Load
Max predicted Load
Min predicted Load
Load
Date


Comparison of actual vs. predicted load for the year 2022 in the Central-Northern Italy.
Actual Load (nload)
Predicted Load (pload)
Max actual Load
Min actual Load
Max predicted Load
Min predicted Load
Load
Date


Logarithmic difference between observed and predicted consumption for 2019 - Central-Northern Italy.
Logarithmic difference (%)
Date
Logarithmic difference between observed and predicted consumption
Start of Forecast


Logarithmic difference between observed and predicted consumption for 2020 - Central-Northern Italy.
Logarithmic difference (%)
Date
Logarithmic difference between observed and predicted consumption
Start of Forecast

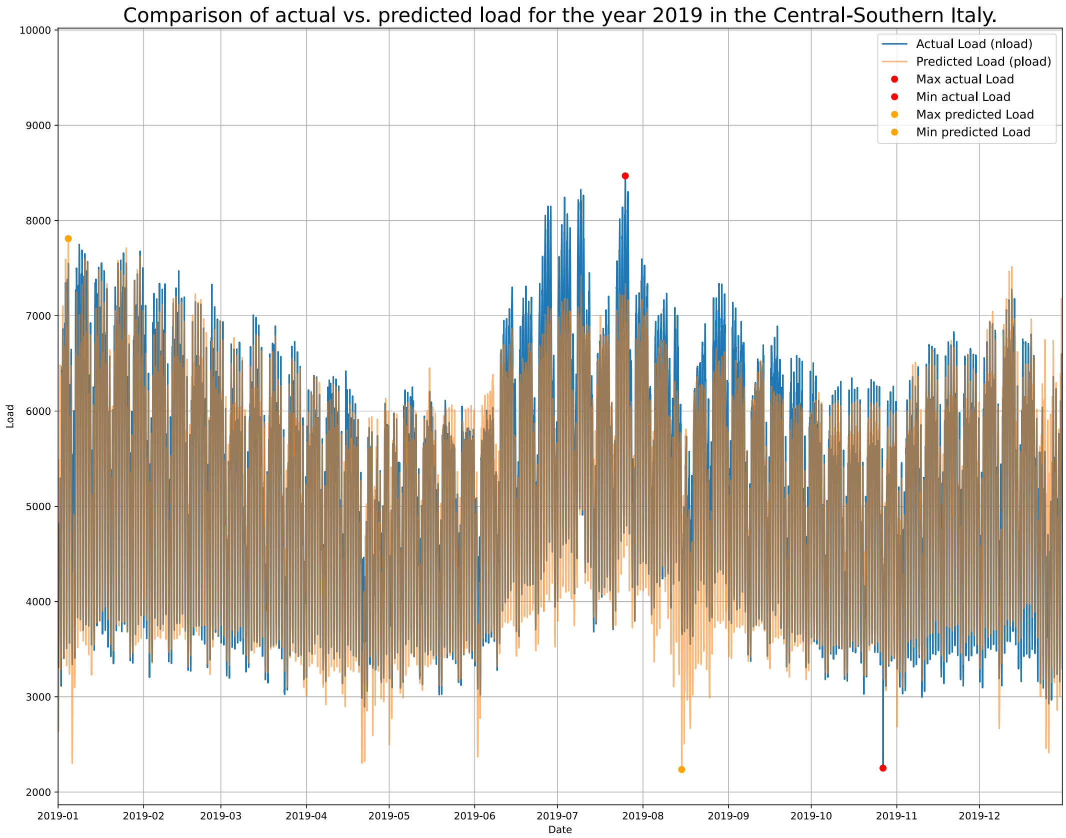

Logarithmic difference between observed and predicted consumption for 2022 - Central-Northern Italy.
Logarithmic difference (%)
Date
Logarithmic difference between observed and predicted consumption
Start of Forecast

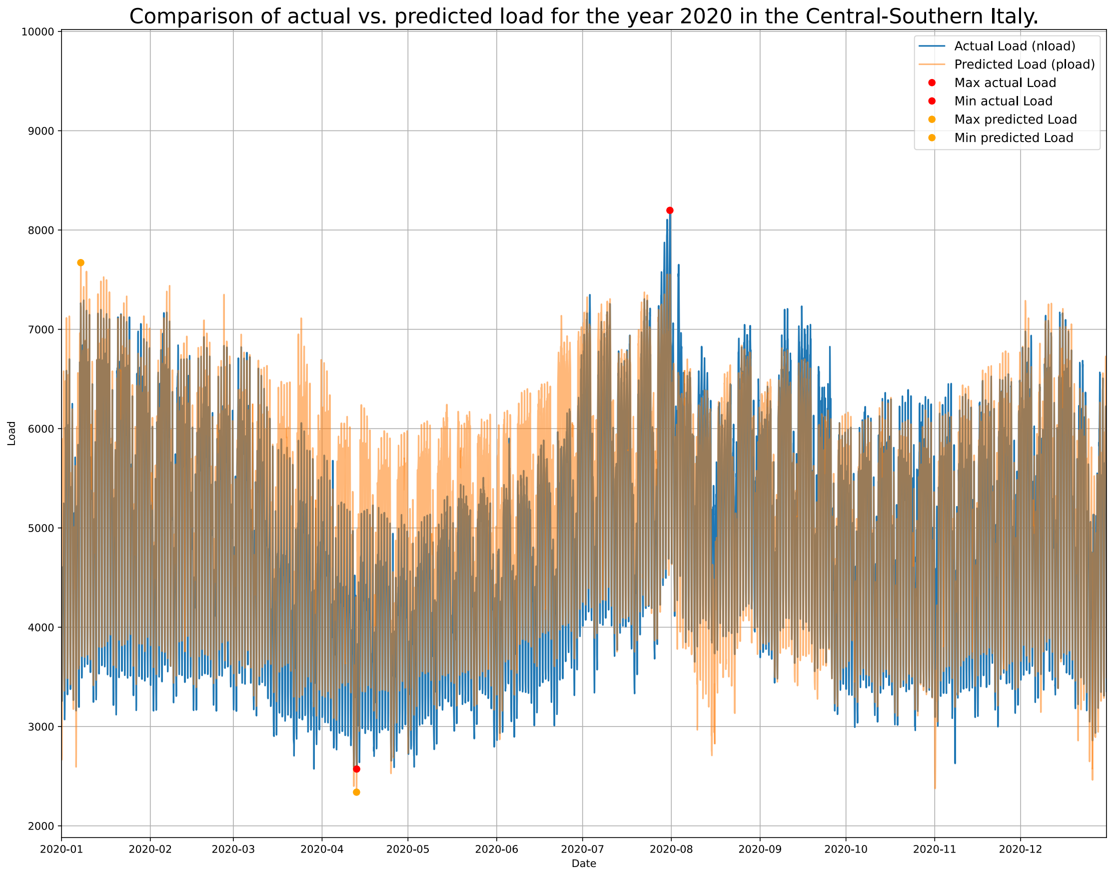
OLS Regression Results: Predicting Electricity Load in Central-Southern Italy using HAC Covariances:

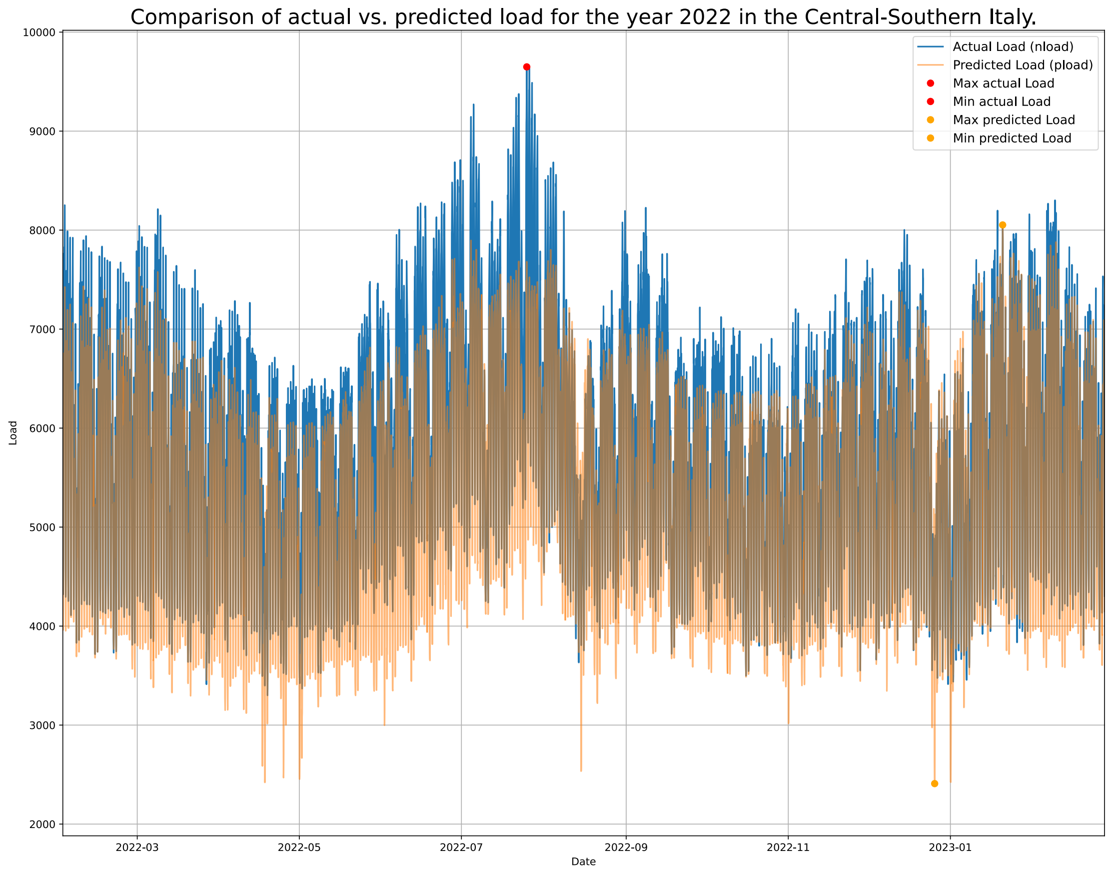
CENTRAL-SOUTHERN ITALY	2019	2020	2022
No. Observations:	26281	35041	52585
R-squared	0.933	0.932	0.888
Adj. R-squared	0.932	0.932	0.887
F-statistic and Prob (F-statistic)	1471.0 (0.00)	1294.0 (0.00)	1228.0 (0.00)

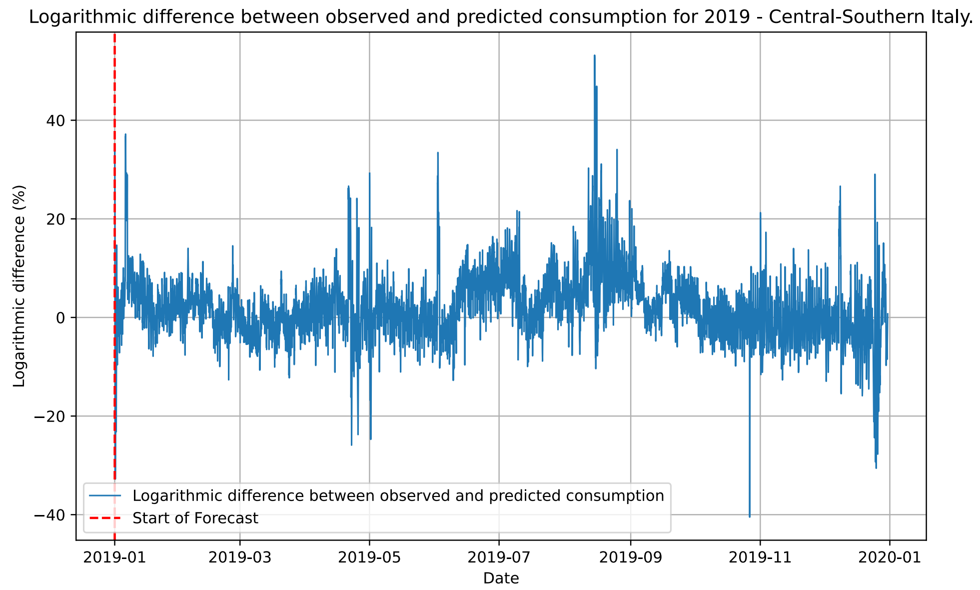
Wald Test for Joint Significance of Dummy Variables - Central-Southern Italy

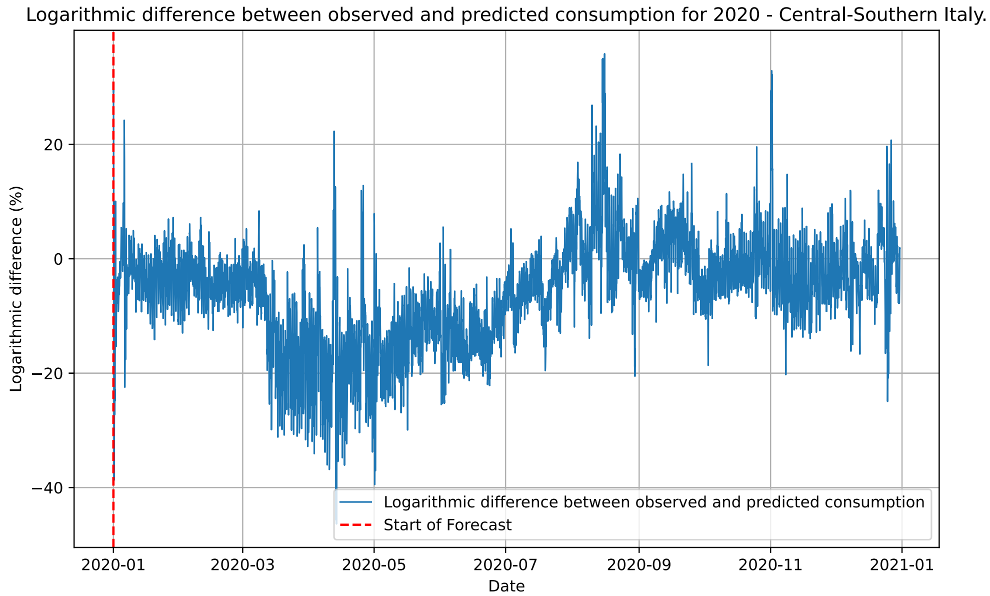
	2019 chi2	2019 p-value	2020 chi2	2020 p-value	2022 chi2	2022 p-value
cool_dummy	30.23 (df: 24)	1.06e-135	41.22 (df: 24)	1.30e-190	46.22 (df: 24)	1.32e-216
heat_dummy	43.45 (df: 24)	1.23e-200	56.69 (df: 24)	3.82e-267	45.49 (df: 24)	5.86e-213
week_dummy	17.53 (df: 51)	1.61e-151	17.37 (df: 51)	1.29e-150	5.68 (df: 51)	5.75e-35
hofw_dummy	260.96 (df: 167)	0.000e+00	240.49 (df: 167)	0.000e+00	206.91 (df: 167)	0.000e+00

