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Electricity Consumption as an Early Economic Indicator During the Covid-19 Pandemic of Europe in 2020

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Any mistakes or errors are our own full responsibility.

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Abstract

The Covid-19 pandemic, and consequent policy measures, is currently causing tremendous losses and costs to humanity, both socially and economically. This drastic and abrupt shock has been followed by policy measures to mitigate economic losses, for businesses and households. For governments and other economic agents, immediate and precise information on the severity of outcomes can be vital in responding properly to the situation. Traditional economic indicators are reported only after-the-fact, and the more urgent need to know creates an incentive to use more creative economic indicators. This thesis aims to examine whether electricity consumption data could have been used as a reliable early predictor of the economic downturn of ten European countries across the two first waves of the pandemic, in 2020. A method of comparing estimated impacts on electricity consumption and GDP is used to analyse this relationship. In estimating these impact measures, we model both daily electricity consumption and quarter-yearly GDP, and compare these with the actual observed levels. The results indicate a positive relationship in the six continental European countries, as expected, though varying in magnitude. The results of the four Scandinavian countries are more dubious, and a clear relationship one way or the other cannot be concluded. We also find that electricity consumption and economic activity impacts diverge towards the end of the year, with electricity consumption levels normalizing. A weakness of the analysis lies in its sole use of aggregate power load data and its generalized modelling. We suspect clearer results could be found in each case if analysed more specifically, and by separating electricity consumption of residential and productive sectors.

Table of Contents

List of Figures

List of Tables

1. Introduction

Pandemic and lockdowns across the world marked 2020 as a difficult and gruelling year for humanity. The economic and social impacts of the Coronavirus disease 2019 (Covid-19) were large, negative, and abrupt, revealing itself in rising unemployment levels and declining Gross Domestic Product (GDP). During times of sudden economic downturns, it is hard to precisely determine the actual magnitude of said downturns contemporaneously. GDP, unemployment, and other normally used indicators of economic activity levels take months to collect, analyse and publish, while the need to know is now. Power load data is quickly and easily available and may be used as such an indicator, leading to our main question: How well could electricity consumption data predict the economic outcomes of the Covid-19 pandemic in Europe in 2020, using GDP as measure of economic level? We also examine the magnitudes of the relationship between these two factors. If electricity consumption is found to having been a good economic indicator in real-time during the pandemic, this knowledge can be useful later if similar sudden economic downturns were to occur. The pandemic must be viewed as an idiosyncratic shock to the economy in its abruptness and in being the primary catalyst for a recession not sparked by underlying economic factors. Still, there is reason to believe that new pandemics or other similar shocks may occur in the future. According to a UN panel on biodiversity, IPBES, the risk of pandemics is increasing, and they view the chances of a deadlier pandemic than the current one to be likely in the future (Daszak et al., 2020).

The Covid-19 disease is caused by the virus SARS-CoV-2, which was discovered in January 2020 (Folkehelseinstituttet, 2020a). The pandemic had its beginning in early 2020, and quickly spread across most countries of the world during the year's first quarter. To varying degree European countries were affected and the political responses were of imposing or encouraging restrictions on social contact between people within and between countries and regions. The extent of policy measures varied across countries, and time, from social and sanitary advice, to lockdowns. Both the pandemic itself and the political response of governments were expected to negatively impact the economic activity of the affected countries and regions. Restrictions on social contact affect workplaces and businesses, unemployment levels and consumer behaviour, while the disease itself is costly as it incapacitates work force and puts people in hospital, diverting resources towards healthcare. The actual developments of the economy of the world and the countries examined in this paper, using GDP as a measure, coincide with the expected developments (Appendix A). A steep drop in electricity consumption of various countries of Europe occurred simultaneously with the spread of disease and the subsequent political measures imposed by governments. Various articles and papers have already analysed and documented this phenomenon. One article in the New York Times (Bui & Wolfers, 2020), describes work by Steve Cicala on how electricity consumption rapidly plummeted below average levels across the United States as stay-at-home orders were imposed in March of 2020 (Cicala, 2020b). The article further describes another paper by Cicala (2020a), showing a similar pattern during the same period in Europe, highlighting the especially sharp decline of electricity consumption in Italy, which was among the hardest hit countries of Europe early on. Earlier papers have done much of the work we are interested in, yet many are premature in that the pandemic was still at an early stage (Beyer et al., 2021; Fezzi & Fanghella, 2020). This gives rise to two main issues, as we see it. One, GDP data was yet to be reported, compared, and analysed with the findings in electricity consumption throughout 2020. Thus, one only has an idea of how the electricity consumption data relates to how well the economy was doing, and no precise answers. Second, the pandemic is still relevant and the same relationship that others have been able to analyse up to a certain point, now can be done for a longer period under the pandemic world situation. This gives the opportunity to see if the effects seen in the research of others, on electricity consumption, was lasting or if a normalization of consumption occurred later. Still, the pandemic is not over yet, and later research will hopefully have the advantage of being able to view the entire span of the pandemic, and its consequences, when it is over.

The aim of this thesis is to contribute to earlier research on the effects of the pandemic, and expand upon the work now that more data is available. This is to see whether the relationships and findings of others still hold, and to examine whether electricity consumption impacts precisely describe the economic impacts of the pandemic. This may be useful information for policy makers, and other economic agents, if other similar shocks were to occur in the future.

In the next chapter we will describe the underlying situation throughout 2020 in more detail and why this paper is relevant, before we present a literature review. Chapters 4 goes through concepts utilized in constructing our methods and modelling, which are further described along with our data in chapter 5 and 6. The results of our analysis are presented and discussed in-depth in chapters 7 and 8, respectively, before concluding remarks in the last chapter.

2. Background

This chapter aims to describe the pandemic situation of Europe in 2020, the policy responses to it, and why early economic indicators may be useful in such a situation.

2.1 The Covid-19 pandemic in Europe in 2020

In 2020 the coronavirus, SARS-CoV-2, caused the most severe pandemic the world has seen at least since the Spanish Flu, 100 years ago. According to the Norwegian Institute of Public Health (Folkehelseinstituttet, 2020a) the disease is characterized by being highly contagious and relatively large variation in symptoms, both severeness and type, inflicted among those infected. Pneumonia-like sickness is most common among symptomatic virus carriers, while some develop more serious symptoms with longer lasting health effects. Some cases are fatal, even with symptomatic treatment at hospitals. They also state that a considerable part of virus carriers never show any sign of symptoms, while still being contagious (asymptomatic infection). The severity of the disease varies greatly between different groups of the population, determined by age, underlying medical conditions and others (Folkehelseinstituttet, 2020b). Longer-lasting effects after Covid-19 are reported in a small number of patients, but the knowledge on this part is still somewhat lacking (Folkehelseinstituttet, 2020a). Without an effective treatment or cure for the disease, mild cases went untreated, while patients with more severe symptoms were hospitalized, and the worst-off needed mechanical assisted breathing to avoid respiratory failure and death. The combination of high contagiousness and many asymptomatic virus carriers contribute to explaining the difficulty of stopping the spread of disease, even with strict measures imposed by governments.

On the 24th of January the first case of coronavirus was reported in Europe, in France according to the European Centre for Disease Prevention and Control (ECDC) (European Centre for Disease Prevention and Control, 2021b). In the following weeks, the disease spread quickly across the continent. By March 13, the World Health Organization (WHO) declared Europe the new epicentre of the pandemic as it surpassed China in new daily cases reported (Braseth, 2020). Three days later, Montenegro was the only European country yet to report any cases of disease within its population (Løf, 2020). Reported accumulated statistics from *Our World in Data* states that more than 23 million people had tested positive for coronavirus in Europe by the end of 2020, with just over 545 000 fatal cases (Johns Hopkins University Center for Systems Science and Engineering (JHU CSSE), 2020). Almost 250 million tests had been reported at the same time. However, this number does not include statistics from numerous countries which have not published official data on test statistics. The statistics are subject to each individual country's own reporting of data. Reporting practices differ between countries which obscures the aggregate data and weakens comparability.

Early on, different governments chose somewhat different approaches to control the spread of disease within their own countries. The most important strategy has been to delay the spread in an attempt to prevent overloading the hospitals and healthcare system with sick patients, until effective treatment or vaccine is developed and available for distribution and use (World Health Organization, 2020). Additionally, keeping the disease away from high-risk groups, such as the elderly and nursing home patients, to avoid severe cases has been important. Some governments have followed a less restrictive strategy, being described by some as attempting to reach some level of herd immunity (Orlowski & Goldsmith, 2020). This strategy has been criticized for being unrealistic and causing more fatalities and disease than necessary.

With no vaccine or other preventative medical treatment available from the start of the pandemic, governments' responses to slow or stop the pandemic have mostly been to recommend and impose non-pharmaceutical interventions (NPIs), with Sweden as an obvious exception (European Centre for Disease Prevention and Control, 2021a). The most important measures have been social distancing in public spaces, self-isolation to avoid public spaces, and hygiene and sanitary measures like handwashing or urged/forced use of face masks in public spaces. Accompanying societal measures include testing to uncover and track the spread of the virus, which helps governments pinpoint measures more effectively and control the spread. The abovementioned measures are dependent of the collaboration of the masses to be truly effective, and as history has taught us the past year it has not been the case that everyone has complied to such restrictive rules with the same enthusiasm (Koon et al., 2021). For this reason, other even more intrusive NPIs have been used in addition to the abovementioned.

The hardest restrictions on everyday life have throughout Europe consisted of closing schools – both primary, secondary and higher education institutions, closing (or restricting number of people allowed inside) venues of entertainment – such as football arenas, theatres and concert venues, closing of basically any business that has difficulty to ensure social distancing like bars and restaurants. In some cases it has involved a full lock-down of all so-called non-essential venues and forced court-ordered curfews (European Centre for Disease Prevention and Control, 2021a).

When examining the data documenting the national public measures taken by governments across Europe (European Centre for Disease Prevention and Control, 2021a), it appears clearly that one can describe the weeks before March 13, when a pandemic was first mentioned, as the start of the first wave of Covid-19 in Europe. Lockdowns or heavy social restrictions generally started in the days surrounding this date. It also appeared the spread of the disease generally went down during the end of May and the start of June. Then it seems societies were "reopened" during the summer and early autumn before a new wave of virus spread took form during October. This led to a second lockdown-period in late October and through November, with countries probably having adjusted measures to now being more regional than national. This is generally speaking as the countries' timelines concerning infection rates are of course not fully aligned.

This on-and-off situation with society never getting fully back up to normal has meant that various establishments and companies have been forced to close shop either directly as a governmental measure or indirectly because of loss of customers, thereby weakening the economy. Because there are only so many jobs and companies the governments dare allow to go bust at the same time, governments have been forced to intervene into the economy with stimulus-packages to help firms through the pandemic, and for household economies to simply not go bankrupt as well (Cassim et al., 2020). Early estimates (from June 2020) of allocated governmental spending during the early stages of the pandemic amounted to staggering 10 trillion dollars worldwide, which is equal to three times the response during the financial crisis in 2008/2009 (Cassim et al., 2020). Western Europe alone is responsible for 4 trillion out of those. So, the pandemic and lockdowns surely have a hefty price for governments and taxpayers.

2.2 The need for early indicators of economic activity level during recessions

During times of recession economic agents at all levels may be negatively impacted and suffer from unpredictable changes in their economic environment. To mitigate such impacts, it is important to have an idea of how actual developments in the economy are turning out in real time. To have precise information of the extents and magnitude of a recession while it is happening will give governments and central banks better opportunity to fine tune and delimit fiscal and monetary policy measures. If successful in accurately distributing the stimulus into the market, private institutions, businesses, and households can all be able to better plan ahead their actions in times of volatile economic prospects to secure their interests. In addition, as one observes the price governments pay to keep the economy from breaking down during such a shock (Cassim et al., 2020), it seems only logical that one obtains the best possible information to make every dollar of every stimulus-package count as much as possible.

Since the traditional, precise economic data measures are not readily available contemporaneously, economic actors may use several proxies that can be acquired at an earlier time. As an example, Eurostat releases their earliest GDP estimates 30 days after the end of the quarter in question (Eurostat, 2021a), which gives a delay on the information needed between 30 and 120 days, depending on when during a quarter the shock happens. Therefore, the proxy data used to “nowcast” the state of economy does not have to be available instantaneously to be better than the traditional data. This results in several different proxies, with different time frames. The Federal Reserve Bank of New York for instance are using a model consisting only of data on a monthly basis (Federal Reserve Bank of New York, 2021). Their proxies are several inputs put together to create an overview, and consists of data concerning manufacturing, housing and construction, retail and consumption, labor markets and more (Federal Reserve Bank of New York, 2021). There exists literature that also combines different inputs to forecast the economy but in near real-time using either data from the financial environment or private companies (Andreou et al., 2013; Chetty et al., 2020). Examining how night light intensity changes through satellite data is another type of nowcasting (Beyer et al., 2021). Other real-time economic indicators one has been looking into are unemployment statistics (Forsythe et al., 2020; Kurmann et al., 2021) and consumer spending data collected from banks (Sheridan et al., 2020). All these methods will provide information about the economy for decisionmakers at a higher frequency than traditional GDP reporting will.

2.3 Preliminary look at the data

Visual analysis of the data plots of electricity consumption for several countries during the early days of the Covid-19 pandemic in 2020 shows sudden drops in electricity consumption at the expected times, which has also shown to be the case for economic activity levels (see chapter 5 for data references). While this indicates cases of electricity consumption pointing in the direction of what we expect it to predict, it does not tell us of how well and precisely it does the job. To be able to state that electricity consumption data could have been used as a precise proxy for economic activity levels during the Covid-19 pandemic, one would need to find that the relationship between electricity consumption and later reported economic activity shows some form of predictability that would have been possible to understand intuitively during the times of the occurrences of 2020 when power load data was available and more direct economic data were not yet reported.

3. Literature review

This chapter reviews some of the most relevant literature related to our research question. First, we point to papers examining the long-term relationship, as an explanation for why one can use electricity consumption as an economic proxy. Then, we look into papers on how electricity consumption has changed during the pandemic, and lastly the papers most closely related to our work, looking into how electricity consumption could have been an economic indicator during 2020.

3.1 Electricity and economic activity

Electricity use and economic development (Ferguson et al., 2000):

This paper questions the assumption of close relationship between total energy consumption and economic activity, and does this by examining over one hundred countries and their correlations between electricity consumption and GDP and in addition between total primary energy supply and GDP. Their data are per capita and controlled for purchasing power parity. Their approach is to look at correlations of time series starting from 1960 (1971 in some cases) ending in 1995. Their findings are correlation coefficients of at least 0.9 for most wealthy countries, with exceptions being big oil producers or refiners. They also find that this relationship is increasing with the wealth of the country, meaning that one uses more electricity the more the economy develops. This paper is from 2000 and the analysis stops in 1995, thus the empirical results are possibly outdated. But the dynamics regarding difference in correlation between countries is worth noting, because it is also evident that the countries we are looking into in our thesis have developed in different ways since 1995. Also, it says nothing about the long-run-/short-run-dynamics.

The relationship between GDP and electricity consumption in 10 Asian countries (Chen et al., 2007):

It is a paper that follows the trail from Ferguson et al. (2000). In contrast to the former though, they look further into the long-run- and short-run-dynamics in the relationship between electricity consumption and GDP growth. Their findings from looking at 10 Asian countries (China, Hong Kong, India, Indonesia, Korea, Malaysia, the Philippines, Singapore, Taiwan and Thailand) support the ones from Ferguson et al. (2000) that there exists at least a long-run relationship. They do this by running tests for cointegration. Further they look for Granger causalities to say if there statistically can be stated that one causes the other or vice versa. While results are mixed from country to country, panel tests show a long-run bi-directional Granger causality, and a short-run unidirectional Granger causality from economic growth to electricity consumption.

Electricity Consumption and Economic Growth: A New Relationship with Significant Consequences? (Hirsh & Koomey, 2015):

This article examines the correlation in the long run for the USA. Their data show that the correlation between GDP and electricity has been going down slowly since the mid 90's. However, they do not correct for yearly fixed effects like technological innovation and thus decreasing energy intensity, which as they point out in the end may be the main reason for these findings. There is still a correlation, however decreasing, so it supports the notion that electricity still in 2015 was somewhat of an economic indicator. But a point about the relevance of the electricity consumption as an economic indicator in the long run, into the far future, may be something to note.

Electricity Use as an Indicator of U.S. Economic Activity (Arora & Lieskovsky, 2016):

This paper continues where Hirsh & Koomey (2015) left off, looking at what adjustments can be made to control for to find the corrected correlation between electricity and GDP growth rates in the USA, and their findings reveal a baseline correlation of 76 percent from the mid 70's until 2013. When controlling for seasonality and decreasing energy intensity they end up with a correlation over the series at 86 percent. So, one can now assume that the long-run relationship between electricity and economic activity is still relevant. Their data series also show that the two move together during recessions, and that the electricity consumption growth rates goes up before the end of the recessions.

Past studies have found evidence of a strong relationship between electricity consumption and economic activity in the long-run, but maybe put too little emphasis on the electricity as a short-run indicator, except Chen et al. (2007) which suggest an additional short-run relationship from economic growth to electricity consumption. Papers looking into this have clearly emerged after the Covid-19 crisis struck, however, and it is this part of the literature that our paper is aiming to contribute further knowledge.

3.2 Electricity consumption during Covid-19

Early Economic Impacts of COVID-19 in Europe: A View from the Grid (Cicala, 2020a):

Cicala here attempts to estimate an impact on electricity consumption stemming from Covid-19 alone. He does this by regressing electricity consumption on various known indicators on electricity consumption. With this method he employs consumption data covering most of EU, to display both on country level, but also a collective drop in electricity consumption during the early stages of the pandemic (last datapoint on April 6). His estimates display drops in consumption that accurately mirror the various timelines of lockdown-implementation and a hypothesis that the European economy generally has shown an historic low. Treating EU as a unit, the drop was estimated at 10 percent. And with that he spurs the question of whether the consumption data accurately proxies the economic data.

Canadian Electricity Markets during the COVID-19 Pandemic: An Initial Assessment (Leach et al., 2020):

Leach, Rivers & Shaffer are with this paper contributing into the literature on how the electricity markets changed during the Covid-19 crisis and how the data tracks the events of the pandemic (in this case on a regional level within Canada). They also investigate changes on the supply side, but we will not go further into that part as it has no relevance to this paper. They look at four different regions and can clearly distinguish the differences both in the size of the shocks due to differing regional economies, differences in how hard the pandemic struck, as well as the timings of drops compared to the pandemic events. The paper questions the actual appropriateness of electricity as a real-time indicator for economic activity, but do not go further into researching this for the current situation. Still, they present the other potential upsides of using electricity data besides the temporal one, which is the granular information one can obtain from such data. This is something that would support an increased use of the data, as they show how one can distinguish the consumption between different consumer classes (commercial, industrial and residential) and even between some industrial sectors. This will be able to give decisionmakers a more detailed picture of a similar situation than maybe other similar proxies can do.

The two papers above clearly showcase how one could use changes in the electricity market to track the demand side changes during the pandemic in 2020. They do not explain further in detail how this would actually track the economic activity, but they show that the data can give an idea of when the downturn probably started and how well the recovery might be going.

3.3 Electricity as an economic indicator during Covid-19

Tracking GDP in real-time using electricity market data: insights from the first wave of COVID-19 across Europe (Fezzi & Fanghella, 2020):

Fezzi & Fanghella aim to document a general methodology that can be used on more than one country seeing that most other similar literature only imply one country in their analysis of electricity as an economic indicator during Covid-19 (Beyer et al., 2021; Janzen & Radulescu, 2020; Menezes et al., 2021). Although they use simplifying assumptions their results seem remarkably significant. The paper examines twelve countries (Austria, Belgium, Denmark, France, Germany, Italy, The Netherlands, Norway, Spain, Sweden Switzerland and The United Kingdom). The central part of the analysis is estimating the counterfactual "normal" 2020 values or electricity consumption, they use similar "prefiltering" methods, as they call it, as seen in Cicala (2020a) and Leach et al. (2020), but with minor adjustments. Then they continue to estimate an economic effect of the downturn by assuming all drop of demand happened outside the residential market and then controlling by the percent of residential load of the total in each country. This gives them a real-time estimate of the change in GDP which correspond with the actual numbers of the two quarters in question (the first and second quarter of 2020) by a correlation coefficient of 0.98. Fezzi & Fanghella had data for 2020 up until the end of August and of that reason only cover the first two quarters of the year, or as they call it, "the first wave of the pandemic". In addition to the impact on electricity and GDP they also compare the chosen countries based on their NPIs to find a best and worst "measure strategy".

Examining the economic impact of COVID-19 in India through daily electricity consumption and nighttime light intensity (Beyer et al., 2021):

Beyer, Franco-Bedoya & Galdo here joins the list of papers examining impact of Covid-19 through the use of electricity data, but also data on nighttime light intensity. But they are doing it in India and therefore gives insight into the approach's usefulness in a country not as developed as European countries and the USA. One difference in their model is that they use data for gross value added (GVA) instead of the more usual GDP. They show a general 0.95 correlation in the long run between the two series in a sample of 123 countries which fits well with earlier findings (Ferguson et al., 2000). Further their coefficient from regressing GVA on electricity consumption seems not too different from the corresponding numbers found by other in Europe. When modelling the electricity consumption their model follows the earlier examples, but as with others, with minor differences, to accommodate the geography of their subject, India. In addition to looking into national data they also examine regional changes to present the heterogeneity within India's economy.

Using electricity consumption to predict economic activity during COVID-19 in Brazil (Menezes et al., 2021):

Menezes, Figer & Jardim give insight into the usefulness of electricity data as an economic indicator in Brazil and follow the same basic method as other similar papers do when constructing a "normal" electricity consumption. In addition to traditional quarterly GDP data they also look at a monthly indicator (IBC-Br) released by the Brazilian Central Bank. Their paper supports the usefulness of electricity data, not only for developed countries in the EU but also for a developing country like Brazil. Their results appear quite strong, as their indicator and the movement of the actual GDP has a correlation coefficient at about 0.98 between February 2020 until May 2020. An extra viewpoint from this proxy is also that it picks up all consumption, which means that also informal activity is included in the indicator. This appears vital for a country like Brazil where the informal sector makes up for almost 40 percent of the economic activity in the country. The paper further gives insight into differences between the customer classes; residential, industrial, and commercial.

Electricity Use as a Real-Time Indicator of the Economic Burden of the COVID-19-Related Lockdown: Evidence from Switzerland (Janzen & Radulescu, 2020):

This paper is a documentation of how the electricity consumption fell during the five weeks defined as the lockdown-period in Switzerland. They do this in another fashion compared to other literature examined as they only analyse hourly load for seven weeks before the lockdown started until the end of the lockdown. Included in the regression on log of load they have usual factors like temperature and temporal dummies, but in addition they include specific dummies denoting each week, seven weeks before and five weeks after the start of the lockdown, and use the coefficients of these to state the change in electricity due to the Covid-19 situation. They further regress these coefficient values on indicators for the severity of the pandemic like number of cases per capita and mobility data. Also, Janzen & Radulescu examine the regional differences inside of Switzerland per canton (political region). However, they do not compare the results to the actual economic data, as they simply assume that economic output attribute to 67 percent of total consumption.

The four papers above using electricity data as an economic indicator mainly derive the change in consumption due to the pandemic with the same basepoint, with the exception of Janzen & Radulescu who isolate the time-fixed effects from the weeks during the lockdown. Their evidence points, however, in the same direction, which is that electricity consumption data did show the market shock that Covid-19 was and its granular usefulness as a tool to get a detailed picture of "impacts" during economic shocks. In addition, the empirical evidence also point towards the data as a reliable indicator (in the short-run), independent of type of economy.

4. Theory and Modelling

This chapter systematically goes through the topics of i) economic growth, ii) electricity consumption, and iii) the relationship between these two. We touch onto some relevant theory, relationships and explanations, and a discussion of modelling, as well as our choices in this regard, of these topics.

4.1 Economic activity

As a measure of economic activity levels we use GDP. We find this to be appropriate as it is the most widely used measure of the value of total outputs of geographical regions and countries. GDP measures the sum of the market values of all goods and services produced within a specified area, and a specified time frame.

4.1.1 Historical economic growth

When viewing historical economic growth of the world there is an obvious upwards-pointing trend. Figures from *Our World in Data* (Roser, 2013), based on data from the World Bank and the Maddison Project Database, show how real world GDP has increased from just above $9 trillion to over $108 trillion from 1950 to 2015, that is a 12-doubling. Viewed linearly the growth trend is increasing, while logarithmically it is slightly decreasing over time, but still obviously rising in absolute values. In aggregated world data over long time spans, such events as the financial crisis of 2008 causes but a small dent in the graphs. It is worth mentioning that from 2008 to 2009 is the only year over said time horizon in which there is a decline in real world GDP, and by 2010 it had already surpassed the 2008 level. However, while economic growth of the world seems to be a "certainty" from year to year, we know that the growth of countries and regions of the world differ from one another and across time. An example of regional declining real GDP can be seen in Europe and Central Asia (The World Bank, 2021). Between 1970 and 2019 the region saw four years of declining GDP spread across three instances. From 1991, there were two years of GDP decline, and GDP had not surpassed 1991 level before 1995. Similarly, after the financial crisis, it took three years to get GDP levels back and above the 2008 level. This is of course just mentioning actual declines in total real GDP, while periods of stagnation and slow growth also occur. When disaggregating the data on even smaller parts, per country and quarter, point-by-point there is often much more going on and a less smooth line to follow. This is even when using data that are adjusted for seasonal variation, as can be seen in the data sets of chosen countries we analyse (see Appendix A).

4.1.2 Modelling economic growth – GDP forecasting

In our analysis of the pandemic's effect on the economy, and whether it is possible to infer a predictable short run relationship between this and the simultaneous electricity consumption levels, we need some measure of what the actual economic impact the pandemic has had. To do this, we attempt to "forecast" the growth of GDP of the countries in our analysis, across the quarters of 2020. This forecast is supposed to be an estimate of the "most likely" growth scenario were the pandemic not to have happened. As explained in our discussion of historic economic growth, the long run growth of economies seems certain. The most important determinants explaining long run economic growth are widely accepted and agreed upon by economists. For example, the Solow model framework allows for a long run steady state economic growth determined by the amount of available labour and capital (Holden, 2016, pp. 477-493). Additionally, the effects of technological developments, productivity increases and human capital can explain additional per capita growth (Steigum, 2011, pp. 161-169). However, in the short run, GDP has a tendency to fluctuate around the long run growth. And these short run fluctuations are harder to predict or explain, as each period's fluctuations may be caused by different factors. Therefore, we believe that any attempt at forecasting GDP levels over a short time horizon is difficult, and is likely to leave a rather large margin of error. Our best guess is to try to forecast the long run growth rate, and hope that the short run movements around this trend would not deviate by much in the scenario that the pandemic did not occur. We will, of course, never know.

