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A chi c'era, c'è e ci sarà

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What research means to me

I would like to say a few words about why I decided to choose this research path and develop this thesis. I think that one of the key elements of a PhD program is to understand the meaning of "Research". It can help the researcher to choose the right path, to enjoy what he/she does, to achieve the best possible results and obtain a high degree of satisfaction.
First, I believe that "Research" is like a forest of trees. When a PhD student is asked to pick a research field, he/she must choose his/her favourite tree. Every tree represents a research field. When I had to decide the research topic that was the best fit for me, I had a number of choices based on my interests: energy economics, behavioural economics and political economy. However, energy economics is the research field which has always attracted me the most, so I was able to overcome temptation elsewhere.
Second, I understood that "Research" has a more complex meaning: it is like climbing a tree with many branches. Energy economics is the tree trunk. Therefore, I had to decide what main branch I wanted to climb: the electricity market was my choice. I was fascinated by the functioning of auctions and the market, after following the optional course of Prof. Luigi Grossi during the last term of the first year of PhD studies.
Third, I think that "Research" asks a number of questions at once. For me the main questions were "What?" and "How?". The answer to the first question is obviously "the electricity market; auctions and market functioning". The answer to the second was not so easy. I was looking for "my way" of running research: something to stimulate my interest and enable me to use my skills. Therefore, my supervisor suggested that I read many articles, with different approaches to research. I am very glad to have found the methodology of "synthetic supply" put forward by Ciarreta et al (2010) for the first time. This methodology allows counterfactuals to be created and observations of the "what would have happened if...." kind. I think that this methodology perfectly reflects my way of thinking.

"Research" has many meanings and every researcher has a different approach. I am very happy to have developed my point of view about "Research" and proud of this PhD thesis.

Contents

Ringraziamenti **I**

Acknowledgments **IV**

What research means to me **VII**

Introduction **1**

1 Chapter 1
Assessing market power in the Italian electricity market: a synthetic supply approach **4**

1.1 Introduction . . . 5
1.2 Literature review . . . 6
1.3 Market Structure . . . 8
1.4 Data . . . 12
1.4.1 GME . . . 12
1.4.2 REF-E . . . 13
1.5 Methodology . . . 14
1.5.1 Association of the plants . . . 15
1.5.2 Translation of the offers . . . 18
1.6 Empirical Analysis . . . 19
1.6.1 Actual Prices vs Synthetic Prices . . . 20
1.6.2 Consumer Surplus Loss . . . 21
1.6.3 Lerner Index . . . 23
1.7 Limitations, Strengths and Future Research . . . 24
1.8 Conclusions . . . 25
References . . . 27

2 Detecting strategic capacity withholding through a synthetic supply approach - *Cui Prodest?* **29**
2.1 Introduction . . . 30
2.2 Literature Review . . . 31
2.3 Data . . . 33
2.4 Methodology . . . 34
2.5 Empirical Analysis . . . 39
2.5.1 Actual Prices vs Synthetic Prices . . . 40
2.5.2 Revenues Analysis . . . 41
2.5.3 Synthetic Strategic Capacity Withholding Index (SSCW) . . . 44
2.6 Limitations, Strengths and Future Research . . . 46
2.7 Conclusion . . . 47
References . . . 49

3 Covid-19 and the Italian electricity market: impacts, developments and implications **52**
3.1 Introduction . . . 53
3.2 Lockdown and restrictive measures . . . 55
3.3 Data . . . 56
3.3.1 GME S.p.A. . . . 56
3.3.2 Terna S.p.A. . . . 57
3.4 Fall in demand and consumption cycles . . . 58
3.4.1 Fall in demand . . . 58
3.4.2 Consumption cycles . . . 64
3.5 Price decrease . . . 68
3.5.1 Market splitting Index . . . 70
3.6 Econometric Analysis . . . 71
3.7 Change in the power generation mix . . . 77
3.7.1 Marginal Technology Index . . . 78
3.7.2 Does decarbonization move faster or slower? . . . 79
3.8 Conclusion . . . 80
References . . . 85

Appendix **88**

A Appendix Chapter 1 **88**

B Appendix Chapter 2 **93**

B.1 Revenues computational details . . . 93

B.1.1 Actual revenues for firm i at hour h . . . 93

B.1.2 Synthetic revenues for firm i at hour h . . . 93

B.1.3 Number of observations in actual and synthetic scenarios: explanatory example . . . 96

B.2 Actual Prices vs Synthetic Prices . . . 98

C Appendix Chapter 3 **123**

C.1 Consumption cycles . . . 123

C.2 Generation mix . . . 131

C.3 Econometric Analysis . . . 139

C.3.1 Autocorrelation functions and residual diagnostics . . . 139

C.3.2 Tables . . . 147

Introduction

The thesis is a collection of three empirical essays focussing on the Italian electricity market.

The first chapter, titled "Assessing market power in the Italian electricity market: a synthetic supply approach", is a joint work with Prof. Luigi Grossi and Prof. Michael. G. Pollitt and was published among the Energy Policy Research Group Working Papers (no. 1930). This chapter investigates the bidding behaviour of the leading firms in the Italian electricity market, in particular on the Italian day-ahead market. The methodology adopted is synthetic supply, proposed by Ciarreta et al (2010), which consists in a two-step procedure, i.e. 1) power plants association and 2) hourly bidding schedule "translation". Thanks to synthetic supply it is possible to create hourly counterfactual supply curves and see if there are differences between actual and synthetic equilibria. In other words, the idea is to investigate the difference in mark-up between the bidding schedules of power plants with very similar features. For this reason, power plants were associated with very strict criteria: technology, energy efficiency and many others. Furthermore, an algorithm in R was developed to compute hourly equilibria in the day-ahead market. This way, it is possible to assess if there are any differences between the bidding behaviour of the leading operators and the bidding behaviour of smaller generators. The empirical analysis investigates the market power of one of the largest Italian generators. The findings suggest that during the years under examination (2015-2018), the market underwent higher prices and a non-negligible consumer surplus loss, especially during the months when above average heating and cooling were required.[1]

The second chapter, titled "Detecting strategic capacity withholding through a synthetic supply approach - Cui Prodest?", puts forward a new methodology in the field of market

[1]The first chapter was presented both to the Department of the University of Verona and to the Joint Research Centre (JRC) of the European Commission, Ispra (VA), Italy. It was also developed during the visiting period at the Energy Policy Research Group of the University of Cambridge. I am grateful for the many suggestions from several energy experts at institutions, universities and firms.

monitoring. The methodology of synthetic supply and the R code are employed. However, the way synthetic supply is used in this chapter is completely new. A four-step procedure is proposed to investigate strategic capacity withholding, i.e. 1) hourly supply curves are created and extra capacity is artificially added to the supply schedule, 2) synthetic and actual prices are compared and anomalous price spikes detected, 3) synthetic and actual revenues are compared, to see if any market operator could have obtained more revenues from a scenario where some capacity was withheld, 4) the SSCW index is proposed to better interpret the results. The chapter carries out an empirical analysis of the Italian day-ahead market in 2018. This approach is a significant contribution to the literature because it enables the analysis of manipulative behaviour with a different perspective compared to the methodology currently available.[2]

The third chapter, titled "Covid-19 and the Italian electricity market: impacts, developments and implications", investigates the effects of the restrictive measures employed by the Italian Government in response to Covid-19 on the Italian electricity market. This chapter presents a data description of the main market variables of the electricity market and uses an econometric model to estimate the effects of geographical and production lockdowns on the zonal quantities purchased and on the PUN (nationwide unit price). Data suggests that both quantity purchased, and prices were affected by the lockdowns, especially in the bidding areas of Northern Italy. The bidding zones of Southern Italy seem to be considerably less affected by restrictive measures. This is also confirmed by the econometric model. In addition, fall in demand led to a smaller quantity purchased, compared to the corresponding weeks in previous years, leading to substantial changes in the mix of energy sources. This chapter proposes a complete description of the evolution of the electricity market during the pandemic and provides useful policy recommendations on how financial resources should be

[2]The second chapter attracted the attention of institutions and academics: I was invited as an "expert on energy markets" by the European Commission and to present the work on 6 December, 2019, during a workshop organized by the JRC. It was the ideal opportunity to discuss the topic with several experts from the European Commission and professors. Furthermore, after this meeting, I was invited by Alessandro Zani PhD to present this work to Ricerca sul Sistema Energetico (RSE) in Milan. This was also a great opportunity to discuss this work with electricity market experts.
In addition, I had the opportunity to present the work to Prof. Zoli and to discuss this research project with him. The research project was also accepted by the Energy Policy Research Group of the University of Cambridge. Unfortunately, due to the pandemic, it was not possible to develop this project jointly with Prof. Michael G. Pollitt.

allocated to relieve the Italian economy.[3]

[3]This chapter differs from the previous two because of the impact of the pandemic which switched my attention from bidding strategy to the phenomenon observed with great interest by myself and my supervisor during the lockdown involving unusual market dynamics. First, this interest led to a publication in Sole24Ore, an Italian economic newspaper, and subsequently to a new chapter in this thesis.

Chapter 1

Assessing market power in the Italian electricity market: a synthetic supply approach[1]

Abstract

The aim of this article is to investigate the effects of the bidding strategies of leading firms on market equilibria. The analysis focusses on the Italian wholesale electricity market from 2015 to 2018. The purpose is to assess if the observed market equilibria are the results of a competitive setting or if more competitive equilibria could have occurred. We use the methodology of synthetic supply proposed by Ciarreta et al. (2010a). This way, a new set of synthetic prices and quantities is computed. The comparison between the actual and synthetic prices allows us to assess the effects of market power on the actual equilibria. Results suggest that whilst there is a significant impact on prices, quantities seem not to be affected, due to the inelastic demand. Moreover, our findings suggest that the main impacts occurred during 2017 especially during those months where above average heating and cooling were required.

[1]This paper is a joint work with Prof. Luigi Grossi (University of Verona) and Prof. Michael G. Pollitt (Energy Policy Research Group, Judge Business School, University of Cambridge).
Paper published in the Energy Policy Research Group Working Papers no. 1930, University of Cambridge.

1.1 Introduction

The Italian electricity market was subject to several changes over the past two decades. Indeed, after liberalization, the market experienced different settings such as the evolution of the bidding zones and of the intraday markets, the improvement of market coupling, the massive introduction of Renewable Energy Sources (RES) and the reduction of market power asymmetries.

It is important to keep in mind that the Italian electricity market is characterized by a large share of generation based on coal and gas and the absence of nuclear generation. However, what is remarkable is the structural change that renewable sources produced in the last years, which affected the bidding behaviours of fossil fuel plants. Indeed, according to Bigerna et al. (2016) the total electricity consumption, generated by RES, drastically increased shifting from 3-4% to 30% between 2010 and 2013. RES, due to their zero marginal costs, tended to significantly affect prices by lowering them. In particular, the sizeable generation produced by solar panels reduced the profit margins of several power plants during the day hours. However, during the night, when the production from solar panels fell, the owners of fossil fuel plants exercised their market power again in order to compensate the losses incurred during the daylight hours.

Despite the fact that the issue related to market power asymmetries has been substantially tackled in these years, uncompetitive behaviours seem to persist. Several examples can be highlighted and quoted. Probably, the most interesting case, occurred in the first months of 2016. Some owners of fossil fuels power plants were capable of drastically increasing their revenues by applying bidding strategies intended to deliberately unbalance the market to achieve extremely high profits in the ancillary service market. This case will be discussed in the literature review. In addition, the exercise of market power may increase when the imported supply drops or during the maintenance of transmission power cables. Therefore, it is extremely important to analyse the operators' behaviours and study their bidding strategies as they keep changing and evolving over time.

This study aims to provide further evidence on the market monitoring field by applying the technique of synthetic supply proposed by Ciarreta et al. (2010a). In particular, the Italian day-ahead market is considered as a case study and its hourly equilibria are analysed. The goal of this paper is to show if the actual equilibria are the result of a competitive setting or if more competitive equilibria might have been possible. Moreover, an estimate of Consumer Surplus Loss will be computed and an alternative version of Lerner Index will be provided. Our findings will be discussed with the aim of achieving a broader and wider understanding of the Italian electricity market.

1.2 Literature review

Market manipulation has been widely discussed in recent years. This topic, due to its complexity and vastness, involves different disciplines. Indeed, in order to have a good understanding of the definition of market manipulation and of the principal techniques for its detection, it is necessary to have a sufficient degree of knowledge of several arguments. The study of this subject requires: a deep understanding of the structure of the market and of its dynamics and history; an advanced knowledge of economics and statistics; and a sufficient but necessary overview of law and electrical engineering. For this reason, several approaches have been proposed for analysing market manipulation. Each approach is characterized by the weights that its authors give to these different disciplines. Pinczynski and Kasperowicz (2016) and Prabhakar Karthikeyan et al. (2013) offer two reviews about the different approaches and techniques.

In this section the main arguments discussed will be microeconomics and law. First it is important to define what is considered market manipulation from a legal point of view. REMIT (Regulation of Energy Market Integrity and Transparency) and its guidance proposed by ACER (Agency for the Cooperation of Energy Regulators) clarify the legal steps required for the identification of market manipulation. Many articles were published on this topic. Feltkamp (2013) proposes a deep analysis of REMIT and gives a detailed interpretation of this regulation. Harris and Ledgerwood (2012) present a concise but complete overview of REMIT. According to these authors, REMIT and the guidance published by ACER do not shed enough light on the concept of market manipulation. In fact, "these definitions were too broad to be easily understood and applied".[2] For this reason, Harris and Ledgerwood (2012) suggested an alternative point of view which indicated the legal steps that should be required for the identification of a market manipulation. It is important to highlight that a legal interpretation of empirical results is necessary. In fact, in order to claim whether market manipulation occurred or not, it is essential to understand if the observed strategic behaviour can be considered a market manipulation or only an uncompetitive behaviour.

[2]Harris and Ledgerwood (2012), p. 1. The report is available at the following link.

Trigger, Target and Nexus are a good starting point for the legal interpretation of results.[3] Once a general legal overview is in place it is possible to proceed with the assessment of market power.

In the literature, there are many articles that discuss how firms may exercise their market power. It is possible to analyse this topic from several perspectives by applying different techniques. For example, Bosco et al. (2013) analysed the bidding strategy of Enel Produzione S.p.A. by studying its profit functions. This approach allowed them to understand when Enel Produzione S.p.A. was exerting its pivotal position. Wolak (2003) studied the market power of five leading operators in California. In this paper, the estimates of their Lerner Indexes are provided. As the marginal costs are unknown, the author proposes to analyse these measures through the estimation of the elasticity of every hourly residual demand faced by each of these companies. By contrast, it is possible to estimate a Lerner Index for operator i by estimating its marginal costs. Ciarreta and Espinosa (2010a) proposed an alternative version of the Lerner Index based on synthetic prices. Bosco et al. (2012) estimated the marginal cost functions for some of the main Italian leading operators and provided further evidence of their Lerner Indexes.

Furthermore, it is essential to bear in mind that leading operators might exploit their market power jointly. A joint bidding strategy could be undertaken by an illegal cartel or, more simply, by tacit collusion. However, from an empirical point of view, it is extremely difficult to test whether collusion occurred or not and it is almost impossible to prove if it was intentional. Macatangay (2003) investigated whether tacit collusion occurred in the wholesale electricity market of England and Wales at the end of the 90s. The firms suspected of this misbehaviour were National Power and PowerGen. The bidding strategies of the operators were analysed. In particular the empirical analysis was run in two stages. In the first step, the author tested whether the bidding strategies of National Power and PowerGen differed from the others. In the second one, the existence of inter-dependence and co-ordination of the leading operators' bidding strategies was investigated. However, despite the intriguing results, the author states that it is not possible to claim if tacit collusion occurred. Sweeting (2007) further investigates this case claiming that "their behaviour was consistent with tacit collusion".[4]

Market splitting and renewables constitute further key elements for an in-depth analysis

[3] See Harris and Ledgerwood (2012), p. 3.

[4] Sweeting (2007), p. 654.

of competition. Bigerna et al. (2016) take into account market splitting in the computation of the Lerner Index, in order to have a more accurate estimate of market power. Indeed, the zonal pricing system may be used strategically by some operators. Furthermore, these authors showed how the bidding behaviours of fossil fuels plants changed after the massive introduction of RES. In particular, it seems that solar panels caused a fall in daytime prices decreasing the relevance of combined cycle gas plants. On the contrary, findings show that during the night the owners of combined cycle gas plants exercised their market power more often. Ciarreta et al. (2017) analysed the effects of RES on fossil fuels plants for the Spanish electricity market. Their findings show that the massive introduction of RES in the market affected the bidding behaviours of fossil fuel plants but only in the short run.

The majority of the available literature focusses on the day-ahead market. Most of the time, intra-day and ancillary service markets are not matters of discussion. However, for a wide and deep analysis of competition in the electricity market it is important to always keep in mind that wholesale electricity market constitutes only the "tip of the iceberg". In 2016, an interesting and complete investigation was carried out by Luigi Gabriele, Rete Italia Consumatori.[5] The analysis reported in this document shows how, in the first semester of 2016, some fossil fuel plants could achieve extremely high revenues, in the ancillary service market, subsequent to strategic behaviours in day-ahead and intraday markets. The Italian Regulatory Authority for Energy (ARERA)[6] stated that anomalous behaviours occurred during these months. In particular, some companies implemented some strategies in order to achieve extra profit in the ancillary service market, namely electricity withdrawal or overbidding. The aim was to unbalance the regular dynamics of the markets in order for their plants to be necessary in the ancillary service market, where prices were way higher than in wholesale and intraday markets.

1.3 Market Structure

Italian electricity market is divided in six macro areas: North, Centre North, Centre South, South, Sicily and Sardinia (See Figure 1.1). These zones are connected to each other and with other countries (France, Switzerland, Austria, Slovenia, Greece and Malta) via transmission power cables.

[5] The report is available at the following link

[6] ARERA's reports are available in the references.

The Italian electricity market is mainly composed of a Spot Electricity Market and a Forward Electricity Market. The analysis proposed in this paper focusses only on the day-ahead market (*"mercato del giorno prima"*) which is a component of the spot electricity market. The other main components are: the intra-day market and the ancillary service market.

Typically the market starts with the day-ahead market's auction and an equilibrium is established. After that, intra-day markets' auctions occur and in every auction an equilibrium is achieved. Both day-ahead market's auction and intra-day markets' ones are uniform price auctions. The final market is the ancillary service market, which consists of several sessions. This is a "pay-as-bid" market. At the end of this procedure the market is balanced.