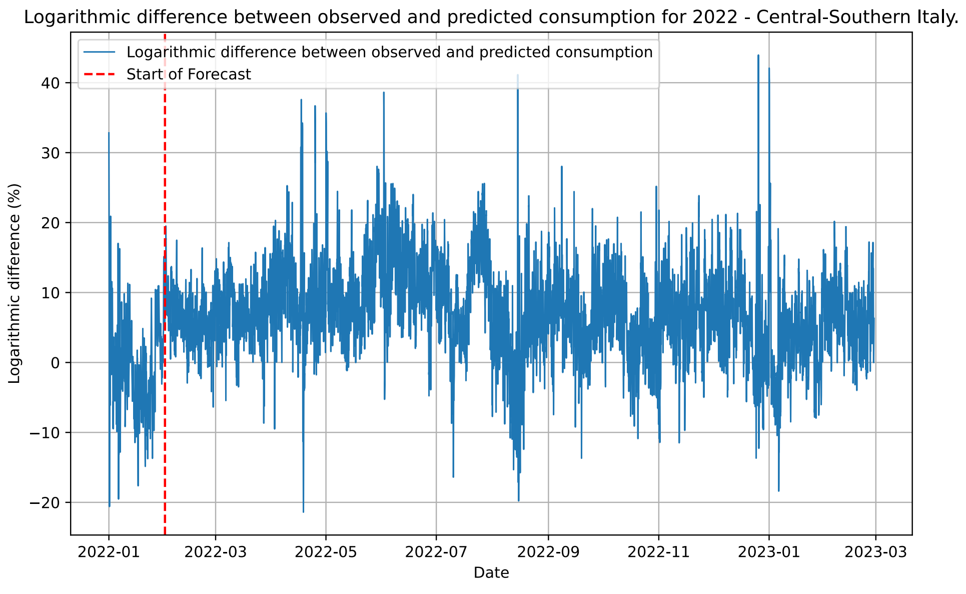



Comparison of actual vs. predicted load for the year 2020 in the Central-Southern Italy.
Actual Load (nload)
Predicted Load (pload)
Max actual Load
Min actual Load
Max predicted Load
Min predicted Load
Load
Date
10000
9000
8000
7000
6000
5000
4000
3000
2000
2020-01
2020-02
2020-03
2020-04
2020-05
2020-06
2020-07
2020-08
2020-09
2020-10
2020-11
2020-12


Comparison of actual vs. predicted load for the year 2022 in the Central-Southern Italy.
Actual Load (nload)
Predicted Load (pload)
Max actual Load
Min actual Load
Max predicted Load
Min predicted Load
Load
Date
10000
9000
8000
7000
6000
5000
4000
3000
2000
2022-03
2022-05
2022-07
2022-09
2022-11
2023-01


Logarithmic difference between observed and predicted consumption for 2019 - Central-Southern Italy.
Logarithmic difference (%)
Date
Logarithmic difference between observed and predicted consumption
Start of Forecast
2019-01
2019-03
2019-05
2019-07
2019-09
2019-11
2020-01


Logarithmic difference between observed and predicted consumption for 2020 - Central-Southern Italy.
Logarithmic difference (%)
Date
Logarithmic difference between observed and predicted consumption
Start of Forecast
2020-01
2020-03
2020-05
2020-07
2020-09
2020-11
2021-01

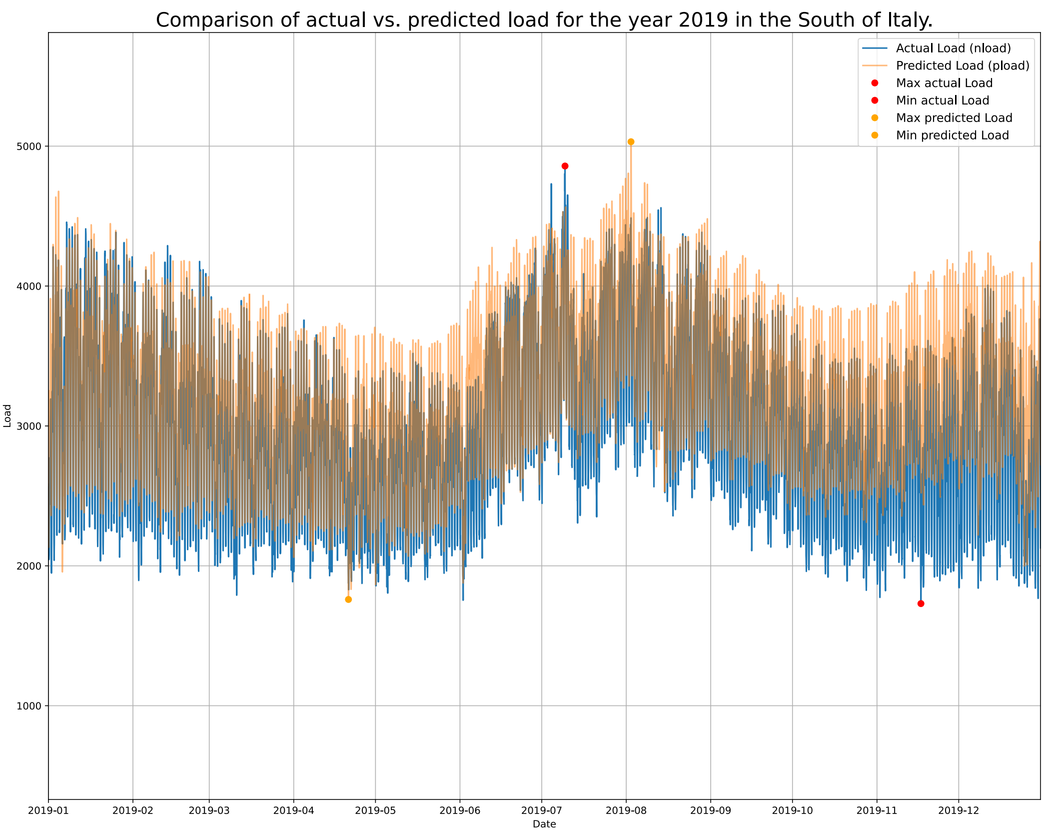

Logarithmic difference between observed and predicted consumption for 2022 - Central-Southern Italy.
Logarithmic difference (%)
Date
Logarithmic difference between observed and predicted consumption
Start of Forecast
2022-01
2022-03
2022-05
2022-07
2022-09
2022-11
2023-01
2023-03

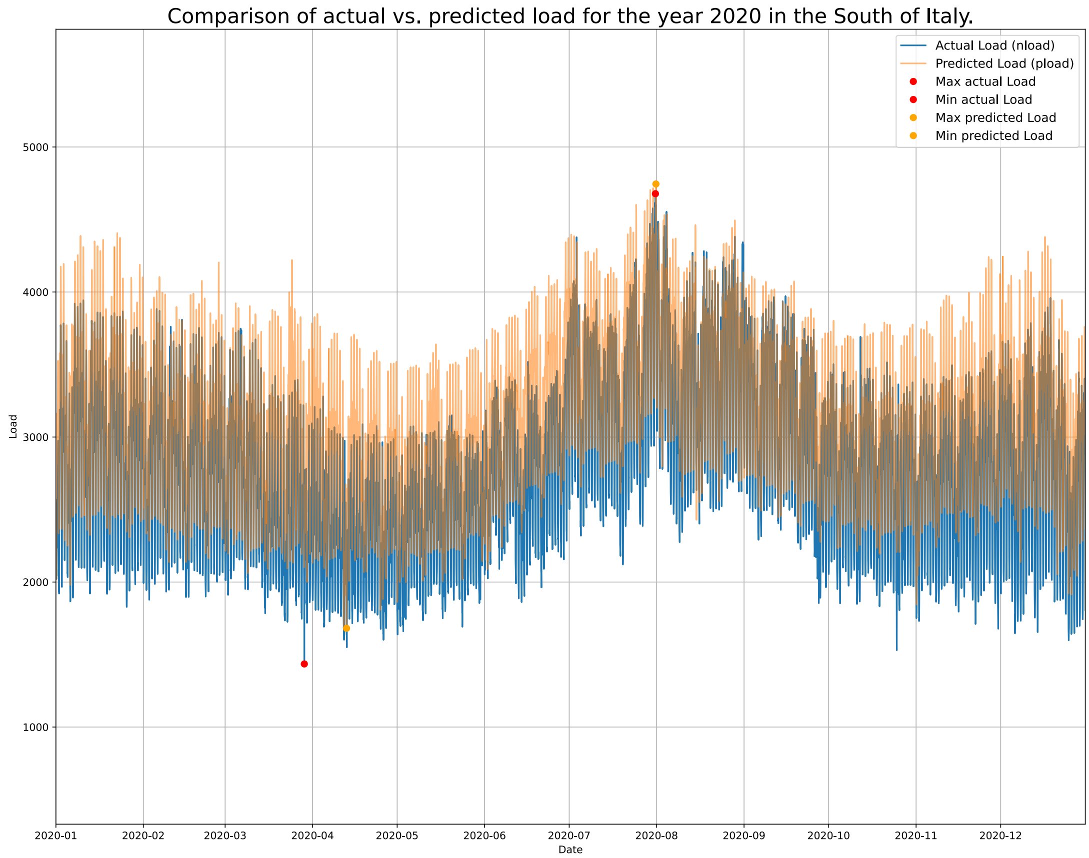
OLS Regression Results: Predicting Electricity Load in South of Italy using HAC Covariances:

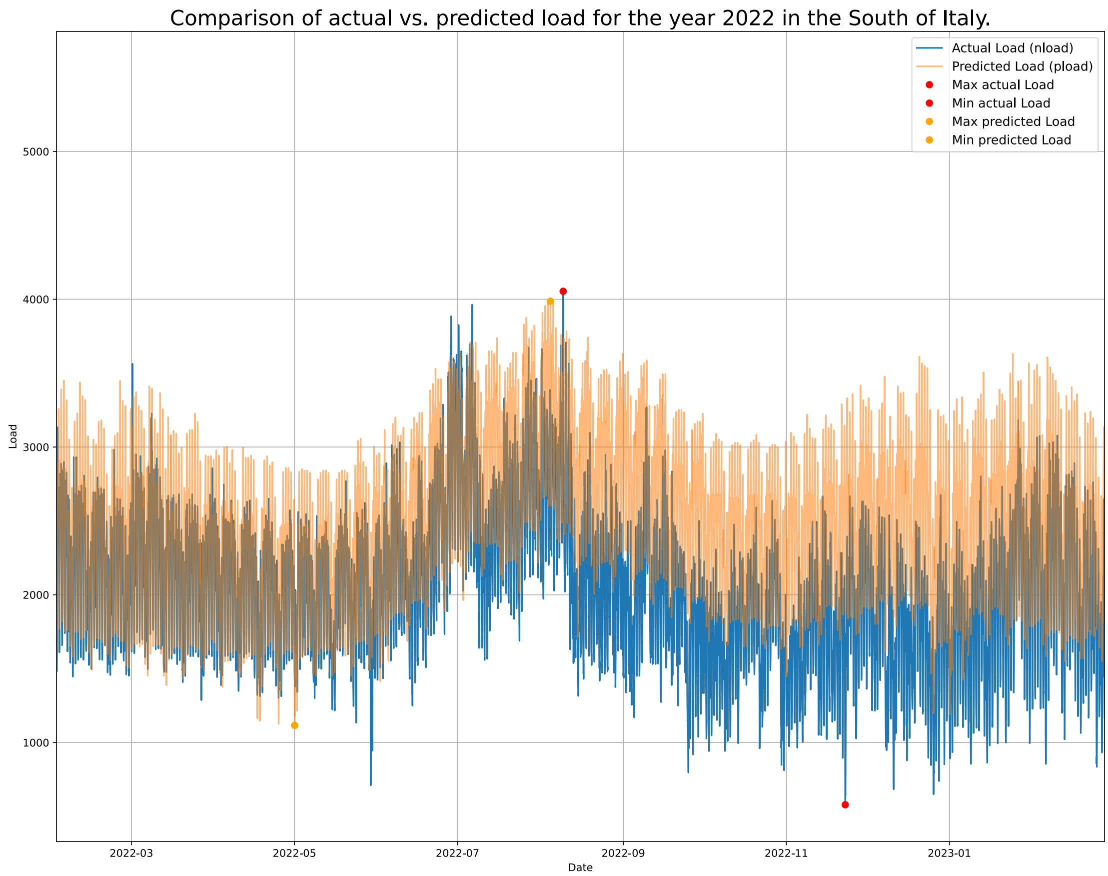
SOUTH OF ITALY	**2019**	**2020**	**2022**
No. Observations:	26281	35041	52585
R-squared	0.852	0.846	0.791
Adj. R-squared	0.851	0.844	0.790
F-statistic and Prob (F-statistic)	683.1 (0.00)	681.3 (0.00)	327.2 (0.00)