The GDP trend line can only truly be estimated some years back in time. Today's ongoings and the growth in the near future will be used to decide the point of the "true" trend growth of today. We "let the data speak for themselves" (Gujarati & Porter, 2009, p. 776) in our forecast models, instead of attempting to forecast based on the factors already mentioned, which we believe to be important in explaining economic growth. Using contemporaneous unemployment levels to forecast economic growth is not viable as that would involve also "forecasting" what unemployment levels should have been, potentially creating more trouble than it would solve. Technological progress is hard to measure in a way usable for our modelling. For simplicity, we have modelled GDP levels, or GDP changes, using autoregressive (AR) models. We only include lagged observations of the dependent variable in our regressions as explanatory variables. Such models will live up to the expectation of economic growth to follow a trend, which is estimated by historical data, and it normally lets the closest past observations be most important in explaining its next level. All countries in our analysis demonstrate generally that their economies grow across the time horizon of data available to us (see Appendix A). In our experience, estimating these models tend to moderately forecast time series data, such as quarterly GDP. Each country's model is also specified using the same principle of letting the data decide. In-depth explanation of how we have chosen to specify the models per country can be found in chapter 6.

We could, instead of attempting to forecast quarterly GDP levels of 2020, have used official GDP forecasts per country published by, for example, the International Monetary Fund (IMF) (International Monetary Fund, 2019), leaving this part of the job to the professionals. In chapter 8 we showcase how IMF's annual forecast differ from our own.

4.2 Electricity consumption

4.2.1 Seasonality in electricity consumption

Electricity consumption data displays multiple layers of patterns determined by time (Hodge, 2020). These are quite predictable in shape across each period, but vary in magnitudes between and within countries' data. Here we discuss the three layers important to describe electricity consumption variation over time: yearly seasonal variation, intra-week variation, and intra-day variation. We also discuss the effects of holidays. We have chosen to use power load data for The Netherlands to show the patterns we discuss on a more general basis. The figures are made

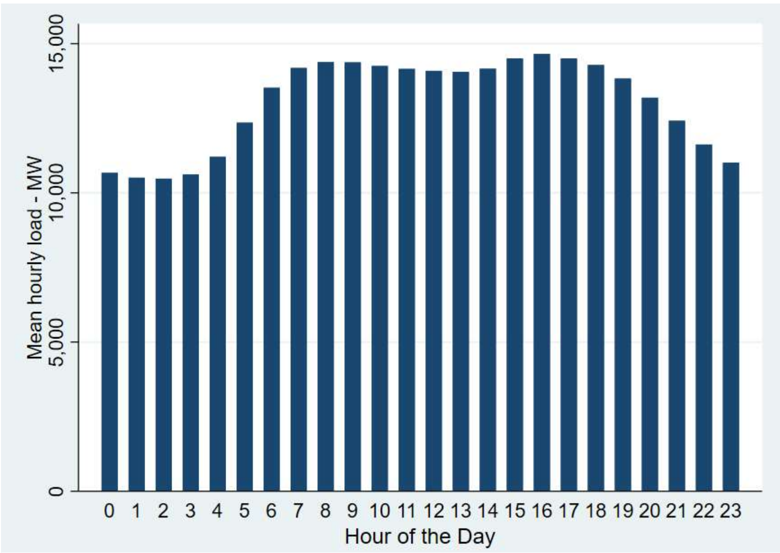

Figure 1: Mean power load for each hour (in UTC) in The Netherlands (2015-2019).

from data recorded in Coordinated Universal Time (UTC), not local time. The patterns are not similar in each country.

Daily variation – figure 1 shows, on the form of the average hourly power load recorded in The Netherlands between 2015 and 2019, per each of the day's 24 hours. Intra-day high and low average load lays at approximately 10 500 MW and 14 500 MW. One can also see a typical pattern of low night-time electricity consumption, and a higher level during day-hours. Through the day, it is normal to see a dip between two highs – in the morning and the evening. This can be explained by a somewhat lower consumption level during working hours than when people are at home, using electric appliances in their daily lives. As Hodge (2020) describes, in the US during summers, the daytime pattern consists more of one high peak. At this time, workplaces and homes use much energy by air-conditioning because it is hot outside. We can reasonably expect the shape of this pattern to be dependent on the climate of each country.

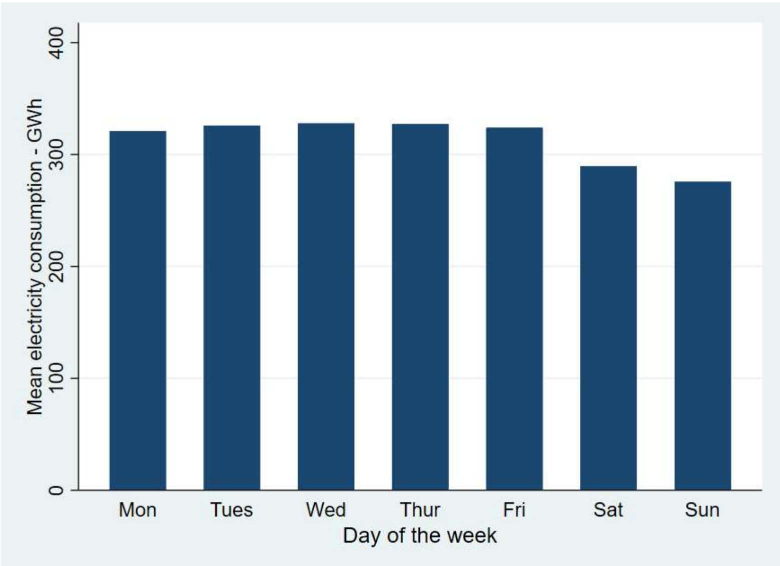

Figure 2: Consumption of electricity per weekday in The Netherlands (2015-2019).

Weekly variation – figure 2 is made using the same method as the previous one. Here, aggregated daily electricity consumption has been averaged per weekday throughout the same period. We have changed the vertical axis to consumption rather than load, although we still use the same data. We explain this choice of wording in the chapter 6. We also use GWh instead of MWh for an easier read. Obviously, the most interesting part of this pattern is the high and quite similar electricity consumption level during normal working days, Monday to Friday, followed by a relatively large decline during weekends. On average, working day consumption is between 10 to 20 percent higher than weekend consumption. This can be explained by the need for less electricity during weekends, when activity in the industrial and commercial sector is low. This effect could be offset somewhat by higher residential consumption because people spend more time at home. The data points towards the former effect being stronger, which we will show later in our "Results" chapter.

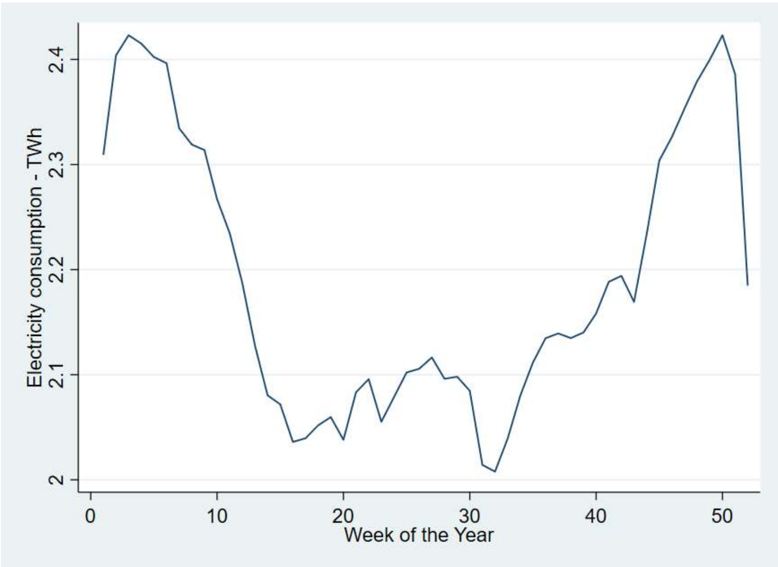

Figure 3: Mean electricity consumption per week in The Netherlands (2015-2019). The weeks are numbered according to Stata's week numbering system.

Seasonality – figure 3 shows, using the same data as before, weekly aggregated average electricity consumption in TWh. Because there is a much smaller number of observations to average on per point on the graph, the figure is less smooth in its movements than the two prior figures. Averaging on only five observations, it will be more affected by outliers, causing a jagged line. These outliers may be caused by such events as easter holidays or summer holidays, which do not fall on the same days each year, or weeks with atypical weather situations and temperature relative to the normal. Still, the most important intuition can be drawn from it. electricity consumption is high during the winter, and lower in the summer, and somewhat higher during the warmest part of summer than the rest. Spring and fall both represent transition periods between the two, with declining and rising trends respectively. These seasonal variations are mostly caused by changes in weather between seasons. During winter, more electricity is needed to combat the cold. Likewise, during summer, air-conditioning is required to cool down buildings. This is a well-known and agreed upon explanation (Yi-Ling et al., 2014). The start and end of the year is markedly low, which can be explained by the Christmas holidays and New Year's Eve/New Year's Day.

Holidays – an extra time variable important to be aware of in explaining variations in electricity consumption, which will not be adequately explained by the already discussed ones, are holidays (Ziel, 2018). All the countries we analyse have some number of official holidays and other non-working days. These are religious holidays, such as easter, national holidays that mark important historic dates, or others like Labour Day and New Year's Day. On these days, one can typically see large drops in electricity consumption relative to comparable weekdays. Sometimes these holidays land on weekends. Then this effect is likely to be less relevant, according to Ziel (2018, p. 196). Holidays are days when many people are home from work, and behavioural patterns deviate from the normal. Relative to the difference between normal working days and weekends, we believe holidays to be of a characteristic more similar to weekends.

4.2.3 Temperature's role in explaining electricity consumption

The role of temperature in explaining variation in electricity consumption has already been hinted at in the past few paragraphs. Yi-Ling et al. (2014) is one paper that studies the relationship between daily electricity consumption and temperature in Shanghai between 2003 and 2007. In Shanghai, which has a warmer climate than our set of European countries (defined in chapter 5), cooling and air-conditioning explains the yearly electricity consumption peak in summer. A smaller peak occurs in winter. From this, we see how peak and trough can differ between warmer and colder regions of the world.

4.2.4 Modelling electricity consumption

Following our discussion of electricity consumption and the factors important in explaining its variation throughout the year, we now have a good foundation to discuss how one could model electricity consumption. We need to create a model so that we may estimate its parameters, and use these to predict electricity consumption levels throughout 2020. Similar to our "forecasting" of GDP, this will be our best estimate of electricity consumption were the pandemic not to have happened. For our analysis, we need predictions that explain as much of the short-run variations as possible within the limits of reasonable simplicity. The model should also be specified in a manner that consider the differences between the countries. The latter is because we have wanted to create a standardized model that could fit many countries, and not specialize in one or a few cases. The need for a high explained share of the variation is to get close and correct predictions. These will be important to be able to trust in our impact estimates of the pandemic. We aim for models that explain upwards of 90 percent of the variation, as this has proven possible by earlier research (Beyer et al., 2021; Cicala, 2020b). We are not especially concerned with causalities or the specific magnitudes of the coefficients we get from estimating our models, as this is not a focus of our analysis.

Temperature – heating degrees and cooling degrees

Probably the most vital piece in modelling short run electricity consumption is to include some variable that accounts for climatic temperature changes throughout the day and year, made obvious by the prior discussion. Having explained how electricity is used both for heating and cooling, we bring up the concept of *heating degrees* (HD) and *cooling degrees* (CD). When using HD and CD to explain variations in electricity load one needs to set a base temperature to fluctuate around (Spinoni et al., 2015). This is opposed to when one simply uses the mean air temperature per day (Fezzi & Fanghella, 2020). Using both HD and CD makes it possible to model a non-linear relationship between temperature and electricity use, where electricity use is expected to be at its lowest at the threshold level. HD and CD defines that the outside air temperature was above or under a certain threshold temperature. Any deviation is assumed to require buildings to either use energy to cool or heat up the rooms. So, if you set a base temperature at say 18 degrees Celsius outside temperature, and the recorded temperature is at 22 degrees, then you have four CD, because that is the amount of degrees a building has to compensate for to get down to 18 degrees. Opposite, 11 degrees recorded temperature means 7 HD in that given timespan. There seems to be no wrong or correct answer as to exactly which threshold one should use. There are many levels for the base temperatures used to determine HD and CD, based on where you look and what general climate there is in this area (Spinoni et al., 2015). In the USA, the national norm for degree day base temperature is 18 degrees Celsius, or 65 degrees Fahrenheit (Alola et al., 2019). This is different from the base temperature mostly used in Europe. Spinoni et al. (2015) argue for the use of the thresholds suggested by UK MET-Office when they established a model for comparing HD and CD across Europe in an historical context. In this article, the base temperature to divert from is divided into two different levels, where the base temperature for estimating HD is set at 15.5 degrees and the base temperature for estimating CD is set at 22 degrees. The reasoning for this type of approach is that one assumes that cooling will not be needed the exact moment heating is no longer required.

There also exist different ways of estimating the impact of HD and CD. The UK-MET version of it looks at the fraction of a day that exceeds this baseline, others can be counting the number of hours where it deviates from baseline and some on the number of days (Spinoni et al., 2015).

So, when examining this we find it hard to decide for an approach based on earlier work, because as Spinoni et al. (2015) is trying to create a universal model to cover all of Europe for different time areas, we only examine ten countries during a much shorter time span and most of the countries have similar North-Atlantic climate. So, if one must acknowledge the imperfections of using HD and CD as explanatory variables, we felt it most important to look for a definition that have similarities to more than one approach and simply test to find an explanatory level within the model that we were happy with, and rather pass the task of finding the "perfect" degree approach for these ten countries onto future research. Drawing from this, we ended up with a single threshold to divert from for both HD and CD that also was lower than the American standard. Our chosen threshold level is set at 16 degrees. This threshold level has proven to contribute productively in explaining a share of the variation in electricity consumption that we are satisfied with.

An issue that arises when using temperature variables in modelling electricity consumption of a large geographical region, is that short-term climatic conditions may vary significantly within the region of interest. Thus, the temperature recorded at one specific location is not necessarily qualified to model the temperature-dependent consumption variation for the whole area. Naturally, the problem will be larger, the larger the geographical region is, the more climatic variation occurs in it, and the more widespread the population is within it. A small country, with a largely centralized population, subject to relatively similar climatic conditions most of the time, may very well be modelled appropriately using temperature recorded from a single weather station. We think of two general ways to solve this problem. If possible, one could try to disaggregate the electricity consumption on more appropriate portion sizes where each part can be appropriately described by recorded temperatures from a local weather station. Alternatively, and seemingly much simpler, it is possible to include more temperature variables, recorded at different locations of choosing. We will be using the latter approach. The downside of this is that there will be some subjectivity in deciding on how many locations to implement, which ones, according to which criteria, and that there may be issues with acquiring quality data from several locations in each country. We have chosen to use temperature data for three locations per country. A short discussion of the criteria we have chosen locations by is included in the Data chapter.

Time-specific patterns

Quickly reviewing the time-specific effects on electricity consumption that we have already discussed. We can roughly divide these into two parts by explanations as to how or why they affect electricity consumption. Firstly. there are behavioural changes from time to time, and secondly, there is the need for keeping inside-temperatures at a comfortable level. The latter explanation is most important in explaining the seasonal variation observed, and may explain some of the intra-day variation. It seems that variation between different weekdays, and holidays, are explained primarily by behavioural changes in consumers. The same applies to much, yet not all, of intra-day variation. While one can account for climatic changes by including temperature variables, variation explained by behavioural changes must be accounted for by themselves. Therefore, it is only logical that one should try to include these factors when modelling electricity consumption.

How one should include time-specific variables, and which ones to include, to a electricity consumption model will vary depending on the end goal of the modelling and, in our case, how large the data set one estimates the model's parameters on is. In our examination of some relevant literature, in which there are numerous articles where high frequency electricity consumption has been modelled and regressed, it is normal to include time-specific dummies for one or a combination of: the hour of the day, the day of the week, the week of the year, the month of the year, and even year (Beyer et al., 2021; Cicala, 2020a, 2020b). One article chooses to omit weekend days altogether from their analysis (Fezzi & Fanghella, 2020). Although our intuition tells us that temperature-dependent variations should be explained by temperature variables alone, our testing of differently specified models by regressions has given the impression that seasons are best explained by models which include both temperature variables and some season-specific dummy.

In our models, we use sets of dummy variables which indicate the day of week, and the week of the year. Day of week dummies are implemented to control for the general weekly variations discussed, and likewise, week of the year dummies control for seasonal variations. Although, some countries' electricity consumption could be better explained by, for example, omitting day of week dummies for normal working days, and only including indicators for weekends, we wanted to create a standardized model. In experimenting with different model specifications, we find that the form we have chosen works well and is generally useful across the countries we analyse.

We have chosen to model daily electricity consumption, and thus we do not explain hourly variation, but rather aggregate the hourly data on a daily basis. We believe daily electricity consumption to be appropriate for our goals. In choosing to work with daily consumption, we allowed ourselves to use data recorded in UTC. This simplified our data preparation significantly, as we did not need to account for time shifts caused by daylight savings, nor different time zones. A justification of this choice is in chapter 5.

Holidays

Again, due to holidays' special role in explaining electricity consumption variation, they require some extra attention. Ziel (2018) addresses this issue with regards to modelling and predicting electricity consumption. Different methods used in research are described and assessed, before giving general recommendations for treatment of holidays. Incorporating holidays can improve forecasting by more than 80 percent on the actual holidays, but also by about 10 percent on all other days. If one chooses to include variables in the model to capture holiday effects, rather than ignoring or omitting holidays, it can be done by treating holidays as weekends or Sundays. Another option is to include one or several new specific holiday dummy variables, while keeping day of week dummies the same or "nullifying" this to prevent double impact from a holiday landing on a Sunday or Saturday. Alternatively, it is possible to set the holiday dummy to zero if it lands on a weekend. Several variations and "hybrid" approaches are also discussed. Ziel (2018) concludes that nullifying day of week effect on holidays to be the most promising method.

In our modelling, we have chosen to implement one general holiday dummy, indicating that a day is an official holiday. If a holiday lands on a Sunday or a Saturday, the holiday indicator is set to zero. Between this approach, and the one involving removing day of week effects on holidays, we have no favourite. In that we desire a standardized model, we find it better to use one single general holiday dummy, rather than specific dummies for each holiday or type of holiday. Still, we acknowledge that such a specification could be better in explaining each specific holiday's variation, as all holidays are not the same and will have differing effects on electricity consumption.

Long run determinants of electricity *consumption*

Yet to be discussed are some of the factors important in explaining how electricity consumption change across the long term. These are factors that explain the structural variation in electricity consumption, that cannot really be observed in the data from day to day, or week to week. A very recent paper (Ma et al., 2021) investigates several possible determinants of electricity consumption for Sweden, in both the short and long run. They conclude with findings of unidirectional long run Granger causalities running from CO_2 emissions, capital formation and GDP to electricity consumption. Of bidirectional Granger causalities, they find both electricity supply and population changes to be of importance. From this we draw that the structural consumption needs of a region are affected by economic performance, which is exactly what we are researching ourselves. It is also determined by environmental quality, demographic changes, and the structure of power supply.

Since we analyse electricity consumption using only a few years of data, and try to forecast on a daily basis just one year ahead, the factors explaining short run variations will be most important in our predictions. Trying to implement specific factors that account for the discussed long run determinants would be an over-complication of our models. Still, we find that from year to year, the general consumption level changes even when controlled for seasonal, weekly and temperature variables. To control for such changes, we implement another set of dummies in our models, which indicate the year. Although not necessarily a significant factor from one year to another, it demonstrates overall significance.

The role of prices in explaining electricity *consumption*

When economists analyse demand and consumption of most goods, energies, and commodities, it is useful to consider the role of prices. This is not necessarily the case when analysing electricity consumption, at least in the short run (Fezzi & Fanghella, 2020). Most consumers are supplied with electricity at fixed tariffs, and consequently, electricity in the short run can be seen as completely inelastic. By analysing electricity demand and supply through a system of simultaneous equations, it has been shown that the quantity of electricity demanded is not affected by price in the day-ahead market instantaneously (Fezzi & Bunn, 2010; Mirza & Bergland, 2011). However, consumers may react to high prices with some delay, which could be modelled using lagged prices. Drawing from this, and that we do not see others, except Mirza

& Bergland (2011), including prices to model daily electricity consumption, we ignore prices in our models.

4.3 The relationship between electricity consumption and economic activity

There does not seem to be much economic theory explicitly explaining or describing the relationship between these two factors that we are interested in. However, as is obvious throughout the literature review, there is a large body of scientific literature on the topic of the empirical sort. Some theoretical application to this issue, that we have seen referenced is the relation to production theory (Mohammadi & Amin, 2015). In this perspective, electricity is viewed primarily as a driver for economic activity in its use as an input factor in production. Aggregated to an entire country, the total electricity consumption level should help explain total production and output levels, *i.e.,* GDP.

4.3.1 Impact assessment of the Covid-19 pandemic, and comparison

The key piece of our research lies in assessing how estimated impacts on both electricity consumption and economic activity levels are related in Europe during the ongoing crisis. As already stated, the goal is to find out whether continuously updated and quickly available electricity consumption data can be used, in the interim period from actual ongoing economic activity till reporting of standard economic indicators, to quantify the effects of this shock to the economy. To be able to do so, we must have a plan for what it is exactly we are looking for.

Once we have modelled, estimated, and "forecasted" both of electricity consumption and GDP development across 2020, we must adjust both of these forecasts for the actual observed data across the same period. In doing so, we get a measure of the difference between the actual situation and what it "should" have been, given that our specified models are realistic and estimated precisely, and maybe a bit naïvely, that no other occurrences affecting either of GDP or electricity consumption would have happened in said scenario. These measures are what we call our estimated impacts of the pandemic. From our discussion of the relationship between electricity consumption and economic activity, we should expect that the results of impact estimation of both correspond with each other positively. In analysing several cases, we are prepared to get differing answers as to the magnitude of the relationship.

5. Data

The data used in this paper is one set of GDP data and another for power load for each country we have chosen to include, as well as temperature data for three different locations in each country. We have prepared our own csv-files for holiday data.

5.1 Choice of countries

We have chosen to include ten European countries in our analysis. This is an attempt to get a broader understanding of our findings than were possible given that we included only just one or very few countries. There could of course be considerable differences between the experiences of countries during this pandemic, and so we have tried to choose a set of countries that may tell different stories. This means that we have included some countries that have been relatively harder struck, and some lesser so, by the pandemic both in respect to severity of lockdowns and number of people affected by the disease. We have drawn a line at ten countries, thinking this seems an appropriate number of cases to paint a picture of what we are looking into. The countries included in this research is as follows: Norway, Sweden, Denmark, Finland, The United Kingdom, The Netherlands, Germany, France, Spain, and Italy.

Our choice of countries does not follow one strict rule for inclusion or exclusion, but rather a couple of simple criteria. The choice has also been affected by availability of precise power load data over our chosen time horizon. First, we include the Scandinavian countries as this is close to us, as Norwegians. Second, the remaining six countries are all relatively large European countries both population-wise and economically, ranked by GDP. In fact, these are the six largest economies of the European area as of 2019, with the exception of Russia (International Monetary Fund, 2021). Russia has been excluded due to lack of available power load data to us. No more countries are included, as we have limited ourselves to only include ten countries.

5.2 GDP data

GDP data has been collected from FRED, the Federal Reserve Bank of St. Louis' website *fred.stlouis.org*. FRED has retrieved their data from Eurostat, the statistical office of the European Commission (Eurostat, 2021b, 2021c, 2021d, 2021e, 2021f, 2021g, 2021h, 2021i, 2021j, 2021l). We have retrieved the data manually by downloading csv-files from the website. The data sets are quarter-yearly noted real gross domestic product per country, which has been adjusted for seasonal and calendar fluctuations, and data points are denominated in the local official currency chained to the 2010 value of said currencies. Real GDP is used for ease of comparison across time as it adjusts for inflation, which ensures that we need not worry about non-comparable values from one quarter to another. Seasonally adjusted data removes fluctuations that occur on a regular basis from quarter to quarter each year. For example, when viewing real GDP data for the UK between 1995 and 2019, which has not been adjusted for such seasonal variations, there is a clear tendency of yearly highs and lows, where typically the year's last quarter is higher, while the first and especially the second quarters are at a lower point (Eurostat, 2021k). The pattern may differ between countries. The removal of such yearly fluctuations helps ensure that the changes we see in the data from quarter to quarter reflect actual changes in the well-being of the economy. The data for the different countries differ in number of quarters recorded. In chronological order, the data starts with the first quarter of 1975 for the UK and France, 1978 for Norway, 1990 for Finland, 1991 for Germany, 1993 for Sweden, 1995 for Denmark, Spain and Italy, and lastly 1996 for The Netherlands. All countries' GDP are recorded up to the fourth quarter of 2020, except the UK, which ends one quarter earlier.

Due to UK's departure from the European Union in 2021 we had to complete our data on GDP in UK ourselves, as our source data were published by Eurostat, and they do not update on UK any longer due to this situation. So, we fetched manually a dataset from the Office for National Statistics (ONS) which is the governmental body responsible for collecting statistics for analysis in the UK (Office for National Statistics, 2021a). Their data was as our original ones published seasonally adjusted and in millions of chained £. However, the data from FRED were posted in chained 2010-£ while the data from ONS were posted in chained 2018-£ (Office for National Statistics, 2021b). When the data is chained to one value, it is not a fixed inflation/conversion, so the relationship between the 2018-£ and the 2010-£ do not follow a fixed ratio. But, as to have a number for the real GDP of the fourth quarter of 2020 for the UK, we needed to use a ratio to estimate a number for our missing value. This was done by dividing the 2010-£ value for the third quarter of 2020, on the 2018-£ value for the same quarter. This gave a ratio of approximately 0.86, which we used to multiply with our 2018-£ value for the fourth quarter of 2020. This produced an estimation of 431 700.5, which we inserted to our data set. This is the value we assume as the real GDP in seasonally adjusted 2010-£ for The United Kingdom. By using the same method for the previous quarter-year the value was overestimated by 1.2 percent.

Table 1: Summary statistics for quarterly GDP data.

Variable	Obs	Mean	Std. Dev	Min	Max
gdp_no	172	520 096	150 566	269 214	755 802
gdp_se	112	828 935	156 986	548 282	1 083 877
gdp_dk	104	450 903	46 028	359 788	541 356
gdp_fi	124	41 772	7 692	28 234	51 616
gdp_uk	184	319 125	92 770	176 836	472 160
gdp_nl	100	153 989	17 076	114 761	182 533
gdp_de	120	620 844	70 559	509 737	747 441
gdp_fr	184	406 180	97 973	237 076	562 352
gdp_es	104	247 872	33 802	176 474	298 463
gdp_it	104	392 803	18 693	332 604	426 063

5.3 Power load data

Power load data for most countries has been made available to us by our supervisor, Olvar Bergland[1], who fetched it from the websites of the European Network of Transmission System Operators for Electricity (ENTSO-E) but seemingly through a different channel than what we had access to (ENTSO-E, 2021a, 2021b), and through the websites of Nord Pool and National Grid ESO (National Grid Electricity System Operator, 2019; Nord Pool AS, 2021). As the data concerning Germany was incomplete, we collected this data ourselves through a different channel than the other data, but still from ENTSO-E's websites (ENTSO-E, 2021b). It is also worth mentioning that the sole difference between the incomplete and the full dataset we used instead was that the latter had a 15-minute frequency instead of hourly. When estimating the mean per hour the two data sets became identical. The data collected from Nord Pool consists of hourly load data for all the Scandinavian countries, and the same qualities also describe the data from National Grid ESO concerning The United Kingdom. All data has been processed as csv-files into STATA (StataCorp, 2019).