Figure 1.1: Market Splitting vs No Market Splitting (Zones)

(a) 12/01/2017 02:00 am

(b) 12/01/2017 05:00 pm

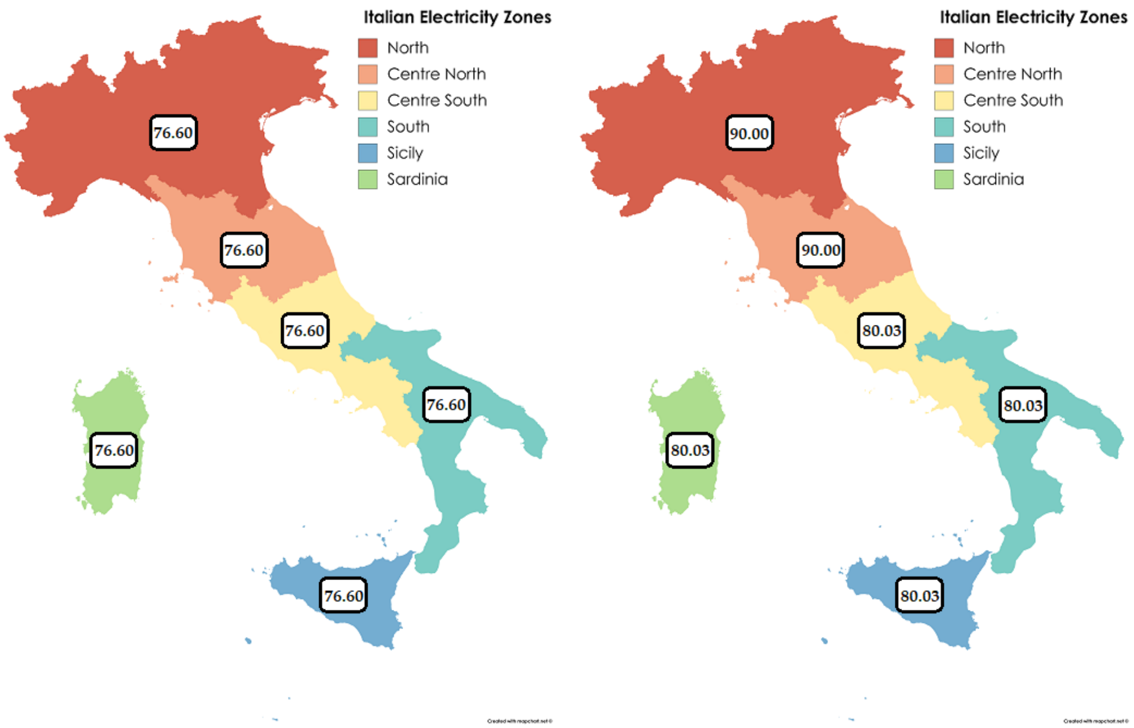


Fig (a) shows a case of no market splitting where all the zonal prices are the same.

Fig (b) shows a case where market splitting occurs: zonal prices are not equal.

Source: Elaboration of GME Data.

Day-Ahead Market

Day-ahead market is structured as a uniform price hourly auction. Each day-ahead market session opens 9 days before the target day and it closes one day before. During this time lapse, operators can submit orders. Each order is a pair containing a price and a quantity. Buyers submit bids whereas sellers submit offers. Each supplier can submit a maximum of four offers from every power plant they own. Therefore, each offer is associated with a specific power plant. GME (*"Gestore dei Mercati Energetici S.p.A."*)[7] receives and registers these bids/offers. In the first instance, it "translates" the bids (submitted by buyers) at zero price. Indeed, these bids are intended to be "at any price" and the price is converted from 0 €/MWh to 3000 €/MWh (maximum price). Once this procedure has been accomplished, GME proceeds with the computation of the demand and supply curves. These curves are computed as the cumulative sum of all the accepted/rejected orders. In particular, for demand, bids are ordered with a decreasing price criterion whereas, for supply, offers are ordered with an increasing price criterion; more precisely, they are ordered through the "Merit Order" condition, but this criterion will not be discussed here. Therefore, at the end of this procedure there will be two step curves for each hour. The intersection point between the two curves is the hourly equilibrium. It may happen that the two step functions intersect not in a point but rather in a segment. This segment can be vertical or horizontal. The former indicates a situation where there is price indeterminacy whereas the latter indicates quantity indeterminacy. In the first case, the equilibrium is set with the mid-price rule: the middle point of the intersection segment is chosen. In the second case, the welfare is maximized if the equilibrium is set when the quantity is maximized: the far right point of the segment is chosen. This equilibrium, is the unconstrained hourly equilibrium that does not take into account market congestion. In other words, unconstrained equilibrium assumes unlimited Available Transmission Capacity (ATC).[8] It may happen that, after the national auction, a zone bought more electricity than the production system of that zone sold. Thus, it is possible to send into that zone a certain amount of electricity. If this amount satisfies the demand, market splitting does not occur (see Figures 1.1(a) and 1.2(a)). On the contrary, if this amount is not enough and the transmission power cable is not able to carry more electricity, market splitting occurs. If market splitting occurs, two or more zonal auctions

[7] The Italian NEMO (Nominated Electricity Market Operator).

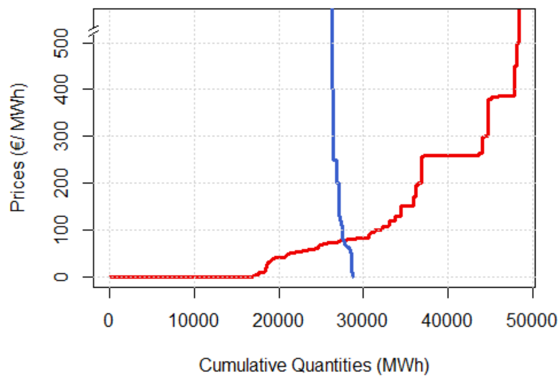
[8] Italian electricity market is characterized by more than one zone. Therefore, more than one zonal price may occur.

are automatically created and new equilibria are computed. This procedure is repeated until transmission power constraints are not violated any more. The output of this procedure are different zonal prices as results of zonal auctions (see Figures 1.1(b), 1.2(b) and 1.2(c)). At the end, sellers will sell the electricity at the zonal price whereas the buyer will buy the electricity according to PUN (*"Prezzo Unico Nazionale"*) which is the final national price computed as the weighted average of zonal prices. Foreign buyers pay the zonal price.

Figure 1.2: Market Splitting vs No Market Splitting (Curves)[a]

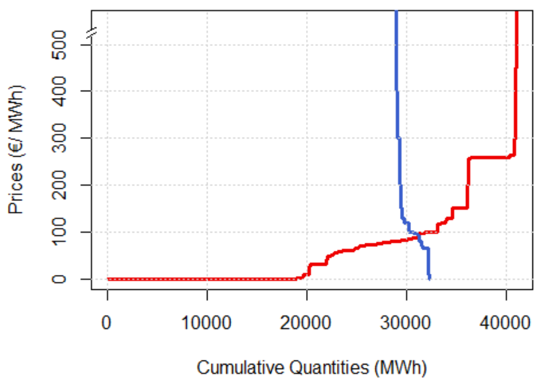
(a) 12/01/2017 02:00 am

All Zones



(b) 12/01/2017 05:00 pm

Zones where $P_{zonal} = 90.00$



(c) 12/01/2017 05:00 pm

Zones where $P_{zonal} = 80.03$

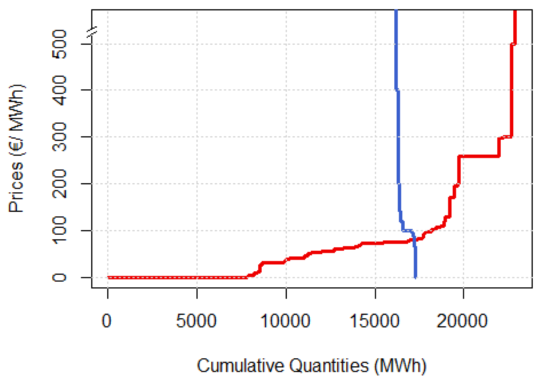


Fig (a) shows a case of no market splitting where only one auction occurs.

Fig (b) and Fig (c) show a case where market splitting occurs: more than one auction occurs.

Source: Elaboration of GME Data.

[a]In these plots, market coupling and zonal electricity flows have been coded following the same criterion exposed in Section 1.4.1. The price cap is 3000 €/MWh. However, plots have been cut at 500 €/MWh to provide a zoom on the intersection points.

1.4 Data

Two sources compose the data set: GME (*"Gestore dei Mercati Energetici S.p.A."*) and REF-E, an Italian consulting company operating in the energy sector. In order to present the structure of the data in the clearest way, they are explained separately here below.

1.4.1 GME

The analysis focusses on the day-ahead market, the so called *"Mercato del Giorno Prima" (MGP)*. The following information is available on the website of GME:

1. Public domain bids/offers data;
2. Market coupling data;
3. Day-ahead market unconstrained prices.

Public domain bids/offers data

All the bidding schedules of the operators are registered in the public domain bids/offers data. The analysis has been carried out using a four-year data set: from March[9] 2015 to December 2018. Each annual data set contains twenty columns and approximately 25 million rows.

The main variables used for the data analysis are: quantity offered (adjusted), price, purpose (bid/offer), status (accepted and rejected; incomplete bids/offers are discarded from the sample), operator's name, power plant's name and hour. Bilateral contracts are included in the bidding schedule as they must be taken into account for the computation of the equilibrium point.

Market coupling data

From February 2015, there are three market coupling "zones": Slovenia Market Coupling, Austria Market Coupling and France Market Coupling. The quantities that every hour flow across the border (incoming/outgoing) affect the hourly equilibria.

[9] Before March 2015 (precisely the 24th of February) another algorithm for the computation of PSV was in place. Therefore, it is not possible, with the R code developed, to perfectly calculate the unconstrained price before this date.

In the data provided by GME, these quantities are not represented by bids/offers submitted by operators, but they are available as aggregate amounts. Therefore, it is only possible to know that a certain quantity has been bought/sold at a certain hour. This is enough for the computation of the equilibria. This hourly information has been coded as bids/offers and added to the daily public domain bids/offers data (bids at 3000 €/MWh and offers at 0 €/MWh). This way, the R code, developed to compute the unconstrained market hourly equilibria, is able to recognize them as orders and take them into account in the construction of the demand and supply curves. Nevertheless, this way of coding the market coupling data does not take into account the hypothesis of market coupling as the price setter.

Day-ahead market unconstrained prices

Information on the unconstrained prices (PSV)[10] is available on the website of GME. This information has been used to check whether the R code was working properly or if some errors had occurred during the computation of the hourly equilibria: if the difference between the actual unconstrained equilibrium published in the GME web page and the actual unconstrained equilibrium computed by the R code was zero the hourly equilibrium was considered correct. At the end of this double-check process, it is possible to claim that the R code works properly in 97% (approximately) of the cases. In the case where the PSV computed from the R code differed from the one published by GME, the observation was dropped.

1.4.2 REF-E

Thanks to REF-E,[11] which provided extensive information about Italian power plants, it was possible to map a consistent share of power plants and identify their main specifications. Here follows the list of the specifications provided:

- Zone: The macro-area;
- Operator: The operators' names;
- Data-in and Data-out: when the power plant started to operate in the liberalized market and eventually when it stopped;
- Technology: The technology involved in the production;

[10] This acronym stands for *"Prezzo Senza Vincoli"*.
[11] Webpage available at: https://www.ref-e.com/it

- Energy Efficiency: REF-E estimated the hourly consumption curve of several thermal power plants with a parabolic model (the quantity produced, expressed in MW, is on the x-axis whereas on the y-axis there is the amount of heat, expressed in Gcal/h, that must be generated in order to produce a certain amount of electricity).

1.5 Methodology

The aim of this study is to analyse if the equilibria, that occurred during the four years considered, are the results of a competitive setting or if more competitive equilibria might have been possible. As discussed above, an equilibrium is a pair of price and quantity and it is the result of all the bids/offers submitted. From a theoretical point of view, if all the suppliers were price takers the equilibria would be the perfectly competitive equilibria. In reality, no operator is a price taker. However, the market is characterized by market power asymmetries on the supply side. Thus, there are operators with a limited market share and some other operators with a more consistent market power.

The bidding strategy of an operator includes a variety of different elements: types of plants and their technologies, the number of plants, the market zone and several other aspects such as markup. Indeed, it is evident from the literature, that strong operators are potentially capable of altering equilibria in order to achieve higher profits. This study aims to analyse what would have happened if leading operators had behaved as small operators. Small operators tend to behave more similarly to a fringe firm rather than a leading operator.[12] Theoretically, a fringe firm should submit offers that coincide with its marginal costs. A small operator will not submit an offer that exactly coincides with its marginal costs, but its bidding strategy will be closer to its marginal cost than a strong operator. Therefore, the task is to force the leading operators to behave as small operators. This way, it is possible to observe what equilibria would have occurred and investigate if there are any differences between these two sets of equilibria.

In this case study, only one of the largest Italian generators is considered the Leading Operator (L.O., hereafter) whereas the other firms considered during the data analysis are smaller generators. In order to achieve this goal, a synthetic supply must be computed for every hour. As first step, it is important to define the following expressions:

Actual Supply:

[12] See Akgün (2004) and Ciarreta and Espinosa (2010b)

$$S_m^{Total} = \sum_{i=1}^{m} y_i$$

The set of offers is given by $\mathbf{y} = (y_1, y_2, ..., y_m)$, where $\mathbf{y}$ contains all the offers submitted by suppliers.

Residual Supply:

$$S_n^{Residual} = \sum_{j=1}^{n} x_j$$

The set of offers except the ones of the leading company is given by $\mathbf{x} = (x_1, x_2, ..., x_n)$, where $\mathbf{x}$ contains all the offers submitted by all suppliers except for the ones submitted by the L.O.

Leading Operator Supply:

$$S_l^{L.O.} = \sum_{k=1}^{l} z_k$$

The set of offers submitted by the L.O. are given by $\mathbf{z} = (z_1, z_2, ..., z_l)$, where $\mathbf{z}$ contains all the offers submitted by the L.O. Therefore:

$$S_m^{Total} = S_n^{Residual} + S_l^{L.O.}$$ [13]

The crucial point is to create $S_p^{L.O.Synthetic}$ (note that $p \neq l$)[14] such that:

$$S_t^{TotalSynthetic} = S_n^{Residual} + S_p^{L.O.Synthetic}$$

This can be achieved by following the methodological approach proposed by Ciarreta and Espinosa (2010a). It requires two steps: 1) association of the plants, 2) translation of the supply schedule. The following two subsections are dedicated to this procedure.

1.5.1 Association of the plants

In the electricity market the marginal costs of the plants depend on several inputs such as: type, technology, vintage, installed capacity and energy efficiency. For this reason, it is reasonable to claim, for example, that the marginal cost of a coal thermal plant built in 1965 does not differ too much from the marginal cost of a plant with the same specifications. Thus, given that the L.O. owns a set of plants the task is to find the most similar plants

[13] Note that m=n+l.

[14] See 1.5.2.

in the market owned by other operators in the market. Therefore, the aim is to associate the highest number of plants with strict criteria. The stricter the matching criteria are, the smaller the bias will result. Every plant has been matched following, at least, two criteria: the type (e.g. thermal and hydro) of plant and the technology (e.g. run-of-river hydro and pumped-storage) used by the plant. Unfortunately, these two criteria are not strict enough to permit a reliable association process for each power plant. For this reason, in order to allow a reliable matching output this procedure has been conducted separately for zero marginal cost plants and for thermal plants.

It is possible to associate zero marginal cost plants using only type, technology, data-in, data-out and zone.[15] The zero marginal costs plants involved in the data analysis are Hydroelectric[16] and Wind power plants. Ciarreta and Espinoza (2010a) proposed vintage as an association criterion. In this paper, the association process for the thermal plants followed different criteria: type, technology, data-in, data-out and energy efficiency[17]. The latter criterion is not based on an existing literature stream. Indeed, this idea is new. This criteria is based on finding the most similar plant through the energy efficiency curve. Therefore, the competitor's plant with the closest curve to the one of the leading operator's plant has been chosen among the list. This was done by computing the integrals between the selected leading operator energy efficiency curve and the ones of other power plants belonging to competitors. The limitation of this method is that each plant has an interval of production and for the computation of the integrals, between the L.O.'s curve and each other curve, the minimum and maximum production power of the leading operator's plant have been chosen as the extremes of the interval for each integral. At the end of this procedure, a list of integrals is

[15]For zero marginal cost plants, the Zone criterion permits to control for the exogenous inputs (for example, wind power) as they depend on the geographical zones.

[16]Only Run-of-River and Storage; Pumped-Storage have marginal costs depending on the type of the pump so they have not been taken into account in the association process.

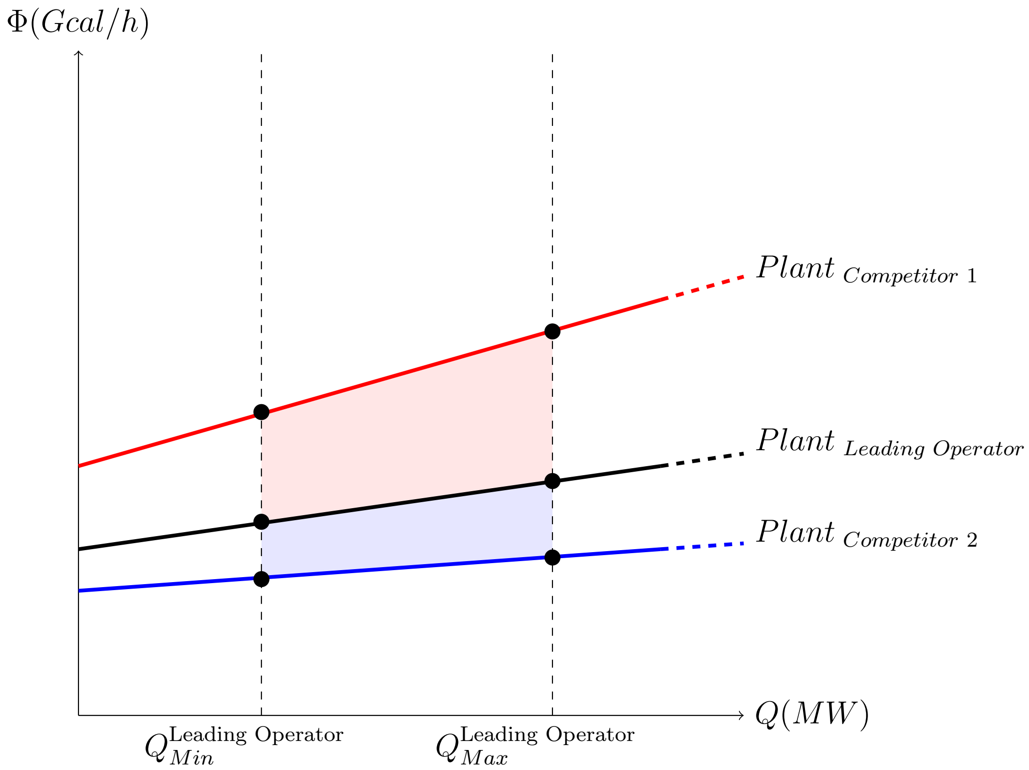
[17]Only a few associations have been made using very similar technologies because the same technologies were not available in some cases.