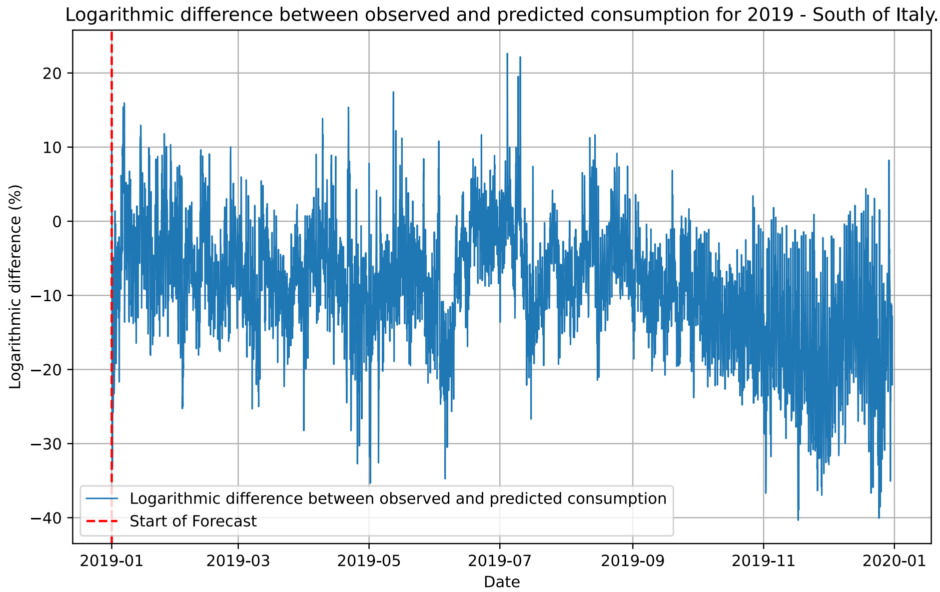
Wald Test for Joint Significance of Dummy Variables - South of Italy

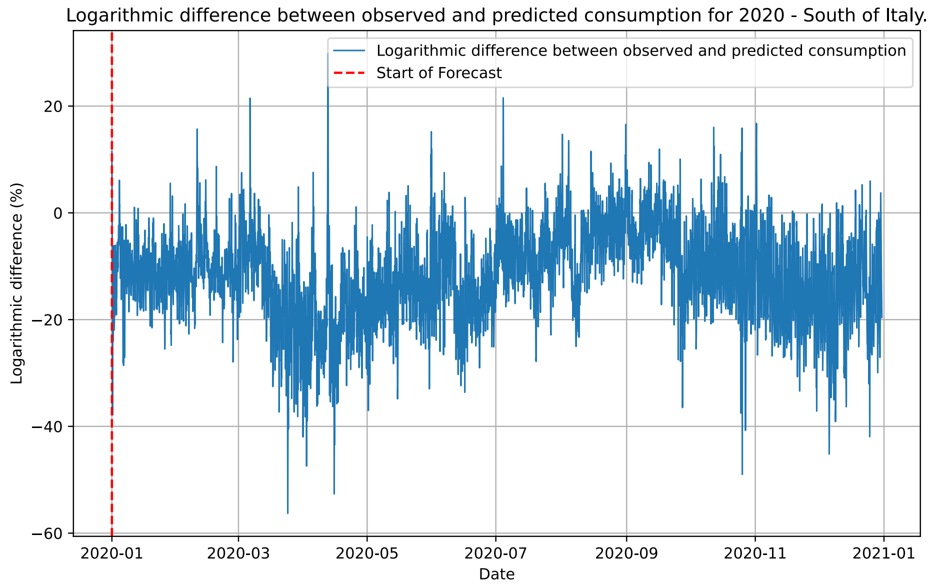
	2019 chi2	2019 p-value	2020 chi2	2020 p-value	2022 chi2	2022 p-value
cool_dummy	21.77 (df: 24)	3.93e-94	27.76 (df: 24)	5.95e-124	22.73 (df: 24)	2.09e-99
heat_dummy	34.47 (df: 24)	1.54e-156	46.69 (df: 24)	1.03e-217	33.41 (df: 24)	1.51e-152
week_dummy	9.32 (df: 51)	1.83e-69	13.52 (df: 51)	1.67e-111	5.48 (df: 51)	4.01e-33
hofw_dummy	218.69 (df: 167)	0.00e+00	196.12 (df: 167)	0.00e+00	88.65 (df: 167)	0.00e+00

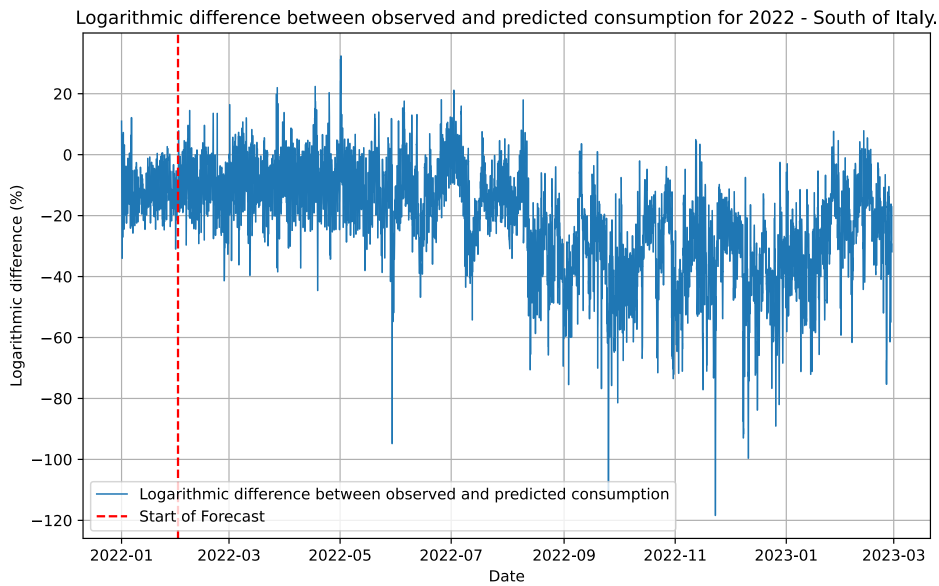



Comparison of actual vs. predicted load for the year 2020 in the South of Italy.
Actual Load (nload)
Predicted Load (pload)
Max actual Load
Min actual Load
Max predicted Load
Min predicted Load
Load
Date
5000
4000
3000
2000
1000
2020-01
2020-02
2020-03
2020-04
2020-05
2020-06
2020-07
2020-08
2020-09
2020-10
2020-11
2020-12


Comparison of actual vs. predicted load for the year 2022 in the South of Italy.
Actual Load (nload)
Predicted Load (pload)
Max actual Load
Min actual Load
Max predicted Load
Min predicted Load
Load
Date
5000
4000
3000
2000
1000
2022-03
2022-05
2022-07
2022-09
2022-11
2023-01


Logarithmic difference between observed and predicted consumption for 2019 - South of Italy.
Logarithmic difference (%)
Date
Logarithmic difference between observed and predicted consumption
Start of Forecast
20
10
0
−10
−20
−30
−40
2019-01
2019-03
2019-05
2019-07
2019-09
2019-11
2020-01


Logarithmic difference between observed and predicted consumption for 2020 - South of Italy.
Logarithmic difference (%)
Date
Logarithmic difference between observed and predicted consumption
Start of Forecast
20
0
−20
−40
−60
2020-01
2020-03
2020-05
2020-07
2020-09
2020-11
2021-01

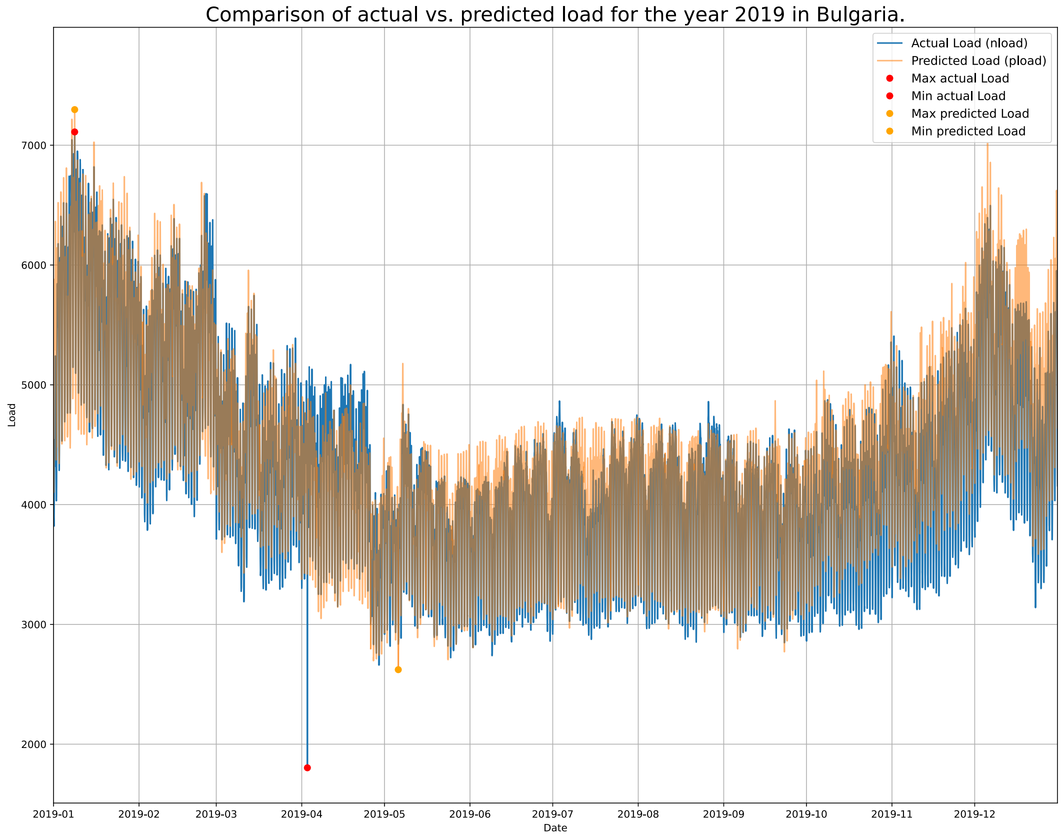

Logarithmic difference between observed and predicted consumption for 2022 - South of Italy.
Logarithmic difference (%)
Date
Logarithmic difference between observed and predicted consumption
Start of Forecast
20
0
−20
−40
−60
−80
−100
−120
2022-01
2022-03
2022-05
2022-07
2022-09
2022-11
2023-01
2023-03

OLS Regression Results: Predicting Electricity Load in Bulgaria using HAC Covariances:

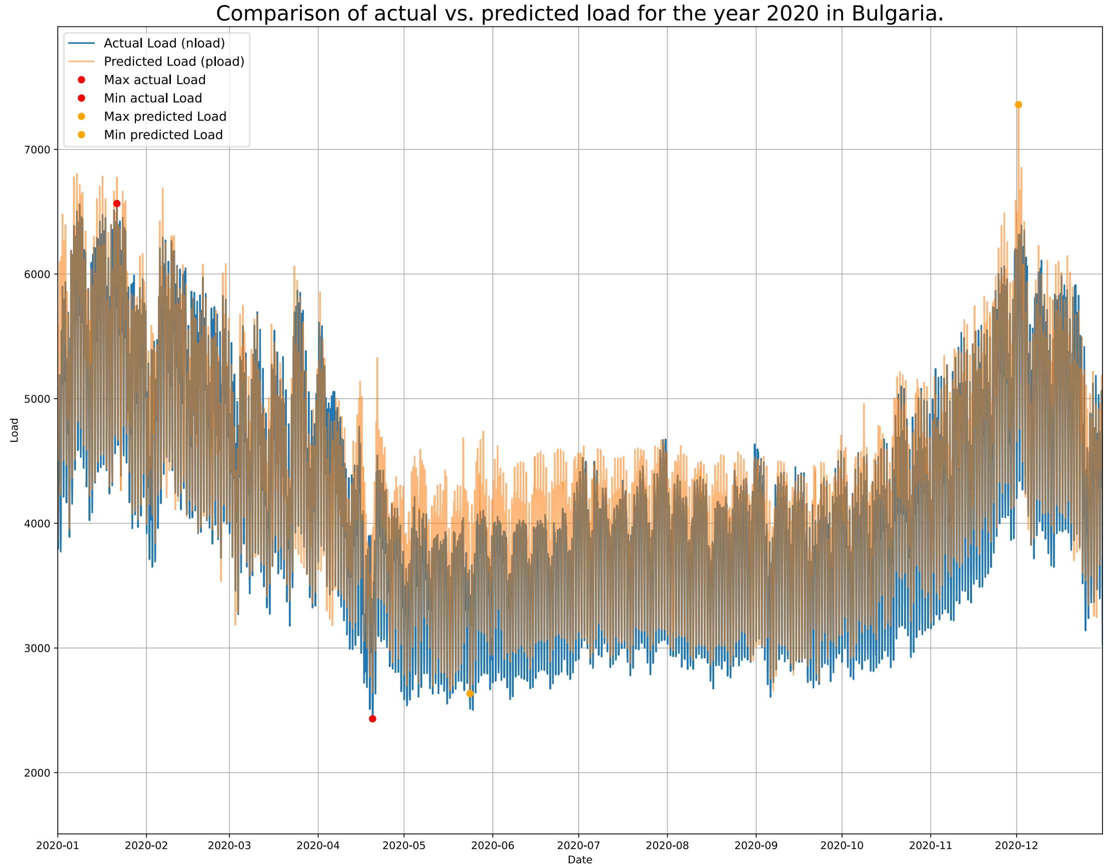
BULGARIA	**2019**	**2020**	**2022**
No. Observations:	26208	34968	52512
R-squared	0.932	0.929	0.926
Adj. R-squared	0.931	0.929	0.926
F-statistic and Prob (F-statistic)	1431.0 (0.00)	1491.0 (0.00)	1648.0 (0.00)