For all countries we have data from at least the beginning of 2015, ending at various points in the early months of 2021. We only make use of data starting from January 1st of 2015 and throughout 2020. For all countries except Germany, the power loads are recorded as hourly load. Load data for Germany is recorded on quarter-hourly basis. Since load is noted as average MW across the observation's time span, the average of the quarterly loads within an hour are comparable to the hourly recorded loads of the other data sets. All data sets follow UTC,

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although none of the ten countries are synchronized with this time standard throughout the year. All countries follow a winter/summer-time standard of (UTC+1/UTC+2), except The United Kingdom (UTC+0/UTC+1) and Finland (UTC+2/UTC+3). For our purposes, we do not see this as a problem. The temperature data we use also follow UTC, which makes the work of combining data sets easier. Since we only concern ourselves with aggregate daily observations in our analysis, we did not see it necessary to transform our data to the proper time standards of each country. All hours that are aggregated on the wrong date will be at local night-time, so that it should not affect the effect work hours and weekend days have in our analysis by much. To any degree it would, it will occur systematically and be picked up accordingly by the time-specific dummies we use. Our end goal is not to explain precisely how our short-term variables explain daily electricity consumption, but rather to create a model that can be utilized to clear out short- and long-term effects on electricity consumption to more clearly see how electricity consumption has been affected in 2020.

There are no recorded missing observations in the Nord Pool data sets. Among the five other countries, the data sets of loads of Spain and France contain some missing observations. Respectively, two and 29 hourly observations are missing, and at most, five in a row. These have already been interpolated beforehand. The data for load of Germany contains one missing observation, which has been covered by averaging the three quarters of the same hour across said hour. By eyeballing histograms and line plots of all the data sets, there are some occurrences of suspiciously low or high loads for a few countries. We cannot know for certain whether these observations are actually correct, or are caused by measurement errors, or some other reason. The potential errors seem to be spread apart and we have not found any obvious patterns among them. If they indeed are faulty, this will cause our analysis to be built on said faulty data. Likewise, the interpolated values in place of missing observations do cause the data to be somewhat less reliable. However, we find that the number of potential errors that can be spotted in the data plots are not many, especially when considering the sizes of the data sets. We assess that the data seem to be of a quality appropriate to its purpose.

Due to lack of access to quality data for the whole of The United Kingdom, the data we use, which is collected from National Grid ESO, only cover load from systems in England and Wales. This of course excludes all load variation from Scotland and Northern Ireland, which most likely will weaken our analysis of The United Kingdom.

Table 2: Summary statistics for daily aggregated electricity consumption data (2015-2020). N = 2192

Variable	Mean	Std. Dev	Min	Max
load_no	362 953	71 000	241 205	542 226
load_se	373 550	70 377	242 293	580 945
load_dk	90 659	10 098	66 007	116 249
load_fi	226 387	33 633	148 260	343 506
load_uk	659 024	103 227	394 249	932 434
load_nl	310 075	30 219	223 657	376 789
load_de	227 803	26 785	159 610	286 604
load_fr	1 283 567	256 794	844 823	2 120 560
load_es	681 672	69 498	476 227	848 155
load_it	827 413	129 639	454 898	1 189 406

5.4 Temperature data

As with most of our power load data, the temperature data we use was fetched by Olvar Bergland (see footnote 1, p. 28). This data stem however from a data series on Iowa State University's websites, and is collected by a collaborating network called Iowa Environmental Mesonet (IEM) through their Automated Surface Observance System (ASOS) network (Iowa Environmental Mesonet, 2021). The observations are mainly registered at airports around the globe. The format of the data is called METAR, which is the primary format used to transmit worldwide airport weather station data, and it is an abbreviation for Meteorological Aerodrome Report (Iowa Environmental Mesonet, 2020; MET Norway Weather API, 2021). The data is on the form of hourly observed temperature for the relevant time frame, which is the same as for the power load data, from 2015 through 2020. Temperature is denominated in Celsius degrees. We have available to us data observed at various locations, at least three different places per country we analyse. Among available sets, we have chosen to use three per country. Using temperature data from multiple locations might mitigate the problem of missing observations at one location, as the other locations could make up for some of the loss.

When choosing between several alternatives we first picked out the capital of each country, or airports close to the capital. The two remaining locations we chose based primarily on geographical spread across each country, but not disregarding population centres. We wanted a geographical spread of our locations so that the data sets more completely describe the temperature across the entire country and wider parts of the population. For example, we expect, naturally, that the temperature observed at two different locations in or close to Paris would be more similar than that which is observed in Paris and Lyon.

All temperature data sets have missing observations within the time frame we are concerned with. The number of missing observations per location vary massively. Between only one missing hourly observation to as many as 364 missing, which amount to 0.69 percent of the observations in the data set. In Appendix B, all the locations we have used, with its corresponding country, number of missing observations and shares thereof are listed in a table. Missing observations have been covered by linear interpolation before we got access to the data. Among our locations, Eindhoven is particularly bad in April 2015. The longest stretch of interpolated observations is recorded in Eindhoven, with 47 adjacent observations, in this month. Umeå has a stretch of 20 observations, likewise Vaasa's longest stretch is 13, and 11 for Torino. These are the worst examples of our data.

Long stretches of time without real observations cause trouble when utilizing the data sets in regressions, as this whole part of the data set will obviously not truly help explain the dependent variable. It will probably both weaken the explanatory power of temperature on electricity consumption, and predictions over days with many interpolated temperature observations will be worse than elsewhere. We view this as a much larger problem for our analysis if the missing observations occur in our prediction period, than if they occur during the period in which we regress and make our variables' parameter estimates. This is because the latter period is longer, and have more observations, which hopefully will mitigate most of the bias caused by the weaknesses in the quality of the data. If large chains of missing observations were to occur in the prediction period, our estimated electricity consumption impact from the pandemic, will be less reliable and consequently less useful to our analysis.

5.5 Holiday data

The data which notes days when holidays occur per country, we have collected and prepared ourselves, from the website *timeanddate.com* (Time and Date AS, 2021). The site contains lists of official holidays, non-working days, and observances per country and year. We have scanned through all relevant countries and years, and noted dates. The categories vary from country to country, but we have tried to follow a rule of including strictly official national holidays, in which the general population are off work. In Appendix C is a listing of holidays included per country.

5.6 Software

We have processed our data and run all our analysis using STATA version 16 (StataCorp, 2019). We have used the package *estout* to make tables of regression outputs and other outputs from the software (Jann, 2005). This package enables Stata to store regression estimates to later be presented into tables that can be produced into text-files, with various options regarding the output displayed and also the layout of the table itself. However, the output from this code looks a bit “raw” so the tables presented in this paper are refined versions of this output.

6. Method

In this chapter we describe, and explain reason for usage, of the methods we have used in our analysis which tries to estimate the impact the pandemic has had on both GDP and electricity consumption, as well as the linkage between these two, for each country. We have utilized one general method for each country case, however the exact specification of the forecast models for GDP differs somewhat.

6.1 Daily electricity consumption regression and prediction

Our first step is to create a model which attempts to estimate electricity consumption over time. Our data does not describe actual electricity consumption, but rather power load denominated in MW. We make the assumption that the power load observations actually represent the electricity consumption in MWh over the hour in which it is observed.

Some alterations must be done to our data before we can use them as variables in our desired regression model. We aggregate the hourly power load, from here-on referred to as electricity consumption, to daily consumption by summing each hourly observation within a day. Then we transform these daily consumption observations to logarithmic form. Next, we create two new variables from each of the three locations we use temperature data from. One we call "Heating", and another we call "Cooling", representing respectively the earlier described HD and CD. They are generated using these formulas:

(1) $$Cooling = (T - 16 | T \geq 16)$$

(2) $$Heating = (-T + 16 | T < 16)$$

These two variables separate temperatures above and below the defined threshold of 16 degrees Celsius. If an observation is not in the specified temperature interval, it is set to zero. After generating these, we aggregate hourly to daily observations, as we did with electricity consumption. However, now we use the mean across the hourly observations instead of the sum.

After transforming all variables to our desired form, in each country, we estimate the following model for daily electricity consumption:

(3) $$\ln(Pwr_t) = \beta_0 + \sum_{i=1}^{3} \beta_i Heat_{it} + \sum_{j=4}^{6} \beta_j Cool_{jt} + \sum_{k=7}^{12} \beta_k DoW_{kt} + \beta_{13} Holi_t + \sum_{l=14}^{64} \beta_l WoY_{lt} + \sum_{m=65}^{69} \beta_m Year_{mt} + u_t$$

The parameters of the model above are estimated using the method of Ordinary Least Squares (OLS). We have run the regressions over the period from January 1, 2015, to February 29, 2020. The ending date is shortly before the large outbreak of the pandemic and consequent political reactions were imposed over Europe. The subscript, t, indicates daily observation of each variable. The βs are the parameters which we estimate. u_t is a scalar which represents unobserved variation in the observations, *i.e.*, the errors. Our dependent variable is the natural logarithm of daily electricity consumption, *Pwr*. The explanatory variables are *Heat*, which is heating temperatures for each location, and similarly *Cool*, is cooling temperatures. *DoW* is an indicator variable which indicates the day of week. We set the baseline level for the day of week to Sunday. As we have discussed earlier, weekends, and especially Sundays, are associated with lower electricity consumption compared to the rest of the week. Therefore, we expect the set of day of week indicators to be positive. *Holi* is an indicator for dates which are holidays or other non-working days, except if such a day lands on a weekend. We expect the coefficient of this variable to be negative, as we expect a holiday to be more similar to a Sunday than a normal working day. *Week* and *Year* are indicator variables for, respectively, each week in a year, and each year, that we have observations from. *Week* number is on the form it is set up in the Stata software. This differs from regular week number. The first seven days of a year are always noted as week 1, the next seven are week 2, and so on. The last week of the year is week 52, thus week 52 contains eight or nine days each year. We have set the first week of the year to be the baseline value. This is simply because we cannot think of a specific reason to choose another baseline, thus the most logical semi-arbitrary choice is the first one. Similarly, 2015 is set as the baseline year.

Using the resulting estimated parameters from the regressions on the model described, we generate daily predictions of daily electricity consumption using the same variables' data across all observations from 2015 through 2020, whereas 2020 after February is our forecasting period.

Newey-West standard errors

To correct our standard errors for potential heteroskedasticity and serial correlations, we use heteroskedasticity and auto-correlation consistent (HAC) standard errors, also called Newey-West standard errors (Wooldridge, 2016, pp. 388-391). In doing so, we must select the number of lags to correct for serial correlation. We have calculated recommended number of lags, g, according to the two suggested methods in Wooldridge (2016, p. 390):

(4) $g = 4(\frac{n}{100})^{\frac{2}{9}}$ or: (5) $g = n^{\frac{1}{4}}$

Inserting n = 1886, days between 2015 and February 29, 2020, we get approximately 7.7 and 6.6 lags recommended, respectively. We picked the middle ground, 7 lags. This also fits with a weekly cycle.

6.2 Estimating impact on electricity consumption

After executing the steps described in the previous paragraph, we generate a new variable using the following formula:

(6) $\text{ImpactPwr}_t = \ln(Pwr_t) - \ln(\widehat{Pwr_t})$

$\ln(Pwr_t)$ is the actual observed electricity consumption, and $\ln(\widehat{Pwr_t})$ represent our predicted values. The new variable, $ImpactPwr_t$ is our adjusted electricity consumption, which we use in the next steps. The subscript, t, still indicates each daily observation. These are the prediction errors from the electricity consumption regression. We view this variable as our estimated measure of the impact of the pandemic on electricity consumption. Given a hypothetical perfectly specified model, and similarly estimated parameters, this *impact* variable should have an expected value of zero if nothing noteworthy occur during our forecasting period. Any exogenous shocks affecting electricity consumption would be shown as a deviation of *impact* from zero.

When we compare the estimated impact on electricity consumption with the estimated impact on economic activity, we use electricity consumption impacts aggregated on weekly and quarter-yearly basis. A note on the method in which we aggregate the impact estimate, can be found later in this chapter.

6.3 GDP forecasting based on autoregressive models

To get an estimate of impact on GDP of the pandemic year, as we have done with electricity consumption, we need first to make a model which can be used to forecast GDP per quarter of 2020. When such a model and its corresponding forecasts are made, we may get an estimate of the impacts we are looking for. First, we convert our GDP time series to logarithmic form as we did with the electricity consumption data previously. From here-on, we use GDP when referring to the logarithmic form, when not stated otherwise.

We use auto-regressive (AR) models for each GDP time series. The simplicity of AR models in that it does not employ any other data or variables besides its own lagged values make them attractive to us. We are not primarily interested in modelling GDP for highly realistic and precise forecasts, but we want some moderate and approximate estimates to compare with our estimates for electricity consumption. The AR models are specified:

$$(7) \qquad \ln\left(GDP_q\right) = \beta_0 + \sum_{i=1}^{X} \beta_i \ln\left(GDP_{q-i}\right) + u_q$$

Where GDP is the dependent variable, and lags thereof are the independent variables. As earlier, βs note the parameters, u is still unobserved variations, the subscript q notes quarter-year, and X is the number of included lags in the model.

6.4 Model selection procedure

The following procedure described is based on Wooldridge (2016). To select the proper form of our AR models, we must first clarify whether we are dealing with stationary or non-stationary data series. To test this, we run Dickey-Fuller (DF) or augmented Dickey Fuller (ADF) tests. If the time series of a country can be concluded to not contain unit roots, the series is stationary. If we believe the series to contain unit roots, the series is non-stationary, and trying to regress on such a series is likely to cause spurious correlations, which will be of little help when trying to forecast on its estimated parameters. Which version of the DF test to use, we decide by running the related regressions of both tests using OLS. We test using different lags for the augmented version, namely from one to eight lagged differences of the GDP, and letting the Bayesian Information Criterion (BIC) be the judge of appropriate DF test to use. We have used up to eight lags when testing different model alternatives against the BIC. Because of this, we "sacrifice" two years of observations in our final models, which we use to forecast. Testing against more lags could in some cases be necessary, but we generally find that less than eight lags are better according to our criterion, and would not want to lose any more precious observations than necessary. BIC compares the explanatory power of different models, penalizing regressions for including extra variables, comparable to how the adjusted R^2 works. The favoured model is the one with the lowest absolute value of the BIC.

We follow a stepwise procedure of regressing the different DF-related regressions described, picking the one favoured according to the BIC, and running the selected version of the DF test. The first step is to include a trend variable to the regressions. If the DF test rejects unit roots, we conclude that the series is stationary, and we can go on to the next step, which will be explained shortly. If not, we test the joint significance of the trend variable and the lag of GDP in the DF-related regression. If they have joint explanatory power in the regression, we conclude the series to contain unit roots, and that we have a random walk with deterministic trend. If they do not, we redo the process, and run new DF tests omitting the trend variable. If we cannot reject the new DF test, we test the joint significance of the lag and constant. Again, we conclude unit roots and a random walk with drift if they show joint significance. If not, we run the procedure one last time. The test is now done with no added extra variables. If we still cannot reject unit roots, we conclude with their presence.

Once we have decided upon whether each series is stationary or non-stationary, we must transform those that are non-stationary to difference form, so that we are only regressing on stationary processes. Differencing has proven to solve the issue of non-stationarity, as we have also DF tested all differenced time series, and all can reject unit roots with very high statistical significance. The now-deemed appropriate time series are then used to create AR models upon. To choose the appropriate number of lags to include per model, either if it is on the regular form or on differenced form, we run all regressions, using the method of OLS, including one to eight lags on the estimation period from as far back as we have observed data, less the two years we sacrificed to the procedure of DF testing, up to the fourth quarter of 2018. We compare the estimated parameters of each model by validating them on the observations for 2019. We select our favoured model to use by primarily which one has the lowest mean squared forecast error.

The results of our unit roots testing are tabled in Appendix D.

6.5 Forecasting

Once we have specified our models, and picked a favourite, we use the parameter estimates to forecast GDP per quarter of 2020. We forecast GDP directly for the stationary time series. For the non-stationary series, we forecast the change in GDP and add this forecasted change to the former periods observed (or estimated) GDP. In forecasting on lags of the dependent variable, we first forecast the first quarter on the last observed relevant lag. For the next three periods, we use the forecasted lag or lags in place of the actual observed GDP as our independent variables.

6.6 Estimating impacts on economic activity levels

Essentially the same as how we estimated the measure we view as the impact on electricity consumption, we create a similar measure for GDP changes out of the prediction errors of the regression on the model:

(8) $\quad \text{ImpactGDP}_q = \ln(GDP_q) - \ln(\widehat{GDP_q})$

This measure should be read the same way as the impact on electricity consumption described earlier.

6.7 Comparing and analysing impacts of electricity consumption and GDP

Once the described procedures are executed, we have estimates of impacts that can be compared and analysed, which will give the key results of our research. Our method of analysis is a combination of visual graph analysis of estimated impacts over the course of the pandemic, until the end of 2020, and comparisons of aggregated quarterly percentage impacts between electricity consumption and GDP.

In aggregating, or averaging across, a set of logarithmic values, the results one gets will not be equal to the sum, or average, of the underlying values. Since we predict logarithmic dependent variables, and use the results to aggregate over periods, we need to make some adjustments to get the correct estimates. Whenever we need to average or aggregate the logarithmic dependent variable, we take the route via the underlying value of the logarithmic dependent. Wooldridge (2016, pp. 190-191) suggests a couple of ways to predict y when log(y) is the dependent variable. We use the method of exponentiating our logarithmic prediction, and adjusting it by multiplying with $e^{\frac{\hat{\sigma}^2}{2}}$, where $\hat{\sigma}$ is the root mean squared error from the OLS regression. The underlying value we get from this will not be unbiased, but consistent. It will be higher after adjusting. It relies on normality of the error term, which we cannot guarantee. Still, our hope is that this adjustment gets us closer to a correct estimate than were we to simply exponentiate without adjusting.

7. Results

This chapter discusses the results from executing the method described in the previous chapter on our data sets for each country case. First, we discuss the results of our regressions on the electricity models, referring to our STATA regression outputs. Accompanying this, we look to graphs showing our electricity consumption predictions and the actual consumption levels. Then we describe the results from our AR models for GDP, by both regression output and graphs comparing our forecasts to actual GDP levels. Lastly, we compare the results of both, to examine their relationship.

7.1 Electricity regressions and predictions

We have run regressions on the general electricity model, as described, for each country case. The key regression results are presented as a table in Appendix E. We have the same number of observations per regression, 1886 days. As stated earlier, we set a goal of creating a model which could explain upwards of 90 percent of the variation in electricity consumption, as this has been proven possible by earlier research. Our worst performing model with regards only to the R^2 statistic is that of The Netherlands, which explains 91.7 percent of the total variation. The model of Norway explains best the total variation, at 98.8 percent over the estimation period. The rest of the models are spread quite evenly in-between. The adjusted R^2 statistic is only one to three permille lower for all models. Overall, this seems a satisfactory preliminary result, and from this alone our expectation and hopes were that we had a model good enough to draw some clear insights from.

It should be noted that the level of the R^2 seem to be much affected by the ratio of seasonal to weekly variation, as can be seen in the figures presented in Appendix F. Countries with more seasonal variation seems to have more total variation, thus an equally precise day-to-day model should have a higher R^2 the more seasonal variation.

Temperature variables

The coefficients of both categories of temperature variables were expected to be positive, as both high and low temperatures around a “comfort” threshold should instigate increased electricity consumption from heating or cooling of indoor areas. The total of the temperature variables’ significance and role in adding to the explanatory power of the models is clear in most countries, at least the joint effects. While the joint effect of all the *heating* variables is highly statistically significant all over, the results are less clear for the *cooling* variables. In the UK, Sweden and Finland, the cooling variables are not jointly significant within the 95 percent critical value. In total, 49 out of 60 temperature variables show the expected sign, while 11 are negative. Among the negative coefficients, three are actually statistically significant, and they are all *cooling* variables. Only 12 of the 30 *cooling* variables are both positive and significant, while for *heating* the number is 25. No *heating* variables are negative and significant. Thus, it is clear that the positive effect on electricity consumption across our set of countries, of cold weather, is much more one-sided and clear than that of warm weather. This is assuming that our threshold temperature is appropriate.

One particular model example we found strange, was that of The Netherlands. While temperatures recorded at Amsterdam are both positive and significant, we found that all others are negative and insignificant. We speculate that this may be explained by the fact that The Netherlands is a small country in area, thus climatic conditions may vary less, and the Amsterdam variables may have "caught" most of the temperature effects. Still, Denmark is similarly small, while having five of six significant variables. Much more could be discussed on this in comparing countries, but an exhaustive discussion of this matter is out of place.

In interpreting the coefficients of the temperature variables, we pick an example. The *heating* variable of Oslo has a coefficient of 0.01. This corresponds to a one percent change in electricity consumption if, *ceteris paribus*, the average HD of Oslo, one day, were to increase by one degree.

Holiday variable

The holiday variable is highly statistically significant in all models, as well as large in magnitude. All coefficients are negative, as we expected them to be. The magnitudes of the coefficients differ by much. A holiday in Finland is expected to decrease electricity consumption by "only" 6.7 percent, while in Italy the decrease is as high as 28.7 percent. In comparing the countries, the "normal" interval is between 12 and 15 percent, in which four countries find themselves. Three are higher, and three are lower, than this interval.

Time-specific dummy variables

Besides the holiday variable, we also have the three sets of time-specific indicator variables, weekdays, week, and year. We do not discuss these again in-depth. The joint significance tests of each set, per regression, shows that all sets, except one, of variables are highly statistically significant within the one permille critical value. We only find that the year indicators of Sweden are somewhat less significant, and only significant within the five percent critical level.

7.1.1 Electricity predictions over the course of the pandemic in 2020

In this section, we discuss our electricity forecast results. We use the resulting graphs from the forecasting of electricity consumption in The Netherlands as an example throughout this part. The results of The Netherlands speak only for themselves, and say nothing about our findings in the other countries we analyse. We chose The Netherlands for two reasons. One, this was the model with the lowest R^2, thus we should not be accused of trying to present a flattering image of how well our method has worked. Two, we thought it results-wise to be moderate, in that it lies somewhere in-between the countries with the most, and least, obvious tendencies with regards to impacts of the pandemic. The equivalent figures per country can be found in Appendix F. We do not present a specific analysis for each country.

Validation of models

When forecasting on time-series, it is often useful to keep a portion of observations between the period in which the forecasting model is estimated on, and the period it is supposed to forecast. This portion is set aside for validating the forecasting ability of the model, either to pick between model specification options, or to get an idea of the average errors of the model. Our need for including a year dummy for 2020 has led us to using another method of validating our models forecasting ability. To clarify, we have found that a specific dummy for 2020 is important for some of the models, and that without it, the forecasts even for January and February are highly unprecise. For example, something occurs in the data for The United Kingdom in the shift from 2019 to 2020, that we believe must be explained by something other than actual electricity consumption changes, be it changes in method of measuring or something else.

Our alternative method of validation is to treat 2019 the exact same way as we did with 2020, viewing the graphs and fetching the forecast errors of these forecasts. This is not a validation of the estimated parameters we use to forecast across 2020. It is rather a validation of the model specification we have chosen. Our assessment of pros and cons of following this method or the correct method of leaving room for a validation period, is that neither are ideal in our case, but we find it to be a bigger problem to omit a 2020 indicator variable.

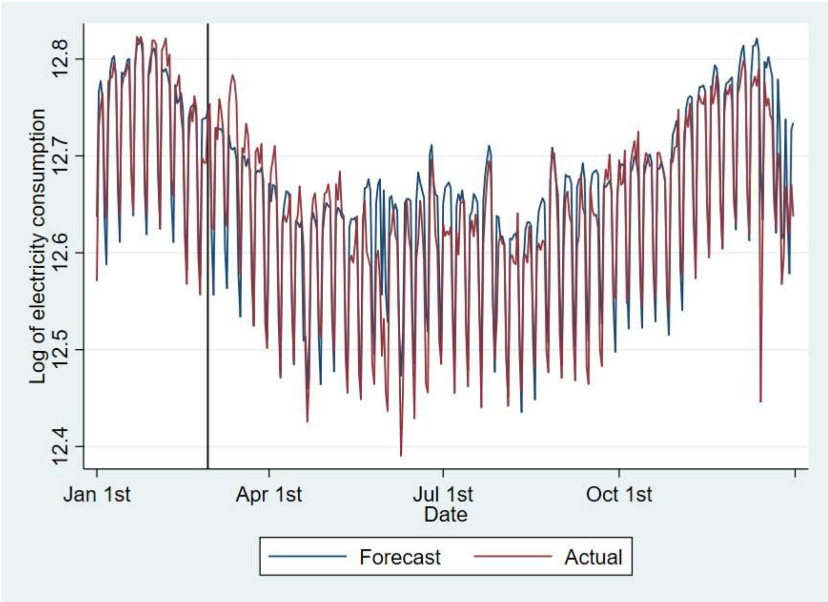

Figure 4: Electricity forecast for The Netherlands in 2019. : The vertical line represents the beginning of the forecast (February 28). Actual represent observed electricity consumption while Forecast is our models predictions.

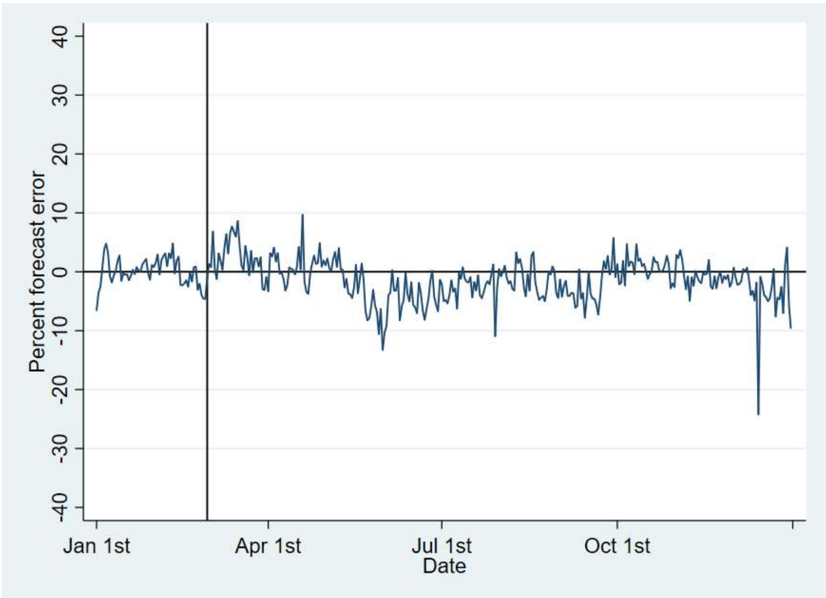

Figure 5: Forecast errors for The Netherlands in the validation period (2019). The vertical line represents the beginning of the forecast (February 28). The percentages are drawn from logarithmic difference between observed and predicted consumption.

Figures 4 and 5 show forecast for 2019, using parameters estimated from the beginning of 2015, up to February 28th of 2019. The closer the *forecast* to *actual* graphs are, the more satisfied we can be with our model specification. The forecast errors do not show as clear deviations over time from zero as for 2020. However, it looks like the early summer period is a few percent lower than forecasted electricity consumption. An example of a possible measurement error can be seen towards the end of 2019.