Moreover, the Zone criterion was not taken into account in the association process of the thermal plants. This can be considered a source of bias as the bidding strategies can be related to the bidding zones. However, Zone criterion would result in a further constraint upon the association process. In fact, it would drastically reduce the amount of power plants available for the association of each L.O.'s power plant. Therefore, it is favourable to identify the most similar plants at a national level than the most similar ones within the same bidding zones. Furthermore, as the analysis focusses on the unconstrained prices, the Zone criterion is less important.

available for each leading operator's plant. The competitor's plant with the lowest integral is chosen for the association.

A further clarification is provided by Figure 1.3. The figure illustrates an example of the association technique based on the energy efficiency criteria. Assume that in the market there are only three power plants (Black, Blue, Red), using the same technology, having efficiency curves represented by the three straight lines: Black (Leading Operator), Red (Competitor 1) and Blue (Competitor 2). The aim is to find what is, among the plants available in the market (in this case, Red and Blue plants), the one which is most similar the one owned by the the Leading Operator. It turns out that the Blue has an efficiency curve more similar to the Black rather then the Red, as the integral computed between Blue and Black is smaller than the one computed between Red and Black. For this reason, the Blue will be chosen as the plant to be associated with the Black.

Figure 1.3: Efficiency Curves



Overall, approximately 50% of the L.O.'s power plants have been associated.[18][19] At the end

[18]Due to a data constraint it was not possible to associate the entire set of the L.O.'s power plants reliably.

[19]We assume the unmatched plants would have the same bidding strategy within the synthetic supply

of this procedure, each plant of the leading operator has three matched plants: first best, second best and third best. There is the need of a second and third best, chosen with the same association criteria, because it may happen that, given a certain hour, the first best is not present in the data set. If this happens, it is replaced by the second and the synthetic offer is computed referring to the second best. Obviously, if the second best is missing, the R code looks for the third one. If the third one is not available either, the R code skips the association and proceeds with the following one.

1.5.2 Translation of the offers

Once the plants have been matched, it is possible to proceed with the "translation" of the bidding strategies. In other words, the aim is to impose the bidding strategy of the competitors to the leading operator. This can be done by changing the bidding schedule of each leading operator's plant with the associated ones. For the sake of simplicity, assume that the aim is to match the plant A (owned by the leading operator) with the plant B (owned by a competitor). This procedure requires the following steps:

- Sum the quantity offered by plant B (we get q^B_{tot}). Divide each quantity offered for the total quantity. This way, we will get a vector of proportions that has from one to four entries (each supplier can submit a maximum of four offers from every power plant they own). Define this vector as $q^B_{proportion} = (q^B_1/q^B_{tot}, ..., q^B_o/q^B_{tot})$ with $o \in (1, 2, 3, 4)$.
- Sum the quantity offered by plant A (we get q^A_{tot}). Multiply q^A_{tot} by each entry of $q^B_{proportion}$. This means that the synthetic supply schedule of A will have the same amount of offers submitted by B. The prices used in the bidding schedule of B are used to construct the synthetic supply schedule of A. This way, the leading operator uses the same bidding strategy of a smaller firm. Therefore, we force the leading operator to behave like a smaller firm.

At the end of this procedure, once that all the offer schedules have been translated, we will get $S^{L.O.Synthetic}_p$. Thus, the synthetic supply is given by:

$$S^{TotalSynthetic}_t = S^{Residual}_n + S^{L.O.Synthetic}_p$$

(note that $t \neq m$).

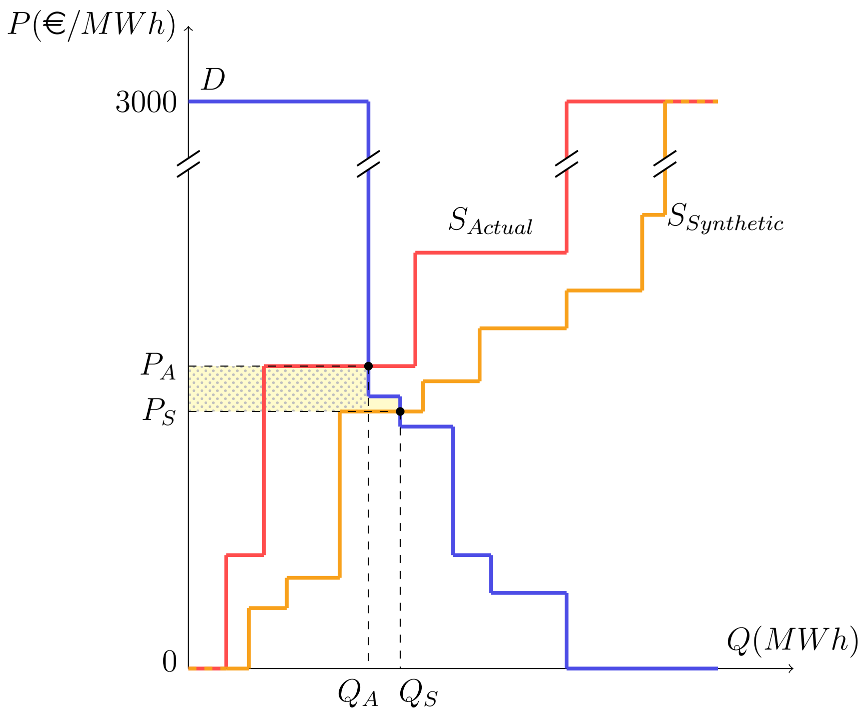
curve as in the observed bid stack.

This way, two intersection points are obtained every hour. Next section explains what the aim of the empirical analysis is.

1.6 Empirical Analysis

Synthetic supply method, illustrated in previous section, allows us to obtain two sets of different equilibria for each hour. The actual equilibria are the ones that we observe in the real market whereas the synthetic ones derive from the intersection between demand curves and synthetic supplies. The latter are obtained by forcing the leading operator to behave as smaller firms. For this reason it is reasonable to assume that synthetic equilibria are more competitive than the actual ones: lower prices and higher quantities should be observed. However, the electricity market is characterized by a very inelastic demand. Thus, only the statement referring to prices seems to be true.

Figure 1.4: Actual Equilibrium, Synthetic Equilibrium and Consumer Surplus Loss



D:Demand; S_{Actual}*:Actual Supply,* $S_{Synthetic}$*: Synthetic Supply;* P_A*: Actual Price;* P_S*: Synthetic Prices;* Q_A*: Actual Quantity;* Q_S*: Synthetic Quantity.*

A further clarification is provided by the example illustrated in Figure 1.4. This plot shows a graphical representation of the methodology proposed above. It shows two different hourly market clearing prices. The actual equilibrium is the intersection point between Demand (in blue) and Actual Supply (in red) whereas the synthetic equilibrium is the intersection point between Demand and Synthetic Supply (in orange). Furthermore, the yellow area represents the consumer surplus loss.

The task of the empirical analysis is two-fold: on one hand, it investigates if there is any statistically significant difference in means between actual and synthetic prices whereas, on the other, it computes the consumer surplus loss in order to evaluate the impact of the bidding strategy of the leading operator. Moreover, an alternative version of the Lerner Index is presented and discussed.

1.6.1 Actual Prices vs Synthetic Prices

The aim is to verify whether actual prices are on average higher than synthetic ones and to test whether the difference is statistically significant. Let the actual prices and the synthetic ones be defined, respectively, as the following vectors with length T= d x 24, where d is the number of days in a year[20]:

$$\mathbf{p}^{Actual} = (p_1^{Actual}, p_2^{Actual}, ..., p_T^{Actual})$$

$$\mathbf{p}^{Synthetic} = (p_1^{Synthetic}, p_2^{Synthetic}, ..., p_T^{Synthetic})$$

However not all the hours are in the sample as already explained above.
The scope of this study is to investigate to what extent the actual prices are higher than the ones computed under the assumption of more competitive bidding strategies. Results are presented in the appendix and are organized in four tables, one for each year, containing the means of actual and synthetic prices computed for every month in different intervals of hours. Monthly means of actual and synthetic quantities are presented. Furthermore, the monthly difference in the means of the actual and synthetic prices and quantities are reported. Moreover, Figure A.1 illustrates the trends of the monthly difference in means, between actual and synthetic prices, for all hours of the day (labelled as "Tot"), daylight hours (going from 8am to 8pm of the same day, labelled as "Day"), night hours (from 9pm to 7am of next day, labelled as "Night"). Results suggest that actual prices have been significantly higher than synthetic ones. The most outstanding discrepancies occurred during 2017, reaching a peak

[20]n= 365 in 2017 and 2018, n=366 in 2016, n= 306 in 2015, because the first two months of 2015 have been discarded for reasons explained earlier in the paper.

of monthly average differences of 8.03 €/MWh (See Table A.3 in the Appendix). It seems that the prices during the day have been generally higher than the ones observed by night. However, there are not remarkable differences between the monthly means of day prices and night ones.

Moreover, a t-test has been run on annual prices to investigate if there is a statistical difference in means between actual and synthetic prices. The null hypothesis is rejected for every year confirming the hypothesis that the two time series differ in mean. However, it should be pointed out that the main assumptions of the t-test are not met. Thus, in order to get rid of time dependency which compromises the assumption of independent observations and the lack of normal distribution, due to the log-normality nature of prices, of actual and synthetic prices, a bootstrap technique has been implemented. Each annual data set, composed by approximately 8760 pairs of hourly actual and synthetic prices, has been randomly sampled 4000 times. Each sample contains 1000 random observations. The mean of each sample has been computed and the t-test has been run on this new data set. This way, the assumptions of normal distribution and independent observations are not violated.

On the contrary, findings show that there are not statistical differences in means between actual quantities and synthetic ones, due to the inelastic demand. Obviously, synthetic quantities are higher than actual ones.

1.6.2 Consumer Surplus Loss

Consumer surplus loss has been computed, for each hour, as the following area[21]:

$$CSL = (P_A - P_S) \times Q_A \tag{1.1}$$

Thereafter, these values have been summed on a monthly and annual basis. Moreover, in order to have a measure that helps to compare the size of the Consumer Surplus Loss under a different scenario, the following relative measure is proposed:

$$CSL^{Rel} = \frac{(P_A - P_S) \times Q_A \times 100}{P_A \times Q_A} \tag{1.2}$$

These results are available in the appendix (see Tables A.1, A.2, A.3, A.4). Ciarreta et al. (2010a) computed the Consumer Surplus Loss as a rectangle trapeze thus adding the triangle

[21]Figure 1.4 provides a graphical example. The estimated Consumer Surplus Loss is represented by the dotted yellow area.

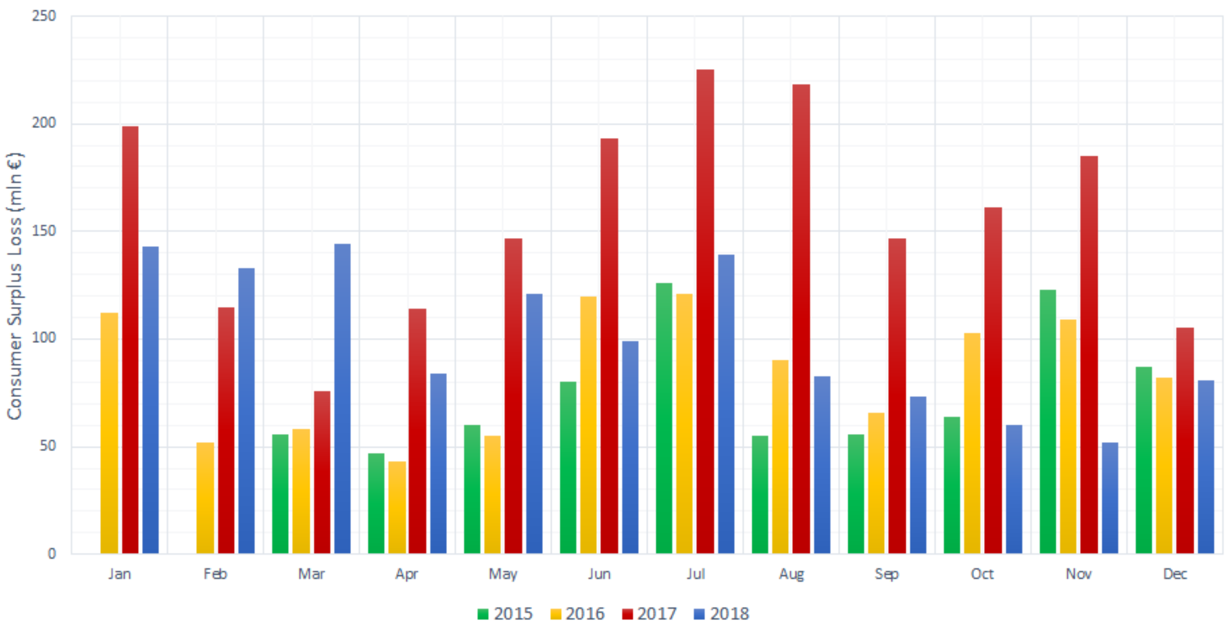
area below

$$\frac{(P_A - P_S) \times (Q_S - Q_A)}{2}$$

However, the choice of excluding the triangle in the estimates has a double motivation. The first one is to prevent the risk of a slight overestimate of the Consumer Surplus Loss. The second one, which is the most important one, is that the demand is very inelastic. Thus, the difference between the synthetic quantity and the actual one is extremely small. Therefore, the area of the triangle marginally affects the Consumer Surplus Loss.

Results suggest that Consumer Surplus Loss has been constantly increasing from 2015 to 2017 reaching its peak in 2017. From the end of 2017 it seems that this growing pattern slowed down, decreasing significantly in 2018. Figure 1.5 illustrates the Consumer Surplus Loss over the years of analysis.

Figure 1.5: Consumer Surplus Loss



The plot illustrates the consumer surplus loss from 2015 to 2018.

January and February 2015 are note reported for the reasons explained above.

This results should be interpreted considering both general and specific factors. The former refer to events which affect the regular market dynamics, whereas the latter refer to both the data analysis and the case study. The results suggest that the main peaks of Consumer Surplus Loss occurred during the high level of electricity demand, which mainly appear during months when heating and cooling were necessary. Indeed, when the demand is high, exercising market power may become easier and the main market operators could take advantage of this. However, the complexity of the dynamics that characterize the electricity markets, makes very hard to find a unique general motivation explaining these results. Indeed, the market is constantly affected by internal and external shocks. For example, in the first six months of 2016, Consumer Surplus Loss might have reduced as some other market operators increased their revenues. Indeed, from a data point of view Consumer Surplus Loss increases when the L.O. raises its markup and the competitors fail to do so. On the contrary, it decreases in two cases. First of all, if the competitors increase their markup whereas the one of the L.O. remains fixed then the Consumer Surplus Loss decreases. Secondly, if the L.O. decreases its markup and those of the competitors remain constant. Moreover, it is important to stress that market operators can constantly change their auction strategies adopting different bidding behaviours throughout the hourly day-ahead market auctions. In other words, the bidding daily schedule of a power plant might vary throughout the hours of the same day. However, the bidding behaviour might also change analysing the day-ahead market at a same hourly auction but on different days. Therefore, the hourly day-ahead market bidding schedules of the associated plants might have changed over the four years.[22] These dynamics, which are extremely difficult to monitor from a data point of view, contribute to the uncertainty in data interpretation. However, even if the question remains open, results suggest that a more competitive setting occurred in 2018 compared to the previous year.

1.6.3 Lerner Index

Ciarreta et al. (2010a) proposed an alternative version of the Lerner Index. In this section, the standard version and the alternative one are presented. Thereafter, results are discussed. The traditional version of Lerner Index is defined as:

$$LI^{Traditional} = \frac{\text{Price} - \text{Marginal Cost}}{\text{Price}} \tag{1.3}$$

The alternative version of Lerner Index is defined as:

$$LI^{Alternative} = \frac{P_A - P_S}{P_A} \tag{1.4}$$

[22]The power plants associated are in operation over the period under analysis, thus closing capacity does not seem to be a source of bias affecting these results.

Where P_A and P_S are respectively the actual and synthetic prices.
This latter version can be consider as a lower bound measure of the standard LI as $P_S >$ Marginal Cost.
Results are presented in Table 1.1. It is crucial to interpret them taking into account that this is a lower bound measure (as the competitors' markup is included in this index) and that only approximately 50% of the L.O.'s power plants have been matched.
$LI^{Alternative}$ highlights a pattern similar to CSL and to the difference in means between actual and synthetic prices. In fact, results suggest that LI is higher during those months where above average heating and cooling were required. The peak of this alternative version of the standard LI occurred in summer 2017.

Table 1.1: Average Alternative Lerner Index

Period	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Year
2015	-	-	0.06	0.06	0.06	0.07	0.06	0.04	0.05	0.05	0.08	0.06	0.06
2016	0.10	0.06	0.06	0.06	0.07	0.14	0.09	0.11	0.06	0.08	0.08	0.06	0.08
2017	0.10	0.09	0.07	0.13	0.16	0.17	0.16	0.12	0.14	0.11	0.11	0.08	0.12
2018	0.11	0.09	0.09	0.08	0.09	0.07	0.08	0.05	0.04	0.03	0.03	0.05	0.07

1.7 Limitations, Strengths and Future Research

Even though this study tried to minimize biases, it is extremely hard to control for some of them. In this section the main sources of bias will be discussed.

The first two limitations refer to the market structure: the unconstrained price (PSV) is considered and only the day-ahead market has been taken into account. Given that PSV does not take into account zonal prices, there is a source of bias, as some information on bidding strategies related to the bidding zones are not considered. However, PSV is an indicator of real prices. On the contrary, the analysis which only focusses on the day-ahead market does not take into account relevant information contained in the successive market sessions. Nevertheless, the day-ahead market is the most relevant market as the largest quantity of electricity is exchanged in this market (approximately 90% of the spot electricity markets).[23] Thus, from this point of view, the analysis cannot be considered complete but is surely

[23]For example, in 2017 the total electricity exchanged in the day-ahead market was 292 TWh compared to 25 TWh exchanged in the intraday markets (see the GME report available in the references.)

important.

The other two main limitations are related to the association process. Indeed, even if the most similar plants have been found and matched with the ones of the L.O., they are just partially representative of the true marginal costs. Moreover, the bias increases with the second and third best as the associated plant will reflect less the technological features of the L.O.'s power plant. Furthermore, only 50% of the L.O.'s power plants were associated. This is a further limitation as some bidding strategies have not been taken into account. The reason why the other power plants were not matched is related to the lack of a reliable association process or to a data constraint. For these reasons, the results of this case study should not be interpreted as a definitive market analysis, but as a starting point for future research.