Wald Test for Joint Significance of Dummy Variables - Bulgaria

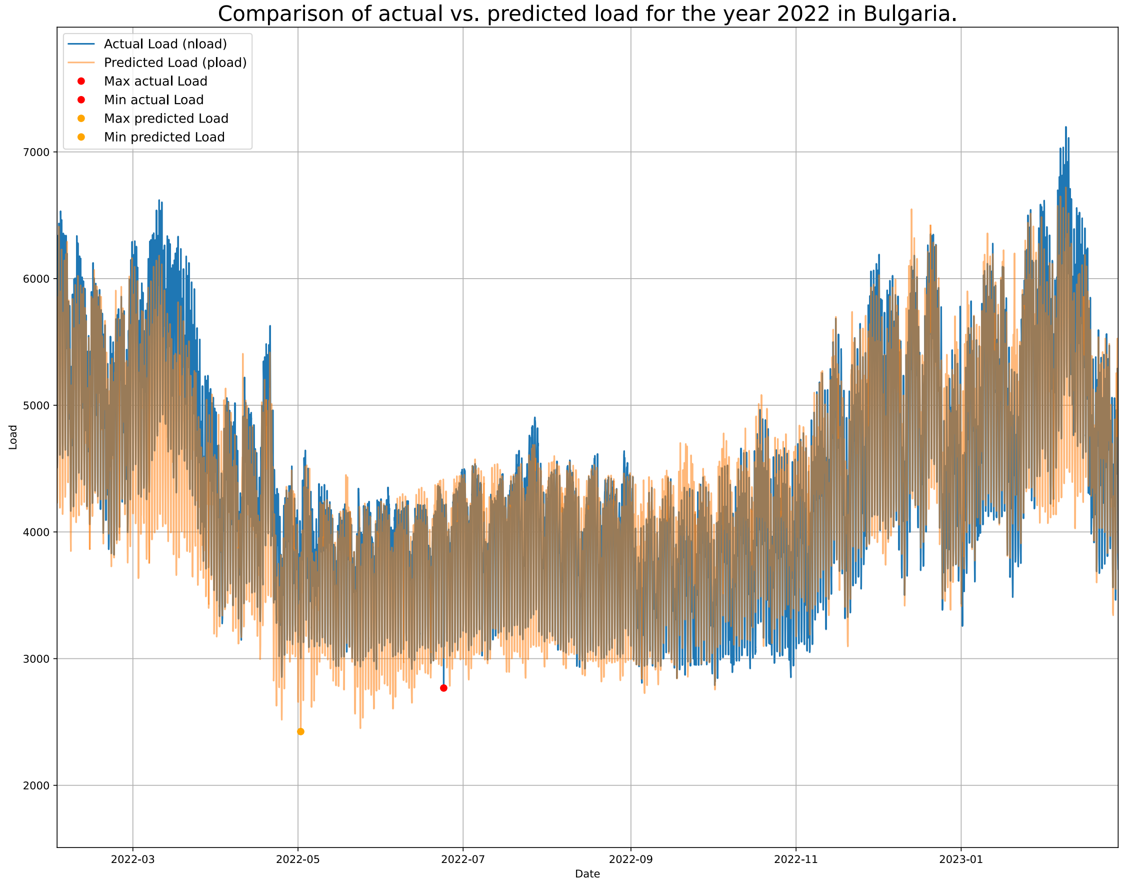
	2019 chi2	2019 p-value	2020 chi2	2020 p-value	2022 chi2	2022 p-value
cool_dummy	25.48 (df: 24)	2.26e-112	33.40 (df: 24)	6.65e-152	35.25 (df: 24)	8.79e-162
heat_dummy	74.50 (df: 24)	0.000e+00	88.83 (df: 24)	0.000e+00	132.56 (df: 24)	0.000e+00
week_dummy	10.50 (df: 51)	4.69e-81	12.19 (df: 51)	3.37e-98	15.16 (df: 51)	1.21e-128
hofw_dummy	406.09 (df: 167)	0.000e+00	362.07 (df: 167)	0.000e+00	424.95 (df: 167)	0.000e+00

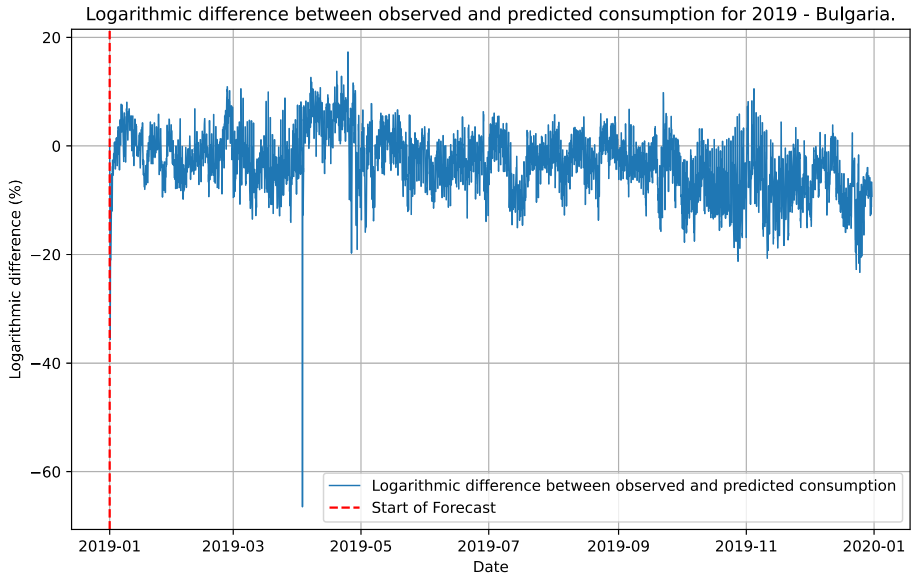


Comparison of actual vs. predicted load for the year 2020 in Bulgaria.

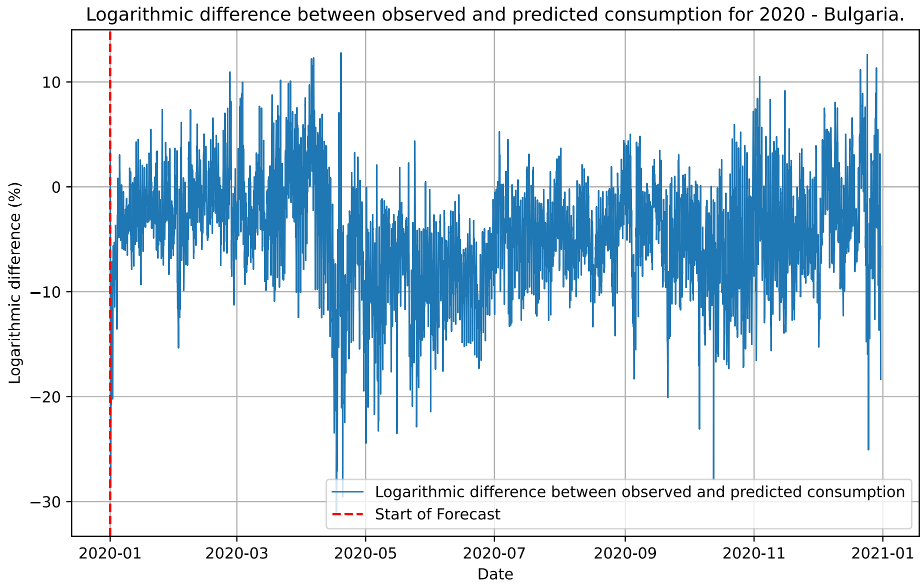


Comparison of actual vs. predicted load for the year 2022 in Bulgaria.

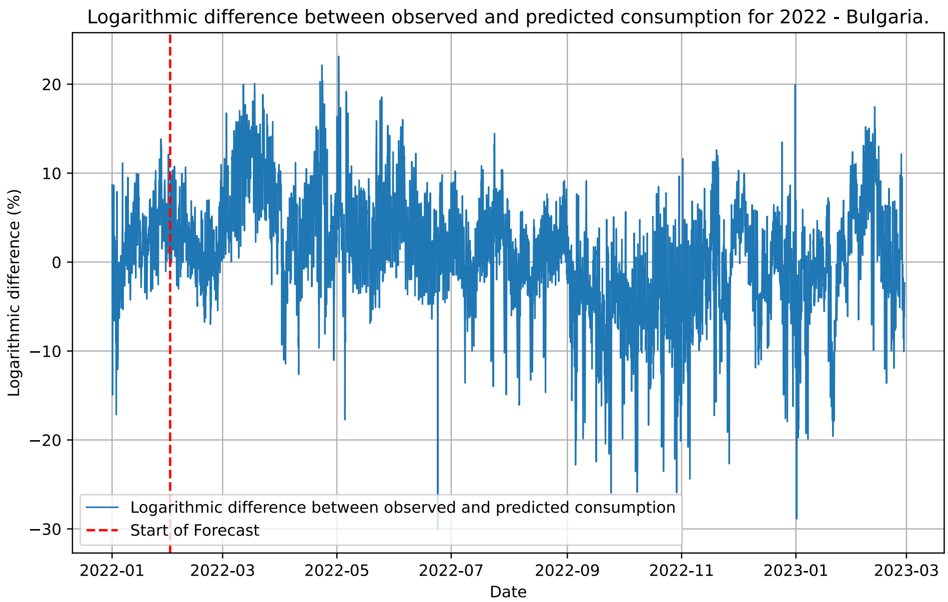




Logarithmic difference between observed and predicted consumption for 2019 - Bulgaria.
Logarithmic difference (%)
Logarithmic difference between observed and predicted consumption
Start of Forecast
Date



Logarithmic difference between observed and predicted consumption for 2020 - Bulgaria.
Logarithmic difference (%)
Logarithmic difference between observed and predicted consumption
Start of Forecast
Date



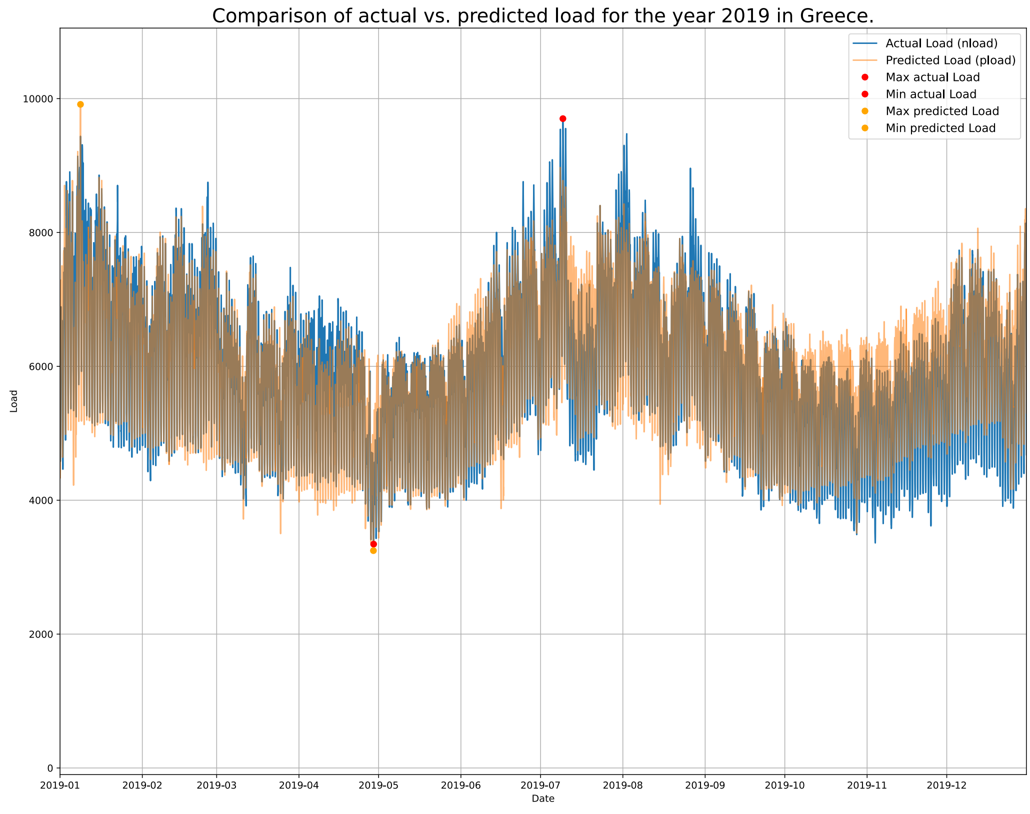
Logarithmic difference between observed and predicted consumption for 2022 - Bulgaria.
Logarithmic difference (%)
Logarithmic difference between observed and predicted consumption
Start of Forecast
Date

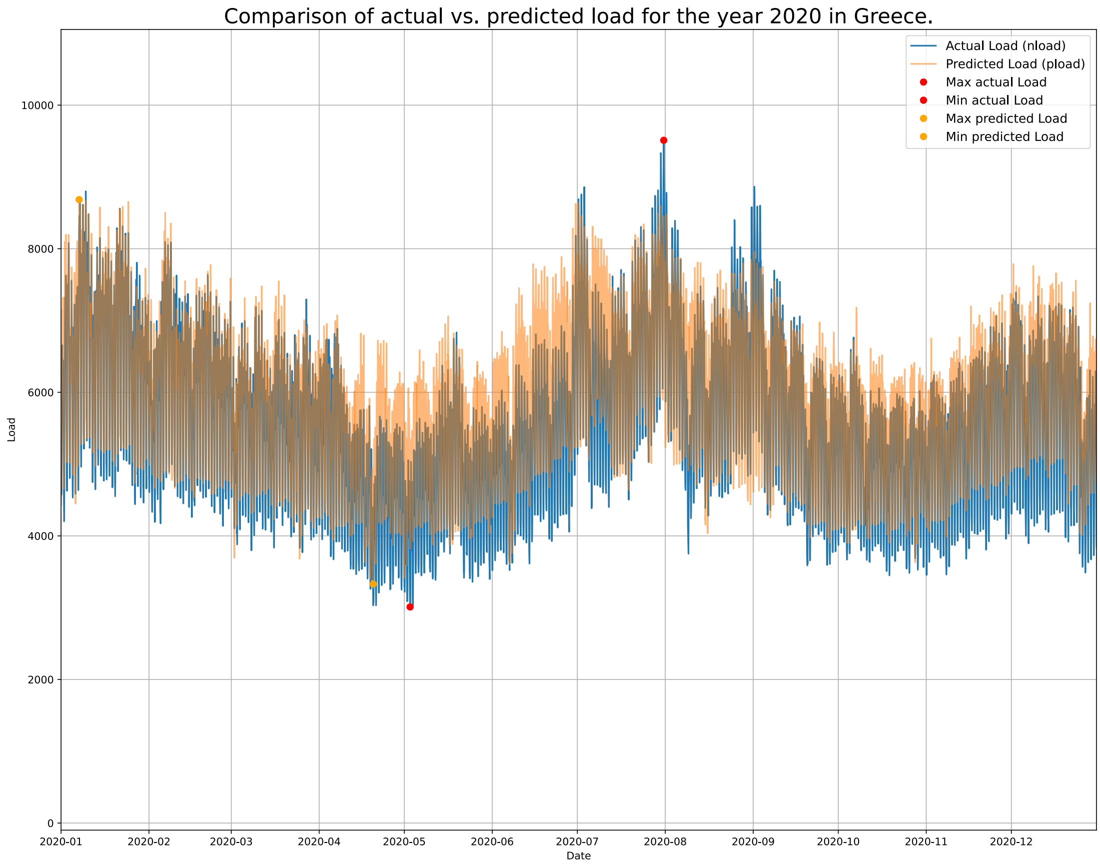
OLS Regression Results: Predicting Electricity Load in Greece using HAC Covariances:

GREECE	**2019**	**2020**	**2022**
No. Observations:	26257	35017	52561
R-squared	0.901	0.900	0.889
Adj. R-squared	0.900	0.899	0.888
F-statistic and Prob (F-statistic)	1412.0 (0.00)	1410.0 (0.00)	1364.0 (0.00)

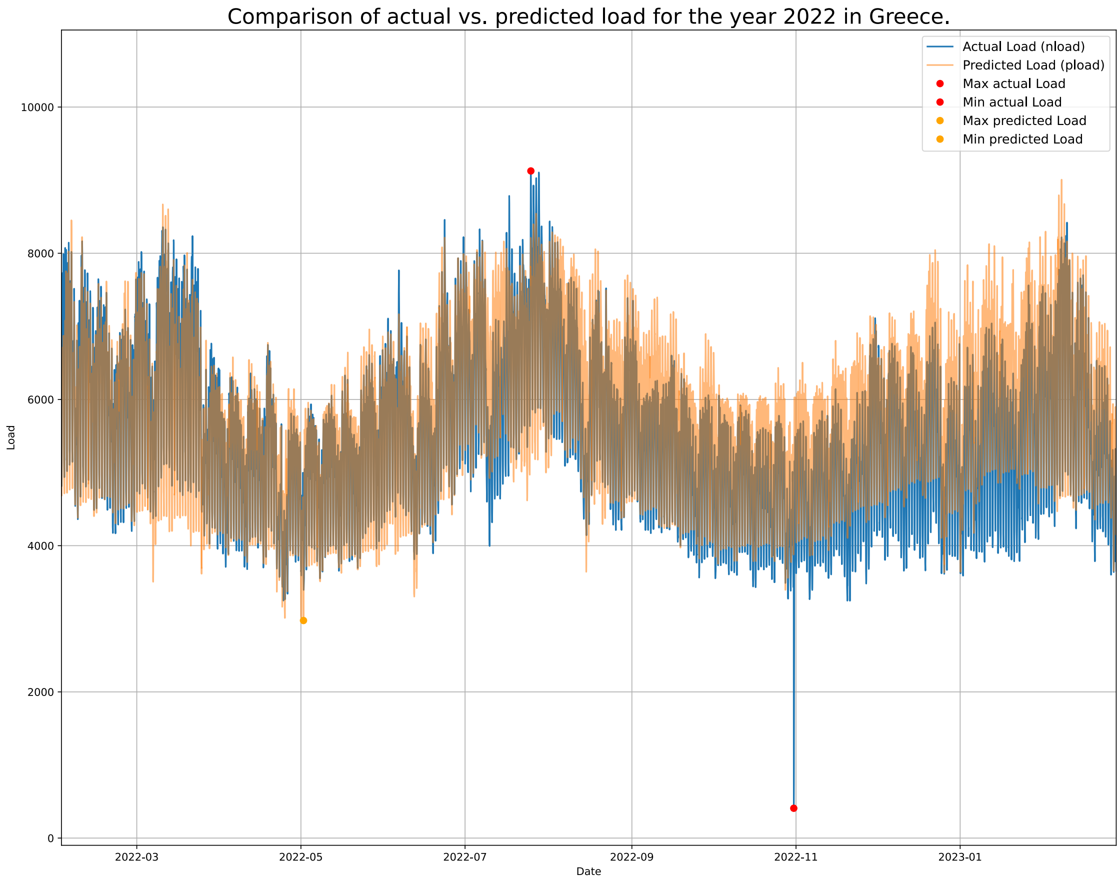
Wald Test for Joint Significance of Dummy Variables - Greece

	2019 chi2	2019 p-value	2020 chi2	2020 p-value	2022 chi2	2022 p-value
cool_dummy	48.35 (df: 24)	1.16e-224	65.53 (df: 24)	1.00e-310	74.99 (df: 24)	0.000e+00
heat_dummy	71.41 (df: 24)	0.000e+00	84.21 (df: 24)	0.000e+00	77.42 (df: 24)	0.000e+00
week_dummy	25.99 (df: 51)	2.44e-237	23.93 (df: 51)	7.69e-218	20.81 (df: 51)	7.90e-187
hofw_dummy	282.35 (df: 167)	0.000e+00	308.74 (df: 167)	0.000e+00	323.57 (df: 167)	0.000e+00

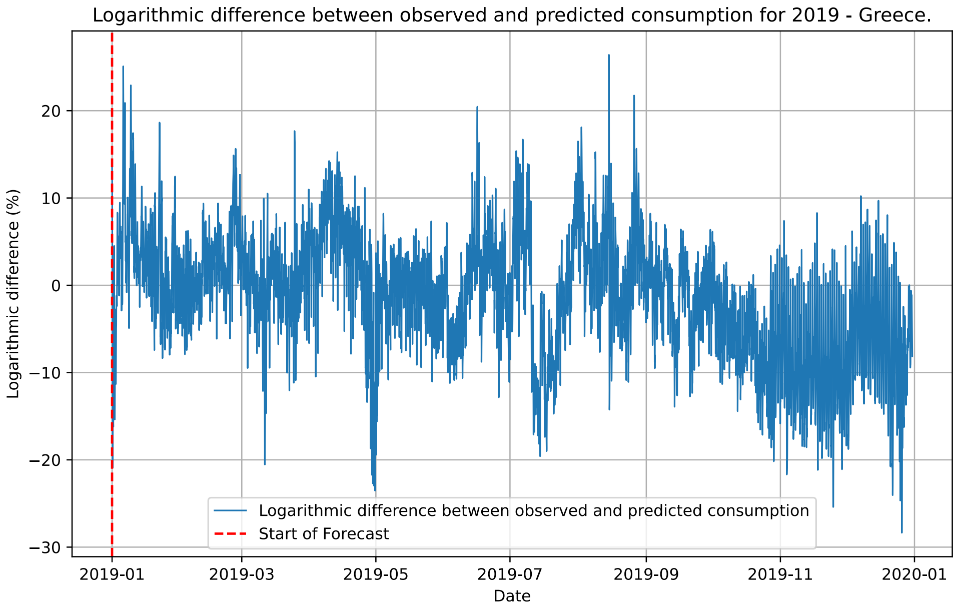




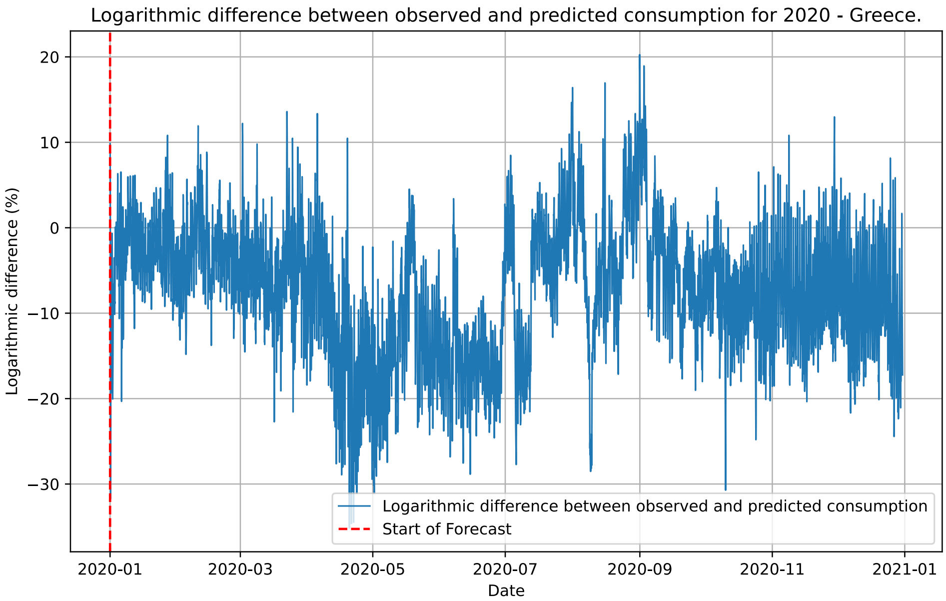
Comparison of actual vs. predicted load for the year 2020 in Greece.
Actual Load (nload)
Predicted Load (pload)
Max actual Load
Min actual Load
Max predicted Load
Min predicted Load
Load
Date
0
2000
4000
6000
8000
10000
2020-01
2020-02
2020-03
2020-04
2020-05
2020-06
2020-07
2020-08
2020-09
2020-10
2020-11
2020-12



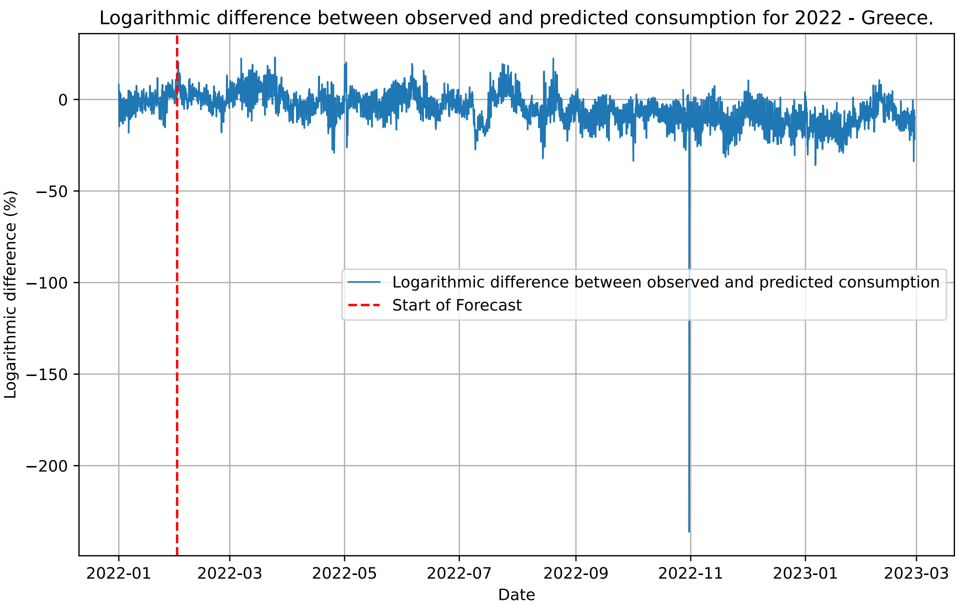
Comparison of actual vs. predicted load for the year 2022 in Greece.
Actual Load (nload)
Predicted Load (pload)
Max actual Load
Min actual Load
Max predicted Load
Min predicted Load
Load
Date
0
2000
4000
6000
8000
10000
2022-03
2022-05
2022-07
2022-09
2022-11
2023-01



Logarithmic difference between observed and predicted consumption for 2019 - Greece.
Logarithmic difference (%)
Date
Logarithmic difference between observed and predicted consumption
Start of Forecast
20
10
0
−10
−20
−30
2019-01
2019-03
2019-05
2019-07
2019-09
2019-11
2020-01



Logarithmic difference between observed and predicted consumption for 2020 - Greece.
Logarithmic difference (%)
Date
Logarithmic difference between observed and predicted consumption
Start of Forecast
20
10
0
−10
−20
−30
2020-01
2020-03
2020-05
2020-07
2020-09
2020-11
2021-01



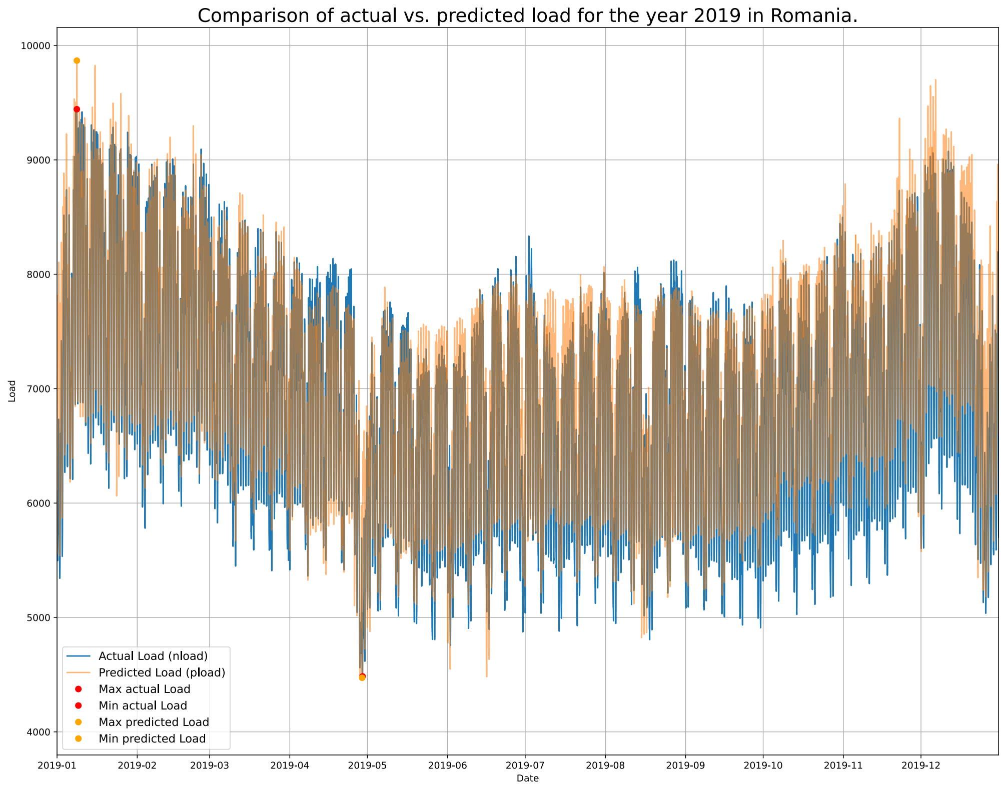
Logarithmic difference between observed and predicted consumption for 2022 - Greece.
Logarithmic difference (%)
Date
Logarithmic difference between observed and predicted consumption
Start of Forecast
0
−50
−100
−150
−200
2022-01
2022-03
2022-05
2022-07
2022-09
2022-11
2023-01
2023-03