Results from the models

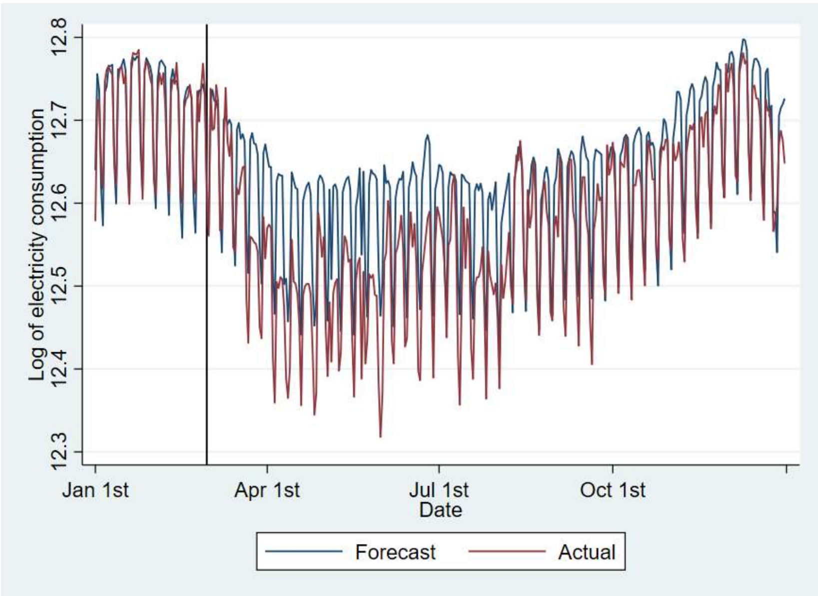

Figure 6: Electricity forecast for The Netherlands in 2020. : The vertical line represents the beginning of the forecast (February 29). Actual represent observed electricity consumption while Forecast is our models predictions.

We are reminded of the importance of including day of week indicator variables when we see the regular, jagged pattern each week throughout the year, shown in figure 6. The figure clearly shows the two graphs corresponding quite well in the estimation period, and about a couple of weeks into the forecasting period as well. Then we see, over the span of a week's time, a large decrease in the actual electricity consumption relative to the forecasted. The timing of the start of the decrease corresponds well with the national government's first implementations of measures against the spread of disease, between the 12th and the 18th of March (European Centre for Disease Prevention and Control, 2021a). The lower relative level of actual consumption stays that way, most of the time, for the rest of the year. However, the relative decrease decreases over time, and is quite small by the end of the year. The effect is most obvious from the first lockdown and through July.

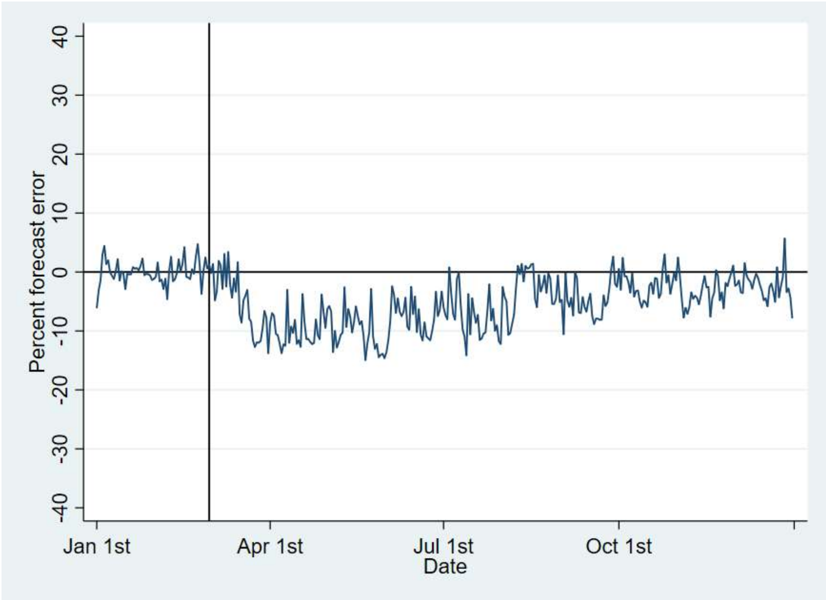

Figure 7: Forecast errors for The Netherlands in 2020. The vertical line represents the beginning of the forecast (February 29). The percentages are drawn from logarithmic difference between observed and predicted consumption.

Figure 7 shows the deviation from the forecasts shown in figure 6. These deviations are the, now much talked about, estimated *impacts* on electricity consumption, that we are interested in. The figure shows, with no complicating noise, how our forecast has overestimated electricity consumption most days after the pandemic shook The Netherlands. The vertical axis is labelled with percentages, taken from the logarithmic scale of the former figure. We can see that during the period in which the pandemic affected electricity consumption the most, electricity consumption was down by about ten percent.

7.1.2 The other countries

After this discussion of the results of electricity forecasting for The Netherlands, we broadly describe the most important features of the results for the rest of the countries. From the lengths of the jagged weekly pattern in each country, we may see the relative importance of intra-weekly versus seasonal variation in consumption between countries (see Appendix F). For example, Finland and Norway show less intra-weekly variation than Germany, at least relative to the seasonal variation. From eyeballing the figures, it is quite clear that at about the same time, all of The United Kingdom, The Netherlands, Germany, France, Spain, and Italy saw large and abrupt decreases in their electricity consumption levels. However, none of the Scandinavian countries exhibit this same trait, although Sweden is a case in doubt. Finland especially, behaves in an unexpected manner. While it is clear from the 2019 validation, that the model specification has trouble "getting" the Finnish electricity consumption, for 2020, we see no sign of the pandemic, while the forecast error lay higher than zero for most days of the year.

7.2 GDP regressions and forecasts

We now turn to describing the results of our modelling and forecasting of GDP over the course of 2020. Appendix D shows the results of our unit roots testing of the time series, as described in chapter 6.

Appendix G presents key results of regression outputs from the AR models in two tables. We list the AR models on log of GDP and the change in log of GDP separately. Among the four "regular" AR models, two comprise of only one lag, while one, Spain, has the most of all ten models, using seven lags. All models have a positive constant, an indication of positive growth, although several of these are not statistically significant. Quite naturally, the differenced variants explain much less variation than the regular ones. All models exhibit at least one variable being statistically significant within the 95 percent critical value, but if not counting the constant term, this is not the case for Denmark and Sweden. The joint explanatory power of

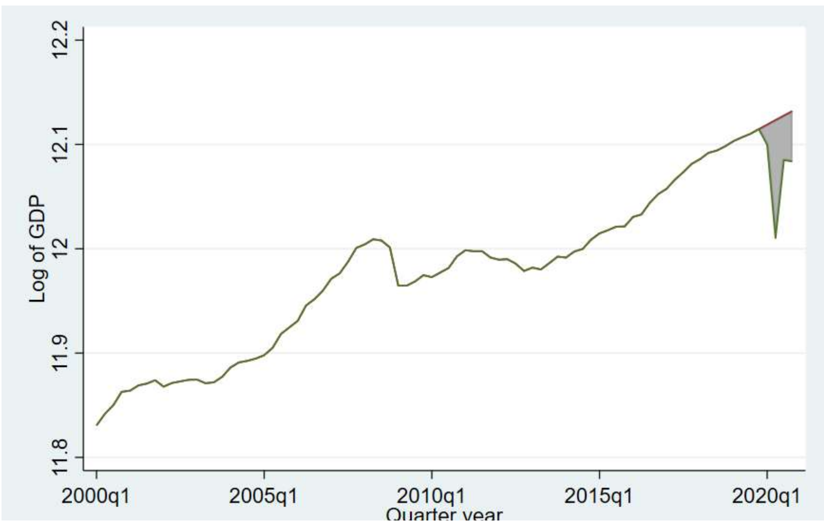

Figure 8: GDP forecast for The Netherlands, with the grey area representing difference between forecast and actual GDP in 2020.

the models is significant within the 99.9 percent value in all cases, except Sweden, within 99 percent, and Denmark, which is not significant at any of the traditional threshold values.

Appendix A shows the graphs of our forecasting on the estimated parameters of the models described through 2020, compared to the actual GDP developments. Still, The Netherlands example is used for illustration purposes (figure 8). All graphs start with the first quarter of 2000, for ease of comparability. We include this 19-year period before our forecasting so that the graphs can be viewed in light of the historic "trend", as we wanted to forecast according to a trend growth as explained in chapter 4. Examining the graphs without economic context, we assess the success of the forecasts by how well they seem to suggest a moderate development path relative to the estimation period. Positive economic growth is expected in all countries, except Italy, according to our forecasts. The forecast for Italy suggests no growth. Countries that experienced negative or stagnant growth in the period immediately before 2020, are forecasted to turn positive, except Italy. In these cases, the forecasting period starts with a kink upwards, *e.g.*, Finland. The transition seems smoother in the countries which exhibit positive growth at the end of 2019.

The actual GDP developments of all the countries show a decrease in the first quarter of 2020, followed by a larger relative decrease in the second quarter, and a "positive correction" in the third quarter. The magnitudes differ substantially, and the developments of the last quarter are ambiguous. As expected, the actual developments are substantially lower than the forecast throughout 2020.

7.3 Impact comparison – GDP and electricity consumption

Finally, we compare the impacts we have estimated for both of electricity consumption and GDP. Figure 9 shows, for The Netherlands, both impact estimates as a percentage deviation, where the percentages are drawn from the logarithmic scales of the actual and forecasted values. We have aggregated the electricity consumption impact in weekly intervals using the method of aggregating described in chapter 6. In Appendix H the equivalent figures per country can be found.

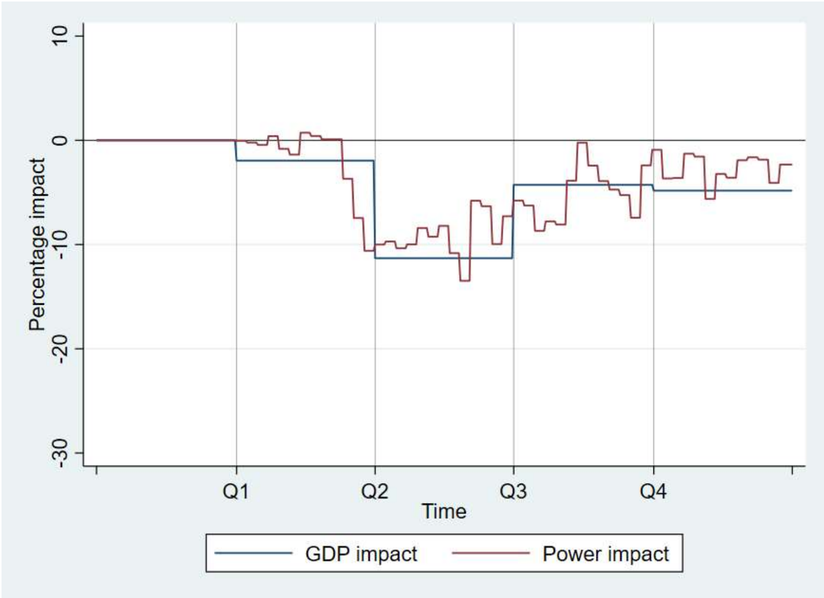

Figure 9: Comparison of change in GDP (quarterly) and electricity consumption (weekly) in The Netherlands. The labels along the horizontal axis mark the beginning of each respective quarter, so that the point "Q1" is on January 1st of 2020.

The graph of weekly electricity consumption impact has the advantage over the daily version that it cancels out much of the variation, making it an easier read. It still allows us to see quite frequently when the estimated impacts occur. From The Netherlands example, we can see how electricity consumption closely follows our forecasts through most of the first quarter, and abruptly falls at the end of the quarter. It is important to keep in mind that, although it looks like the electricity consumption impact falls down to, and thus predicts, the GDP of the second quarter, already at the end of the first quarter, that these are not comparable as they are impact estimates of different periods. The abrupt negative electricity impact at the end of the first quarter corresponds only to the relatively small negative GDP impact we see in the first quarter. However, the abrupt electricity impact in these few weeks are followed by a lengthy period of time with similar effects, which seem to align quite closely to the economic impact of the second quarter. Similarly, both impact estimates converge towards their respective forecasts in the second half of the year.

The Scandinavian countries do not show clearly the relationship that we are expecting. The Finnish electricity impact is positive most weeks of all quarters, even though the economic impact is estimated to be negative in all quarters. Norway and Denmark show little effect on its electricity impact, and one cannot claim from viewing their graphs that there exists any relationship or predictability between the impact measures. The same is true for Sweden, while it at least exhibits a somewhat negative electricity impact through most of the "pandemic part" of the year. Still, it is not clear enough that we are comfortable claiming that there is a positive relationship between the impacts. Of the continental European countries, we can generally claim that from the beginning weeks of the pandemic and through the second quarter, there is a clear positive relationship between the electricity consumption and GDP, although the magnitudes are unclear and unequal between countries. The electricity impacts are less clear in the second half of 2020. While the GDPs stay at about the same negative impact level in the third and fourth quarter, electricity impact tends towards normalizing around zero. Ironically, with regards to our stated reasons to use The Netherlands as our example case, The Netherlands' graphs seem to be the most closely following each other throughout the period.

Table 3 below shows the percentage impacts of both measures aggregated on a quarter-yearly basis. Clearly, both the economy and electricity consumption were most affected by the pandemic in the second quarter, except the Scandinavian cases, which do not show as clear an electricity consumption drop. Electricity consumption normalizes to a much greater extent through the quarters (Q3 and Q4) than economic activity levels.

Table 3: Percentage impact on electricity and GDP per quarter and country.

	Q1		*Q2*		*Q3*		*Q4*	
Country	*Electric*	*GDP*	*Electric*	*GDP*	*Electric*	*GDP*	*Electric*	*GDP*
Norway	0.4 %	-1.8 %	0.4 %	-6.8 %	1.3 %	-2.8 %	0.6 %	-2.5 %
Sweden	0.6 %	-0.6 %	-2.2 %	-8.9 %	-2.0 %	-3.0 %	0.1 %	-3.7 %
Denmark	-0.7 %	-1.8 %	-1.6 %	-9.2 %	-0.1 %	-4.5 %	-0.1 %	-4.2 %
Finland	1.9 %	-1.2 %	3.1 %	-5.7 %	1.1 %	-2.8 %	3.7 %	-2.7 %
The UK	-1.4 %	-3.5 %	-14.2 %	-24.6 %	-2.6 %	-10.2 %	0.7 %	-10.8 %
Netherlands	-1.6 %	-1.9 %	-9.2 %	-11.3 %	-5.1 %	-4.3 %	-2.7 %	-4.8 %
Germany	-1.1 %	-2.2 %	-7.5 %	-12.6 %	-4.1 %	-4.7 %	-0.3 %	-4.5 %
France	-1.7 %	-6.2 %	-8.3 %	-20.8 %	-0.4 %	-4.1 %	0.8 %	-5.9 %
Spain	-1.4 %	-5.7 %	-11.7 %	-25.7 %	-1.8 %	-10.7 %	-0.4 %	-10.5 %
Italy	-4.3 %	-5.5 %	-15.0 %	-19.4 %	-2.4 %	-4.7 %	-1.3 %	-6.7 %

Table 4: Correlation coefficients between GDP and electricity consumption impact estimates, per country.

Country	*Corr.*
Norway	0.27
Sweden	0.70
Denmark	0.70
Finland	-0.38
The UK	0.89
The Netherlands	0.94
Germany	0.88
France	0.96
Spain	0.95
Italy	0.96
All observations	*0.82*

Table 4 shows per country, the correlations between the impacts listed in table 3. The correlations, in essence, confirms our claims of the clearness of the relationships that we are looking at. The impact of the pandemic on the level of electricity consumption and economic activity in general clearly correlates on aggregated quarterly levels for the continental European countries, while the relationship is substantially weaker in Sweden and Denmark, though they seem to exist. The relationship is unclear, if not non-existent in Norway and Finland, which actually has a negative correlation.

Figure 10 below shows a scatter plot of all quarter-yearly estimated impacts denoted in percentages. It shows that, on average, there is an approximate two-to-one relationship from GDP impact to electricity impact. The plot is heavily distributed close to zero electricity impact, which makes the results quite uncertain in applicability to specific cases.

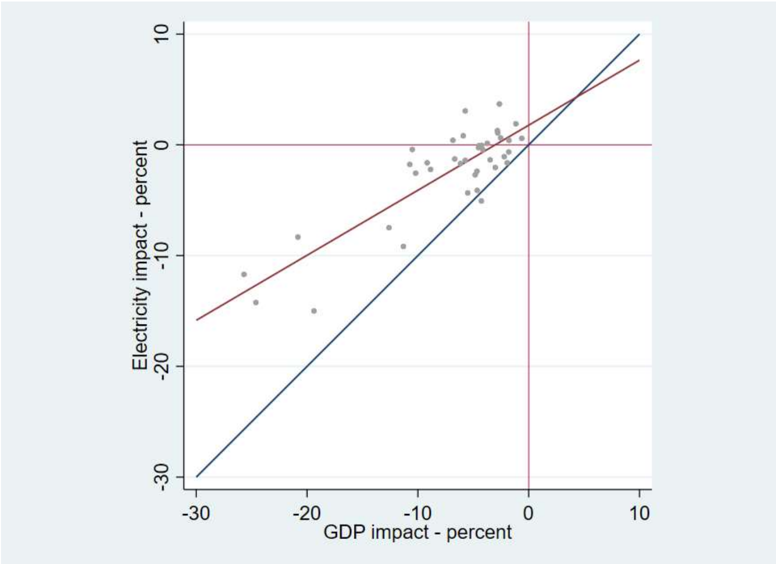

Figure 10: Scatter plot of the impacts. The horizontal axis shows GDP impact, and the vertical axis shows the electricity impact. The axes are quadratic, and the blue line is a 45-degree line through the origin, which represent a hypothetical best fit line with a perfect one-to-one relationship between the impacts, for reference. The red line through the scatter plot is the actual best fit line.

7.4 Results summary

In summary, we have found that all countries show a quite similar pattern of negative economic impact of the pandemic through 2020, although the exact magnitudes differ significantly. Electricity consumption impacts, according to our forecasts, have been much less clear. While we find that electricity consumption is way down in continental Europe, the Scandinavian countries do not show the same tendency. The impacts of the pandemic are abrupt and large from the beginning of the first wave at the end of the first quarter of 2020, and through the second quarter. The economic activity levels continue to be low through the second half of the year, while electricity consumption eventually catches up to the "normal" levels, which is our forecasts.

8. Discussion

8.1 Modelling electricity consumption – alternative methods

Our results depend heavily on the effectiveness and preciseness of our electricity consumption models' ability to forecast correctly electricity consumption during times of normal economic activity levels. Generally, our assessment of our models is that they leave room for improvement. Though they somewhat reveal what we are interested in when aggregating the forecasts on larger periods than a single day, the day-to-day variability is considerable, even during the period in which they are estimated, which can be seen in the forecasting errors figures on the left side of the vertical line (Appendix F).

Our modelling of electricity consumption has relied on a generalized method, which has the advantage of being easily and quickly applicable to many cases, while it may suffer from weaknesses that specific and tailor-made models could improve upon. Such models could i) treat variables differently, ii) omit unnecessary variables that does little to nothing in explaining electricity consumption, or iii) add new variables important in explaining specific cases.

Alternative variants of our included variables

The way we have treated temperature in our models could be altered in various ways. We have already discussed how the inclusion of several locations generally helped in making the models stronger with regard to total explained variation, we have also seen the effect of including a third location to vary between countries. It is realistic to assume that a more specific modelling process would have resulted in some countries' electricity consumption to be better modelled on less than three locations, or maybe more. The threshold level of cooling and heating could also be assessed on a case-by-case basis. While we have discussed how the standard thresholds differ between the US and Europe, we also believe that different levels could be appropriate in countries with such large climatic differences as Finland and Spain. Leaving a gap between cooling and temperature, a so called "comfort zone", could also be appropriate.

We have also discussed how holidays can be implemented various ways. We have large variation in the coefficients of holidays in our models. We believe it to be realistic that not all holidays have an equal effect on electricity consumption, thus it may be appropriate to categorize these more specifically for some countries. We have also assumed that the holiday data we have been able to find is an appropriate representation of holidays per country. We have little insight in the importance of each holiday, and how they affect people's behavioural patterns, per country. One example of a holiday's effect which possibly has been underestimated for some countries, is that of New Year's Day. We observe that our models' predictions are too high for this day. This also apply to January 2nd, which is not a holiday, but maybe a de-facto holiday in some countries.

For some countries, there is little difference between the normal working days of the week. In such cases, it may be suitable to only include a weekend-specific dummy, for example. The week and year indicator variables, when included, we cannot see a reasonable alternative way to use.

Omitting, adding, or switching variables

We have seen how including year specific indicators can be used in explaining the long run structural changes in the consumption patterns of electricity. Likewise, week indicators can be used to explain regular seasonal variations. Alternatives to both these variables, could be to omit week variables, and rather use month indicators in their place. We do not believe omitting seasonal variables altogether can be a viable option, as we have observed that they help considerably in explaining consumption variation. The problem of using month indicators, which already is a potential problem of using year indicators, is that they may create steps at the changing of month, or year, if their coefficients are large. One could also use quarter-yearly indicators as a hybrid between a seasonal and long run explanatory variable.

We do not really observe much use of other included variables in high frequency electricity modelling of the kind we are interested in. However, we thought about the way in which temperature affect consumption levels, and how this effect may not be suited to be one fixed coefficient for all days. If weekend electricity consumption is relatively more affected by household consumption than that of normal working days, and household electricity consumption is differently affected by temperature than industrial and commercial consumption, could it not be the case that temperature's effect on electricity consumption will be unequal on a Saturday compared to a Wednesday? A similar argument could also be made, and maybe even more legitimately, for various seasonal temperature variables.

8.2 GDP forecasts comparison to IMF estimates

The normal variation, in recent years, in GDP is small compared to the large volatility that has been seen during 2020. Because of this, the exact level one sets as the forecasted level to compare with the actual level does not change the conclusions by much, in the end. This is if the forecast level one uses is moderate. We have modelled our own forecasts for GDP, but we do acknowledge, of course, that our modelling is very simple and not economical of nature. History does not tell what the future brings, so we do not really think it is correct to use such simple methods to forecast GDP, generally. Nevertheless, we believe we have explained thoroughly enough already the rationale behind our choice.

If instead of trying to forecast GDP, we were to let the professionals do the job for us, we could have fetched these probably more qualified forecasts, and used them for comparing in place of our own. To see how this could have affected our results, we present the IMF's forecasts for GDP of 2020, published in the autumn of 2019 (International Monetary Fund, 2019). From table 5 we can see how the IMF, in 2019, had a somewhat more positive outlook on the economic performance of European countries than our forecasting. All, except The Netherlands, are thought to experience higher growth according to the IMF. By only a tiny margin, we overestimate on IMF's forecast for The Netherlands. We are aligned with IMF within 0.5 percentage points for half the countries, and we miss by up to 1.25 percentage points, for Finland. Finland was already the country which showed results furthest from our expectations. By IMF's forecasts, the hypothesis of a positive relation of impacts would have weakened further for the case that is Finland.

Table 5: GDP forecast comparison, between our own and IMF's estimates

Country	*Our estimate*	*IMF's estimate*	*Difference*
Norway	2.18 %	2.44 %	-0.26
Sweden	0.98 %	1.46 %	-0.48
Denmark	1.54 %	1.91 %	-0.37
Finland	0.22 %	1.47 %	-1.25
The UK	1.32 %	1.45 %	-0.13
The Netherlands	1.68 %	1.64 %	0.04
Germany	0.51 %	1.25 %	-0.74
France	0.44 %	1.26 %	-0.82
Spain	1.28 %	1.85 %	-0.57
Italy	-0.47 %	0.54 %	-1.01

Note: The table shows per country, our estimated GDP change in 2020 from 2019, according to the results from the AR models. The quarter-yearly log of GDP estimates have been converted to estimates of GDP, using the method described in the method section, for our forecasts of 2020. Our estimates for GDP of 2020 are then summed up. For 2019 GDP, we simply use the raw data to aggregate on. The percentages in the column "*Our estimate*" are the logarithmic change from 2019 and 2020.

The IMF estimates have been retrieved from the World Economic Outlook, October 2019 (International Monetary Fund, 2019).

8.3 What causes the differences in results from case to case?

What is it about the situation in Scandinavia that makes the electricity to GDP relationship more unclear than in continental Europe during the pandemic? We try to point to some factors which could explain the causes of differing results between countries with regards to our research question.

Productive sector versus residential sector consumption

Only analysing the total aggregated electricity consumption of a region or country has the disadvantage of not separating differences occurring in the impact of various sectors. If the short run relationship that we hypothesize is caused by electricity as an input in production, the results could be diluted by the effects on non-industrial sectors' electricity consumption. Between countries, comparability may suffer from sectoral size and electricity consumption variation.

Table 6: Share of total electricity consumption by customer classes

Country	*Residential*	*Productive*	*Commercial*	*Industrial*	*Other*
Norway	35 %	65 %	22 %	41 %	3 %
Sweden	35 %	65 %	22 %	40 %	3 %
Denmark	31 %	69 %	34 %	28 %	7 %
Finland	27 %	73 %	22 %	48 %	3 %
UK	35 %	65 %	31 %	31 %	3 %
Netherlands	21 %	79 %	34 %	33 %	11 %
Germany	25 %	75 %	27 %	45 %	3 %
France	36 %	64 %	31 %	28 %	4 %
Spain	31 %	69 %	31 %	33 %	4 %
Italy	22 %	78 %	32 %	40 %	6 %

Note: The shares are calculated based on data from IEA's websites (International Energy Agency, 2020), using the indicator called "Electricity final consumption by sector".

From table 6 it is not easy to see from the pre-pandemic sectoral electricity consumption shares any patterns that may describe the differences occurring in the results between countries (International Energy Agency, 2020). There are countries with relatively high and low residential consumption shares that show more clearly a relationship, for example France and the UK, respectively. Likewise, the cases of Norway and Finland demonstrate less correlations, while they also exhibit widely varying residential consumption shares. Thus, we find that this factor alone is not suited to explain the variation in our results. Similarly, we cannot clearly see that differences in relative sizes of commercial and industrial sectors matter much either. The IEA has only updated this statistic up to including 2018 consumption. For this reason, changes in consumption shares for 2020 has not been analysed, but we believe that these may be used in the future to help explaining the variability in results we find.

Cicala (2020b) estimates, for the US, changes in sectoral electricity consumption during the second quarter of 2020, finding that the productive sectors' consumption decreases, and that residential consumption has increased. The article also finds a positive association between the share of the labour force able to work from home, and the increase in electricity consumption. This may indicate that the difference of relationship may be diluted more heavily by the residential sector inclusion in countries with a larger portion of potential home offices.

Differences in pandemic severity and mitigation policy measures

Another part that can explain the differing results, might also be the country-specific heterogeneity of the pandemic, in as the various responses and contagion, but also simply cultural/societal differences between countries led to different societal impacts. As shown in table 3, it is clear that the countries with the least impact on GDP (Scandinavia) also have very small impact if any on the electricity consumption. Given an equal margin of error, correlations in cases of small changes is likely to be less clear compared to cases of larger impacts.