However, this research contributes to the existing literature by adding new evidence and findings. It is important to point out that this technique partially controls for start-up costs (as they are included in the competitors' bidding strategies). For this reason, they are capable of representing some market dynamics more than other methodologies, as there is a control for start-up costs.

Moreover, the technique of synthetic supply can be applied in several ways.[24] This study focusses only on a case study of market power, but the potential of this technique is extremely broad.[25] In particular, synthetic supply could be employed in the computation of competitive benchmarks for the market. Indeed, it will be possible to obtain an estimate of benchmarks of a perfect competitive market if the offers of all the power plants are calibrated on marginal costs. Start-up costs may be included as well in order to achieve a more accurate set of results. Furthermore, synthetic supply could also be employed to investigate the changes in bidding behaviours throughout the different hourly market auctions which are observed in the different markets (day-ahead market, intraday market, ancillary service market). This way, this tool could provide useful evidence on cross-market manipulation.

1.8 Conclusions

Market monitoring is a difficult task, as the electricity market is a dynamic environment, which constantly evolves both from a technological and a regulatory perspective. Therefore,

[24]See, for example, Ciarreta et al. (2017) or Ciarreta et al. (2010b).

[25]The methodology presented in this paper easily adapts to those markets where the offers are associated with the power plants.

the bidding strategies of the operators need to constantly adapt to achieve the best market performance. It is essential to constantly monitor the evolution of these markets in order to bring new evidence, methodologies, suggestions and policy recommendations.

The aim of this article is to provide further evidence on the topic and apply the synthetic supply approach to the Italian electricity market. In fact, this methodology, which does not follow the approach based on the inverse of the residual demand elasticity (see Wolak, 2003), enables us to analyse the Italian electricity market presenting results from a new perspective. Our results seem to suggest that a more competitive setting occurred in 2018 and that the market is experiencing a decreasing market power path, even though the results highlight the presence of persistent and non-negligible Consumer Surplus Loss. However, as previously discussed above, it is important to bear in mind that the question of whether significant market power is being exercised remains open and that a further and deeper analysis is required to extensively monitor the market. For this reason, even though the findings presented are intriguing and contribute to the existing literature, it is appropriate to stress that they are not definitive but rather a further step in developing a deeper and more comprehensive market analysis.

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Chapter 2

Detecting strategic capacity withholding through a synthetic supply approach - *Cui Prodest?*

Abstract

This research puts forward a new tool for the detection and assessment of strategic capacity withholding. The aim of this chapter coincides with Bataille et al. (2019), albeit it follows a different approach. The purpose of the methodology proposed in this paper, inspired by the well-established synthetic supply methodology,[1] is to investigate the hourly equilibria of the wholesale electricity market and assess if any market operator might have taken advantage hypothetically by withholding capacity. For this purpose, a four-step procedure has been adopted: the simulation of counterfactual scenarios, constructed under the assumption of lack of capacity withholding, comparison between the actual and counterfactual equilibria, the hourly analysis of the revenues for each market operator in both scenarios and, finally, the Synthetic Strategic Capacity Withholding Index, which is presented and discussed. This puts forward an original, alternative point of view to detect strategic capacity withholding.

[1]See Ciarreta et al. (2010a), Ciarreta et al. (2010b), Ciarreta et al. (2014) and Ciarreta et al. (2017).

2.1 Introduction

Dealing with the detection of strategic capacity withholding has always been a major challenge for the authorities worldwide (e.g. Chauve et al. (2009), CNMC (2015) and Gabriele (2016).[2]) Indeed, there are several issues related to the detection of this strategic misbehaviour due to its peculiarities. First of all, it is important to recall that there are two different types of strategic capacity withholding: economic and physical (see Joskow and Kahn, 2002). Although they have the same aim, economic and physical withholding substantially differ in the way they are employed. Economic capacity withholding results in bids at a price above the expected market clearing price. On the contrary, physical capacity withholding results in no bids at all, thus generating a missing data issue. In other words, in the first case bids are submitted, at a price that is unlikely to be consistent with power plants costs, and are registered by the ISO[3]/NEMO[4] whereas, in the second case, bids are not submitted and thus they are not registered by the ISO/NEMO. In both cases, the task is to intentionally and strategically subtract capacity from the market to affect market equilibria. Different strategies require different detection techniques given that the questions to be answered differ. "What bids, in the bid stack, have been intentionally submitted at a price higher than the market clearing price?" is the key question for detecting economic withholding, whereas "How many bids have been intentionally subtracted from the bid stack?" characterizes physical withholding detection. The problem is even more complex where an operator uses a mixture of both strategies.

This paper investigates physical capacity withholding using alternative approach,[5] based on a simulation algorithm based on well-established synthetic supply.[6] As dealing with physical capacity withholding means dealing with a lack of data, several hourly simulations are run to assess the effects on hourly equilibria of an additional capacity in the supply schedule. Moreover, this approach aims to identify who might have taken advantage from a capacity withholding strategy through revenues analysis. A review of the literature, data, methodology and results is presented and discussed in the following sections. It is worth stressing that

[2]For further details on this case see the reports, available in the references, by ARERA: the Italian Authority in charge of the electricity market surveillance.

[3]Independent System Operator.

[4]Nominated Electricity Market Operator.

[5]Compared to the existing literature mostly based on an econometric approach (e.g. Bataille et al., 2019 and Bergler et al., 2017).

[6]See Ciarreta et al. (2010a), Ciarreta et al. (2010b), Ciarreta et al. (2014) and Ciarreta et al. (2017).

this paper does not investigate the market but simply puts forward a new early-stage tool for detecting capacity withholding. The Italian wholesale electricity market is considered as a case study.

The chapter is structured as follows: the following section reviews the literature and the data are described in section 2.3. Section 2.4 presents the methodology and its theoretical underpinning. Section 2.5 presents the empirical analysis and results. Sections 2.6 and 2.7 respectively are dedicated to the discussion of the limitations, strengths and future research of this approach and to conclusions.

2.2 Literature Review

The literature on market manipulation is vast. Academics, institutions and companies have always shown great interest in this topic due to its economic, political and financial relevance. According to REMIT[7] and its guidance proposed by ACER (2016), several types of conduct of market operators can be considered market manipulation. Many publications and reports analyse the effects of such conduct and investigate different electricity markets worldwide.

Bosco et al. (2012) and Bigerna et al. (2017) provide estimates of market power in the Italian electricity market. The former includes a Lerner Index obtained by estimating marginal costs, and the latter provides a measurement of the ZLI (Zonal Lerner Index), paying particular attention to RES (Renewable Energy Sources). Bergler et al. (2017) and Fogelberg and Lazarczyk (2019) investigate the effects of strategic capacity withholding in the German-Austrian and Swedish electricity markets respectively. Ciarreta et al. (2010a) studies market power in the Spanish electricity market using the synthetic supply tool. Synthetic supply was used to simulate more competitive suppy schedules, obtained by forcing the leading operators to behave as smaller firms. Wolak (2003) and Joskow and Kahn (2002) present evidence on California's wholesale electricity market proposing a Lerner Index measurement based on the estimate of the inverse of residual demand elasticity, and an analysis of price spikes, respectively.

However, despite the vast literature on the topic, detecting bad conduct, potentially linked to market manipulation, remains a great challenge. Moreover, as the electricity market is in constant evolution, strategic bidding behaviours keep changing and operators might

[7]See Feltkamp (2013) and Harris and Ledgerwood (2012) for articles including observations about REMIT.

employ new strategies. Bergler et al. (2017) defined "quite innovative"[8] the way in which operators applied strategic bidding behaviours in past decades. In particular, the authors investigated the relationship between capacity withholding and power plant failure in the German-Austrian electricity market. Their results suggest that power plant failure might be adopted to intentionally and strategically withhold capacity in order to induce a rise in the price and extra profits. Fogelberg and Lazarczyk (2019) investigate the same topic focussing on the Swedish electricity market. Even though the approach differs from Bergler et al. (2017), the findings seem to come to the same conclusion: power plant failure might be used to intentionally increase the market clearing price.

Strategic capacity withholding is one of the most difficult types of bad behaviour and the literature available on the topic is relatively scarce compared to other literature streams related to the detection of market manipulation. Bataille et al. (2019) puts forward the RWC Index (Return on Withholding Capacity), a measure that provides useful information on possible incentives to an operator to withhold capacity in a given hour. The idea behind the index is to assess the benefit for an operator if it withheld 1 MWh of capacity, thus probably inducing a price increase. The German-Austrian bidding zone is considered as a case study. The RWC Index is structured as follows:

$$RWC = \frac{\Delta p \times (\text{Running Capacity}_{i,h} - 1)}{\text{Market Price}_h} \tag{2.1}$$

where Δp is the estimated value of the price premium expected by the supplier i for withholding one MWh capacity at hour h. In this paper, Δp was estimated following two econometric approaches: OLS and IV.[9] Therefore, Bataille et al. (2019) provide an estimation of Δp. However, this value might be computed, rather than estimated, through a simulation model[10] which should replicate the supply and subtract 1 MWh from the supply

[8] Bergler et al. (2017), p. 210.

[9] Bataille et al. (2019) suggest that there is a cubic relationship between residual demand (without renewable energy sources) and market clearing prices. This is the starting point for the estimation of Δp. The main variables used for its estimation are: residual demand, market clearing prices and the prices of gas, coal and CO2. Therefore, the OLS estimation is as follows:

$$(1) \quad p_t = \beta_0 + \beta_1 \times Lresid_t + \beta_2 \times Lresid_t^2 + \beta_3 \times Lresid_t^3 + \beta_4 \times pcoal_t + \beta_5 \times pgas_t + \beta_6 \times pCO2_t + \epsilon_t$$

$$(2) \quad \frac{\delta p_t}{\delta Lresid_t} = \beta_1 + 2\beta_2 Lresid_t + 3\beta_3 Lresid^2 = \Delta p$$

Lagged residual load was used as instrument variable for the IV model.

[10] The simulation model could be similar to the R model developed in this paper. For further details about this R model see Rossetto et al. (2019).

schedule of each operator under examination. This way, supply shifts to the left and an artificial equilibrium is computed for every hour. The artificial price obtained through this methodology could be used to compute the price premium.
The main idea of Bataille et al. (2019) is to provided a tool, useful for the electricity market watchdog, to better monitor the market. The authors claim that the RWC Index is able to provide better information on strategic capacity withholding than the previous available indices, namely RSI (Residual Supply Index) and PSI (Pivotal Supplier Index). This index provides a major contribution to the existing literature stream related to market monitoring indices.

The aim of this paper is to provide a tool which is able to provide useful evidence about manipulative behaviours such as strategic capacity withholding. The underlying idea is to add capacity to the supply schedule, rather than subtracting it as in Bataille et al. (2019), and assess what operator might have taken advantage from having hypothetically withheld this added capacity. Extra capacity is added to the supply schedule, thus shifting it to the right, to see what might have happened under different capacity withholding scenarios.[11] In other words, the comparisons between actual and synthetic scenarios provide evidence about the convenience of a hypothetical capacity withholding strategy. Hence, a new and innovative methodology is proposed to analyse strategic capacity withholding.

2.3 Data

The analysis carried out using the Italian day-ahead market. On the website of the Italian Nominated Electricity Market Operator (*"Gestore dei Mercati Energetici S.p.A."*, hereafter, NEMO) public domain bids/offers data are available. An annual data set comprises approximately 25 million rows and 20 columns containing a great deal of information[12] about the

[11]The Italian wholesale electricity market is characterized by stepwise aggregated curves, and not linear piecewise aggregated curve (see Euphemia Public Description p. 14). Therefore, subtracting only one MWh would most probably not result in any change in the market clearing price. Therefore, $\Delta p = 0$ and this means that nobody has the incentive to withhold capacity. For this reason, as we need to deal with stepwise aggregated curves, several attempts at adding/subtracting capacity (depending on which approach the analysis is following) to/from the supply schedule is recommended rather than subtracting only one MWh.

[12]The most important information is: Day (yyyymmdd), Hour, Bidding Zone (North, Centre North, Sardinia, ...), Bilateral Contract (True/False), Operator Name, Purpose (Bid for buyer, Offer for seller), Bid Status (Accepted, Rejected, ...), Quantity Offered, Adjusted Quantity, Awarded Quantity, Awarded Price, Price Proposed.

bid stack. Moreover, these data sets contain information about foreign buyers/sellers from Malta, Greece, Slovenia, Austria, Switzerland and France. However, information about market coupling is not included in public domain bids/offers. These data are aggregated and are available on the Italian NEMO website. Only the information on the quantity bought and sold per coupling zone (Austria Coupling, France Coupling, Slovenia Coupling) is available. This information is enough to compute the unconstrained equilibria. A market algorithm, developed in R, computes the market equilibria. The algorithm is employed to run market simulations. For further details of the functioning of the algorithm,[13] Italian electricity market structure and the Italian day-ahead market see "Market coupling data" section 1.4.1, chapter 1.

2.4 Methodology

The approach taken by this paper is rooted in the synthetic supply methodology put forward for the first time in Ciarreta et al. (2010a) and further developed in more recent articles by Ciarreta et al. (2010b), Ciarreta et al. (2014) and Ciarreta et al. (2017). The idea behind synthetic supply is to create a counterfactual supply to assess what might have happened in the market under some assumptions. As the aim is to investigate potential cases of capacity withholding, in this paper the counterfactual is constructed under the assumption of the lack of such misbehaviour. Thereafter, the methodology is used to assess who might have benefited from a capacity withholding strategy through revenue analysis. Specifically, the proposed methodology consists in a four-step procedure:

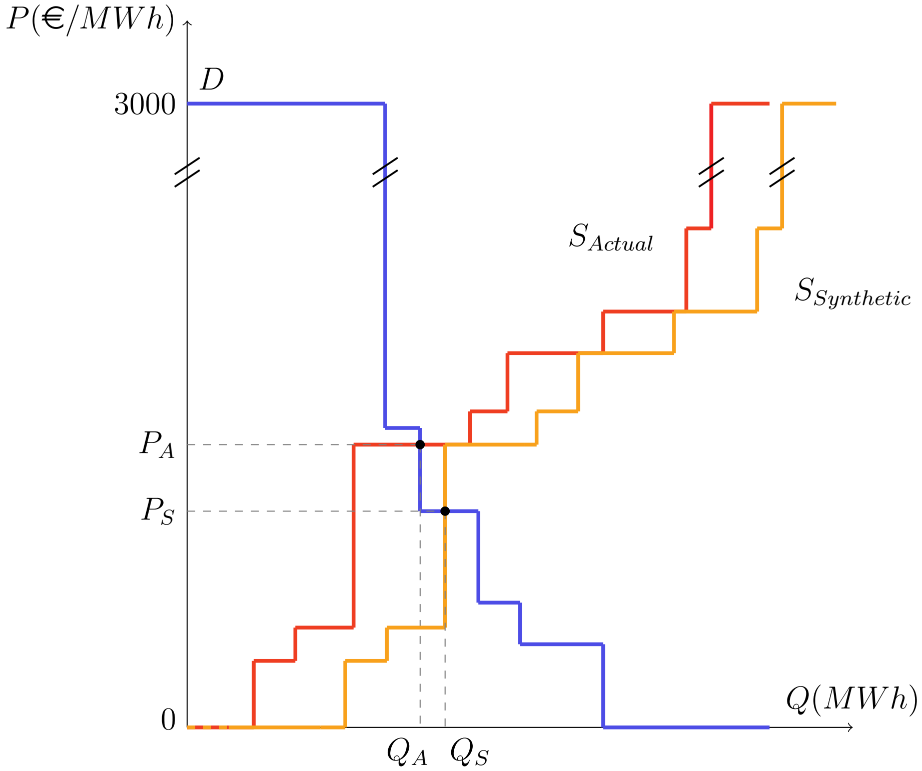
1) Given that we cannot directly observe capacity withholding from the data, it could have happened every hour. For this reason, the task is to create several hourly scenarios under the assumption of the absence of capacity withholding. To achieve this, additional capacity must be added to the total supply to "offset" the hypothetical capacity withheld. Therefore,

[13]In order to introduce the additional quantity in the simulation scenario, it has to be coded as an offer. To achieve this, an artificial offer is created at price zero with a quantity equal to the percentage chosen. This extra capacity causes a shift to the right of the supply, thus reducing the amount of real accepted offers by existing market operators. Obviously, this offer does not belong to any market operator. Therefore, it is possible that in the synthetic scenario there are fewer operators than in the actual case. Operators not listed in the hourly synthetic scenario are deleted from the sample as for them it would not have been convenient to employ a capacity withholding strategy. Indeed, for them, withholding would have driven them from the market with zero profit.

it is important to make the best assumptions about the amount of quantity hypothetically withheld and its price, given that we cannot know if a capacity withholding event occurred and how it occurred. To face this challenge, several hourly counterfactual scenarios are constructed changing the amount of the extra capacity offered. The amount of extra capacity offered must reflect the wholesale market at that given hour. Therefore, in order to reflect the changes in the market, the additional capacity offered must be a small percentage of the quantity exchanged in the market (for example 0.5%, 1%, 2%, ...). This way, the procedure adapts to the different hourly market settings. The extra capacity can be added at different prices. Simulations are run according to the zero price criterion, thus the right shift of supply always affects the hourly equilibrium.[14] At the end of this procedure, a pair of actual and synthetic equilibria are obtained for every hour in each simulation scenario. In particular, the synthetic equilibrium $\{P_S; Q_S\}$, is computed as the intersection point between actual demand and synthetic supply, whereas actual equilibrium $\{P_A; Q_A\}$ is computed as the intersection point between actual demand and actual supply. Figure 2.1 provides further clarification about the construction of synthetic supply. In the example, the additional capacity is at price zero, shifting the whole curve to the right. The actual equilibrium is the intersection point between actual demand (in blue) and actual supply (in red) whereas the synthetic equilibrium is the intersection point between actual demand and synthetic supply (in orange). Further graphic examples are provided in the appendix (see figures in appendix B.1)

[14]The strength of this methodology is its remarkable flexibility, enabling several simulations to be carried out according to different additional capacities at different prices. This paper puts forward a new methodology and assesses its results considering only one of the most important simulation scenarios: right supply shifts occurred every hours. However, this methodology should be further developed in software where several simulations can be run according to different pairs of additional quantities and prices.
Moreover, the zero price criterion constitutes a source of bias as discussed in section 2.6.

Figure 2.1: Actual Supply vs Synthetic Supply



D: Demand; S_{Actual}: Actual Supply; $S_{Synthetic}$: Synthetic Supply; P_A: Actual Price; P_S: Synthetic Prices; Q_A: Actual Quantity; Q_S: Synthetic Quantity.

2) Compare hourly actual and synthetic prices $\{P_A; P_S\}$. An anomalous pattern in actual prices might suggest strategic bidding behaviour. However, an analysis relying solely on real prices may not be enough. The comparison with counterfactual time series constitutes a useful tool for enhancing the detection of price anomalies.