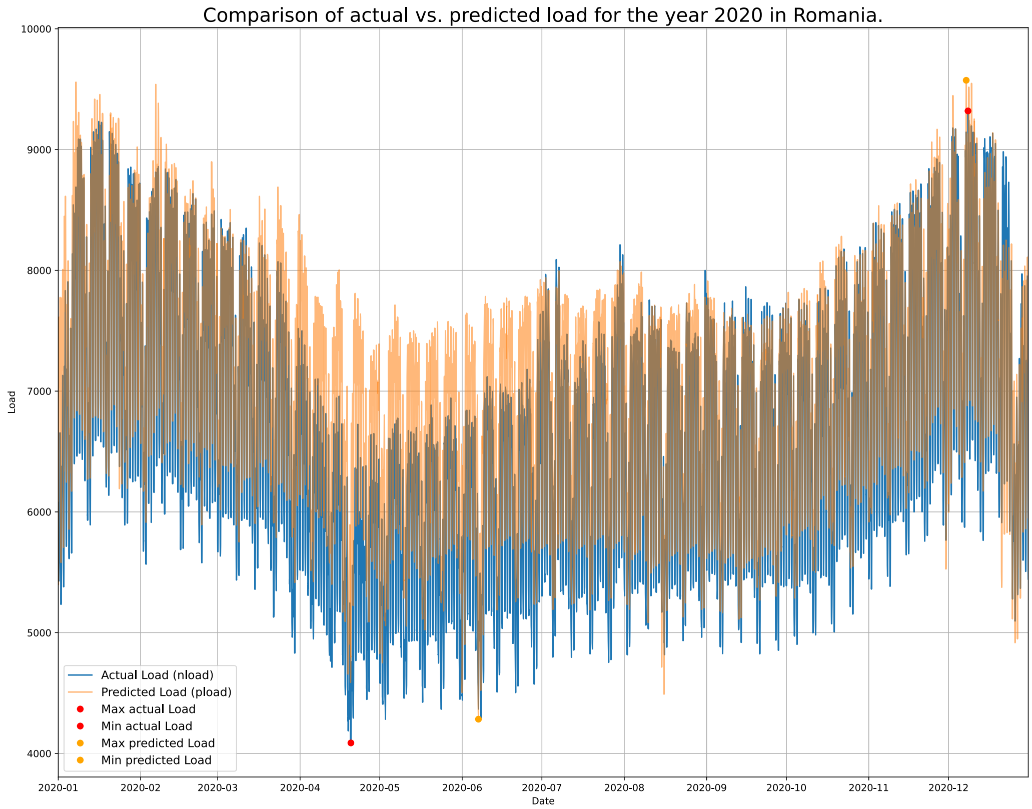
OLS Regression Results: Predicting Electricity Load in Romania using HAC Covariances:

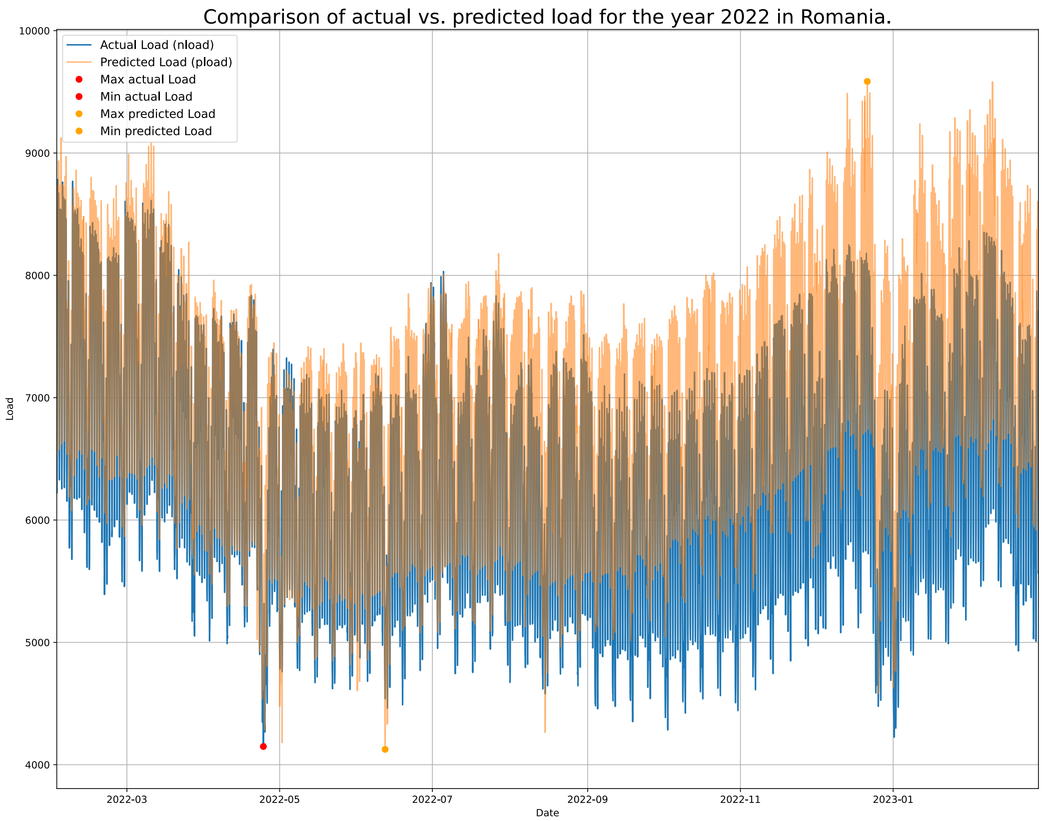
ROMANIA	**2019**	**2020**	**2022**
No. Observations:	26281	35041	52561
R-squared	0.943	0.935	0.921
Adj. R-squared	0.942	0.935	0.921
F-statistic and Prob (F-statistic)	2290.0 (0.00)	1948.0 (0.00)	1967.0 (0.00)

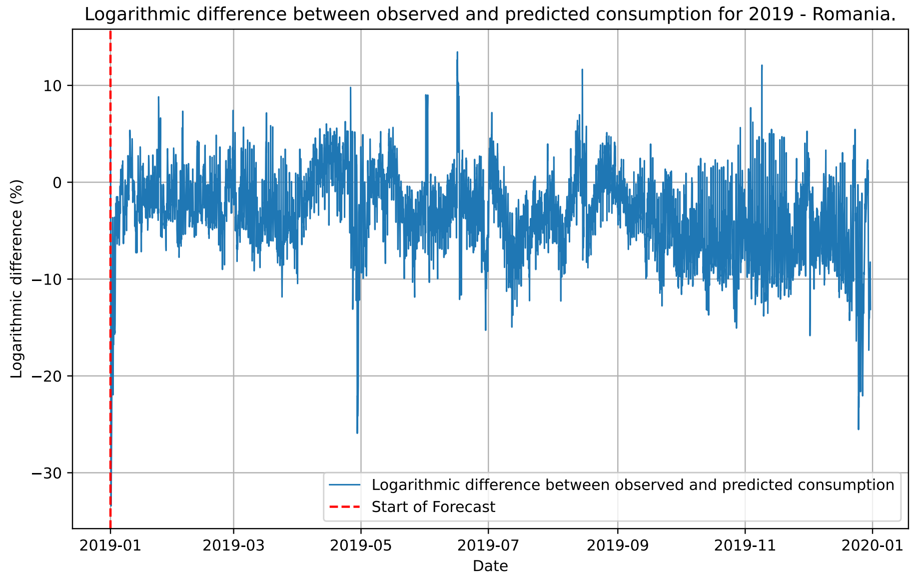
Wald Test for Joint Significance of Dummy Variables - Romania

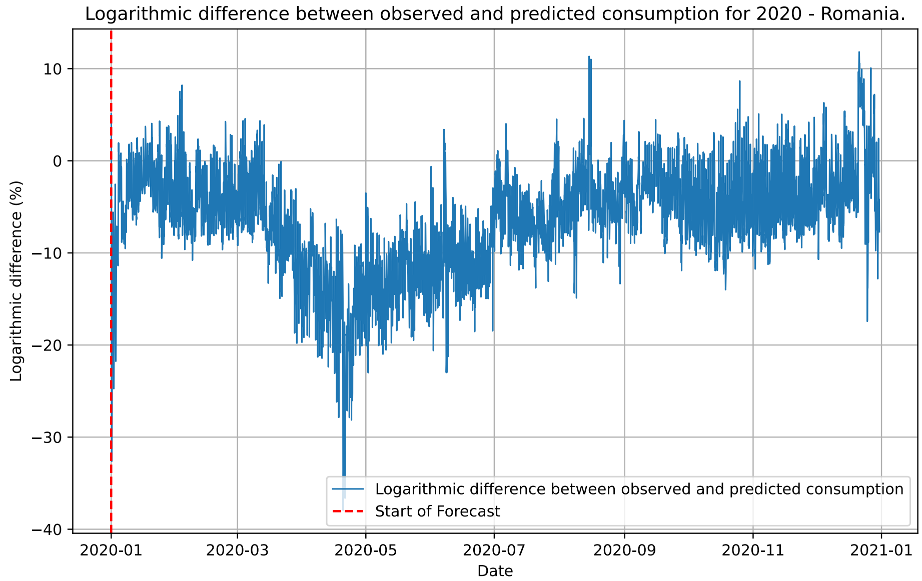
	2019 chi2	2019 p-value	2020 chi2	2020 p-value	2022 chi2	2022 p-value
cool_dummy	30.82 (df: 24)	1.38e-138	33.53 (df: 24)	1.48e-152	33.91 (df: 24)	4.79e-155
heat_dummy	62.63 (df: 24)	2.61e-294	61.90 (df: 24)	7.14e-293	79.07 (df: 24)	0.000e+00
week_dummy	24.33 (df: 51)	1.54e-220	11.97 (df: 51)	5.63e-96	11.78 (df: 51)	2.23e-94
hofw_dummy	732.13 (df: 167)	0.000e+00	696.08 (df: 167)	0.000e+00	610.48 (df: 167)	0.000e+00