Table 7: Countries arranged from "best to worst" by the number of deaths per 1 000 000 people by the end of 2020

Country	Total deaths per million
Norway	80.4
Finland	101.3
Denmark	224.1
Germany	403.3
The Netherlands	672.6
Sweden	864.1
France	992.1
The United Kingdom	1084.5
Spain	1087.3
Italy	1226.5

Note: Data collected Our World in Data's websites (Johns Hopkins University Center for Systems Science and Engineering (JHU CSSE), 2020)

Speaking of the difference in policy measures it seems that most consumer behavioural changes may mostly be due to fear of infection and not the force of lockdown (Sheridan, 2020). This can also be seen through the example of Sweden, where the downturn has been just as clear as in the other countries, although they differ in political responses (European Centre for Disease Prevention and Control, 2021a). Despite Sweden's more "loose" NPIs, it is still more comparable to the other Scandinavian countries in terms of economic impact. However, from table 7 we see that they had quite a different situation, more similar to continental Europe, in terms of deaths per million. Otherwise, the rest of the countries' mortality rates are aligned quite closely to economic impacts of the pandemic.

The societal differences mentioned include how the general level of hygiene was before the pandemic, that may lead to certain countries more easily containing virus spread. But also, how do people generally live? If they are poor, how easy is it to socially distance in daily life, and what kind of jobs do they have? It may be easier to stop the virus if people in general have higher standards of living (both at home and at work). In the end our findings show that the non-Scandinavian countries was harder affected by the Covid-19 pandemic in terms of drop in electricity consumption and GDP levels, and they also have the highest correlation between GDP impact and electricity consumption impact. This could mean that Nordic countries in general and their residents everyday living is more adaptable in a situation in need of social distancing and other measures to fight a pandemic.

8.4 Why does electricity seem to normalize, while economic activity remains low?

The evolution of the time series in the fourth quarter of 2020, where the electricity consumption seems to rise up to, or close to, the levels before the pandemic, while the GDP numbers does not, is somewhat of a question to us. Is there a lag in the normalization process between the electricity use and the economy? Looking at time series for the U.S. during five earlier recessions there might be empirical evidence of such (Arora & Lieskovsky, 2016). The article finds that during all the recessions assessed, the electricity retail sales series is rising before the GDP growth rates rises, and for all except one, the downturn in consumption first starts after the start of the recession. So, as this has similarities to the series we are looking at, we might expect that the two series would move closer again in the first quarter of 2021. It also depends on whether the Covid-19 crisis is a shock that actually can be compared to earlier economic downturns or not.

9. Conclusion

The research question of this thesis can be described in two parts. First, could the economic impact of the Covid-19 pandemic on European countries precisely and predictably be described through 2020, by analysing changes in high frequency electricity consumption/load data? Second, given some relationship, what are the relative magnitudes between changes in economic activity and electricity consumption?

In answering these questions, we have used hourly load data for ten European countries, which we have aggregated to daily observations. We have modelled and forecasted electricity consumption using temperature and time-specific variables, to get an estimate of "non-pandemic" consumption levels to compare with the actual consumption levels. We describe our measured difference between the forecast and actual levels as the impact of the pandemic. Likewise, we model quarterly GDP, and estimate an economic impact as well. We analyse the impact on economic activity and electricity consumption visually by graphs, aggregating our results for electricity consumption impacts on a weekly basis to show how electricity consumption developed through each quarter.

We find that there are clear correlations between the quarter-yearly aggregated impacts on electricity consumption and economic activity in the six continental European countries we analyse, while the results are less clear to non-existent among the four Scandinavian cases. The same can be found through visual analysis of weekly aggregated electricity consumption impacts, although the volatility from week-to-week is quite large in most cases. Of those countries we conclude to exhibit the expected positive relationship, the magnitudes differ significantly and most often the economic impact is larger than the electricity consumption impact. We find that the relationship was clearer and more as expected early on in the course of the pandemic, than towards the end of 2020, when electricity consumption seemed to normalize, while economic activity levels remained low.

Thus, from our analysis we cannot conclude that there generally exists a relationship, so clear in direction and magnitude, that it could be used to understand, precisely and predictably, the extent of the economic downfall during 2020, following from the pandemic and consequent policy measures. This does not mean that we do not conclude a relationship at all. As stated, in continental Europe we see a clear simultaneous impact in both factors, although not equal in magnitude. Something close to a one-to-one relationship can be found only in The Netherlands.

We have limited our research to only analysing aggregated power load data per country. It would be sound to redo our analysis using power data from only productive sectors, as residential sector consumption may blur the results. Economic activity is analysed only by quarter-yearly GDP, while including other economic indicators, *e.g.*, unemployment, could help in providing a fuller picture.

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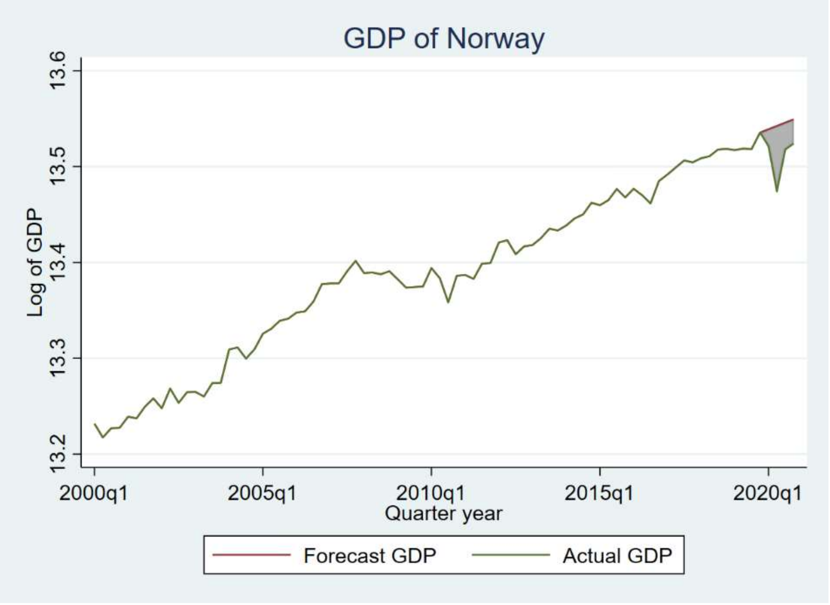
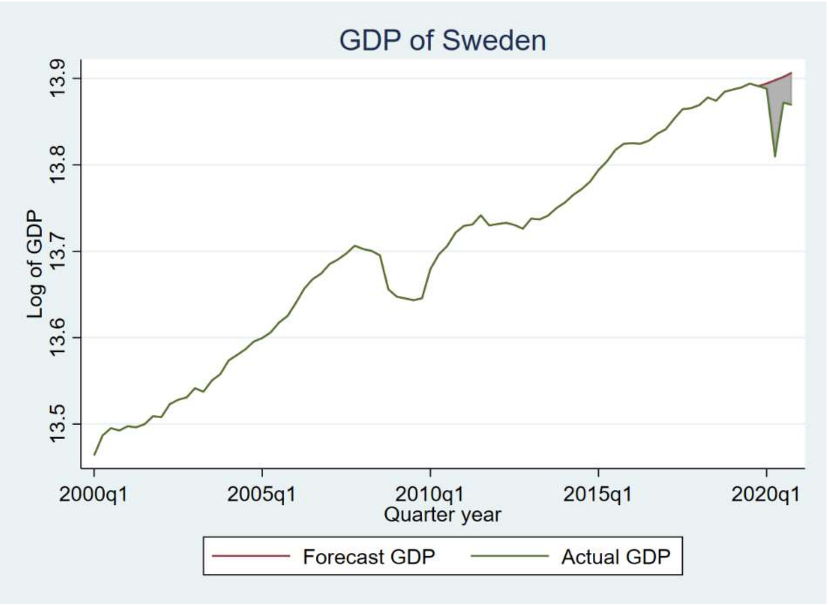
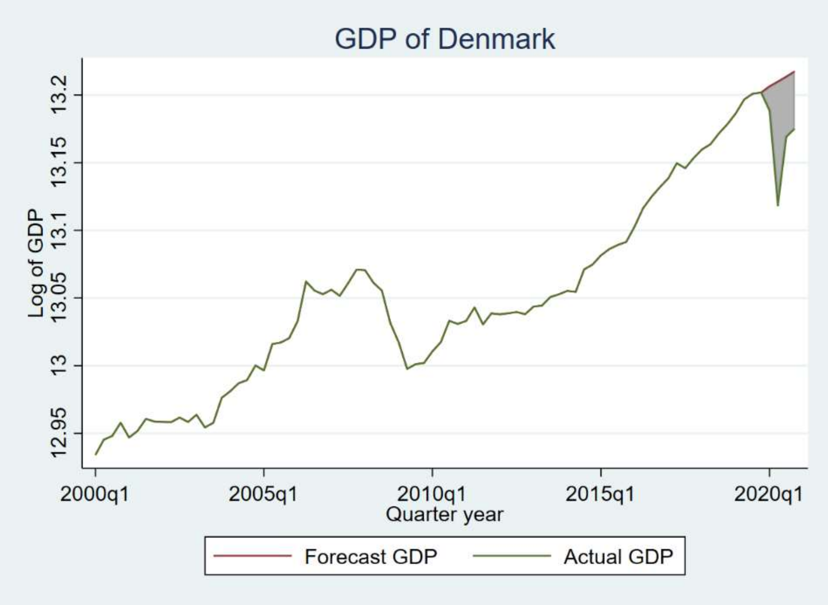
11. Appendices

Appendix A – GDP forecast 2020

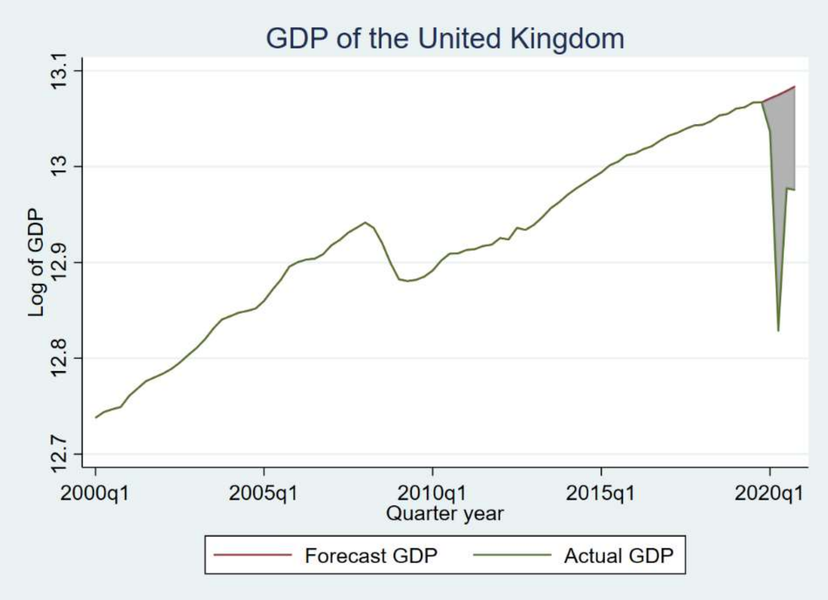
The following figures show GDP developments, per country, from 2000 through 2020, quarter-yearly noted. For 2020, we also include the results of our forecasts on GDP. The gray-shaded area, between the two graphs, represents the estimated economic downfall during the first year of the pandemic.



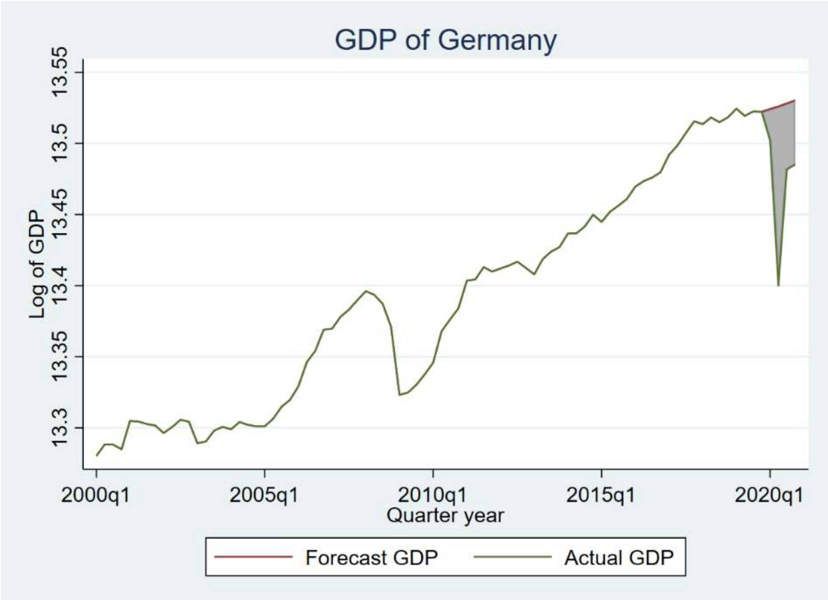


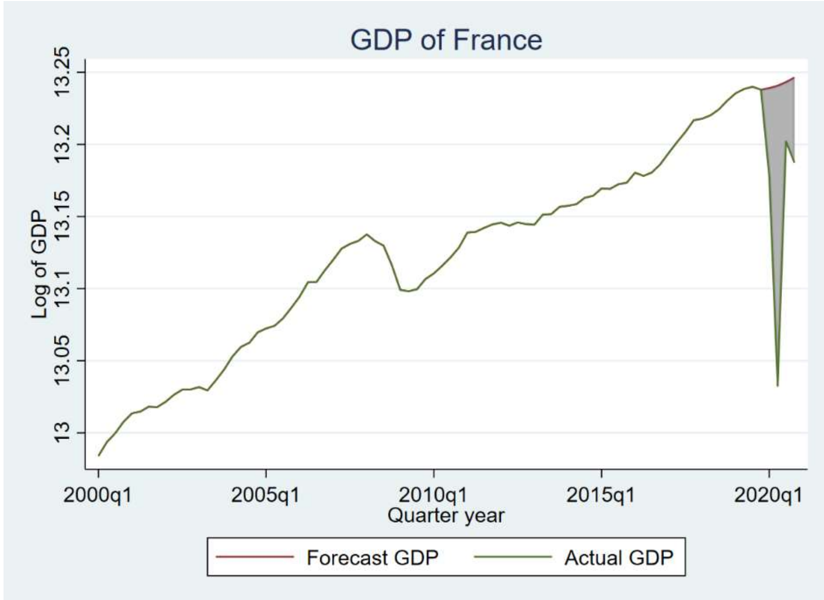

GDP of Denmark
Log of GDP
12.95
13
13.05
13.1
13.15
13.2
2000q1
2005q1
2010q1
2015q1
2020q1
Quarter year
Forecast GDP
Actual GDP


GDP of Finland
Log of GDP
10.5
10.6
10.7
10.8
10.9
2000q1
2005q1
2010q1
2015q1
2020q1
Quarter year
Forecast GDP
Actual GDP

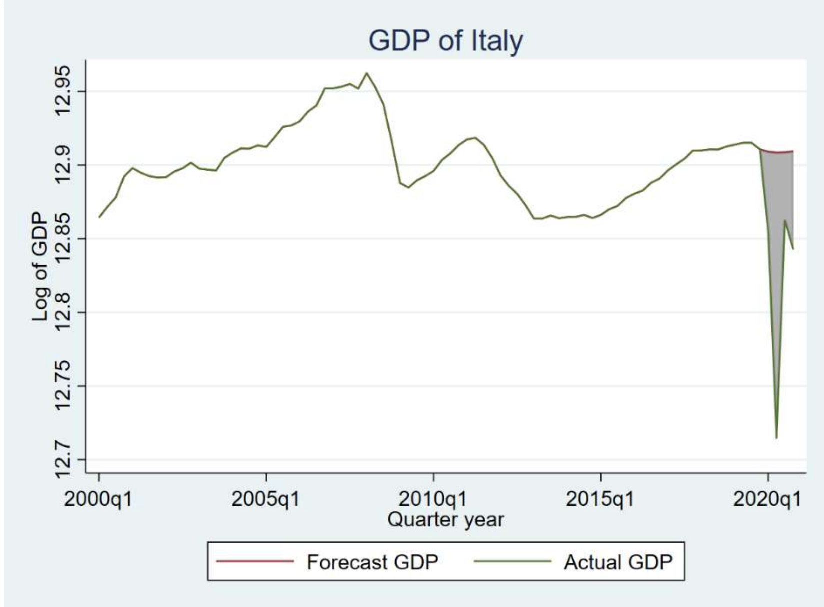

GDP of the United Kingdom
Log of GDP
12.7
12.8
12.9
13
13.1
2000q1
2005q1
2010q1
2015q1
2020q1
Quarter year
Forecast GDP
Actual GDP


GDP of the Netherlands
Log of GDP
11.8
11.9
12
12.1
12.2
2000q1
2005q1
2010q1
2015q1
2020q1
Quarter year
Forecast GDP
Actual GDP


GDP of Germany
Log of GDP
13.3
13.35
13.4
13.45
13.5
13.55
2000q1
2005q1
2010q1
2015q1
2020q1
Quarter year
Forecast GDP
Actual GDP


GDP of France
Log of GDP
13
13.05
13.1
13.15
13.2
13.25
2000q1
2005q1
2010q1
2015q1
2020q1
Quarter year
Forecast GDP
Actual GDP


GDP of Spain
Log of GDP
12.3
12.4
12.5
12.6
2000q1
2005q1
2010q1
2015q1
2020q1
Quarter year
Forecast GDP
Actual GDP


GDP of Italy
Log of GDP
12.7
12.75
12.8
12.85
12.9
12.95
2000q1
2005q1
2010q1
2015q1
2020q1
Quarter year
Forecast GDP
Actual GDP

Appendix B – Temperature data locations

Country	*Station ID*	*Location*	*Missing*	*Share*	*Missing 2020*	*Share 2020*
Denmark	EKCH	Copenhagen - Kastrup	20	0.04 %	0	0.00 %
Denmark	EKYT	Aalborg	67	0.13 %	0	0.00 %
Denmark	EKAH	Aarhus	19	0.04 %	0	0.00 %
Finland	EFVA	Vaasa	88	0.17 %	15	0.17 %
Finland	EFJY	Jyvaskyla	14	0.03 %	5	0.06 %
Finland	EFHK	Helsinki	4	0.01 %	3	0.03 %
France	LFLL	Lyon	20	0.04 %	1	0.01 %
France	LFBO	Toulouse	28	0.05 %	0	0.00 %
France	LFPG	Paris - CdG	8	0.02 %	3	0.03 %
Germany	EDDL	Düsseldorf	1	0.00 %	0	0.00 %
Germany	EDDB	Berlin - Schönenfeld	1	0.00 %	0	0.00 %
Germany	EDDS	Stuttgart	2	0.00 %	0	0.00 %
The United Kingdom	EGLL	London	1	0.00 %	0	0.00 %
The United Kingdom	EGGD	Bristol	48	0.09 %	19	0.22 %
The United Kingdom	EGNT	Newcastle	165	0.31 %	21	0.24 %
Italy	LIRF	Rome - Fiumicino	121	0.23 %	6	0.07 %
Italy	LIBD	Bari	294	0.56 %	48	0.55 %
Italy	LIMF	Torino	130	0.25 %	30	0.34 %
Norway	ENGM	Oslo - Gardermoen	6	0.01 %	2	0.02 %
Norway	ENVA	Trondheim	32	0.06 %	3	0.03 %
Norway	ENBO	Bodø	10	0.02 %	0	0.00 %
Spain	LEBL	Barcelona	3	0.01 %	0	0.00 %
Spain	LEGR	Granada	191	0.36 %	0	0.00 %
Spain	LEMD	Madrid	1	0.00 %	0	0.00 %
Sweden	ESSA	Stockholm - Arlanda	67	0.13 %	3	0.03 %
Sweden	ESMS	Malmö	56	0.11 %	5	0.06 %
Sweden	ESNU	Umeå	96	0.18 %	19	0.22 %
The Netherlands	EHEH	Eindhoven	364	0.69 %	0	0.00 %
The Netherlands	EHRD	Rotterdam	6	0.01 %	0	0.00 %
The Netherlands	EHAM	Amsterdam	8	0.02 %	0	0.00 %

Note: The table shows the location of recorded temperature that we use, and the weather station identifier code. It contains three separate locations per country. For some locations that are airports, we have noted the airport name after the name of corresponding city. The *Missing* column and *Missing 2020* note how many missing, interpolated, observations are in each location's data, in respectively, the full period 2015-2020 and in 2020. The *Share* columns are the percentage of observations in said periods that are interpolated.

Source: (Iowa Environmental Mesonet, 2021)

Appendix C – Official holidays and non-working days

Holiday	*Type*	*Date*	*NO*	*SE*	*DK*	*FI*	*UK*	*NL*	*DE*	*FR*	*ES*	*IT*
New Year's Day	General	Jan 1	X	X	X	X	X	X	X	X	X	X
Maundy Thursday	Religious	NA	X		X							
Good Friday	Religious	NA	X	X	X	X	X	X	X		X	
Easter Sunday	Religious	NA	X	X	X			X				X
Easter Monday	Religious	NA	X	X	X	X		X	X	X		X
Labour Day	General	May 1	X	X	X	X			X	X	X	X
Ascension Day	Religious	NA	X	X	X	X		X	X	X		
Whit Sunday	Religious	NA	X	X	X			X				
Whit Monday	Religious	NA	X		X			X	X	X		
Christmas Day	Religious	Dec 25	X	X	X	X	X	X	X	X	X	X
Boxing Day	Religious	Dec 26	X	X	X	X	X	X	X			X
National Day	National	NA	X	X	X	X		X	X	X	X	X
Epiphany	Religious	Jan 6		X		X					X	X
Midsummer Day	General	NA		X		X						
All Saint's Day	Religious	NA		X		X				X	X	X
King's Birthday	National	Apr 27						X				
Assumption of Mary	Religious	Aug 15								X	X	X
Immaculate Conception	Religious	Dec 8									X	X
Hispanic Day	National										X	
Victory Day	National	May 8								X		
Armistice Day	National	Nov 11								X		
Bank - May	Bank	NA					X					
Bank - Spring	Bank	NA					X					
Bank - Boxing	Bank	NA					X					
Liberation Day	National	Apr 25										X

Note: The table marks, per country, official holidays and non-working days. Type indicates the nature of the holiday, as we understand it. Date is noted for holidays which land on the same date, each year, in each relevant country. Not all holidays are celebrated each year. Some countries operate with substitute holidays if certain holidays land on a weekend. In these cases, we have used the substitute day as a holiday.

Source: (Time and Date AS, 2021)

Appendix D – Results of unit roots testing of GDP time series

Country	DF testing, I(0)								Conclusion	DF testing, I(1)	
	BIC (1)	DF (1)	t=0	BIC (2)	DF (2)	a=0	BIC (3)	DF (3)		BIC (4)	DF (4)
NO	1	0.974	0.399	1	0.024*				Reject unit roots - stationary series, I(0).		
SE	5	0.736	0.132	5	0.095	0.006*			Unit roots - random walk with drift, test I(1).	4	0.000*
DK	0	0.723	0.121	0	0.170	0.069	0	1	Unit roots - random walk, test I(1).	0	0.000*
FI	0	0.968	0.259	0	0.034*				Reject unit roots - stationary series, I(0).		
UK	2	0.755	0.167	2	0.212	0.007*			Unit roots - random walk with drift, test I(1).	1	0.000*
NL	1	0.249	0.029*						Unit roots - random walk with trend, test I(1).	0	0.000*
DE	2	0.017*							Reject unit roots - stationary series, I(0).		
FR	2	0.702	0.141	2	0.063	0.001*			Unit roots - random walk with drift, test I(1).	1	0.000*
ES	1	0.396	0.059	1	0.011*				Reject unit roots - stationary series, I(0).		
IT	1	0.261	0.028*						Unit roots - random walk with trend, test I(1).	0	0.000*

The table shows the results of our unit roots testing of the GDP time series per country. The procedure is described in the method section. The number in parentheses besides BIC and DF note the step of the "elimination" process: 1 – testing unit roots including trend, 2 – testing unit roots including a drift term, and 3 - testing unit roots without trend or drift. The BIC columns show the recommended, and tested number of lags according to the BIC per variant of the DF test. The numbers in the rest of the columns indicate the p-value of each test. "t=0" signifies the F-test on trend and the lag of GDP. "a=0" signifies the F-test on the constant and the lag of GDP.

The series concluded to be integrated of order 1, I(1), have been tested again, to see if the difference in GDP time series contains unit roots. All of them are highly significant. These time series have been modelled on the difference form of GDP.

* symbolizes that a test is significant within the 5 percent critical value, in which we may conclude on the properties of the time series.

Appendix E – Regression outputs of electricity models

The following tables show the regression outputs, per country, of our electricity models on daily electricity consumption from 2015, through 29 February 2020.