It is well known that a capacity withholding strategy results in a price increase. Therefore, a suspicious price spike might suggest a capacity withholding strategy and requires further investigations. However, a price spike is just one of the potential cases in which capacity withholding might have taken place. For example, could capacity withholding have occurred during a decreasing pattern in prices?[15] In other words, can capacity withholding be employed in order not to let the price fall too much? If so, how can capacity withholding be spotted

[15] For example, figures from B.16 to B.27, available in the appendix, highlight this feature: in many cases synthetic prices might have been way lower than the actual prices during decreasing patterns.

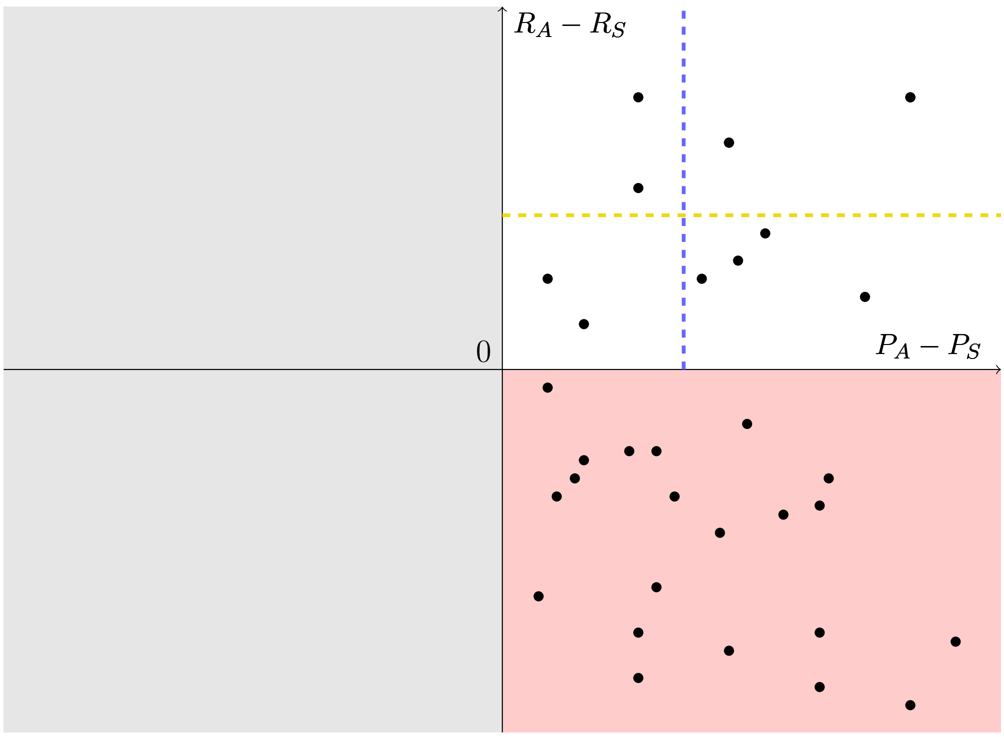
in these cases simply by analysing actual data?

3) Compute the hourly revenues for each operator in the actual case (R_A) and in each counterfactual scenario (R_S).[16] For operator i, at hour h, if $R_A^{i,h} - R_S^{i,h} > 0$, the observation remains part of the sample, otherwise it is discarded. The positive differences between actual and synthetic revenues highlight the suppliers who benefit from being in the actual rather than synthetic scenarios. This evidence suggests that these operators ("detected operators", hereafter) might have taken advantage of a capacity withholding strategy. In other words, for what operator at hour h was a market output where some capacity was withheld convenient? It is important to stress that, when actual revenues of a given operator are higher than its synthetic revenues, this does not imply that the operator employed a capacity withholding strategy, but that it would have benefited from it. However, such evidence suggests that deeper analysis are required.

Figure 2.2 represents the scatter plot $R_A - R_S$ vs $P_A - P_S$. This way, it is possible to merge two pieces of information and assess when the most significant impact on prices occurred and what operator achieved extra revenues. Therefore, we are only interested in the top right part of the scatter plot. Indeed, to the left (grey shadowed area) there are no observations at all ($P_A > P_S$). The bottom right (red shadowed area) of the scatter plot, where most of the observations are concentrated, is irrelevant as we are only interested in operators with actual revenues higher than the synthetic equivalents. Moreover, there is an open question. Should we consider any thresholds (blue and yellow dotted line) in $R_A - R_S$ and $P_A - P_S$? In other words, is a very limited impact on prices and with low extra revenues significant? In general, both effects should be important. First of all, a strategy which does not significantly affect the market equilibrium should not be considered. Where it does have a significant effect on the market outcome, it is important to assess whether the detected operator achieved extra profits or not. Where high extra revenue is achieved, it should be considered of interest and further analysis should be carried out. The issue of thresholds is tackled in the next subsection.

[16]See the appendix for calculated revenue details.

Figure 2.2: $R_A - R_S$ vs $P_A - P_S$



D: Demand; S_{Actual}: Actual Supply; $S_{Synthetic}$: Synthetic Supply; P_A: Actual Price; P_S: Synthetic Prices; Q_A: Actual Quantity; Q_S: Synthetic Quantity.

4) Data interpretation in this field is very difficult because of the many factors that should be taken into account. Despite this, points 2) and 3) provide useful evidence although there are still many open questions regarding their interpretation. Hence, it is necessary to create a unique measure to detect potential strategic capacity withholding. This paper puts forward the Synthetic Strategic Capacity Withholding (SSCW) Index. The index is structured as follows:

$$SSCW^{n\%} = \frac{Q_A^{i,h} \times (P_A^h - P_S^h)}{P_A^h \times Q_A^h} \tag{2.2}$$

Where:

- n% is the percentage of the simulation scenario (0.5%, 1% or 2%). In other words, n% represents the amount of extra capacity added to the total supply. As discussed above, this chapter presents three levels of additional capacity: 0.5%, 1% or 2% of the total quantity sold.

- $Q_A^{i,h}$ is the quantity sold by operator i at hour h. $Q_A^{i,h} > 0$;
- Q_A^h is the total quantity exchanged in the market at hour h. $Q_A^h > 0$;
- P_A^h is the actual price at hour h;
- P_S^h is the synthetic price at hour h. $P_A^h \geq P_S^h$.

The numerator of equation (2.2) is the product of the actual quantity sold by operator i at hour h and the difference between actual and synthetic prices at the same hour. The denominator is the product of the actual market clearing price at hour h and the quantity exchanged at the same hour. The index is weighted by the real market outcome, as suggested by Bataille et al. (2019) for the construction of their Return on Withholding Capacity Index. Therefore, the SSCW Index ranges from 0 to 1, where 0 indicates an almost irrelevant case and 1 a case where serious deeper analysis must be carried out. The index takes value 0 when $P_S^h = P_A^h$. The economic meaning of $P_S^h = P_A^h$ and thus SSCW=0 is that, at hour h the market was not affected by potential misbehaviour. In fact, the market clearing price remains unchanged. The index can theoretically be equal to 1 if $Q_A^{i,h} = Q_A^h$ and $P_S^h = 0$, indicating that there is only one operator that satisfies the demand. However, this is very unlikely to occur from an empirical point of view. Nonetheless, the higher the SSCW, the more significant the observation.

Following the approach of Bataille et al. (2019), the 90th or 95th percentile of the distribution of the index are suggested as a threshold to detect possible anomalous behaviour.

2.5 Empirical Analysis

The methodology described in the previous section allows us to investigate on the one hand the effects of an additional quantity in the supply side on the market hourly equilibria and, on the other, to detect the operator(s) who might have taken advantage of the withdrawal of capacity from supply.

Since dealing with capacity withholding means dealing with a lack of data, assumptions about the hypothetical amount of capacity withheld are needed. Several simulations are run to offset the bias of a fixed amount of additional capacity. In other words, if capacity withholding did occur, the quantity withheld is unknown. For this reason, different counterfactual scenarios can present different market outcomes. If different counterfactual scenarios spot similar anomalous patterns this would suggest that a deeper investigation should be carried out at that hour As discussed above, the quantity injected in the market is a percentage of the quantity sold at that hour. Three counterfactual scenarios were run for each hour. The chosen percentages were: 0.5%, 1% and 2%. What should we expect from these simulations? By increasing the quantity injected in the market we obtain a decrease in synthetic prices.[17] Consistent differences between actual and synthetic prices could highlight anomalous patterns in actual prices. There is a trade-off between the percentage injected in the market and the number of the operators detected during revenue analysis. In fact, no company is interested in withholding an enormous amount of megawatts because this would result in a loss of profit. Companies may only be interested in withholding an amount of megawatts that guarantees higher profits. For this reason, if we compute the revenues in both scenarios (see B.1 in the Appendix) withholding is a convenient strategy for none of the operators if the quantity is excessive. Indeed, it would be more convenient to stay in the synthetic scenario rather than in the actual scenario. This is discussed in more detail below in section 2.5.2.

The empirical section is divided into three subsections: the first is dedicated to price comparisons, the second to revenue analysis and the third to the Synthetic Strategic Capacity Withholding Index.

2.5.1 Actual Prices vs Synthetic Prices

This section presents the results for actual and synthetic prices. The aim of this analysis is to investigate the timing of the most significant discrepancies between actual prices and those obtained through the simulation scenarios. Define the actual and synthetic prices as the following vectors with length T = number of hours in a year:

$$\mathbf{p}^{Actual} = (p_1^{Actual}, p_2^{Actual}, ..., p_T^{Actual})$$

$$\mathbf{p}^{Synthetic \mid \text{n\%}} = (p_1^{Synthetic \mid \text{n\%}}, p_2^{Synthetic \mid \text{n\%}}, ..., p_T^{Synthetic \mid \text{n\%}})$$

As discussed above, each simulation scenario is structured according to a different amount of additional quantity offered. Therefore, $n\%$ represents the different percentages chosen for the simulations (0.5%, 1% and 2%) in the three scenarios analysed in this work.

The aim of the analysis is to spot, as a first step, anomalous patterns in the differences

[17] Obviously, in each scenario $P_A \geq P_S$

between the two time series ($\mathbf{p}^{Actual} - \mathbf{p}^{Synthetic \mid \text{n}\%}$), which are presented in Figure B.3[18] in the Appendix. As discussed above, it is reasonable to expect that the main discrepancies are the results of the simulation scenario with the greatest extra capacity injected. Discrepancies decrease with decreasing extra capacity offered as confirmed by Figure B.3. Monthly actual and synthetic time series are presented in Figures B.16 - B.27 in the appendix.

What should we expect from the synthetic time series?

At this stage it is only possible to observe when anomalous spikes occurred and no conclusion can be drawn. Moreover, it is difficult at this stage to understand which simulation scenario is the most significant one. In other words, looking at Figure B.3 in the appendix is the yellow peak significant when at the same time, blue lacks correspondence? It is not possible to answer at this stage. These results are only parts of a puzzle. A clearer overview appears when more puzzle pieces are added to the framework. Indeed, only a multi-evidence setting can provide a complete overview.

2.5.2 Revenues Analysis

This section presents the actual and synthetic revenues. Actual and synthetic revenues are computed for every market participant at every hour. Samples of approximately 800,000 observations are obtained: number of suppliers[19] $\times$ hours. Synthetic samples have fewer observations compared to actual ones, and an increase in the percentage of additional capacity results in a decrease in observations.[20] Indeed, a supply right shift pushes some offers to the right of the market clearing price. Therefore, it might happen that, in synthetic cases, some operators are excluded from the market compared to the actual scenario.[21]

In order to investigate the differences between revenues, the same number of operators is needed at every hour. Therefore, operators not in the synthetic scenario are dropped from the actual case. This is not a significant loss in data given that operators that are out of the market, offered a very low amount of capacity. Therefore, it is unlikely that they employed a capacity withholding strategy.

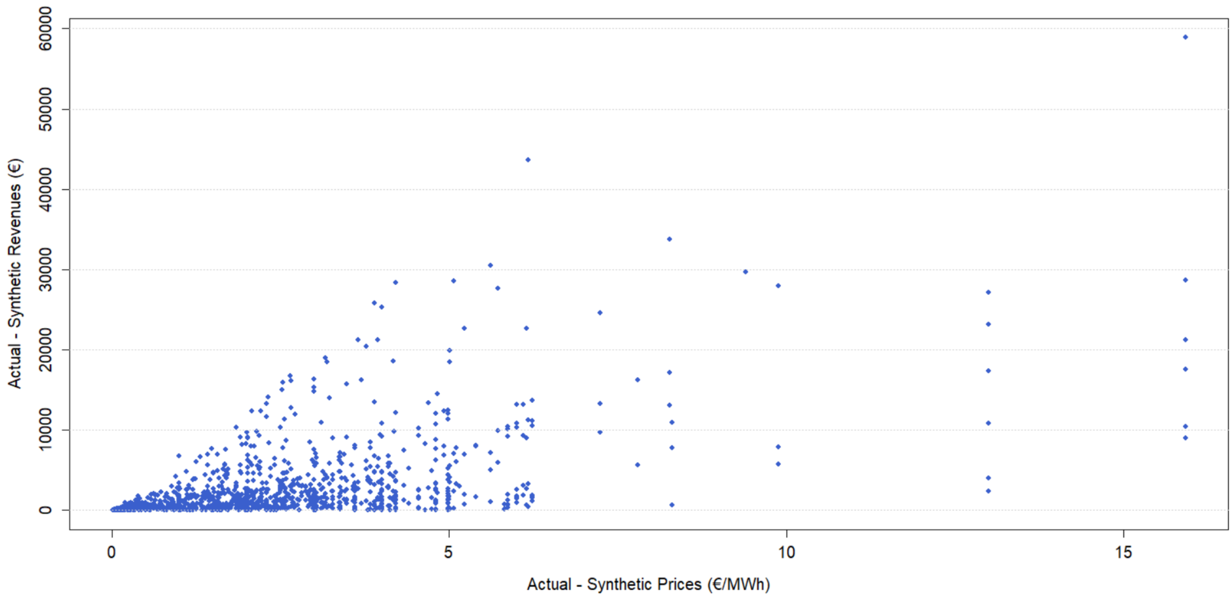
[18]The blue lines represent the differences between actual and synthetic prices obtained through the simulation algorithm at 0.5% of extra capacity, in red and yellow, respectively, those obtained through the simulation algorithm at 1% and 2% of extra capacity.

[19]In 2018, approximately 140 suppliers operated in the market. However, this does not mean that each supplier participated in every hourly auction.

[20]This also occurs because the demand is inelastic.

[21]For further clarification, see the example available in the appendix.

Figure 2.3: $R_A - R_S$ vs $P_A - P_S$ | 0.5% | 2018

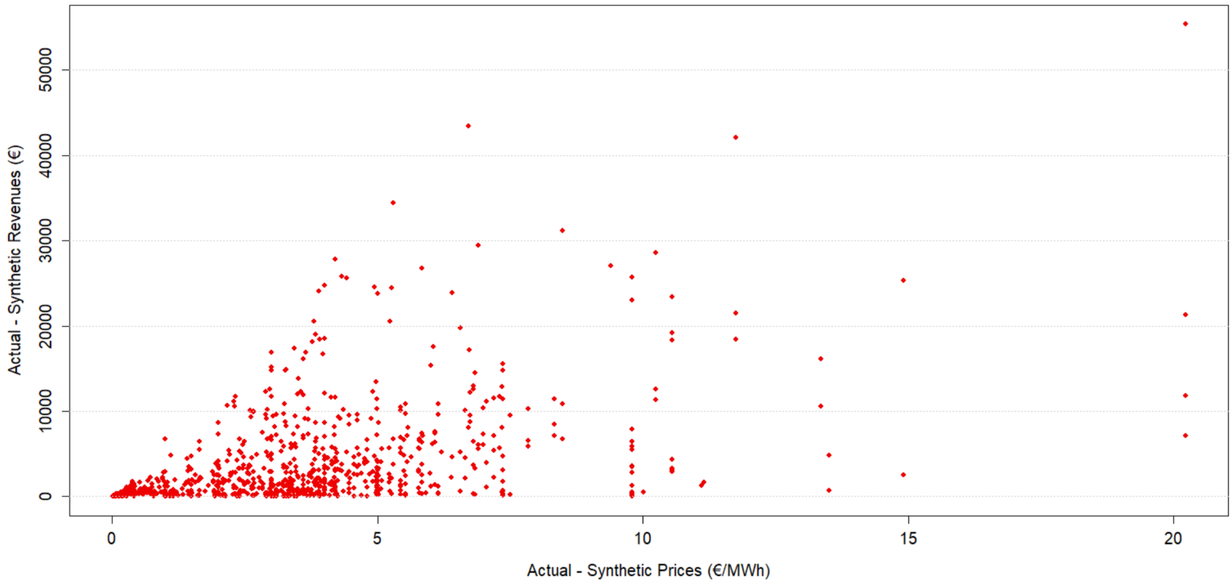


Scatter plot of the differences between actual and synthetic revenues vs the difference between actual and synthetic prices over 2018. Simulation scenario at 0.5% additional capacity. According to the assumptions, only the positive differences are considered important.

Once revenues are calculated,[22] the differences between actual and synthetic revenues are computed for every operator i at every hour h ($R_A^{i,h} - R_S^{i,h}$). Under the assumption that synthetic scenarios are the ones that are not affected by capacity withholding strategies and that $R_A^{i,h} - R_S^{i,h} > 0$ suggests that operator i at hour h might have benefited from a market outcome where less capacity was offered, only positive difference is investigated. The scatter plots $R_A - R_S$ vs $P_A - P_S$ are illustrated in Figures 2.3, 2.4 and 2.5: in blue the scatter plot referring to the synthetic scenario at 0.5%, in red and yellow the ones referring to 1% and 2%, respectively.

[22]See Appendix for revenues computational details.