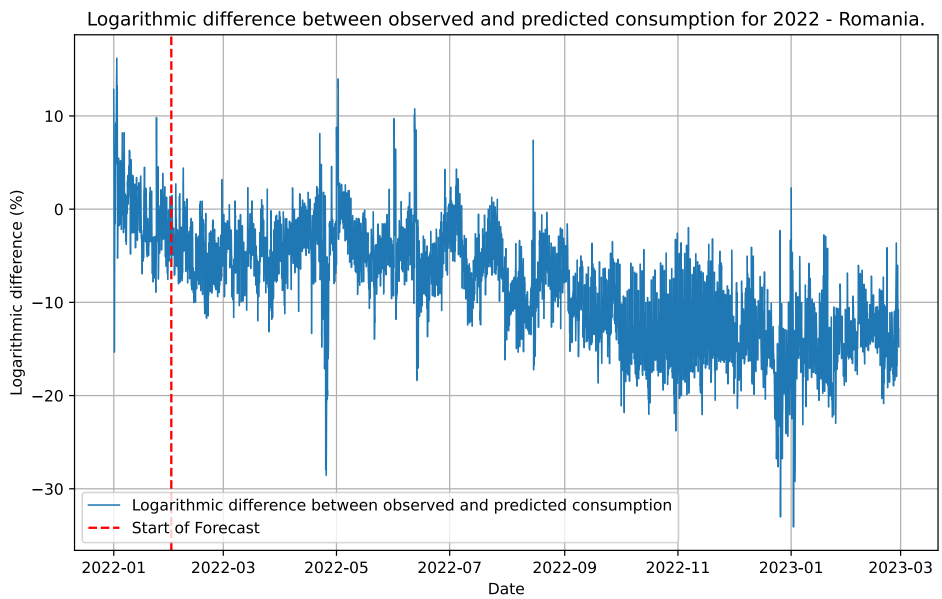


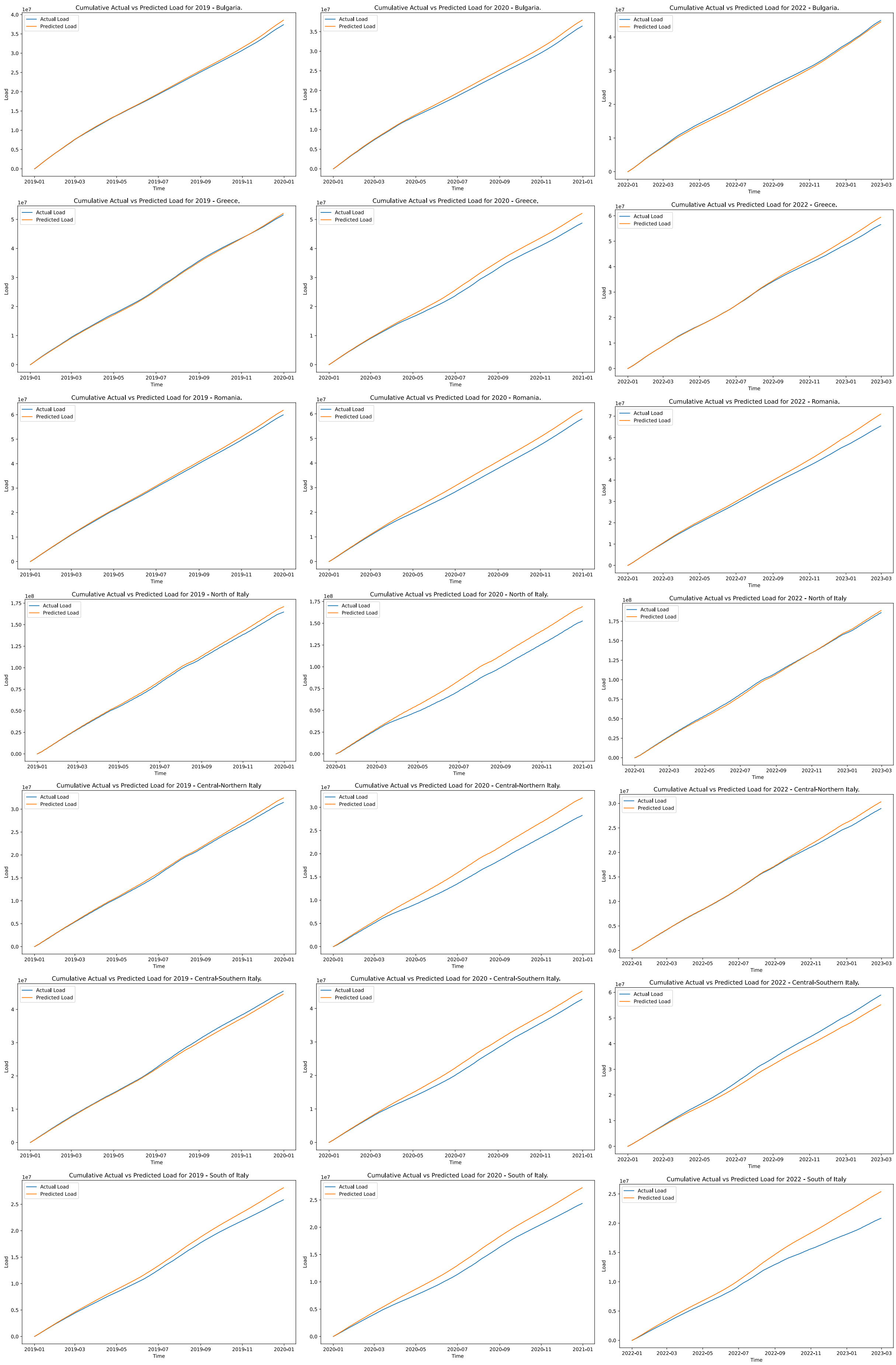

Comparison of actual vs. predicted load for the year 2020 in Romania.
Load
Date
10000
9000
8000
7000
6000
5000
4000
2020-01
2020-02
2020-03
2020-04
2020-05
2020-06
2020-07
2020-08
2020-09
2020-10
2020-11
2020-12
Actual Load (nload)
Predicted Load (pload)
Max actual Load
Min actual Load
Max predicted Load
Min predicted Load


Comparison of actual vs. predicted load for the year 2022 in Romania.
Load
Date
10000
9000
8000
7000
6000
5000
4000
2022-03
2022-05
2022-07
2022-09
2022-11
2023-01
Actual Load (nload)
Predicted Load (pload)
Max actual Load
Min actual Load
Max predicted Load
Min predicted Load


Logarithmic difference between observed and predicted consumption for 2019 - Romania.
Logarithmic difference (%)
Date
Logarithmic difference between observed and predicted consumption
Start of Forecast
2019-01
2019-03
2019-05
2019-07
2019-09
2019-11
2020-01


Logarithmic difference between observed and predicted consumption for 2020 - Romania.
Logarithmic difference (%)
Date
Logarithmic difference between observed and predicted consumption
Start of Forecast
2020-01
2020-03
2020-05
2020-07
2020-09
2020-11
2021-01


Logarithmic difference between observed and predicted consumption for 2022 - Romania.
Logarithmic difference (%)
Date
Logarithmic difference between observed and predicted consumption
Start of Forecast
2022-01
2022-03
2022-05
2022-07
2022-09
2022-11
2023-01
2023-03


Cumulative Actual vs Predicted Load for 2019 - Bulgaria.
Cumulative Actual vs Predicted Load for 2020 - Bulgaria.
Cumulative Actual vs Predicted Load for 2022 - Bulgaria.
Cumulative Actual vs Predicted Load for 2019 - Greece.
Cumulative Actual vs Predicted Load for 2020 - Greece.
Cumulative Actual vs Predicted Load for 2022 - Greece.
Cumulative Actual vs Predicted Load for 2019 - Romania.
Cumulative Actual vs Predicted Load for 2020 - Romania.
Cumulative Actual vs Predicted Load for 2022 - Romania.
Cumulative Actual vs Predicted Load for 2019 - North of Italy
Cumulative Actual vs Predicted Load for 2020 - North of Italy.
Cumulative Actual vs Predicted Load for 2022 - North of Italy
Cumulative Actual vs Predicted Load for 2019 - Central-Northern Italy
Cumulative Actual vs Predicted Load for 2020 - Central-Northern Italy.
Cumulative Actual vs Predicted Load for 2022 - Central-Northern Italy.
Cumulative Actual vs Predicted Load for 2019 - Central-Southern Italy.
Cumulative Actual vs Predicted Load for 2020 - Central-Southern Italy.
Cumulative Actual vs Predicted Load for 2022 - Central-Southern Italy.
Cumulative Actual vs Predicted Load for 2019 - South of Italy
Cumulative Actual vs Predicted Load for 2020 - South of Italy.
Cumulative Actual vs Predicted Load for 2022 - South of Italy
Actual Load
Predicted Load
Load
Time

Appendix 5 – Estimating the effects of COVID-19 and energy crisis on electricity consumption

OLS Regression Results: Estimating the effects of crises in North of Italy using HAC Covariances:

NORTH OF ITALY	**COVID-19 hourly impact**	**COVID-19 weekly impact**	**energy crisis hourly impact**	**energy crisis weekly impact**
No. Observations:	55417	55412	62689	62689
R-squared	0.912	0.919	0.905	0.909
Adj. R-squared	0.911	0.918	0.904	0.908
Prob (F-statistic)	(0.00)	(0.00)	(0.00)	(0.00)

Wald Test for significance of COVID-19 dummy variable hourly impact – North of Italy 2020

	F-statistic	p-value	df_num	df_denom
0	16.993489	3.602428e-71	24.0	55124.0

Wald Test for significance of COVID-19 dummy variable weekly impact – North of Italy 2020

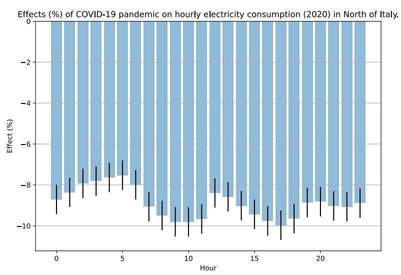
	F-statistic	p-value	df_num	df_denom
0	4.019384	1.172544e-20	52.0	55096.0

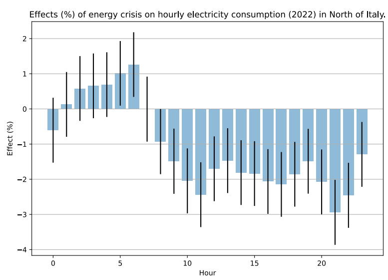
Wald Test for significance of energy crisis dummy variable hourly impact - North of Italy 2022

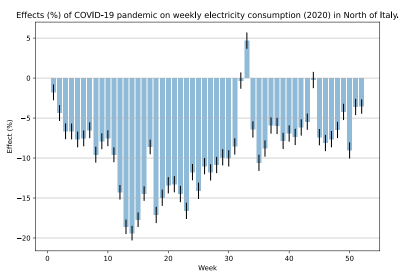
	F-statistic	p-value	df_num	df_denom
0	12.395484	7.262327e-49	24.0	62396.0

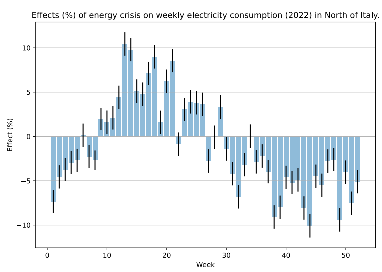
Wald Test for significance of energy crisis dummy variable weekly impact - North of Italy 2022

	F-statistic	p-value	df_num	df_denom
0	9.437739	2.347720e-72	52.0	62368.0









OLS Regression Results: Estimating the effects of crises in Central-Northern Italy using HAC Covariances:

CENTRAL-NORTHERN OF ITALY	COVID-19 hourly impact	COVID-19 weekly impact	energy crisis hourly impact	energy crisis weekly impact
No. Observations:	55417	55412	62689	62689
R-squared	0.902	0.910	0.880	0.885
Adj. R-squared	0.901	0.910	0.880	0.884
Prob (F-statistic)	(0.00)	(0.00)	(0.00)	(0.00)

Wald Test for significance of COVID-19 dummy variable hourly impact – Central-Northern Italy 2020

	F-statistic	p-value	df_num	df_denom
0	20.307185	1.847030e-87	24.0	55124.0

Wald Test for significance of COVID-19 dummy variable weekly impact – Central-Northern Italy 2020

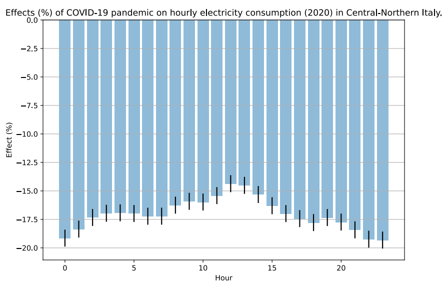
	F-statistic	p-value	df_num	df_denom
0	10.10972	4.296239e-79	52.0	55096.0

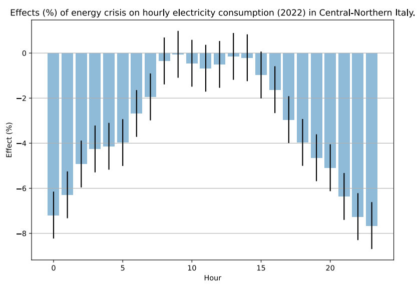
Wald Test for significance of energy crisis dummy variable hourly impact - Central-Northern Italy 2022

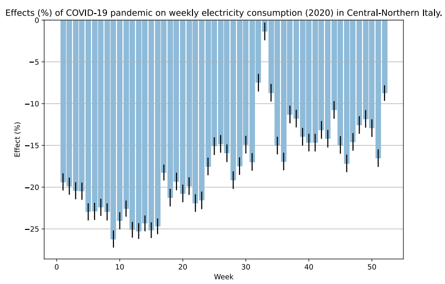
	F-statistic	p-value	df_num	df_denom
0	12.204306	6.016528e-48	24.0	62396.0

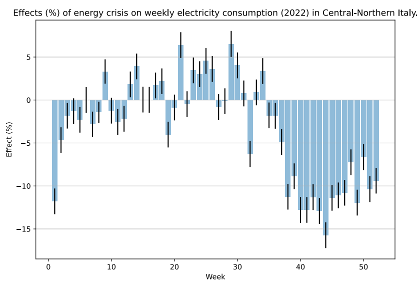
Wald Test for significance of energy crisis dummy variable weekly impact - Central-Northern Italy 2022

	F-statistic	p-value	df_num	df_denom
0	6.422557	1.161460e-42	52.0	62368.0









OLS Regression Results: Estimating the effects of crises in Central-Southern Italy using HAC Covariances:

CENTRAL-SOUTHERN OF ITALY	COVID-19 hourly impact	COVID-19 weekly impact	energy crisis hourly impact	energy crisis weekly impact
No. Observations:	55417	55412	62689	62689
R-squared	0.894	0.902	0.901	0.904
Adj. R-squared	0.893	0.901	0.901	0.903
Prob (F-statistic)	(0.00)	(0.00)	(0.00)	(0.00)

Wald Test for significance of COVID-19 dummy variable hourly impact – Central-Southern Italy 2020

	F-statistic	p-value	df_num	df_denom
0	8.153566	8.177249e-29	24.0	55124.0

Wald Test for significance of COVID-19 dummy variable weekly impact – Central-Southern Italy 2020

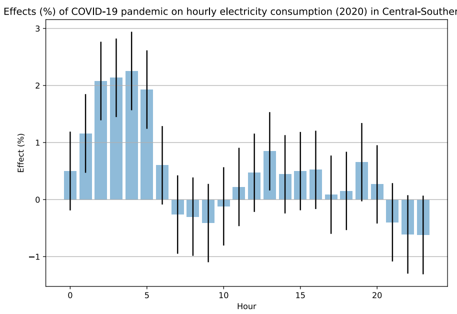
	F-statistic	p-value	df_num	df_denom
0	1.723701	0.000927	52.0	55096.0

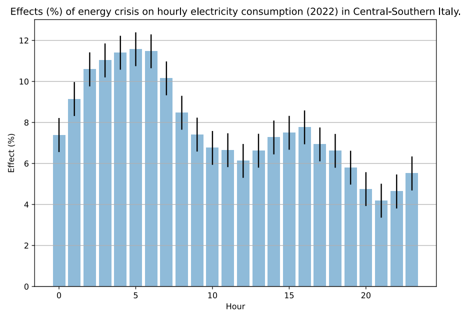
Wald Test for significance of energy crisis dummy variable hourly impact - Central-Southern Italy 2022

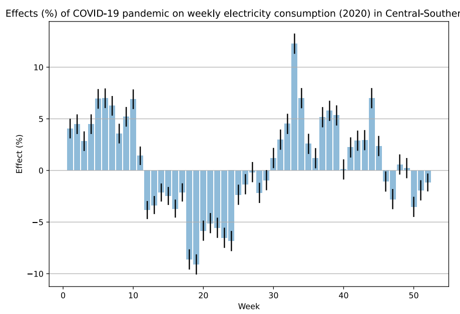
	F-statistic	p-value	df_num	df_denom
0	20.919167	1.560141e-90	24.0	62396.0