Forecasting Load Norway

	Electricity consumption	Std. Error
Coolingdegrees Oslo	-0.0028***	(0.00088)
Heatingdegrees Oslo	0.0102***	(0.00034)
Coolingdegrees Trondheim	0.0007	(0.00077)
Heatingdegrees Trondheim	0.0022***	(0.00034)
Coolingdegrees Bodø	0.0001	(0.00088)
Heatingdegrees Bodø	0.0026***	(0.00042)
Holiday dummy	-0.0711***	(0.00420)
Observations	1886	
R^2	0.988	
Adjusted R^2	0.987	
Joint F-stats Weekday dummy	606.44¤¤¤	
Joint F-stats Week dummy	51.84¤¤¤	
Joint F-stats Year dummy	31.44¤¤¤	
Joint F-stats heating	692.22¤¤¤	
Joint F-stats cooling	3.34¤	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
¤ F-prob<0.05, ¤¤ F-prob<0,01, ¤¤¤ F-prob<0,001

Forecasting Load Sweden

	Electricity consumption	Std. Error
Coolingdegrees Stockholm	0.0004	(0.00124)
Heatingdegrees Stockholm	0.0079***	(0.00044)
Coolingdegrees Malmø	0.0012	(0.00150)
Heatingdegrees Malmø¸	0.0076***	(0.00044)
Coolingdegrees Umeå	0.0002	(0.00119)
Heatingdegrees Umeå	0.0019***	(0.00033)
Holiday dummy	-0.0935***	(0.00471)
Observations	1886	
R^2	0.981	
Adjusted R^2	0.980	
Joint F-stats Weekday dummy	674.27¤¤¤	
Joint F-stats Week dummy	50.52¤¤¤	
Joint F-stats Year dummy	2.42¤	
Joint F-stats heating	886.77¤¤¤	
Joint F-stats cooling	0.81	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
¤ F-prob<0.05, ¤¤ F-prob<0,01, ¤¤¤ F-prob<0,001

Forecasting Load Denmark

	Electricity consumption	Std. Error
Coolingdegrees København	0.0072***	(0.00142)
Heatingdegrees København	0.0065***	(0.00120)
Coolingdegrees Aalborg	0.0102***	(0.00189)
Heatingdegrees Aalborg	0.0048***	(0.00129)
Coolingdegrees Aarhus	-0.0078***	(0.00233)
Heatingdegrees Aarhus	-0.0025	(0.00144)
Holiday dummy	-0.1433***	(0.00654)
Observations	1886	
R^2	0.940	
Adjusted R^2	0.937	
Joint F-stats Weekday dummy	1187.46¤¤¤	
Joint F-stats Week dummy	28.92¤¤¤	
Joint F-stats Year dummy	39.38¤¤¤	
Joint F-stats heating	90.22¤¤¤	
Joint F-stats cooling	47.95¤¤¤	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
¤ F-prob<0.05, ¤¤ F-prob<0,01, ¤¤¤ F-prob<0,001

Forecasting Load Finland

	Electricity consumption	Std. Error
Coolingdegrees Helsinki	0.0027	(0.00167)
Heatingdegrees Helsinki	0.0056***	(0.00074)
Coolingdegrees Jyvaskyla	-0.0024	(0.00222)
Heatingdegrees Jyvaskyla	0.0031***	(0.00065)
Coolingdegrees Vaasa	0.0014	(0.00158)
Heatingdegrees Vaasa	0.0016**	(0.00056)
Holiday dummy	-0.0671***	(0.00533)
Observations	1886	
R^2	0.964	
Adjusted R^2	0.963	
Joint F-stats Weekday dummy	598.61¤¤¤	
Joint F-stats Week dummy	32.32¤¤¤	
Joint F-stats Year dummy	28.57¤¤¤	
Joint F-stats heating	500.67¤¤¤	
Joint F-stats cooling	1.98	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
¤ F-prob<0.05, ¤¤ F-prob<0,01, ¤¤¤ F-prob<0,001

Forecasting Load The United Kingdom

	Electricity consumption	Std. Error
Coolingdegrees London	0.0028	(0.00169)
Heatingdegrees London	0.0103***	(0.00115)
Coolingdegrees Bristol	-0.0025	(0.00216)
Heatingdegrees Bristol	-0.0006	(0.00128)
Coolingdegrees Newcastle	0.0028	(0.00267)
Heatingdegrees Newcastle	0.0030***	(0.00069)
Holiday dummy	-0.1396***	(0.01014)
Observations	1886	
R^2	0.939	
Adjusted R^2	0.937	
Joint F-stats Weekday dummy	704.58¤¤¤	
Joint F-stats Week dummy	55.31¤¤¤	
Joint F-stats Year dummy	166.36¤¤¤	
Joint F-stats heating	229.87¤¤¤	
Joint F-stats cooling	2.53	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
¤ F-prob<0.05, ¤¤ F-prob<0,01, ¤¤¤ F-prob<0,001

Forecasting Load The Netherlands

	Electricity consumption	Std. Error
Coolingdegrees Amsterdam	0.0102***	(0.00272)
Heatingdegrees Amsterdam	0.0067***	(0.00179)
Coolingdegrees Eindhoven	-0.0001	(0.00190)
Heatingdegrees Eindhoven	-0.0012	(0.00090)
Coolingdegrees Rotterdam	-0.0038	(0.00268)
Heatingdegrees Rotterdam	-0.0028	(0.00186)
Holiday dummy	-0.1211***	(0.01033)
Observations	1886	
R^2	0.917	
Adjusted R^2	0.914	
Joint F-stats Weekday dummy	1396.82¤¤¤	
Joint F-stats Week dummy	43.35¤¤¤	
Joint F-stats Year dummy	5.90¤¤¤	
Joint F-stats heating	18.94¤¤¤	
Joint F-stats cooling	34.02¤¤¤	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
¤ F-prob<0.05, ¤¤ F-prob<0,01, ¤¤¤ F-prob<0,001

Forecasting Load Germany

	Electricity consumption	Std. Error
Coolingdegrees Berlin	0.0031***	(0.00071)
Heatingdegrees Berlin	0.0011*	(0.00057)
Coolingdegrees Düsseldorf	-0.0017*	(0.00071)
Heatingdegrees Düsseldorf	0.0010	(0.00062)
Coolingdegrees Stuttgart	0.0018*	(0.00074)
Heatingdegrees Stuttgart	0.0015**	(0.00059)
Holiday dummy	-0.2318***	(0.00680)
Observations	1886	
R^2	0.950	
Adjusted R^2	0.948	
Joint F-stats Weekday dummy	2166.14¤¤¤	
Joint F-stats Week dummy	23.88¤¤¤	
Joint F-stats Year dummy	16.52¤¤¤	
Joint F-stats heating	23.64¤¤¤	
Joint F-stats cooling	26.76¤¤¤	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
¤ F-prob<0.05, ¤¤ F-prob<0,01, ¤¤¤ F-prob<0,001

Forecasting Load France

	Electricity consumption	Std. Error
Coolingdegrees Paris	0.0020**	(0.00062)
Heatingdegrees Paris	0.0102***	(0.00075)
Coolingdegrees Lyon	0.0039***	(0.00061)
Heatingdegrees Lyon	0.0073***	(0.00075)
Coolingdegrees Toulouse	0.0007	(0.00057)
Heatingdegrees Toulouse	0.0050***	(0.00075)
Holiday dummy	-0.1362***	(0.00520)
Observations	1886	
R^2	0.976	
Adjusted R^2	0.976	
Joint F-stats Weekday dummy	778.93¤¤¤	
Joint F-stats Week dummy	62.81¤¤¤	
Joint F-stats Year dummy	12.85¤¤¤	
Joint F-stats heating	634.06¤¤¤	
Joint F-stats cooling	44.61¤¤¤	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
¤ F-prob<0.05, ¤¤ F-prob<0,01, ¤¤¤ F-prob<0,001

Forecasting Load Spain

	Electricity consumption	Std. Error
Coolingdegrees Madrid	0.0052***	(0.00068)
Heatingdegrees Madrid	0.0029***	(0.00079)
Coolingdegrees Barcelona	0.0107***	(0.00108)
Heatingdegrees Barcelona	0.0080***	(0.00088)
Coolingdegrees Granada	0.0005	(0.00095)
Heatingdegrees Granada	0.0029***	(0.00071)
Holiday dummy	-0.1746***	(0.00938)
Observations	1886	
R^2	0.921	
Adjusted R^2	0.918	
Joint F-stats Weekday dummy	2547.75¤¤¤	
Joint F-stats Week dummy	18.17¤¤¤	
Joint F-stats Year dummy	9.08¤¤¤	
Joint F-stats heating	114.41¤¤¤	
Joint F-stats cooling	104.88¤¤¤	

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
¤ F-prob<0.05, ¤¤ F-prob<0,01, ¤¤¤ F-prob<0,001

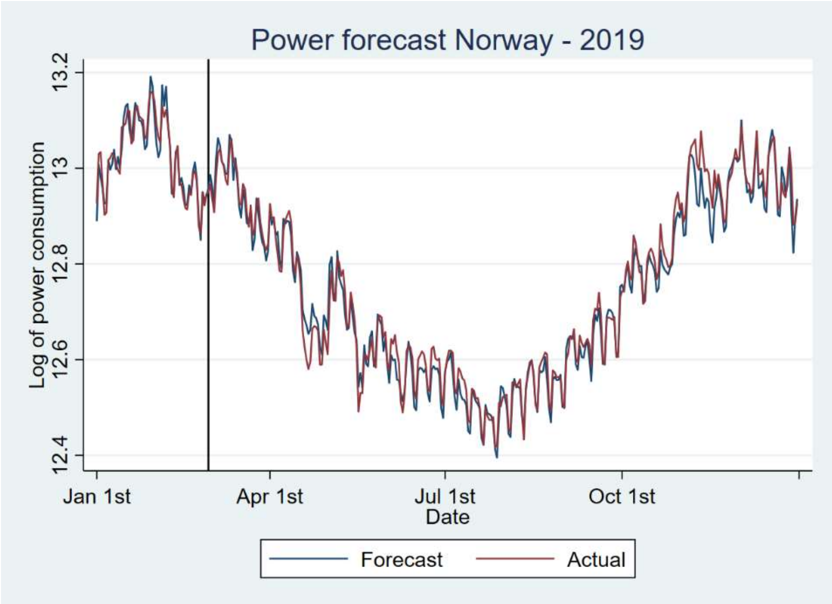
Forecasting Load Italy

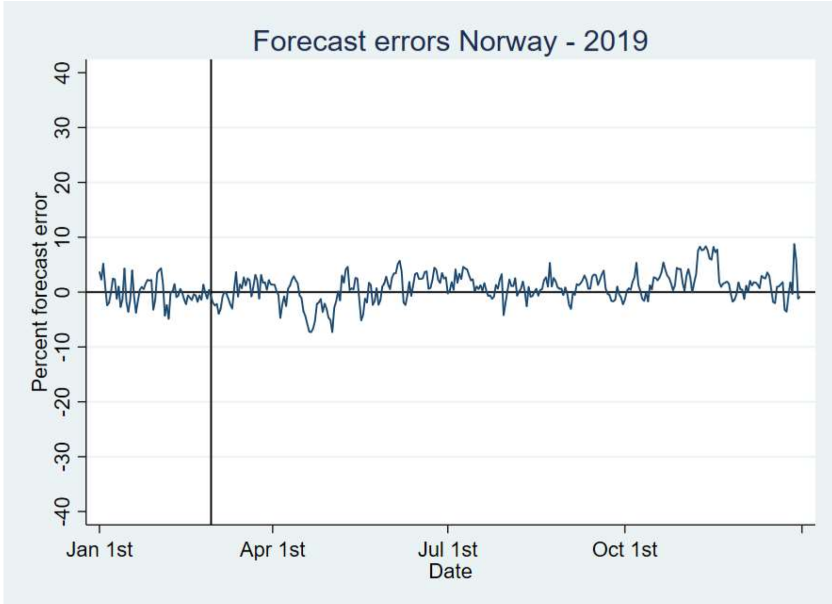
	Electricity consumption	Std. Error
Coolingdegrees Roma	0.0069***	(0.00154)
Heatingdegrees Roma	0.0023**	(0.00088)
Coolingdegrees Torino	0.0090***	(0.00092)
Heatingdegrees Torino	0.0057***	(0.00071)
Coolingdegrees Bari	0.0071***	(0.00107)
Heatingdegrees Bari	0.0027***	(0.00078)
Holiday dummy	-0.2873***	(0.00946)
Observations	1886	
R^2	0.948	
Adjusted R^2	0.946	
Joint F-stats Weekday dummy	1488.17¤¤¤	
Joint F-stats Week dummy	32.34¤¤¤	
Joint F-stats Year dummy	192.76¤¤¤	
Joint F-stats heating	76.46¤¤¤	
Joint F-stats cooling	80.33¤¤¤	

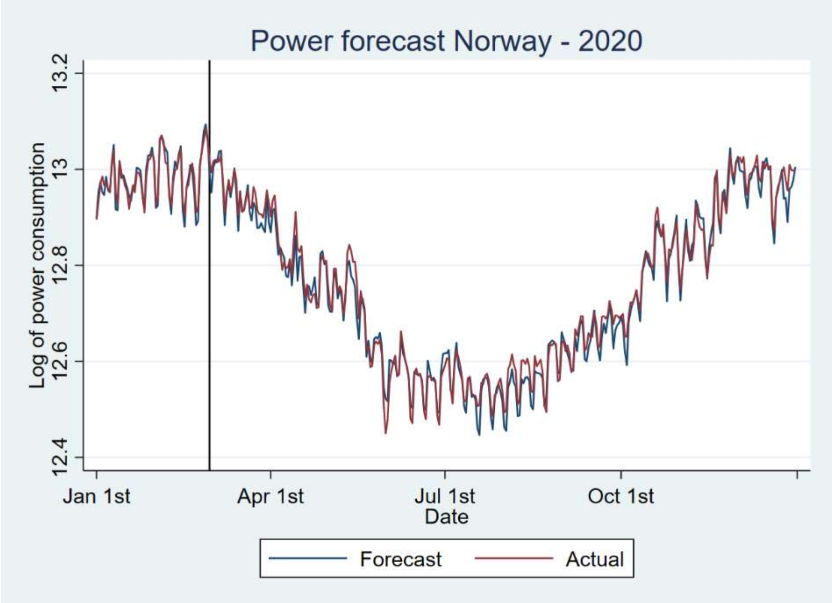
Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
¤ F-prob<0.05, ¤¤ F-prob<0,01, ¤¤¤ F-prob<0,001

Appendix F – Electricity forecasts and forecast errors (including validation)

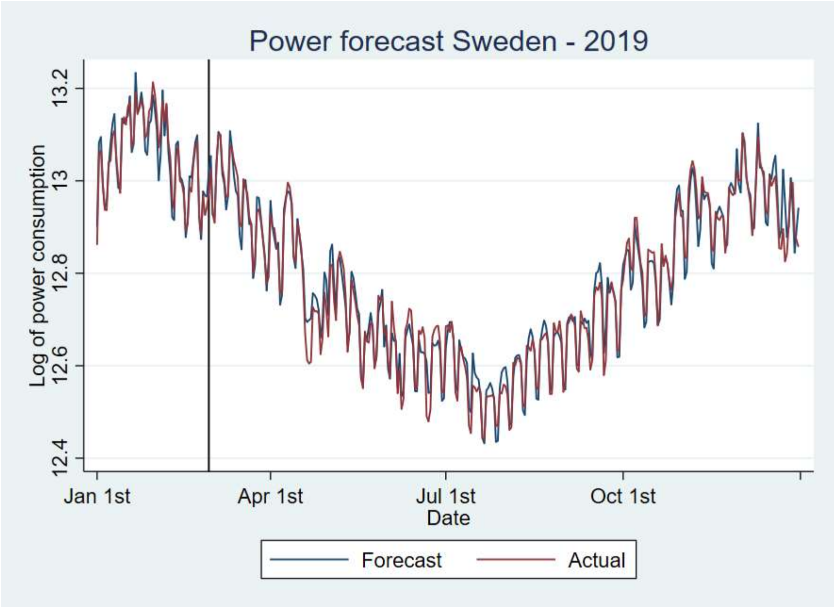
This appendix shows, one country per page, four figures. Electricity forecast – 2019, shows the results of predicting electricity consumption of 2019 based on a model estimated on the period from 2015 through February 28, 2019, compared to the actual consumption levels. The vertical line separates the estimation and forecasting periods. Likewise, electricity forecast – 2020, shows the same based on a model estimated up to February 29, 2020. The two forecast error figures show the corresponding forecast errors of the electricity forecast figures. The 2019 versions of the figures is the comparable results that hopefully shows how well the model specification works.

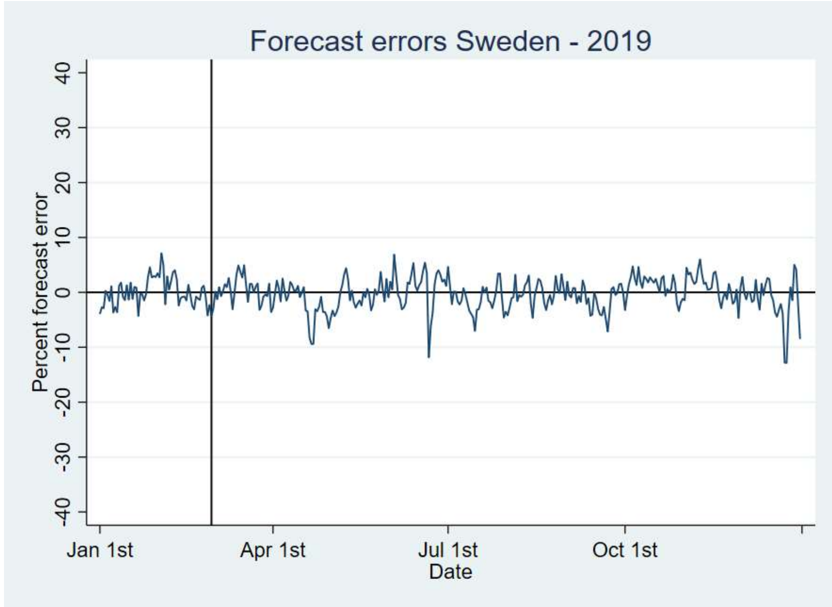

Power forecast Norway - 2019
Log of power consumption
13.2
13
12.8
12.6
12.4
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date
Forecast
Actual


Forecast errors Norway - 2019
Percent forecast error
40
30
20
10
0
-10
-20
-30
-40
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date


Power forecast Norway - 2020
Log of power consumption
13.2
13
12.8
12.6
12.4
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date
Forecast
Actual


Forecast errors Norway - 2020
Percent forecast error
40
30
20
10
0
-10
-20
-30
-40
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date


Power forecast Sweden - 2019
Log of power consumption
12.4
12.6
12.8
13
13.2
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date
Forecast
Actual


Forecast errors Sweden - 2019
Percent forecast error
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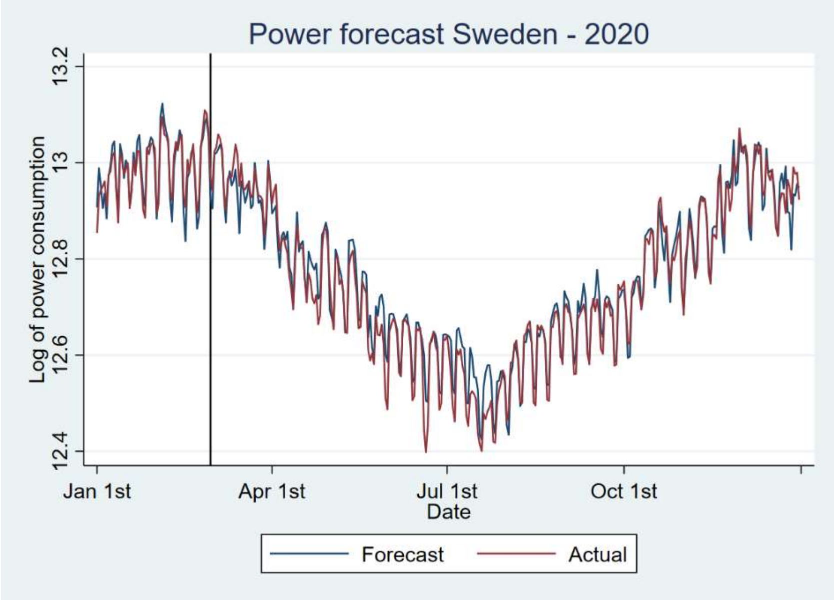
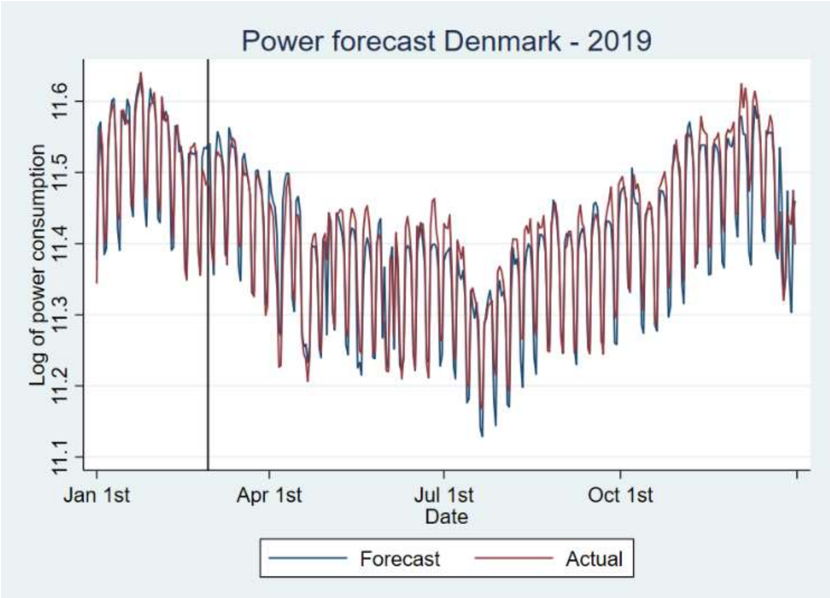
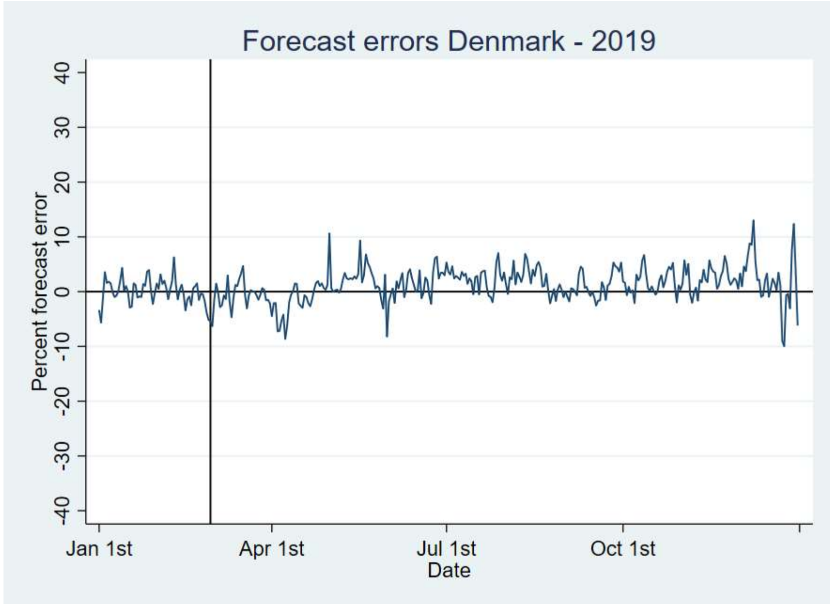
-30
-20
-10
0
10
20
30
40
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date


Power forecast Sweden - 2020
Log of power consumption
12.4
12.6
12.8
13
13.2
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date
Forecast
Actual


Forecast errors Sweden - 2020
Percent forecast error
-40
-30
-20
-10
0
10
20
30
40
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date


Power forecast Denmark - 2019
Log of power consumption
11.1
11.2
11.3
11.4
11.5
11.6
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date
Forecast
Actual


Forecast errors Denmark - 2019
Percent forecast error
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-30
-20
-10
0
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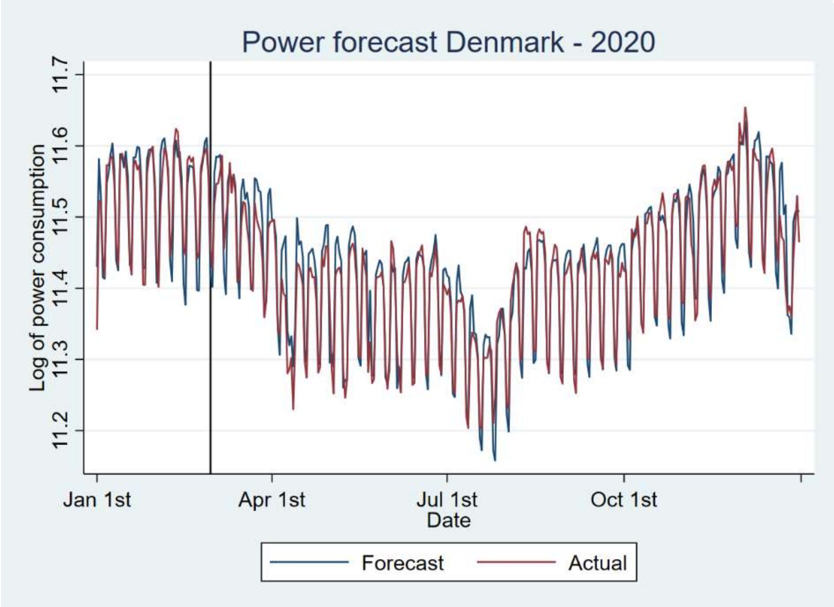
20
30
40
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date


Power forecast Denmark - 2020
Log of power consumption
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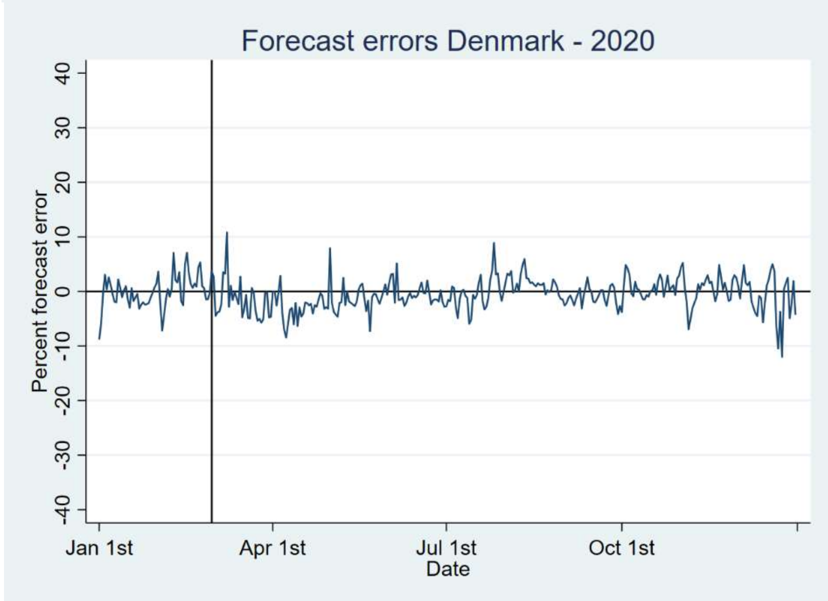
11.3
11.4
11.5
11.6
11.7
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date
Forecast
Actual


Forecast errors Denmark - 2020
Percent forecast error
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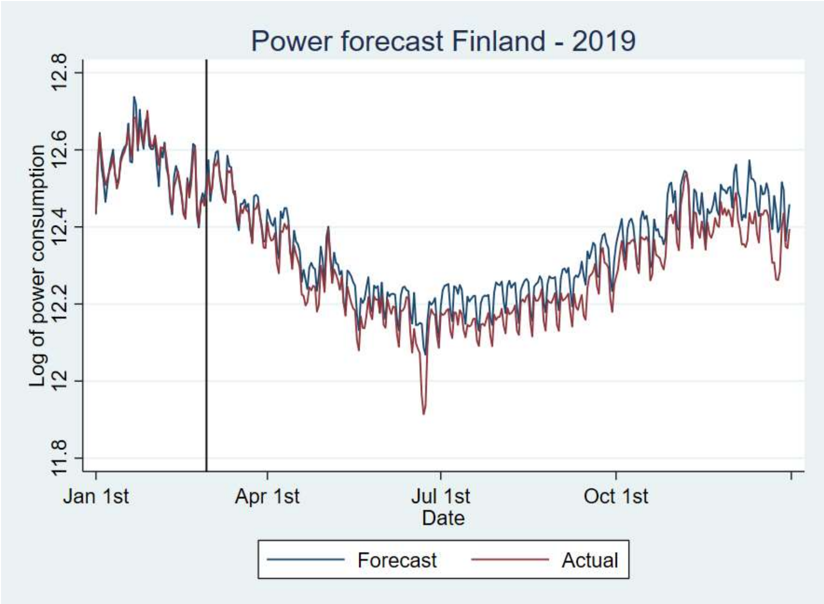
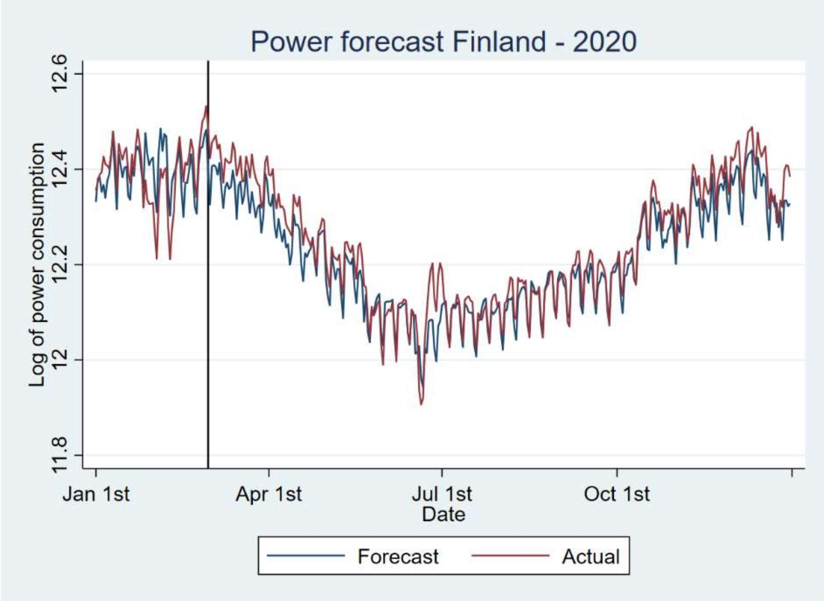
-30
-20
-10
0
10
20
30
40
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date