Figure 2.4: $R_A - R_S$ vs $P_A - P_S$ | 1% | 2018

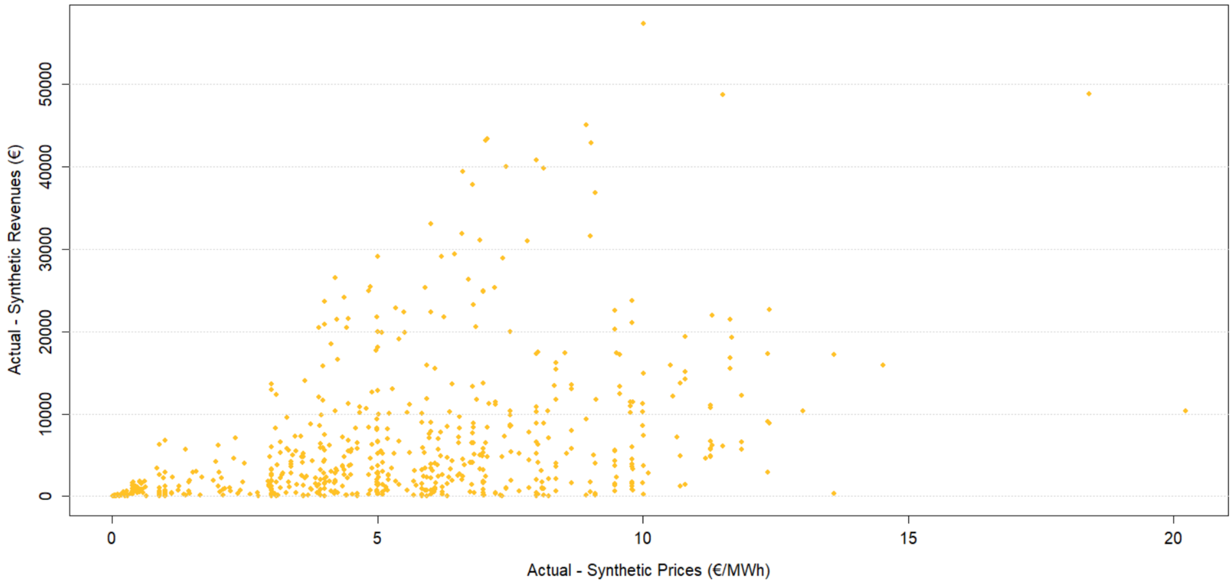


Scatter plot of the differences between actual and synthetic revenues vs the difference between actual and synthetic prices over 2018. Simulation scenario at 1% additional capacity. According to the assumptions, only the positive differences are considered important.

Looking at these plots it can be seen that fewer than one thousand observations out of approximately 800,000 have been selected. The amount of observations decreases by increasing the percentage of extra capacity. Therefore, blue is the most numerous, red and yellow coming respectively thereafter. This is in line with the above hypothesis. A sample of one thousand observations is a result that could be consistent with what the methodology looks for. Moreover, the trade-off between additional capacity and sample size confirms the fact that withholding too much capacity is not profitable.

At this stage, more pieces are added to the puzzle and the overview becomes clearer. Indeed, most of the differences between actual and synthetic prices are dropped and the attention is focussed on the remaining cases. Furthermore, the analysis focusses on approximately 0.1% of the total amount of the sample containing the hourly revenues of operators. Comparing the dynamics of the synthetic scenarios becomes easier and anomalous patters can be spotted more easily. In particular, what catches the eye are the high revenues obtained when the impact on prices is high.

Figure 2.5: $R_A - R_S$ vs $P_A - P_S$ | 2% | 2018

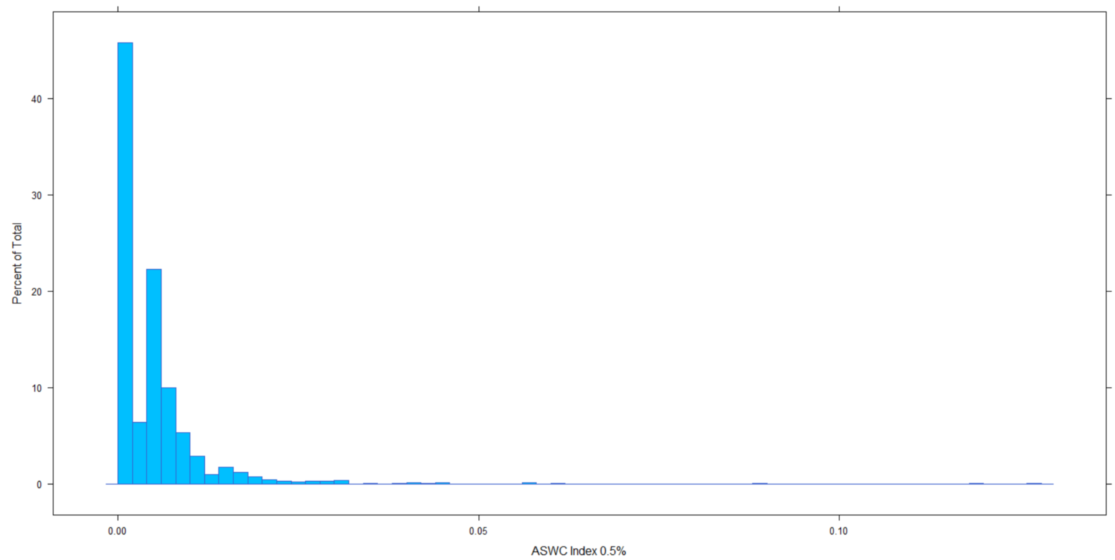


Scatter plot of the differences between actual and synthetic revenues vs the difference between actual and synthetic prices over 2018. Simulation scenario at 2% additional capacity. According to the assumptions, only the positive differences are considered important.

2.5.3 Synthetic Strategic Capacity Withholding Index (SSCW)

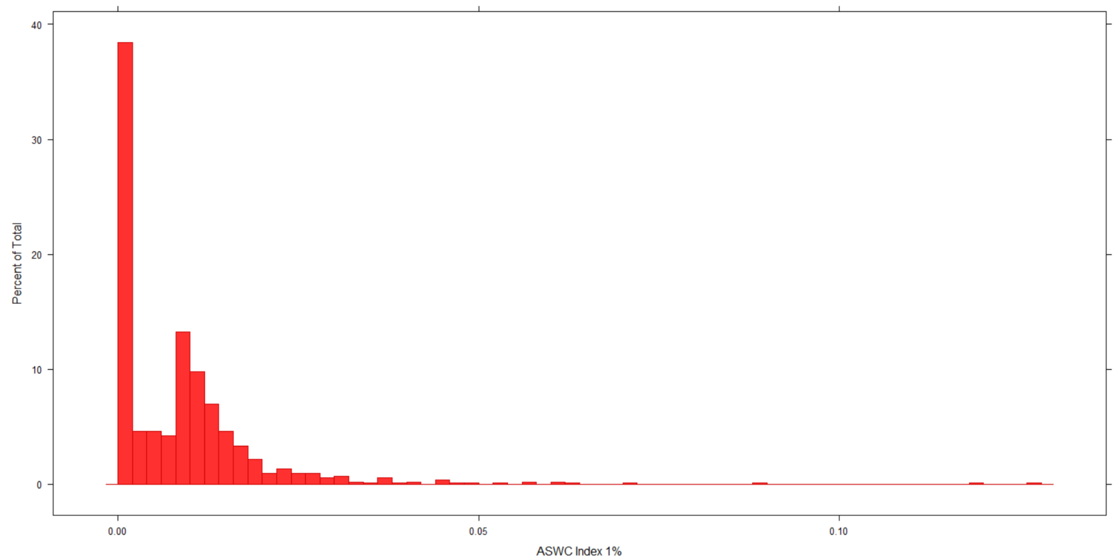
To interpret the results of the simulation scenarios, SSCW plots are presented and discussed. In each plot, the modal frequency of the distribution is close to zero, given that there are many observations in the bottom left of the scatter plots presented in the previous section. As discussed above, an observation in the scatter plot gains importance when located in the top right part of the plot. The reason is two-fold: 1) the operator might have obtained a considerable revenue increase and 2) the market clearing price (P_A^h) might have been subject to non-negligible manipulation. For this reason, the suggestion is to consider the 90th or 95th percentiles of the index distribution. Only observations having $R_A^{i,h} - R_S^{i,h} > 0$ are considered at this stage.

Figure 2.6: $SSCW^{0.5\%}$ | 2018



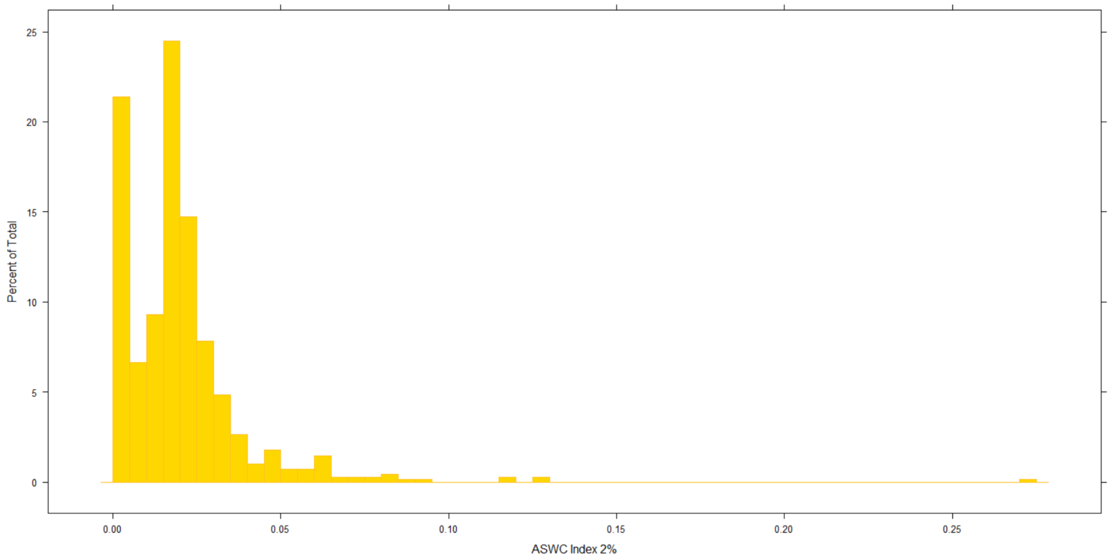
The plot illustrates the $SSCW^{0.5\%}$ index over 2018. Simulation scenario at 0.5% additional capacity is presented.

Figure 2.7: $SSCW^{1\%}$ | 2018



The plot illustrates the $SSCW^{1\%}$ index over 2018. Simulation scenario at 1% additional capacity is presented.

Figure 2.8: $SSCW^{2\%}$ | 2018



The plot illustrates the $SSCW^{2\%}$ index over 2018. Simulation scenario at 2% additional capacity is presented.

2.6 Limitations, Strengths and Future Research

The data analysis and the methodology proposed contain both limitations and strengths. The methodology faces the issue of capacity withholding presenting a new and different approach based on simulations constructed under several assumptions. These assumptions constitute the main strengths and limitations. In fact, the opportunity to have a flexible tool able to adapt to the market makes it possible to investigate several market scenarios by simply changing the amount of potential capacity withheld. Hence, evidence can be collected which is useful for monitoring the market. Nonetheless, as the information about the hypothetical scenario is obviously not given, assuming a certain amount of electricity potentially withheld undoubtedly constitutes a source of bias.

Assuming that all market operators could be responsible at the same time for strategic capacity withholding is certainly a strong assumption and unlikely to happen. Moreover, small operators with very limited installed capacity are very unlikely to manipulate the market equilibria due to insufficient capacity.[23] However, discarding them from the sample,

[23] See, for example, Bergler et al. (2017), p. 211. The authors suggest that a successful practical implementation of a capacity withholding strategy depends on two conditions: multi-unit operators and a certain

if the difference between synthetic and actual revenues is larger than zero, costs nothing. Moreover, taking all market operators into consideration would guarantee a complete analysis and wide-ranging market monitoring. The ability to link revenues to prices constitutes a strong point and this allows analysis of each market operator and an assessment of which operator less supply would have provided with higher revenues. However, revenue analysis does not take fixed and variable costs into account, so a profit analysis would be more accurate and appropriate.

Two other limitations concern the market structure rather than the methodology. The analysis is only run on the day-ahead market analysing its unconstrained prices (PSV). This is obviously a limitation as it does not take into account strategic behaviours in the other market sessions. Moreover, the analysis of unconstrained prices does not consider zonal prices and strategies. However, PSV is an indicator of real prices. Prices are a strength: the analysis does not refer only to actual but also to synthetic prices. A counterfactual time series, allows both to be investigated and compared to assess potential discrepancies.

Due to its flexibility, this methodology can be further developed in several ways. The analysis could be led using Euphemia (Pan-European Hybrid Electricity Market Integration Algorithm), the algorithm for the computation of the equilibria in each European market, maximizing market welfare. Hence, the computation of prices would be more accurate and the analysis could be focussed on zonal prices and the PUN (*"Prezzo Unico Nazionale"*).[24] Moreover, creating a link with power plant failures (see Bergler et al. (2017)) would contribute to a wider overview of the market.

2.7 Conclusion

Strategic capacity withholding is one of the most difficult forms of misbehavior to detect in electricity markets. Furthermore, as discussed above, operators can employ such misbehaviour in two different ways: economic and physical (see Joskow and Kahn, 2002). In addition, where an operator has misbehaved, it clearly seeks to conceal its bad conduct. For example, hiding a capacity withholding strategy through production breakdowns might be a new,"smart" way to thwart detection.

market power.

[24]The PUN is computed as the weighted average of Italian zonal prices. Buyers pay PUN whereas sellers get the zonal price. Foreign buyers pay the zonal price. For further information on PUN and Italian day-ahead market see section 1.3 of chapter 1.

This paper provides a new early-stage tool whose aim is to investigate cases which could be interpreted as possible strategic capacity withholding behaviour. Indeed, simulation scenarios can spot if any operator might have taken advantage of a capacity withholding strategy and, if so, quantify the extra revenues obtained. Moreover, a well developed simulation model can consider production failures. This way, it can be verified whether any case spotted coincides with a power plant failure or not. This further information aids data interpretation, leading to discarding or confirming some observations. This obviously depends on whether the strategic production failure is considered intentional or not.

Although some suspect cases can be identified, it is not possible to reach a definitive conclusion due to sources of bias that need to be addressed. Moreover, it is important to stress that the suggested procedure does not answer the question "Are there operators that employed a capacity withholding strategy?" but rather "Are there operators that might have benefited from a scenario where less capacity was offered?". This implies a lack in causality between those who might have adopted a strategic capacity withholding strategy and those who benefited. In fact, an operator who adopts a capacity strategy makes all the other operators happy. In other (more technical) words, "any one firm would prefer that some other firm assume the burden of output reduction so that it could free ride on the resulting price increase".[25]

[25]See Kwoka and Sabodash (2011), p. 292.

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Chapter 3

Covid-19 and the Italian electricity market: impacts, developments and implications

Abstract

The aim of this chapter is to describe and analyse the effects of Covid-19 on the Italian electricity market. It includes a precise and in-depth description of the main market variables during the pandemic and an assessment of the effects and implications during this period. In particular, the fall in demand, as a result of the government-imposed lockdowns, is the starting point for investigating the change in prices, power generation mix and in daily consumption cycles. To provide the best interpretation of the market development, an overview of the economic and social restrictions is included, so data can be compared before, during and after the lockdown. Data processing suggests a sharp fall in prices, a drop in fossil fuel generation, heterogeneous changes in zonal quantities sold and in consumption cycles.

3.1 Introduction

Like all the other countries seriously hit by Covid-19, Italy underwent a severe health, economic and social crisis. The discussion relating to the health crisis is left to experts in this field, whereas the economic implications are briefly introduced in this chapter with the sole purpose of providing a general overview to better assess and interpret changes in the electricity market dynamics during the pandemic.[1] In light of this, Chapter 3 analyses Italian electricity market data before, during and after the lockdown, taking into account the main events that characterized the months of lockdown.

Italy was one of the first countries worldwide to suffer from the critical effects of Covid-19, and for many weeks had the highest number of confirmed cases and deaths. To reduce the spread of virus, the Government introduced many restrictive measures. Gradual lockdowns were introduced involving at the beginning few towns, and subsequently provinces, regions and finally the whole of Italy. All economic activities were gradually shut down except for those considered essential. This anomalous situation led many firms to reorganize their activities and production processes. In particular, many companies had to reduce the inputs required for their economic activities. This phenomenon had significant impacts on the workforce and commodities.

In this context, the consumption of electricity fell sharply leading to anomalous market dynamics. For example, during the last three weeks of March, the Italian electricity market underwent a considerable decrease in electricity demand. According to a report published by RSE,[2] these three weeks, compared to the previous year, recorded a decrease in electricity consumption respectively of 5.5%, 15.6% and 24%. The fall in demand led to multiple events, including a fall in prices, a change in the power mix of energy sources and decarbonization.

The aim of this chapter is to provide a clear and detailed overview of the main Italian electricity market-related effects caused by the pandemic,[3] thus contributing to the growing

[1]The aim of this chapter is to provide an overview of the main effects of Covid-19 on the Italian electricity market. Therefore, other areas of research, hurried results and public health implications are excluded. An article by Bloomberg discusses this issue and highlights how some social scientists are, in some cases, "giving public-health advice and predicting the future trajectory of the pandemic without seriously discussing the limits of their knowledge or the credibility of their assumptions". This chapter is totally on board with its side.

[2]See the report published on the RSE website.

[3]Antonelli, Desideri and Franco (2018) discusses the evolution of many market features by proposing

literature on the topic[4] To achieve this goal, a brief summary of the most important restrictive measures is presented.[5] This fundamental tool is useful for the interpretation of the data, focussing on the main changes in prices, mix of energy sources and consumption. In order to have a complete and fulfilling assessment, two data sources are considered in the the data analysis: Terna S.p.A.[6] and GME S.p.A.[7]. (*"Gestore dei Mercati Energetici"*). The two data sources enable the analysis of several aspects of the market under different perspectives. For example, to assess the change in mix of energy sources, GME data are used to investigate the development in the marginal technology index in the day-ahead market, whereas Terna data are used to analyse the change in the overall mix of energy sources in the entire Italian electricity market.

Furthermore, an autoregressive econometric model is used to assess the impact of restrictive measures, in response to Covid-19, on the quantity purchased and on the PUN. The aim is, on the one hand, to estimate the relative impact of the geographical and production lockdowns on the quantity purchased and the PUN, and on the other, to verify whether the impact was homogeneous across the bidding zones.

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a complete set of descriptive statistics, giving a complete overview of the main market variables. The comparison between the descriptive statistics presented in this chapter and those proposed by Antonelli, Desideri and Franco (2018) further contextualizes the critical changes in the Italian electricity market during the pandemic.

[4]The effects of corona virus have drawn the attention of academics, institutions and companies. Therefore, there is a growing early-stage literature and an active debate on this topic. Some examples of the recent literature are set out below:

The Florence School of Regulation has produced several articles on the impacts of covid-19 on the market worldwide, see for example Conti I. 11/05/2020) and Nouicer A. 13/05/2020); Batalla J., (05/2020) provides an overview of the evolution of the main market variables during the pandemic in many energy markets with a particular focus on the Spanish electricity market; Graf C., Quaglia F. and Wolak F. A., (11/06/2020) discusses the price trend, during the lockdown, in the Italian electricity market with a particular focus on the re-dispatch cost and market power; Oliver Wyman provides a report where the effects of the virus on the electricity demand are discussed; RSE has compiled a dossier where the effects on the Italian electricity market are presented; the report by IEA discusses the effects of the pandemic on the energy market worldwide and on the energy transition. Many other articles are available in the references.

[5]See the Italian Government website for further information on the restrictive measures and policies adopted after January.