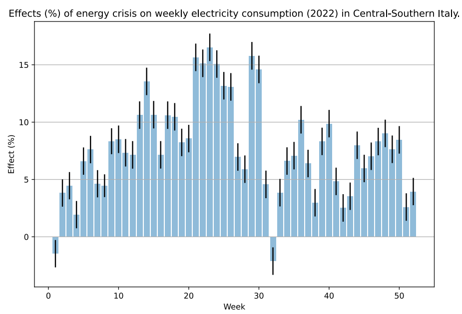
Wald Test for significance of energy crisis dummy variable weekly impact - Central-Southern Italy 2022

	F-statistic	p-value	df_num	df_denom
0	4.464927	1.494402e-24	52.0	62368.0









OLS Regression Results: Estimating the effects of crises in South of Italy using HAC Covariances:

<u>**SOUTH OF ITALY**</u>	**COVID-19 hourly impact**	**COVID-19 weekly impact**	**energy crisis hourly impact**	**energy crisis weekly impact**
No. Observations:	55417	55412	62689	62689
R-squared	0.811	0.822	0.776	0.800
Adj. R-squared	0.810	0.821	0.775	0.799
Prob (F-statistic)	(0.00)	(0.00)	(0.00)	(0.00)

Wald Test for significance of COVID-19 dummy variable hourly impact – South of Italy 2020

```
   F-statistic        p-value  df_num  df_denom
0    23.373443  1.258660e-102    24.0   55124.0
```

Wald Test for significance of COVID-19 dummy variable weekly impact – South of Italy 2020

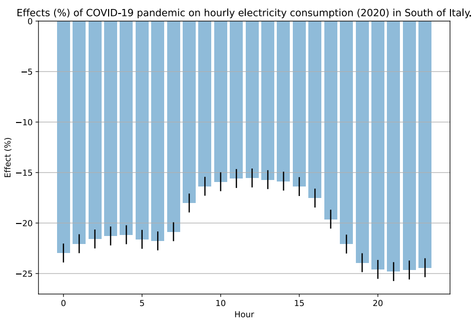
```
   F-statistic        p-value  df_num  df_denom
0    12.850169  3.867731e-107    52.0   55096.0
```

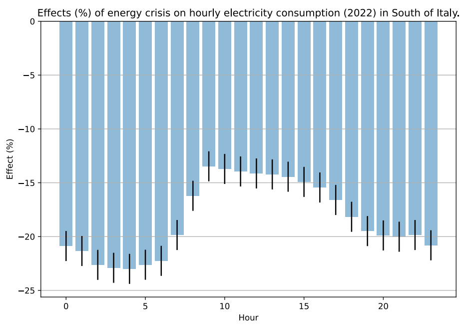
Wald Test for significance of energy crisis dummy variable hourly impact - South of Italy 2022

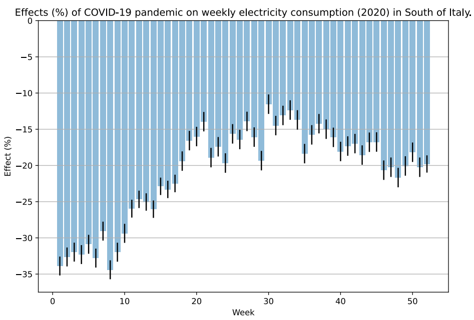
```
   F-statistic       p-value  df_num  df_denom
0    15.363803  3.071358e-63    24.0   62396.0
```

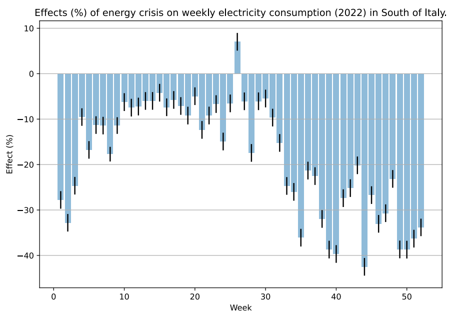
Wald Test for significance of energy crisis dummy variable weekly impact - South of Italy 2022

```
   F-statistic        p-value  df_num  df_denom
0    13.129988  4.035118e-110    52.0   62368.0
```









OLS Regression Results: Estimating the effects of crises in Bulgaria using HAC Covariances:

BULGARIA	COVID-19 hourly impact	COVID-19 weekly impact	energy crisis hourly impact	energy crisis weekly impact
No. Observations:	55344	55344	62616	62616
R-squared	0.927	0.933	0.923	0.930
Adj. R-squared	0.927	0.932	0.923	0.930
Prob (F-statistic)	(0.00)	(0.00)	(0.00)	(0.00)

Wald Test for significance of COVID-19 dummy variable hourly impact – Bulgaria 2020

	F-statistic	p-value	df_num	df_denom
0	18.679579	1.922681e-79	24.0	55051.0

Wald Test for significance of COVID-19 dummy variable weekly impact – Bulgaria 2020

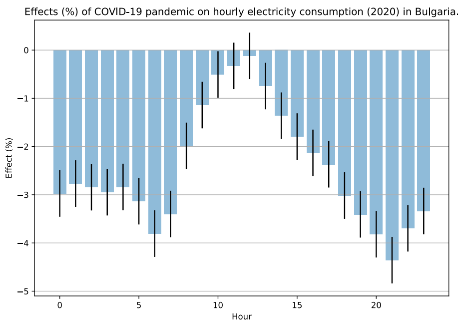
	F-statistic	p-value	df_num	df_denom
0	2.452528	2.834353e-08	52.0	55023.0

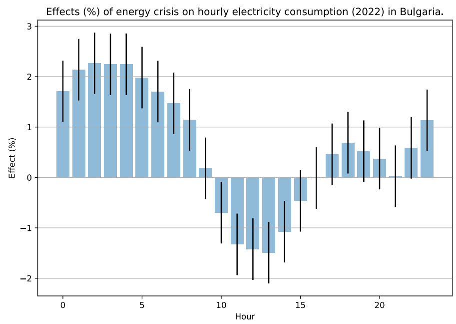
Wald Test for significance of energy crisis dummy variable hourly impact - Bulgaria 2022

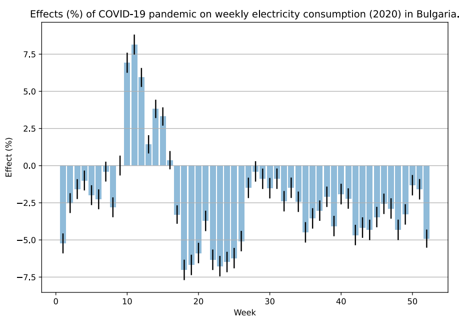
	F-statistic	p-value	df_num	df_denom
0	6.875463	5.563230e-23	24.0	62323.0

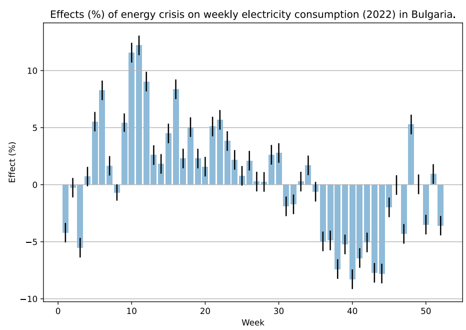
Wald Test for significance of energy crisis dummy variable weekly impact - Bulgaria 2022

	F-statistic	p-value	df_num	df_denom
0	10.71784	2.516733e-85	52.0	62295.0









OLS Regression Results: Estimating the effects of crises in Greece using HAC Covariances:

GREECE	COVID-19 hourly impact	COVID-19 weekly impact	energy crisis hourly impact	energy crisis weekly impact
No. Observations:	55393	55393	62665	62665
R-squared	0.895	0.905	0.881	0.891
Adj. R-squared	0.895	0.904	0.880	0.891
Prob (F-statistic)	(0.00)	(0.00)	(0.00)	(0.00)

Wald Test for significance of COVID-19 dummy variable hourly impact – Greece 2020

	F-statistic	p-value	df_num	df_denom
0	11.381596	5.402907e-44	24.0	55100.0

Wald Test for significance of COVID-19 dummy variable weekly impact – Greece 2020

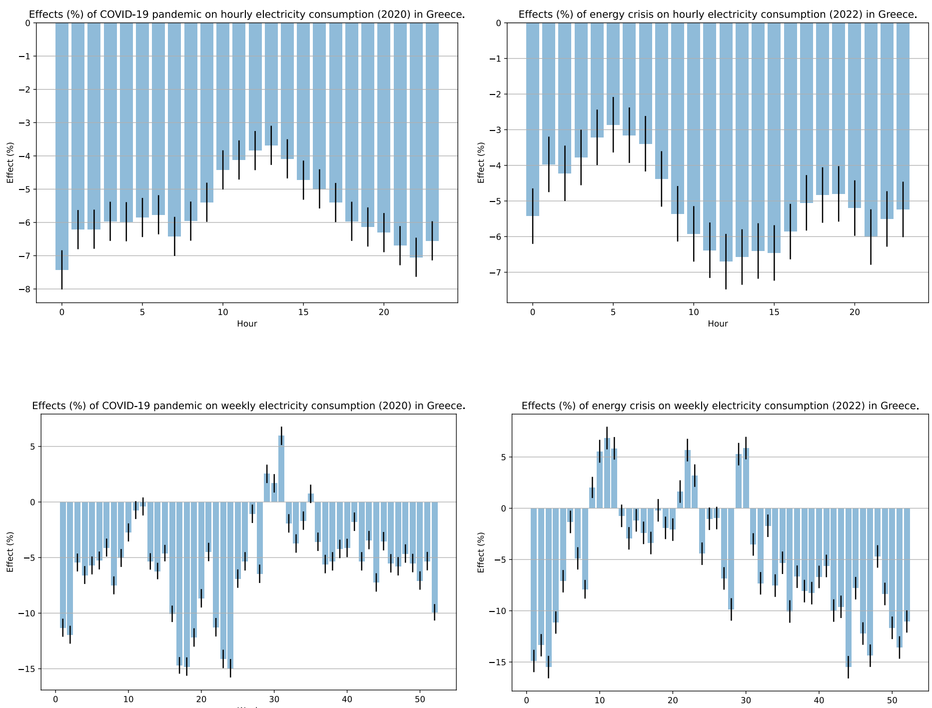
	F-statistic	p-value	df_num	df_denom
0	3.99923	1.746458e-20	52.0	55072.0

Wald Test for significance of energy crisis dummy variable hourly impact - Greece 2022

	F-statistic	p-value	df_num	df_denom
0	13.079894	3.676283e-52	24.0	62372.0

Wald Test for significance of energy crisis dummy variable weekly impact - Greece 2022

	F-statistic	p-value	df_num	df_denom
0	14.559195	5.727017e-125	52.0	62344.0



OLS Regression Results: Estimating the effects of crises in Romania using HAC Covariances:

ROMANIA	**COVID-19 hourly impact**	**COVID-19 weekly impact**	**energy crisis hourly impact**	**energy crisis weekly impact**
No. Observations:	55393	55393	62665	62665
R-squared	0.921	0.923	0.912	0.923
Adj. R-squared	0.920	0.923	0.911	0.922
Prob (F-statistic)	(0.00)	(0.00)	(0.00)	(0.00)

Wald Test for significance of COVID-19 dummy variable hourly impact – Romania 2020

	F-statistic	p-value	df_num	df_denom
0	21.659183	3.875674e-94	24.0	55100.0

Wald Test for significance of COVID-19 dummy variable weekly impact – Romania 2020

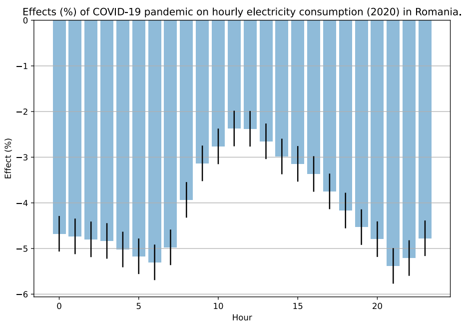
	F-statistic	p-value	df_num	df_denom
0	1.94097	0.000057	52.0	55072.0

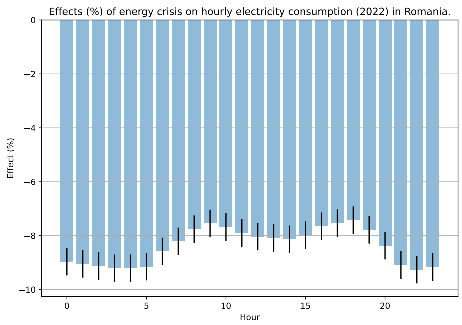
Wald Test for significance of energy crisis dummy variable hourly impact - Romania 2022

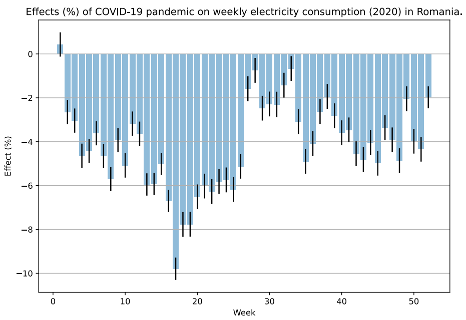
	F-statistic	p-value	df_num	df_denom
0	13.184047	1.155540e-52	24.0	62372.0

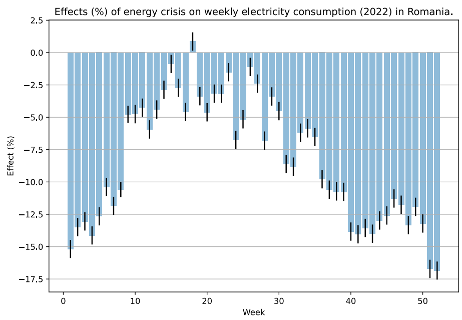
Wald Test for significance of energy crisis dummy variable weekly impact - Romania 2022

	F-statistic	p-value	df_num	df_denom
0	43.671175	0.0	52.0	62344.0









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