Power forecast Finland - 2019
Log of power consumption
11.8
12
12.2
12.4
12.6
12.8
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date
Forecast
Actual


Forecast errors Finland - 2019
Percent forecast error
-40
-30
-20
-10
0
10
20
30
40
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date


Power forecast Finland - 2020
Log of power consumption
11.8
12
12.2
12.4
12.6
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date
Forecast
Actual


Forecast errors Finland - 2020
Percent forecast error
-40
-30
-20
-10
0
10
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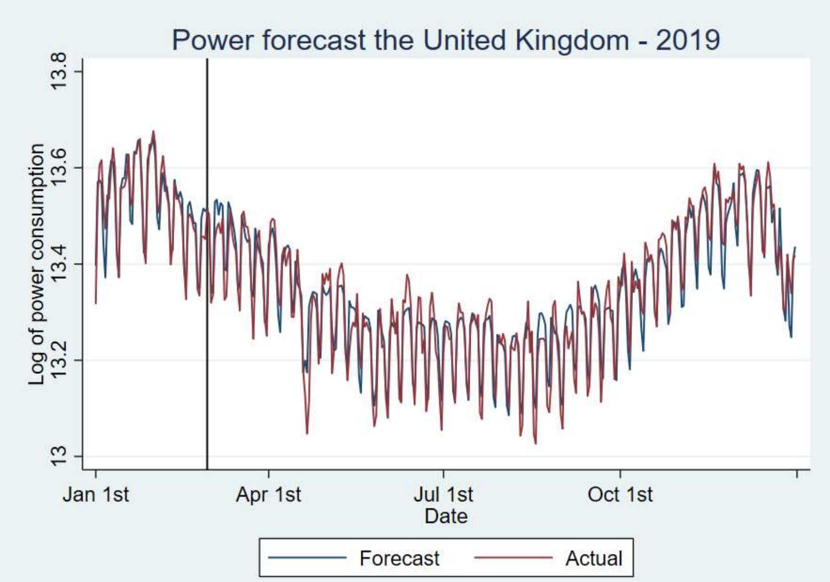
40
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date



Power forecast the United Kingdom - 2019
Log of power consumption
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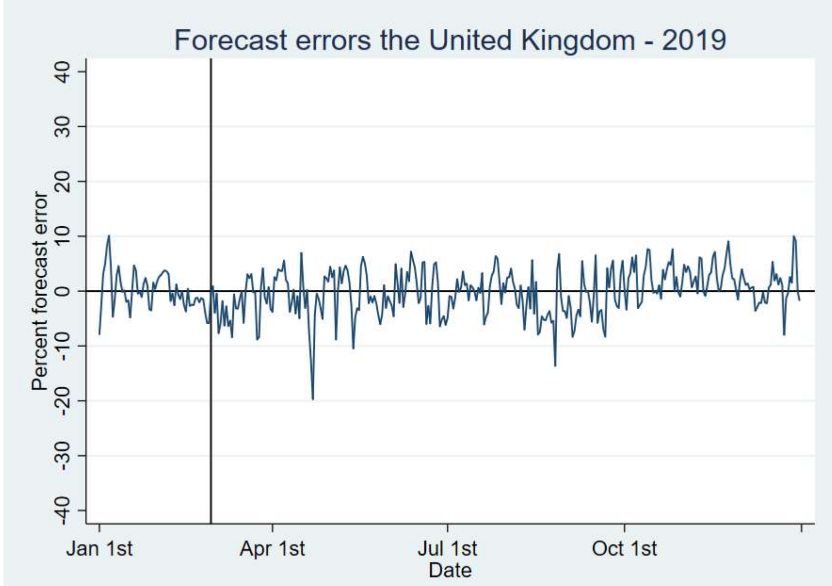
13.2
13.4
13.6
13.8
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date
Forecast
Actual



Forecast errors the United Kingdom - 2019
Percent forecast error
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-10
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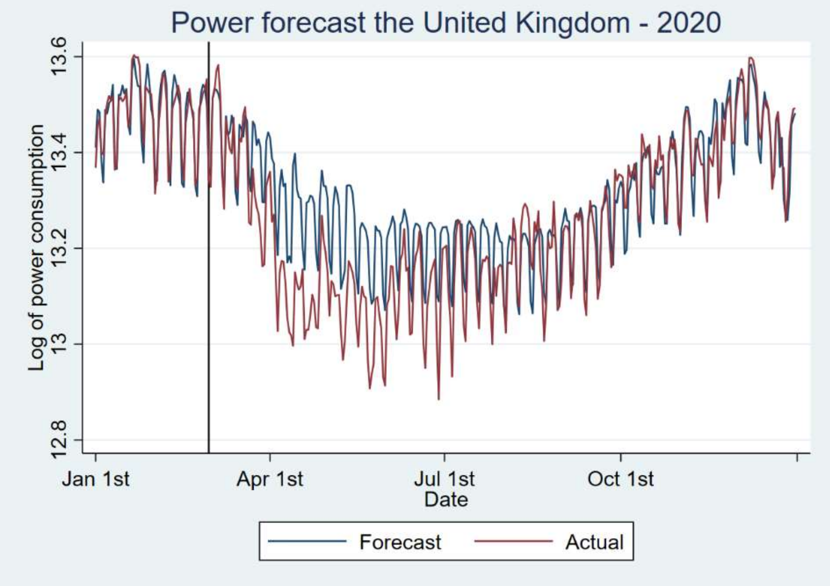
40
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date



Power forecast the United Kingdom - 2020
Log of power consumption
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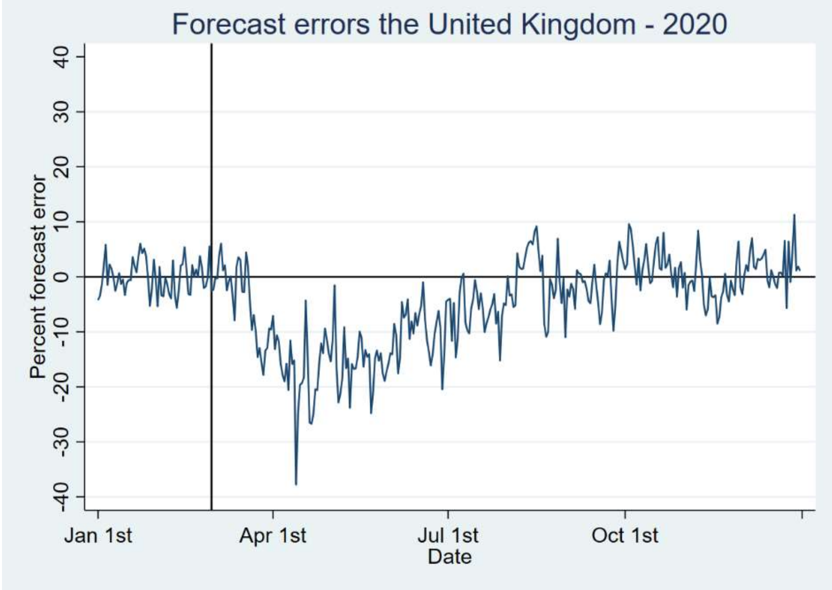
13.2
13.4
13.6
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date
Forecast
Actual



Forecast errors the United Kingdom - 2020
Percent forecast error
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-30
-20
-10
0
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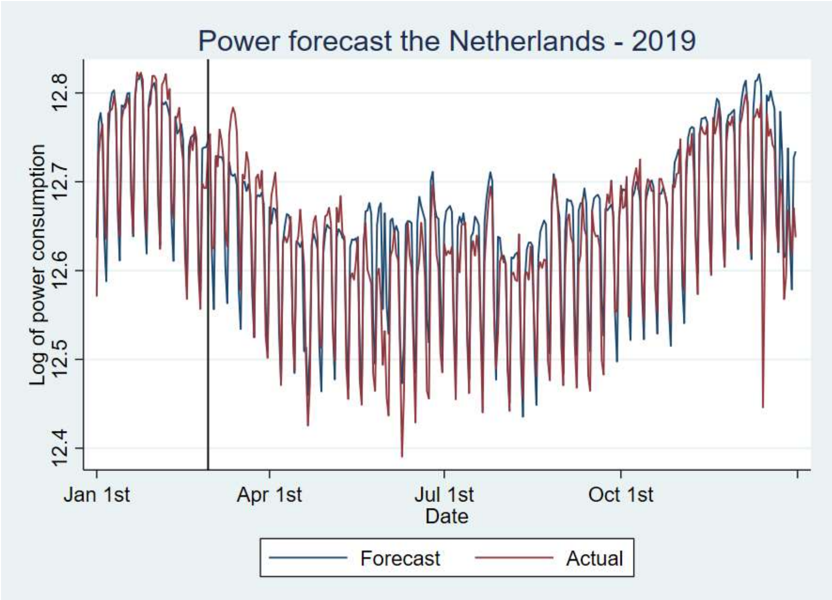
30
40
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date


Power forecast the Netherlands - 2019
Log of power consumption
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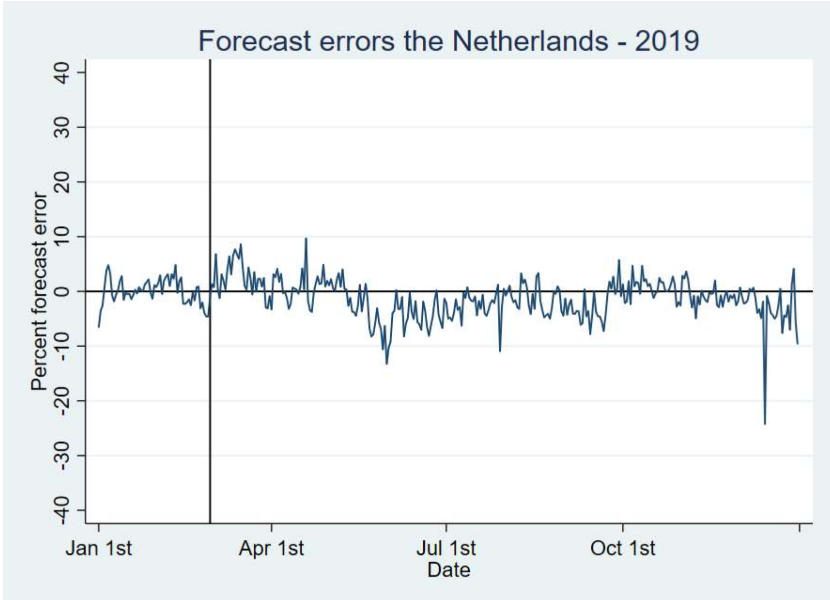
12.6
12.7
12.8
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date
Forecast
Actual


Forecast errors the Netherlands - 2019
Percent forecast error
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-10
0
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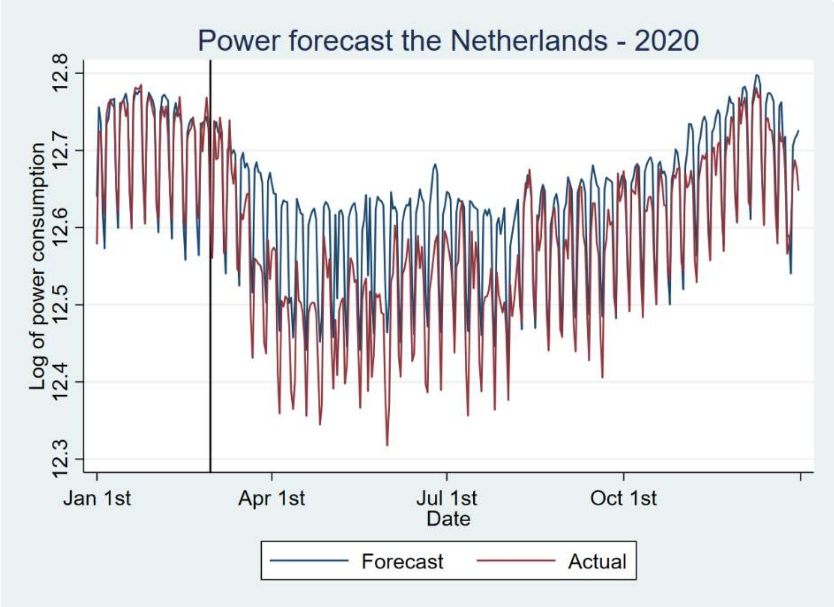
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date


Power forecast the Netherlands - 2020
Log of power consumption
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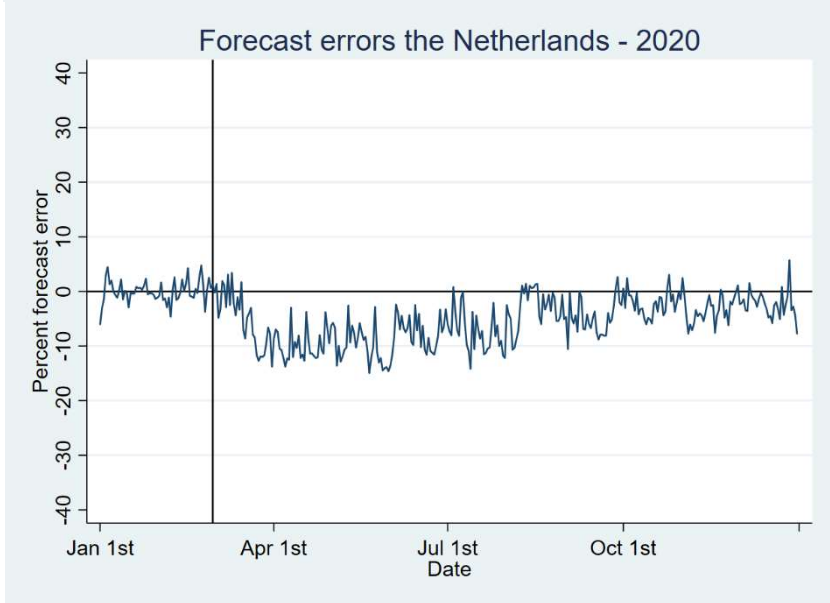
12.6
12.7
12.8
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date
Forecast
Actual


Forecast errors the Netherlands - 2020
Percent forecast error
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20
30
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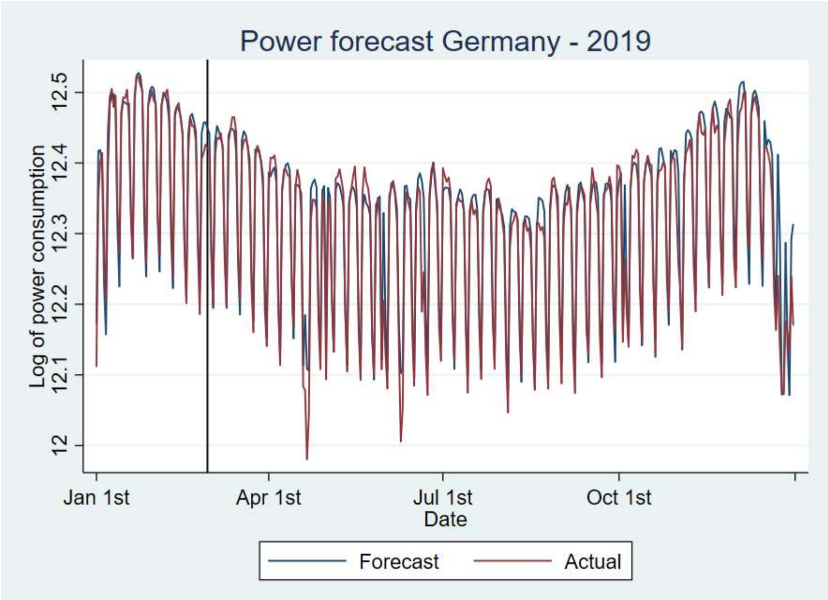
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date


Power forecast Germany - 2019
Log of power consumption
12
12.1
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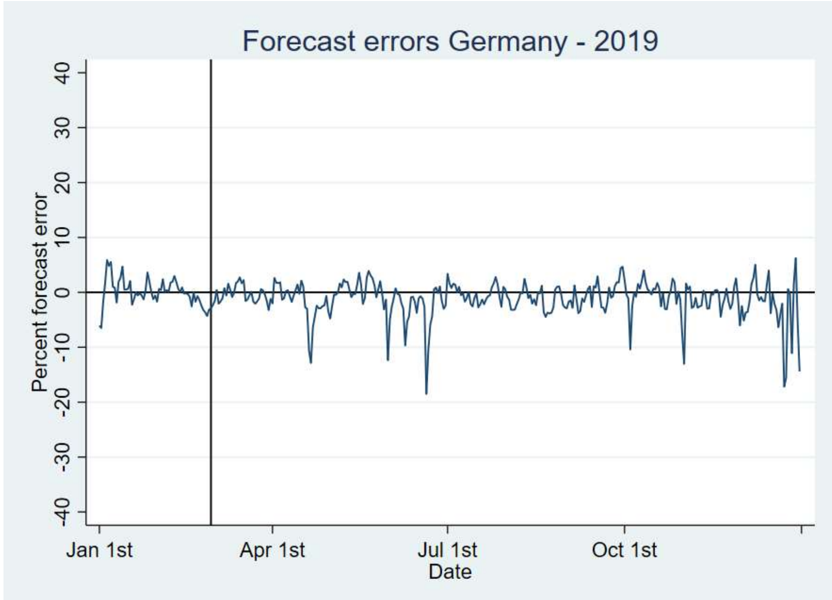
12.3
12.4
12.5
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date
Forecast
Actual


Forecast errors Germany - 2019
Percent forecast error
-40
-30
-20
-10
0
10
20
30
40
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date


Power forecast Germany - 2020
Log of power consumption
12
12.1
12.2
12.3
12.4
12.5
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date
Forecast
Actual


Forecast errors Germany - 2020
Percent forecast error
-40
-30
-20
-10
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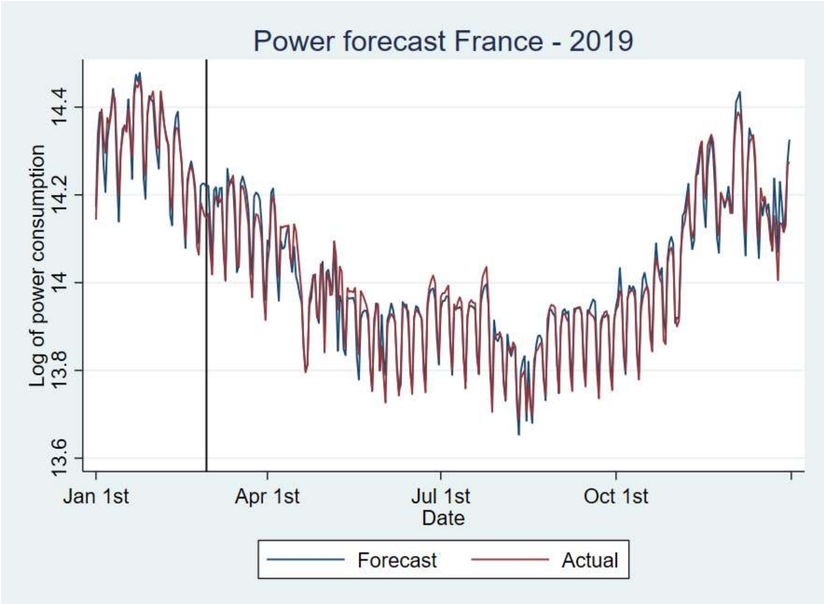
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date


Power forecast France - 2019
Log of power consumption
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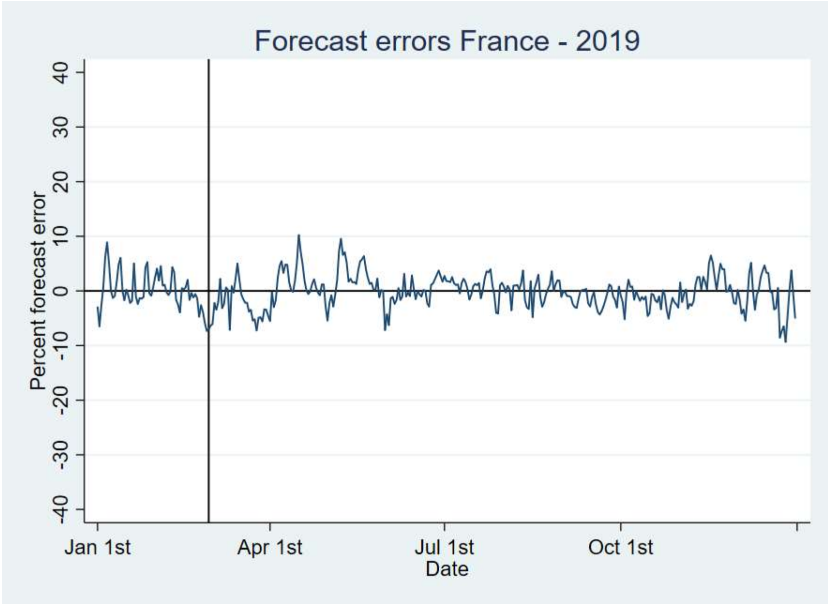
13.8
14
14.2
14.4
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date
Forecast
Actual


Forecast errors France - 2019
Percent forecast error
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Jan 1st
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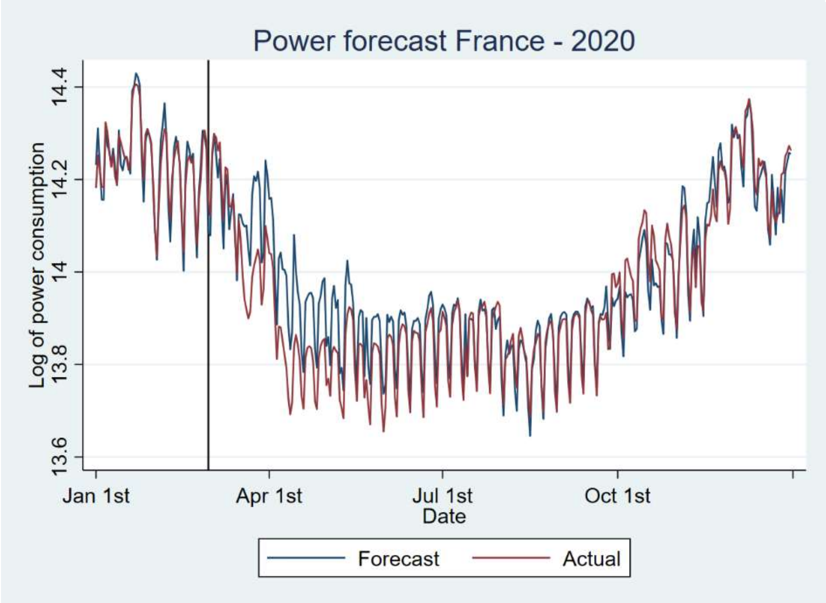
Oct 1st
Date


Power forecast France - 2020
Log of power consumption
13.6
13.8
14
14.2
14.4
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date
Forecast
Actual


Forecast errors France - 2020
Percent forecast error
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-30
-20
-10
0
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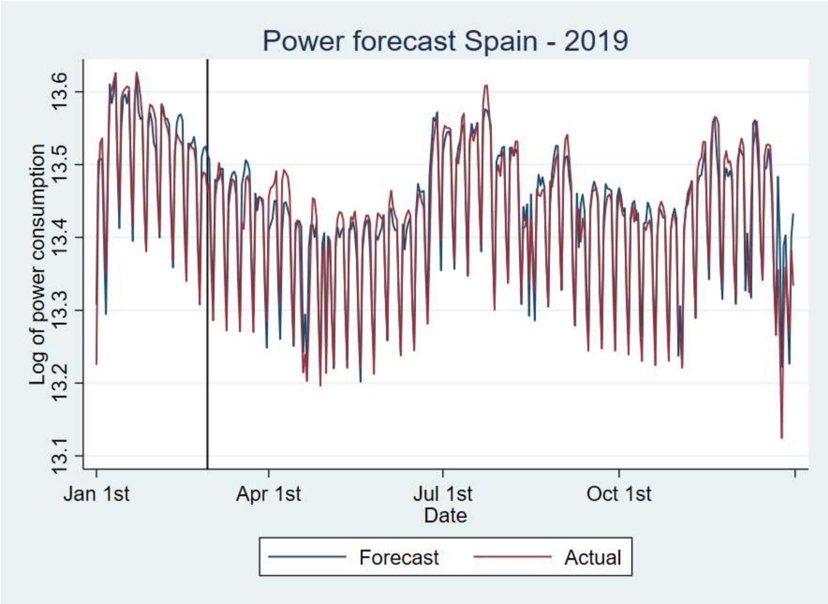
40
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date


Power forecast Spain - 2019
Log of power consumption
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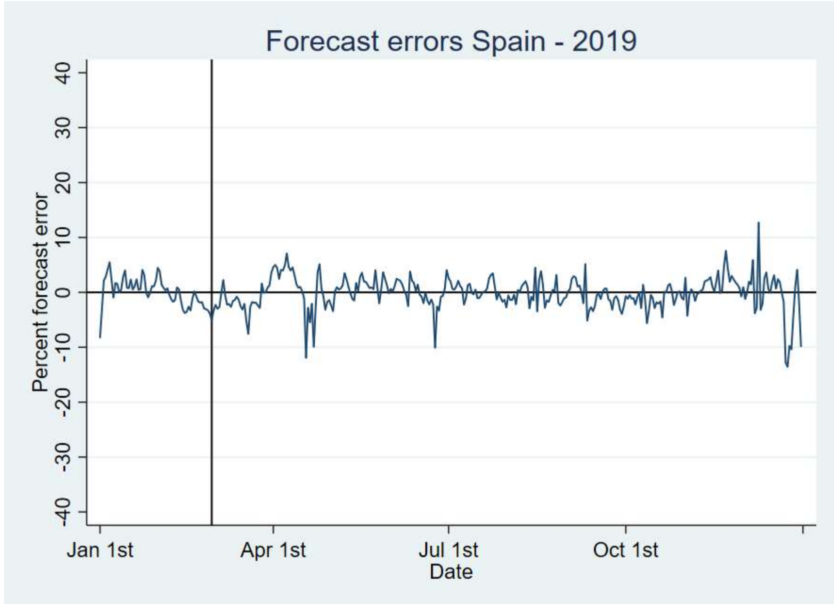
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date
Forecast
Actual