[6]Terna S.p.A. is the Italian TSO (Transmission System Operator). TSO data are available on its website at the following link

[7]GME S.p.A. is the Italian NEMO (Nominated Electricity Market Operator). NEMO data are available on its website at the following link

The chapter is structured as follows: the next section is dedicated to the description of the restrictive measures in response to Covid-19 and the reopening steps adopted by the Italian Government. Data are described in section 3.3. Section 3.4 presents both the fall in demand resulting from the decrease in commercial/production activities, and the changes in consumption cycles across the bidding zones. In sections 3.5 and 3.7, the main effects of a fall in demand are analysed and discussed. Section 3.6 presents the econometric model and the empirical results. Section 3.8 is dedicated to conclusions.

3.2 Lockdown and restrictive measures

Italy was one of the first countries to employ restrictive measures in response to the spread of Covid-19. The first lockdown was established in late February, involving 11 towns located in the North of Italy; afterwards, schools were gradually closed.[8] At the beginning of March, the lockdown was extended to the entire Lombardy Region and to many cities located in the Veneto and Emilia-Romagna Regions.[9] In mid-March, the whole of Italy was under lockdown; many commercial activities were closed.[10] In late March, restrictive measures were further tightened: most production activities closed, except for those considered essential.[11] This can be considered the peak of the restrictive measures in Italy.

During the month of April, the lockdown was relaxed, thus allowing economic activity to gradually restart. In early to mid-April activities such as stationery stores, bookstores, sylviculture and timber industry were allowed to restart.[12] Between the end of April and the beginning of May, many other commercial and production activities were allowed to reopen.[13] This can be considered the start of the so-called "Phase 2".

However, it is important to highlight that it seems that some economic activities reopened

[8]On February 23, Italian Prime Minister Giuseppe Conte signed the DPCM (Prime Ministerial Decree) containing the restrictive measures in response to the Covid-19 spread. DPCM 23/02/2020.

[9]On March 8, Italian Prime Minister Giuseppe Conte signed the DPCM containing additional restrictive measures in response to the Covid-19 spread. DPCM 08/03/2020.

[10]On March 11, Italian Prime Minister Giuseppe Conte signed the DPCM containing further restrictive measures in response to the Covid-19 spread. DPCM 11/03/2020.

[11]On March 22, Italian Prime Minister Giuseppe Conte signed the DPCM containing further restrictive measures in response to the Covid-19 spread. DPCM 22/03/2020.

[12]On April 10, Italian Prime Minister Giuseppe Conte signed the DPCM containing directions for the reopening of some commercial and production activities. DPCM 10/04/2020.

[13]On April 26, Italian Prime Minister Giuseppe Conte signed the DPCM containing directions for the reopening of further commercial and production activities. DPCM 26/04/2020.

before the scheduled reopening process. This was reported by media and institutions. For example, in early to mid-April, the President of the Veneto Region Luca Zaia stated that more than 60% of the companies in the Region had already reopened.[14] This is an important statement for the interpretation of the data presented in the following sections; for the purpose of evaluating changes in the electricity market, the facts on the ground need to be borne in mind rather than simply the legal status of the lockdown.

In this context, electricity demand fell sharply from early to mid-March as a consequence of restrictive measures and the health crisis. This led to anomalous market dynamics, such as: very low market clearing prices, a low rate of market splitting, a significant change in consumption cycles (especially in Northern Italy) and in the mix of energy sources. In particular, Renewable Energy Sources (RES) met a greater share of demand in this period and were price setters in many more hours compared to the previous months. However, it seems that after from mid to late April, quantity purchased returned to the same levels as in the previous three years.

For further information on the impact of different containment measures taken by European countries, see Bahmanyar et al. (2020). Bahmanyar et al. (2020) assesses the impact of different restrictive measures, in response to Covid-19, as adopted by several European countries, on electricity consumption. Specifically, it sets out a comparison of severe (Italy, Spain, United Kingdom and Belgium) and mild (Netherlands and Sweden) restrictive measures.

3.3 Data

Two data sources comprise the data set: GME (“*Gestore dei Mercati Energetici S.p.A.”*) and Terna. The analysis has been carried out in the months of March, April and May in the four years of 2017, 2018, 2019 and 2020. Therefore, the analysis focusses on the thirteen weeks during these three months. In order to present the structure of the data in the clearest way, they are explained separately below.

3.3.1 GME S.p.A.

The data analysis mainly focusses on the day-ahead market, the so-called “Mercato del Giorno Prima”. The following information, contained in “historical data”, is available on the website of Italian NEMO:

[14] See for example CORRIERE DELLA SERA.

Day-ahead market clearing price

"Historical data" includes the hourly market clearing prices of all the Italian and foreign bidding zones, both physical and virtual, in the Italian electricity market. Moreover, the data set contains the PUN ("*Prezzo Unico Nazionale"*) and the PSV ("*Prezzo Senza Vincoli"*), respectively the final national price computed as the weighted average of zonal prices and the unconstrained price[15]. The data analysis considers only the physical Italian bidding zones, namely: North, Centre North, Centre South, South, Sicily and Sardinia. This information is used to investigate the evolution of prices and market splitting rates.

Day-ahead market quantity purchased

"Historical data" includes the hourly quantity purchased and sold in all Italian and foreign bidding zones, both physical and virtual, in the Italian electricity market. The data analysis considers only the quantity purchased in the Italian bidding zones. This information is used to investigate the evolution of quantity demanded.

Day-ahead market marginal technology

"Historical data" includes the hourly marginal technologies of all the Italian and foreign bidding zones, both physical and virtual, in the Italian electricity market. The technologies listed in this data set are as follows: *coal, combined cycle gas turbine, natural gas, fuel oil, oil-coal, oil-natural gas, pumped storage, gas turbine, run of the river, basin hydro power plant, other renewable energy sources, MC, foreign virtual zones, Other.*[16] This information is used to investigate the evolution of the marginal technology index.

3.3.2 Terna S.p.A.

This information enables further investigation of the market dynamics regarding the overall load and the mix of energy sources. The following information is available on the website of the Italian TSO.

[15] For further details see Chapter 1, Section 3.

[16] Below are set out further explanatory details regarding some of the technologies listed:

Other renewable energy sources: Renewable energy sources: Solar, wind, geothermal and others

MC: MC is a state of uncertainty in which the technology that has set the price, based on the mechanism of Market Coupling, is not uniquely identifiable

Other: Other technologies not listed above.

Mix of energy sources

Hourly information on the total electricity produced by the different technologies is provided. The technologies listed in the data set are as follows: *thermal, hydro, solar, wind, geothermal and self consumption.* This information is used to investigate the evolution of the portions of each electricity source.

3.4 Fall in demand and consumption cycles

At the beginning of March, restrictive measures led to a considerable fall in demand, never before experienced. Quantity purchased was falling for almost 2 months, and only at the end of April were there faint signs of recovery. Although all the Italian bidding zones experienced a fall in demand, the change in quantity purchased was very heterogeneous across those bidding zones, both in absolute and relative terms. In fact, Northern Italy experienced a substantial fall in demand compared to Southern Italy. This reflects the enormous difference in the economic framework between the North and South of Italy. Moreover, consumption cycles also changed during the pandemic: the closure of many economic activities altered daily electricity consumption patterns. A clear example of this is that the daily peak of the North of Italy shifted from morning to evening, which is typical of the South of Italy. This section is divided into two subsections: fall in demand and consumption cycles.

3.4.1 Fall in demand

The fall in demand arising from the drastically reduced need for electricity by industry began at the beginning of March and evolved differently in the six Italian geographic zones. Figure 3.1 shows the evolution of quantity purchased in Italy over the thirteen weeks under examination. The evolution of quantity purchased in Italy strongly depends on the quantity purchased in the North of Italy, because it is the geographic zone with the highest demand for electricity, due to the intense commercial and production activities. Therefore, the quantity purchased in Italy and the North of Italy (see Figure 3.2) follows the same trend: the decrease starts in the first week; there is a sharp fall between the second and fourth weeks; the minimum is reached in the sixth week; in the seventh week, the average weekly quantity purchased starts to grow at a constant rate; at the end of May, the quantity purchased is almost in line with the consumption of the corresponding period of the previous years, with a percentage change in zonal quantity purchased[17] of approximately -7% in the last week under examination. The North of Italy experienced the highest percentage change in zonal quantity purchased, reaching the minimum in the sixth week of approximately -30%, as shown in Figure 3.8.

These features are somewhat similar in the other five geographic zones, but there are a few dissimilarities: in the Centre North of Italy, during the first month consumption fell less sharply than in the North of Italy. Figure 3.3 confirms that the curve for the Centre North is flatter than for the North during the first weeks. However, the recovery of consumption is also slower. In late May, the quantity purchased almost reached the same levels as in previous years. Electricity consumption in Centre South follows a similar trend to Centre North, even though the recovery looks slower and the percentage change is more limited than in the Centre North. South of Italy, Sicily and Sardinia (see Figures 3.5, 3.6 and 3.7) experienced a very slight percentage change in zonal quantity purchased during the weeks under examination and a similar trend in the first weeks. However, the recovery of quantity purchased in Sardinia and South of Italy was slower than in Sicily, and broader than in any other geographic zone, indicating a more persistent negative shock.

Furthermore, it is important to highlight, that understanding the evolution of electricity consumption provides useful insights into the overall economy. In fact, the change in quantity purchased can be used as a proxy for the revenues achieved by firms, providing useful evidence about the industrial and commercial sectors during the weeks of the pandemic. Therefore, it is essential to consider this aspect to obtain an understanding of the impacts on the economy, to properly allocate financial resources and set the right policies to support industrial and commercial activities.

[17] In other "words" the weekly percentage change in quantity purchased is as follows:

$$\Delta Q\% = \frac{(\text{Covid week} - \text{Pre-Covid week}) \times 100}{\text{Pre-Covid week}}$$

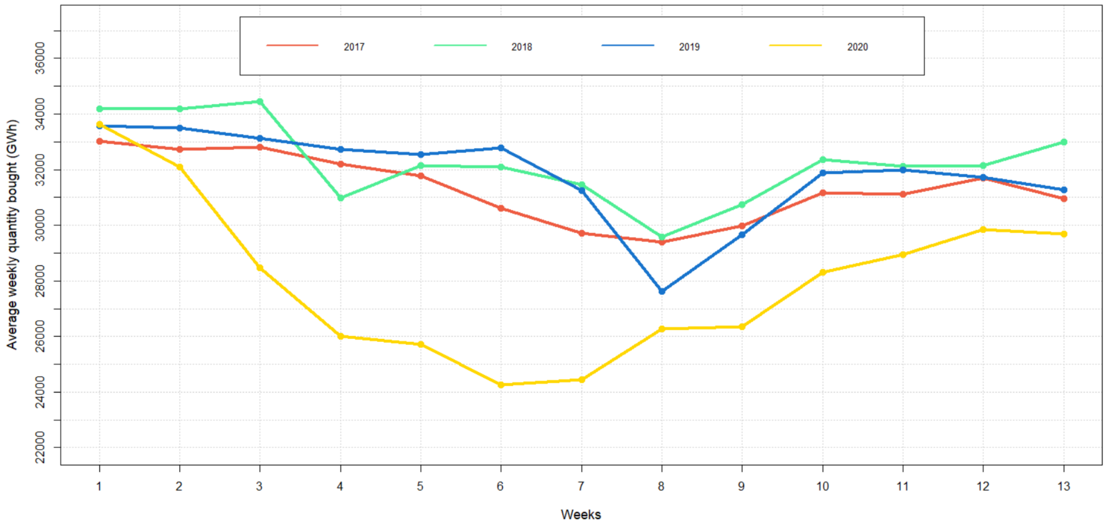
Where: Covid week $= \frac{1}{h}\sum_{i=1}^{h} q_i^{2020}$

Pre-Covid week $= \frac{1}{3}(\frac{1}{h}\sum_{i=1}^{h} q_i^{2017} + \frac{1}{h}\sum_{i=1}^{h} q_i^{2018} + \frac{1}{h}\sum_{i=1}^{h} q_i^{2019}$

q is the hourly quantity purchased

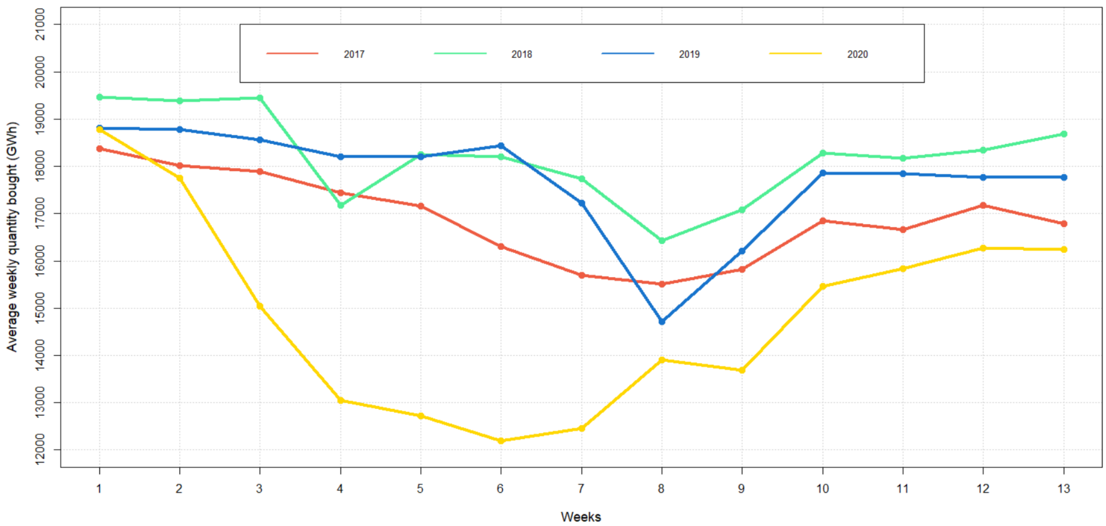
h is the number of hours in a week (168 in 12 weeks, 167 in 1 week).

Figure 3.1: Quantity purchased | Italy



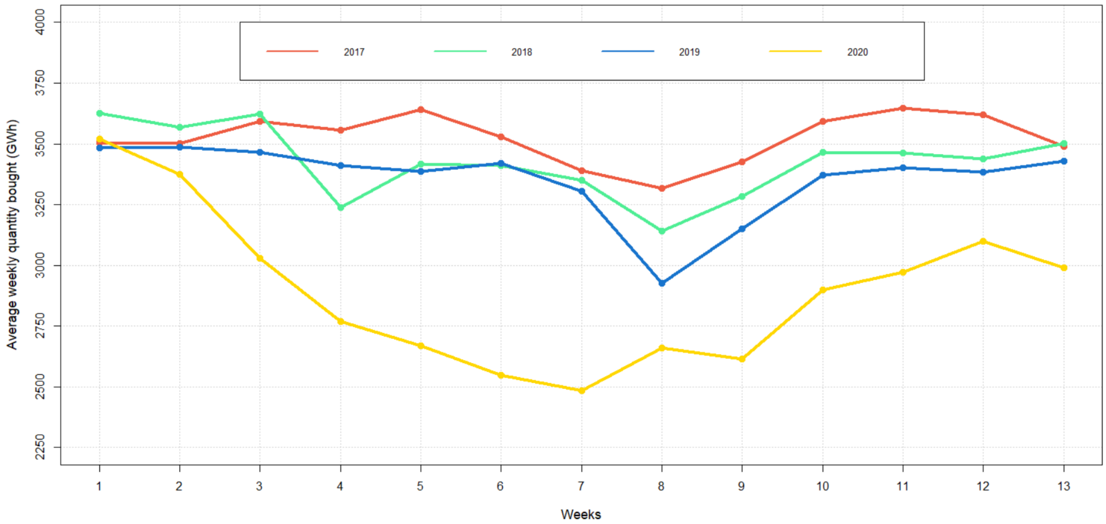
The plot presents the average weekly quantities purchased over 13 weeks from March to May. Yellow, blue, green and red represent the corresponding weeks of 2020, 2019, 2018 and 2017, respectively.

Figure 3.2: Quantity purchased | North Italy



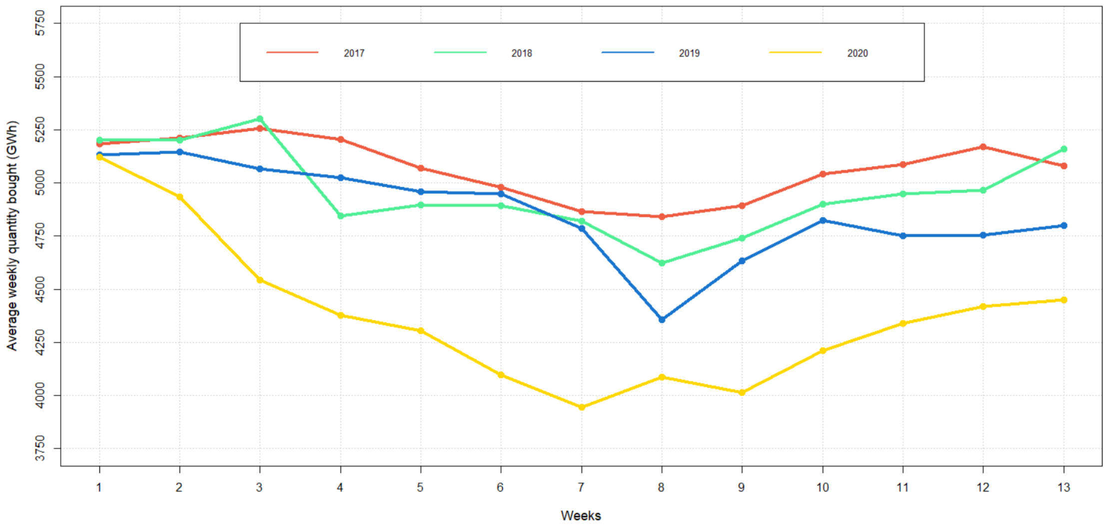
The plot presents the average weekly quantities purchased over 13 weeks from March to May in the north of Italy. Yellow, blue, green and red represent the corresponding weeks of 2020, 2019, 2018 and 2017, respectively.