Forecast errors Spain - 2019
Percent forecast error
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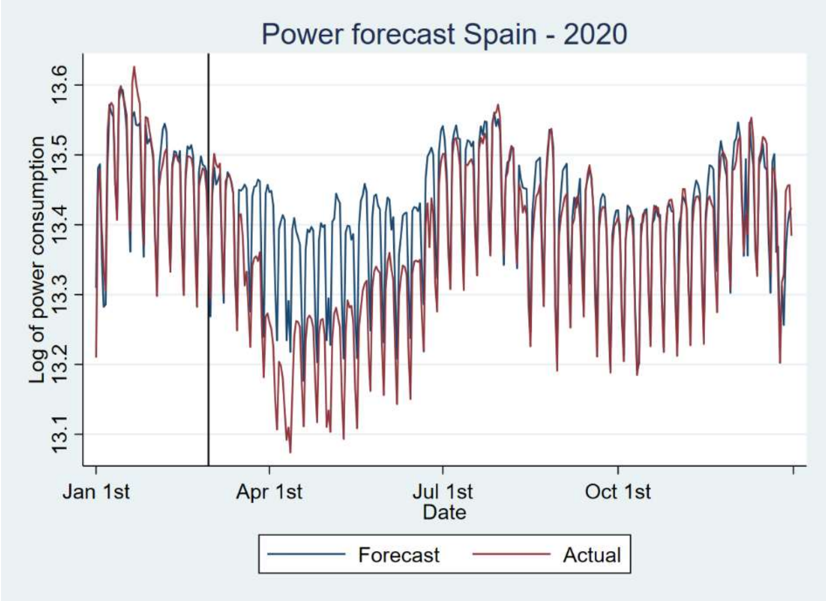
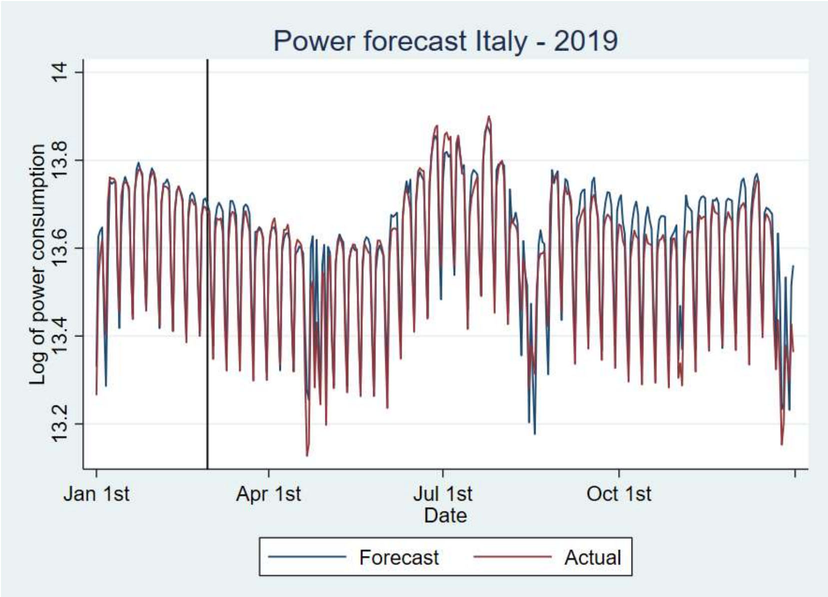
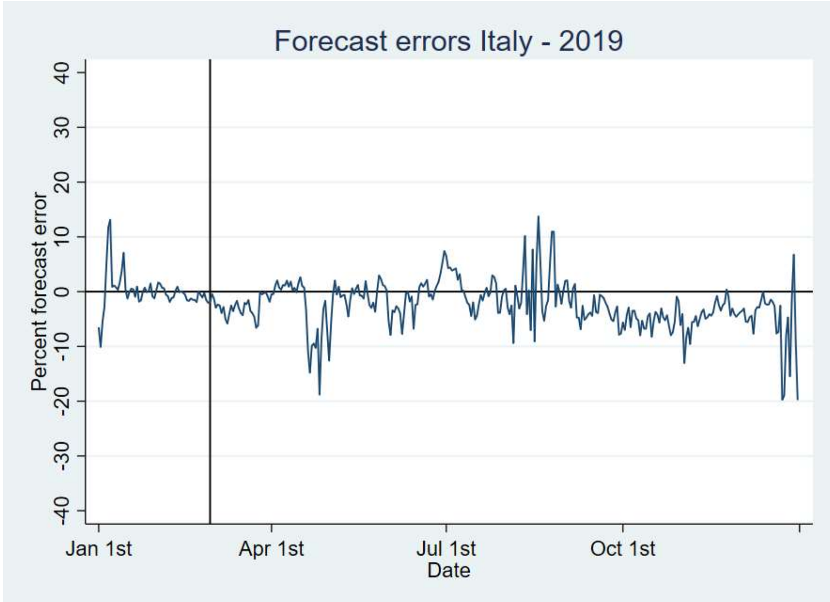
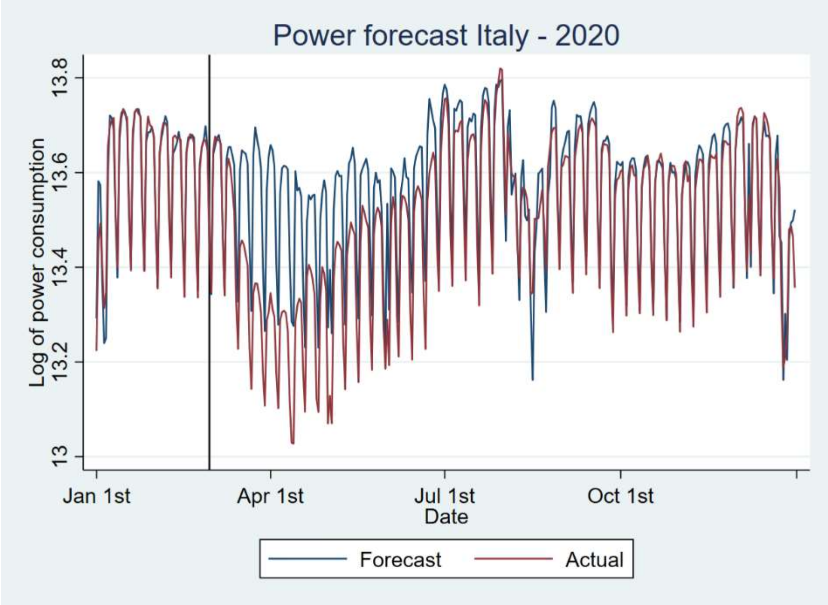
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date

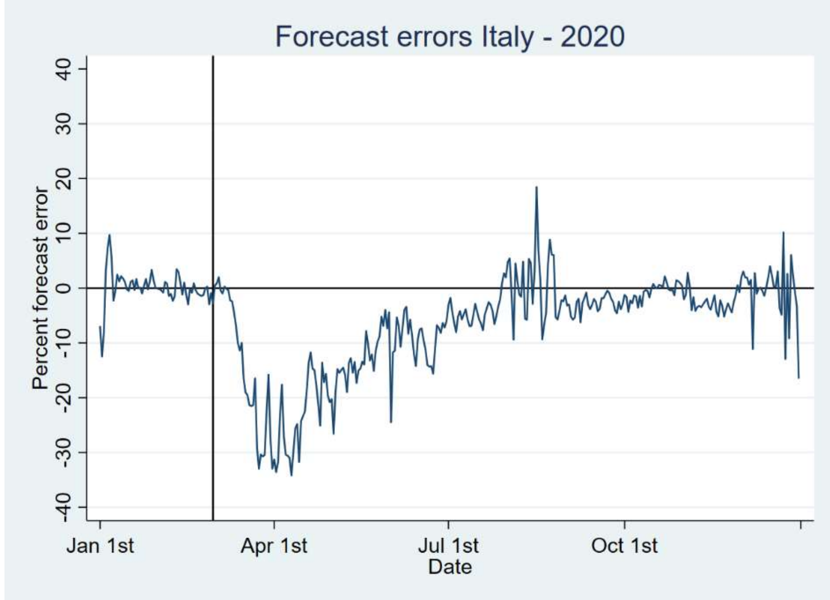

Power forecast Spain - 2020
Log of power consumption
13.1
13.2
13.3
13.4
13.5
13.6
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date
Forecast
Actual


Forecast errors Spain - 2020
Percent forecast error
-40
-30
-20
-10
0
10
20
30
40
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date


Power forecast Italy - 2019
Log of power consumption
13.2
13.4
13.6
13.8
14
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date
Forecast
Actual


Forecast errors Italy - 2019
Percent forecast error
-40
-30
-20
-10
0
10
20
30
40
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date


Power forecast Italy - 2020
Log of power consumption
13
13.2
13.4
13.6
13.8
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date
Forecast
Actual


Forecast errors Italy - 2020
Percent forecast error
-40
-30
-20
-10
0
10
20
30
40
Jan 1st
Apr 1st
Jul 1st
Oct 1st
Date

Appendix G – Regression output of AR models

The following tables show the regression outputs of our AR models on GDP, per country. The first table shows the standard AR models, while the second table shows the AR models on differenced form of the dependent variable.

GDP-AR Models

	(1) Norway	(2) Finland	(3) Germany	(4) Spain
L.lgdp	0.9941***	0.9866***	1.1732***	1.7567***
	(0.00360)	(0.00727)	(0.10037)	(0.11093)
L2.lgdp			-0.0192	-0.9097***
			(0.15433)	(0.22434)
L3.lgdp			-0.1555	0.4155
			(0.15450)	(0.24511)
L4.lgdp			-0.0027	-0.4039
			(0.10051)	(0.24484)
L5.lgdp				0.1906
				(0.24419)
L6.lgdp				-0.0961
				(0.22221)
L7.lgdp				0.0385
				(0.10772)
_cons	0.0828	0.1477	0.0583	0.1042*
	(0.04727)	(0.07721)	(0.10845)	(0.04740)
N	156	108	104	88
R^2	0.998	0.994	0.994	0.999
adj. R^2	0.998	0.994	0.993	0.999
F	76174.9925¤¤¤	18430.7824¤¤¤	3888.8733¤¤¤	11305.0461¤¤¤

Standard errors in parentheses
Coefficients per lag
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
¤ F-prob<0.05, ¤¤ F-prob<0.01, ¤¤¤ F-prob<0.001

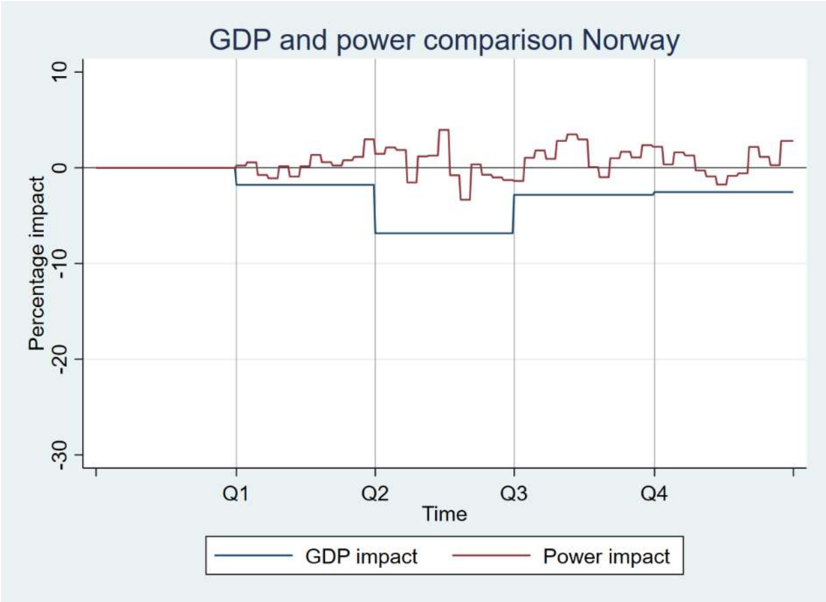
GDP-AR Models on First Difference Form

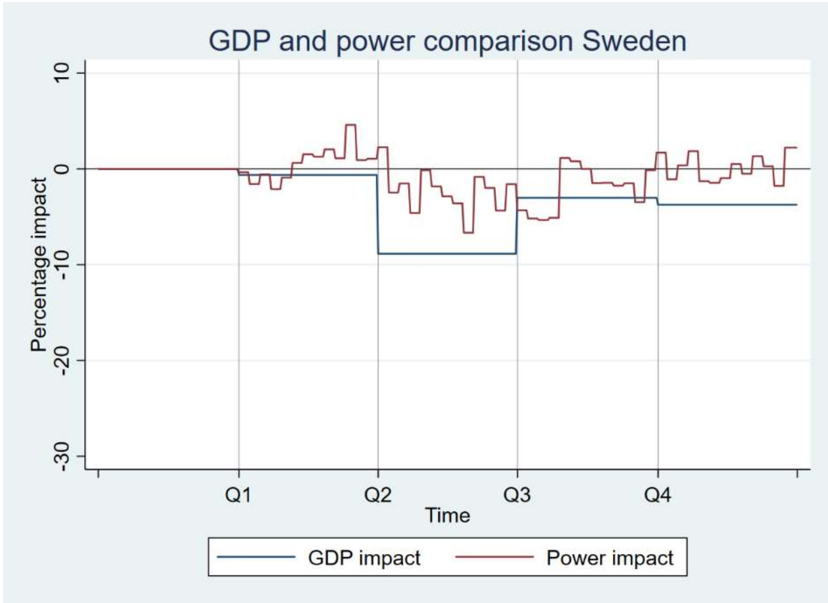
	(1) Sweden	(2) Denmark	(3) The UK	(4) Netherlands	(5) France	(6) Italy
L.dlgdp	0.1981	0.0588	0.1290	0.4364***	0.4189***	0.5040***
	(0.10429)	(0.10929)	(0.07655)	(0.09829)	(0.07566)	(0.10769)
L2.dlgdp	0.1875	0.2011	0.2787***		0.2368**	0.0910
	(0.10737)	(0.10868)	(0.07436)		(0.07527)	(0.10772)
L3.dlgdp	0.1113	0.1176	0.0972			
	(0.10622)	(0.10427)	(0.07608)			
L4.dlgdp		0.0168				
		(0.10486)				
_cons	0.0031*	0.0024*	0.0026**	0.0024**	0.0016***	0.0006
	(0.00118)	(0.00112)	(0.00079)	(0.00081)	(0.00045)	(0.00065)
N	96	88	168	84	168	88
R^2	0.135	0.071	0.145	0.194	0.342	0.314
adj. R^2	0.106	0.027	0.130	0.184	0.334	0.298
F	4.7702¤¤	1.5964	9.2813¤¤¤	19.7150¤¤¤	42.9067¤¤¤	19.4979¤¤¤

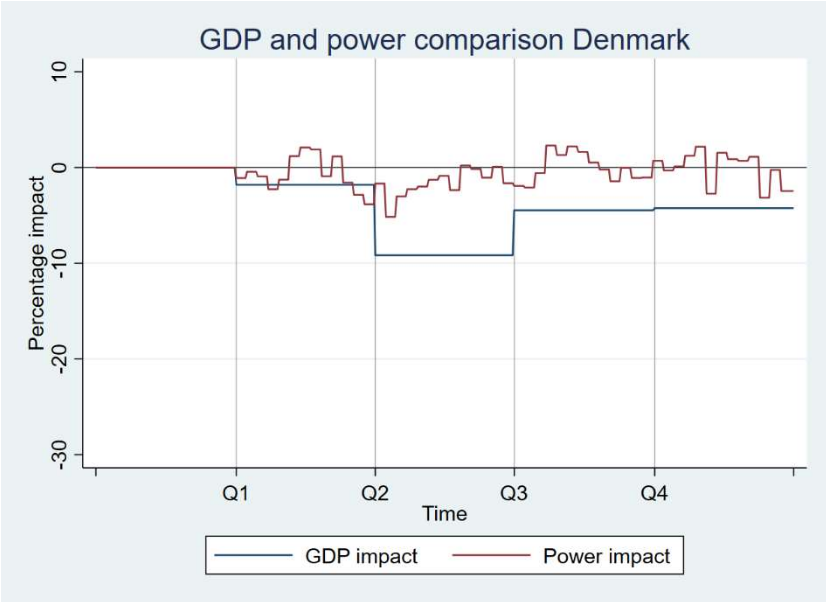
Standard errors in parentheses
Coefficients per lag
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
¤ F-prob<0.05, ¤¤ F-prob<0.01, ¤¤¤ F-prob<0.001

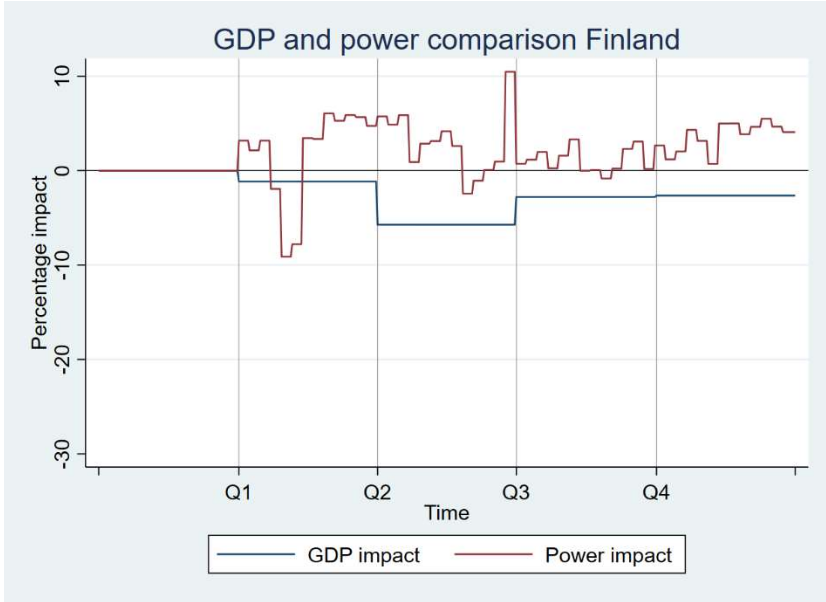
Appendix H – Timeline of the estimated impacts, quarter-yearly GDP and weekly electricity consumption

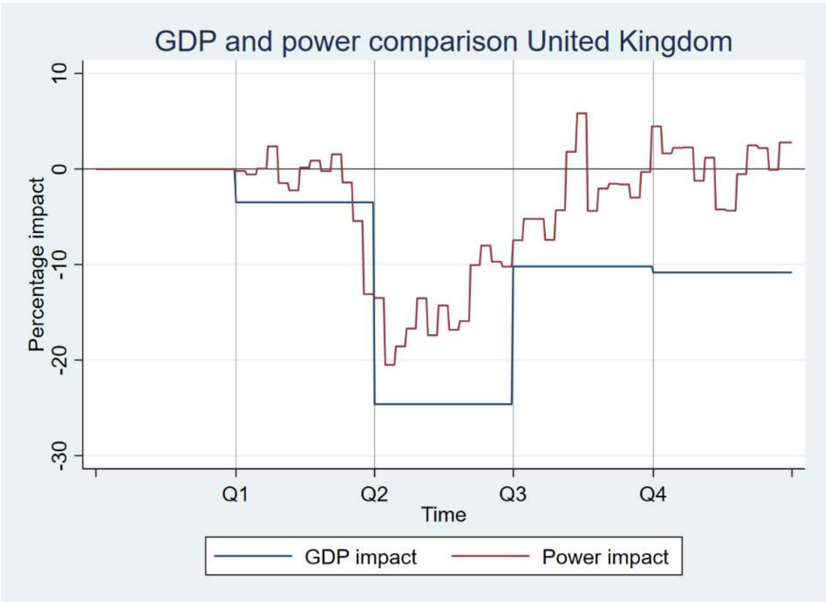
The following ten figures shows, per country, quarter-yearly economic impact and weekly electricity impacts, as estimated using our described method.

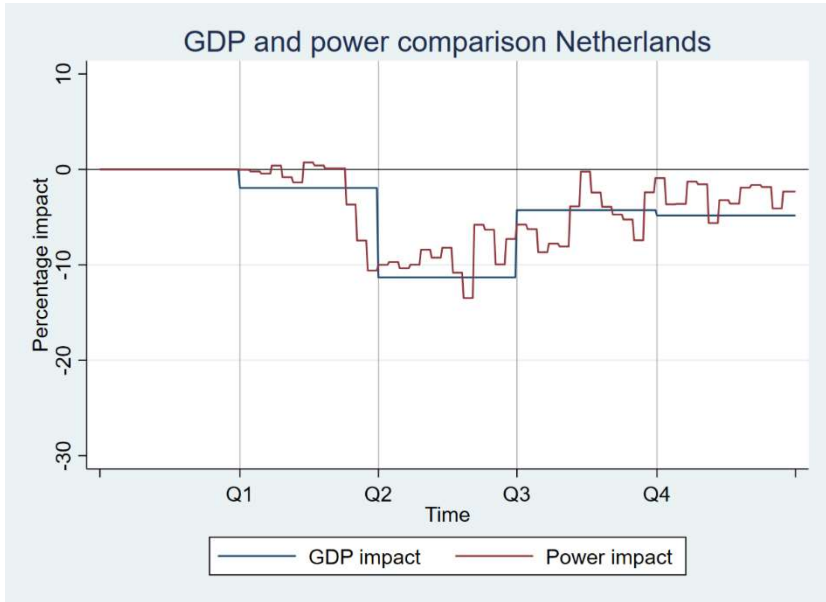


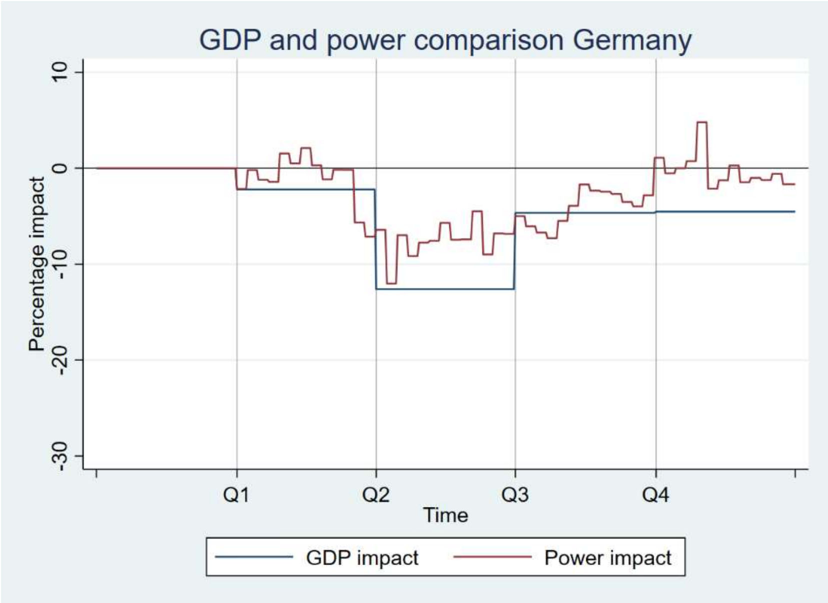



GDP and power comparison Denmark
Percentage impact
10
0
-10
-20
-30
Q1
Q2
Q3
Q4
Time
GDP impact
Power impact

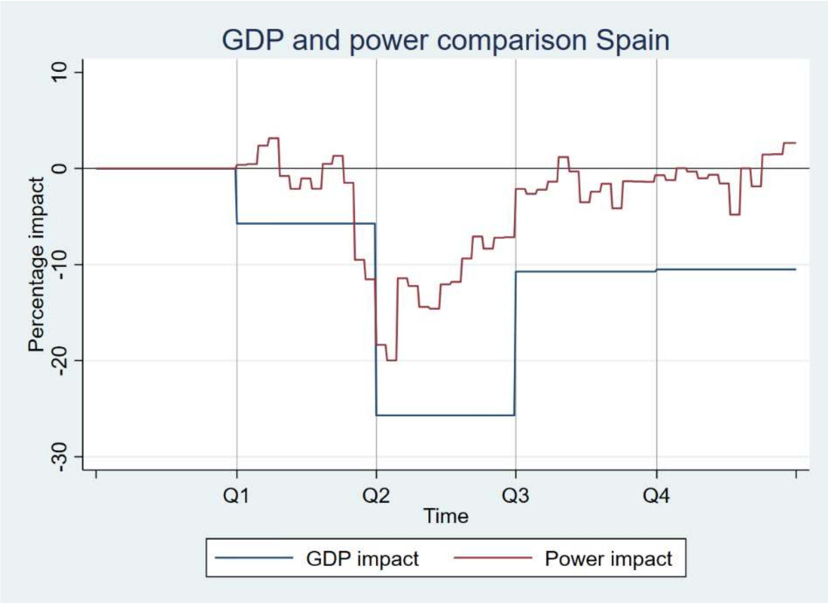

GDP and power comparison Finland
Percentage impact
10
0
-10
-20
-30
Q1
Q2
Q3
Q4
Time
GDP impact
Power impact

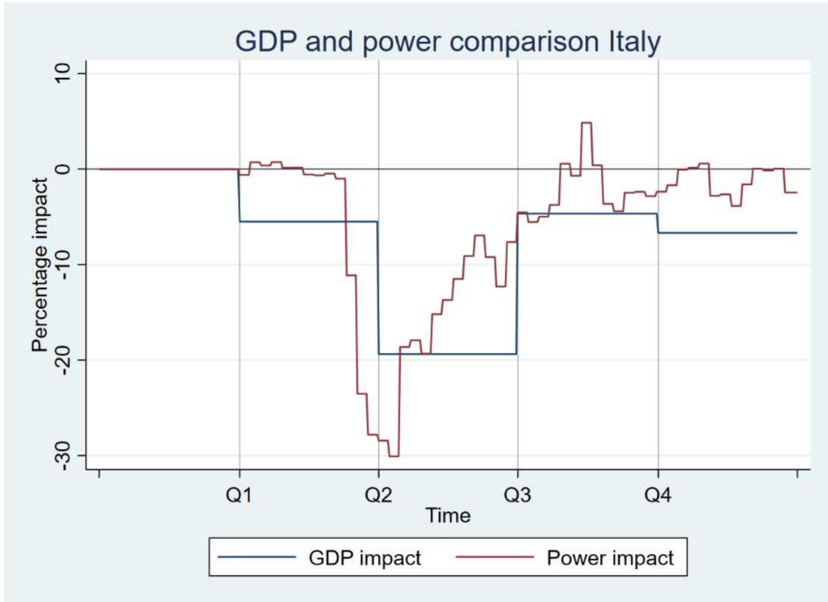

GDP and power comparison United Kingdom
Percentage impact
10
0
-10
-20
-30
Q1
Q2
Q3
Q4
Time
GDP impact
Power impact


GDP and power comparison Netherlands
Percentage impact
10
0
-10
-20
-30
Q1
Q2
Q3
Q4
Time
GDP impact
Power impact


GDP and power comparison Germany
Percentage impact
10
0
-10
-20
-30
Q1
Q2
Q3
Q4
Time
GDP impact
Power impact


GDP and power comparison France
Percentage impact
10
0
-10
-20
-30
Q1
Q2
Q3
Q4
Time
GDP impact
Power impact


GDP and power comparison Spain
Percentage impact
10
0
-10
-20
-30
Q1
Q2
Q3
Q4
Time
GDP impact
Power impact


GDP and power comparison Italy
Percentage impact
10
0
-10
-20
-30
Q1
Q2
Q3
Q4
Time
GDP impact
Power impact

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