Figure 3.3: Quantity purchased | Centre North Italy



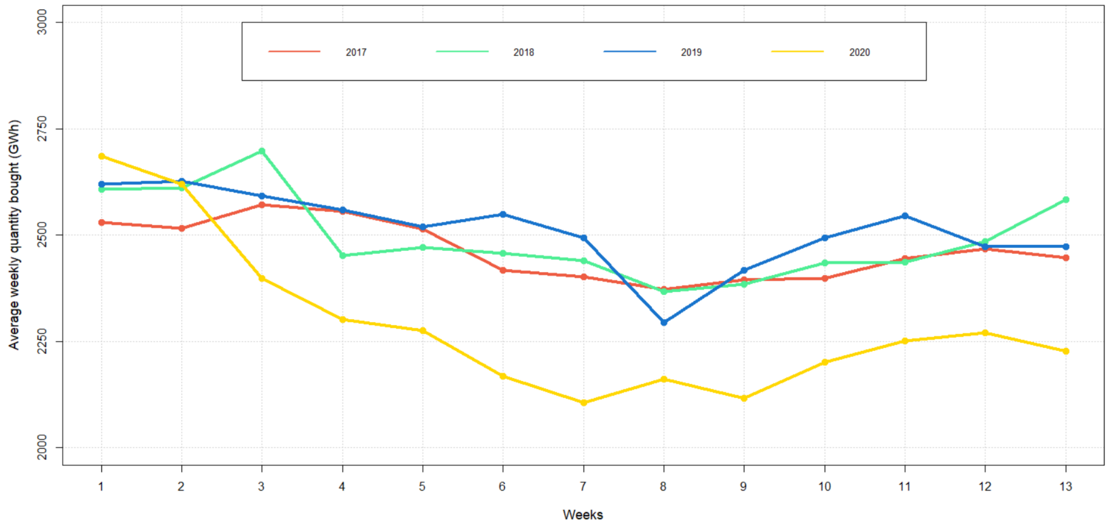
The plot presents the average weekly quantities purchased over 13 weeks from March to May in the centre north of Italy. Yellow, blue, green and red represent the corresponding weeks of 2020, 2019, 2018 and 2017, respectively.

Figure 3.4: Quantity purchased | Centre South Italy



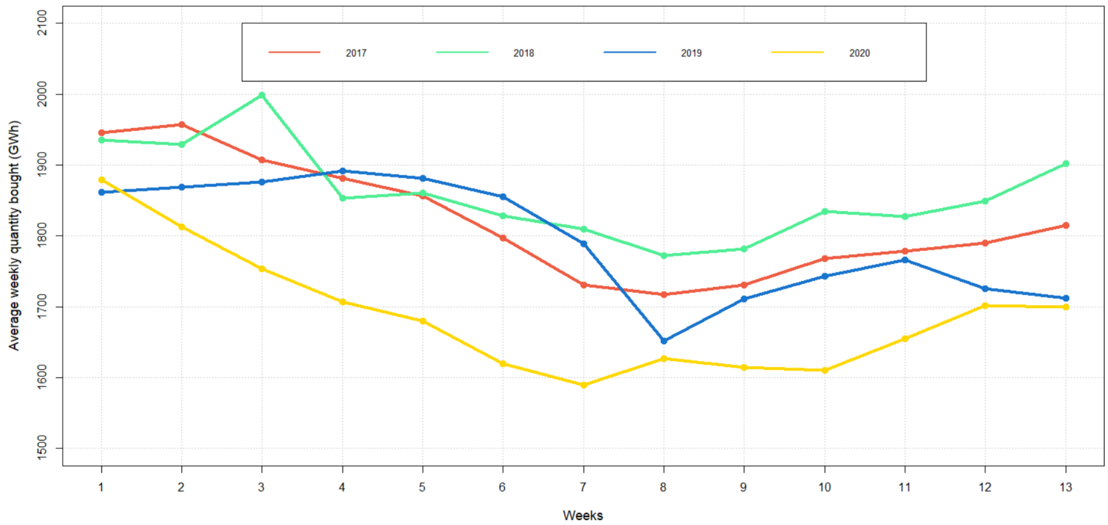
The plot presents the average weekly quantities purchased over 13 weeks from March to May in the centre south of Italy. Yellow, blue, green and red represent the corresponding weeks of 2020, 2019, 2018 and 2017, respectively.

Figure 3.5: Quantity purchased | South Italy



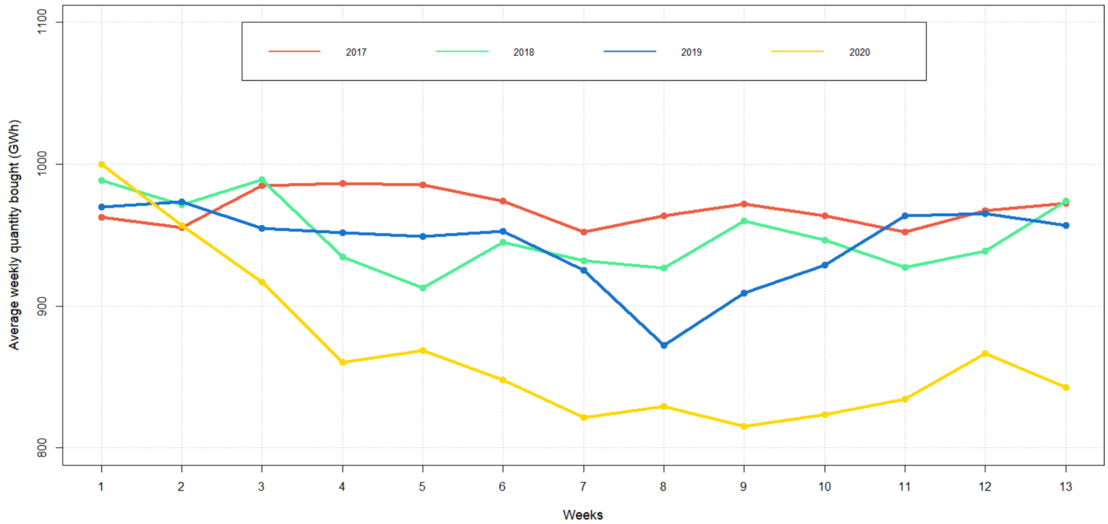
The plot presents the average weekly quantities purchased over 13 weeks from March to May in the south of Italy. Yellow, blue, green and red represent the corresponding weeks of 2020, 2019, 2018 and 2017, respectively.

Figure 3.6: Quantity purchased | Sicily



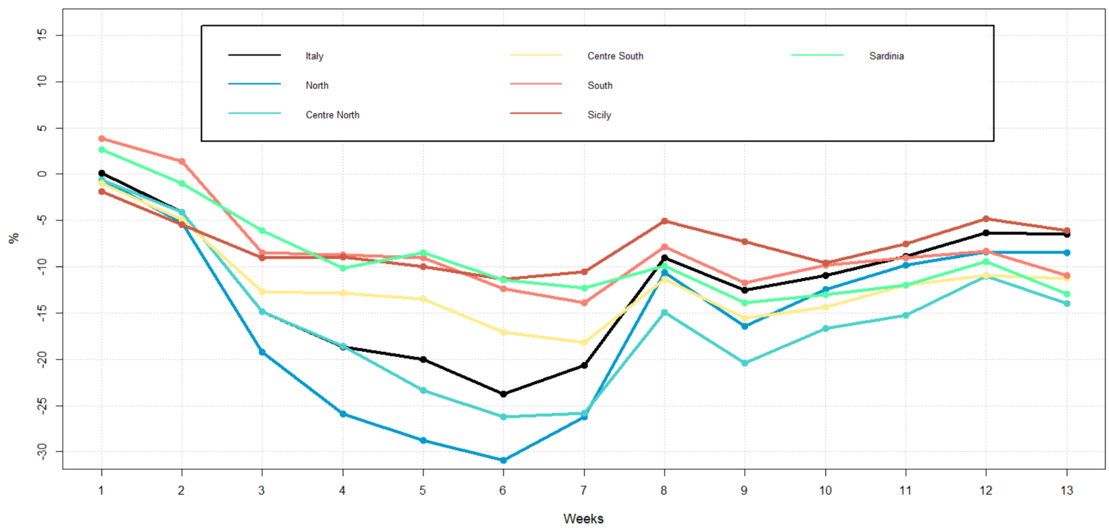
The plot presents the average weekly quantities purchased over 13 weeks from March to May in Sicily. Yellow, blue, green and red represent the corresponding weeks of 2020, 2019, 2018 and 2017, respectively.

Figure 3.7: Quantity purchased | Sardinia



The plot presents the average weekly quantities purchased over 13 weeks from March to May in Sardinia. Yellow, blue, green and red represent the corresponding weeks of 2020, 2019, 2018 and 2017, respectively.

Figure 3.8: Percentage change in zonal quantity purchased



The plot presents the percentage changes between the quantity purchased during the 13 weeks of 2020 and the average quantity purchased in the same period of the previous three years. The plot illustrates the percentage changes across all six geographic zones and in the whole of Italy.

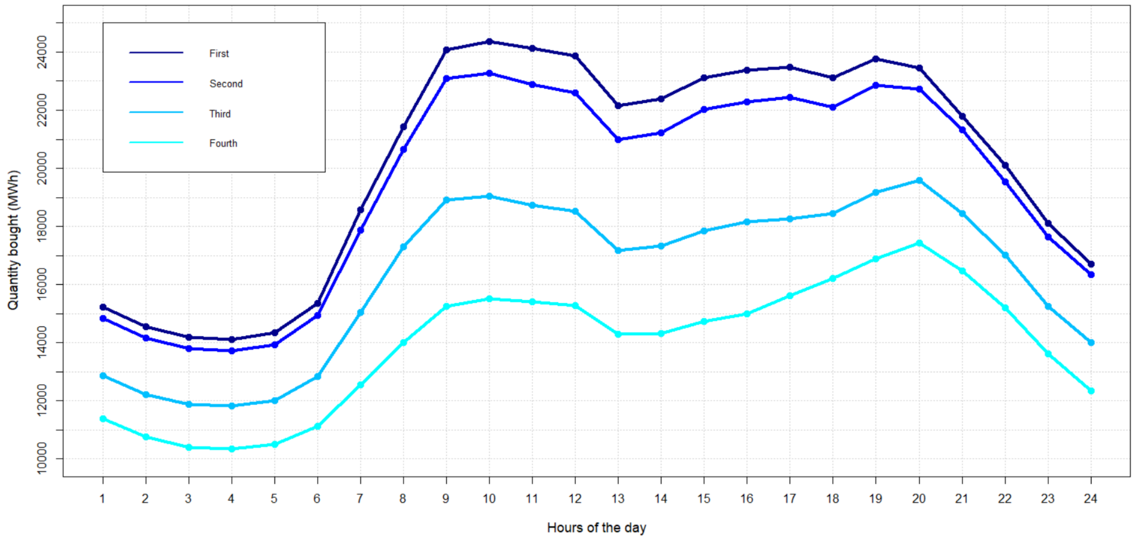
3.4.2 Consumption cycles

The heterogeneous changes in quantity consumed in the different zones of Italy involved not only the amounts purchased but also the consumption cycles, which are typically very different. The North of Italy is generally characterized by 2 daily peaks: early to mid-morning (8-10 am) and evening (7-9 pm). Morning peaks are higher than evening peaks. By contrast, the South of Italy is characterized only by one significant daily peak, i.e. in the evening (7-9 pm) whereas the morning peak is far less marked. These differences reflect the different needs for electricity during the day; in the North of Italy the pronounced morning peaks reflect the industrial activities which are concentrated in the northern regions, whereas the evening peaks are more household-related in both areas. Both zones are characterized by minimums during the first hours of the day, generally between 2-4 am.

Restrictive measures altered only the intraday seasonality of the northern regions of Italy, leading to a drastic change in the typical consumption pattern. From the third week the North of Italy started to have the same consumption cycles as the South of Italy: the highest peak shifted from morning to evening. This anomalous intraday seasonality lasted until the ninth week. Figures 3.9, 3.10 and 3.11 show the evolution of intraday seasonality in the North of Italy. From the third week, the highest peak in the North zone shifted from morning to evening. This anomalous behaviour lasted until the end of April. From May, or more precisely from the tenth week, the highest daily peak returned to the morning. This daily trend is particularly clear at the end of the month (thirteenth week), where the morning peak is clearly far higher than the evening one.
Regarding the intraday seasonality of the south zone, there were no particular changes in consumption cycles. Indeed, Figures 3.12, 3.13 and 3.14 confirm that the highest peak remained unchanged during the pandemic.

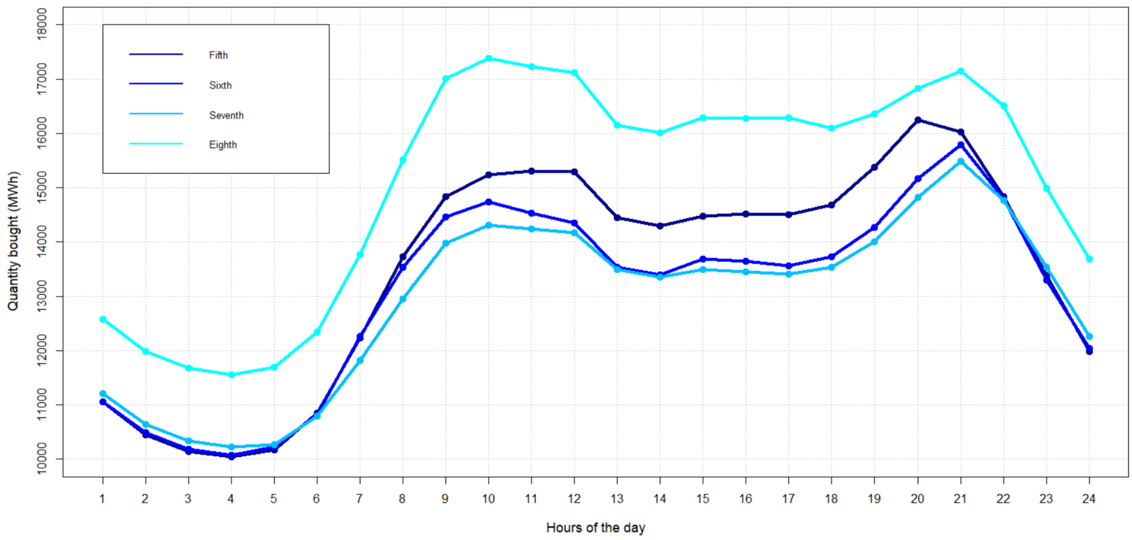
Moreover, it is important to highlight that there were also substantial differences in the change in the total quantity purchased during the traditional peaks in the north and south. In fact, the morning peak of the north (9 am) ranged from 24000 MHh (in the first week, when there were almost no restrictive measures) to 14000 MHh (in most of the weeks between the end of March and the beginning of May), i.e. a percentage variation between the maximum and the minimum of -41%. By contrast, the evening peak of the South of Italy ranged from 3500MHh (also in the first week) to 2850 MHh (in almost all the weeks of from mid to late April to the end of May), with a percentage variation between the maximum and the minimum of -18%.

Figure 3.9: Average hourly quantity purchased | North Italy | First, second, third and fourth weeks



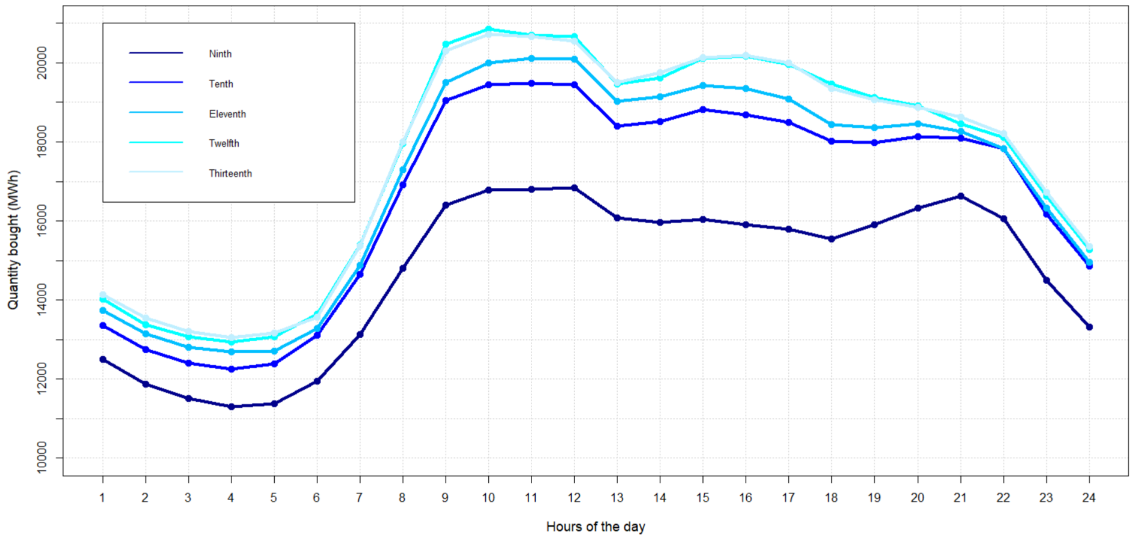
Average hourly quantities purchased over the first four weeks in March in North Italy.

Figure 3.10: Average hourly quantity purchased | North Italy | Fifth, sixth, seventh and eighth weeks



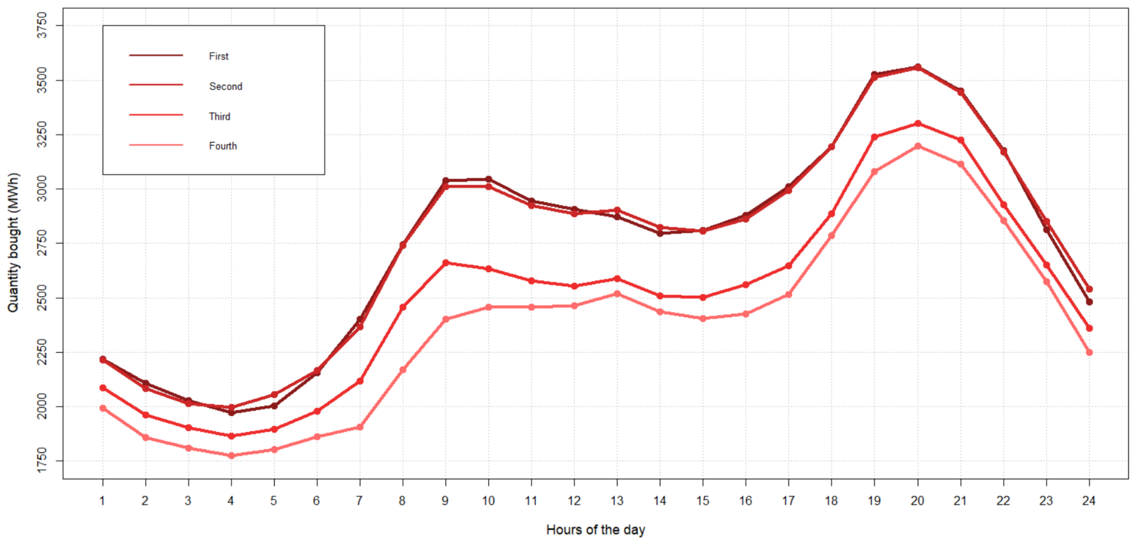
Average hourly quantities purchased over the four weeks between the end of March and the end of April in North Italy.

Figure 3.11: Average hourly quantity purchased | North Italy | Ninth, tenth, eleventh, twelfth and thirteenth weeks



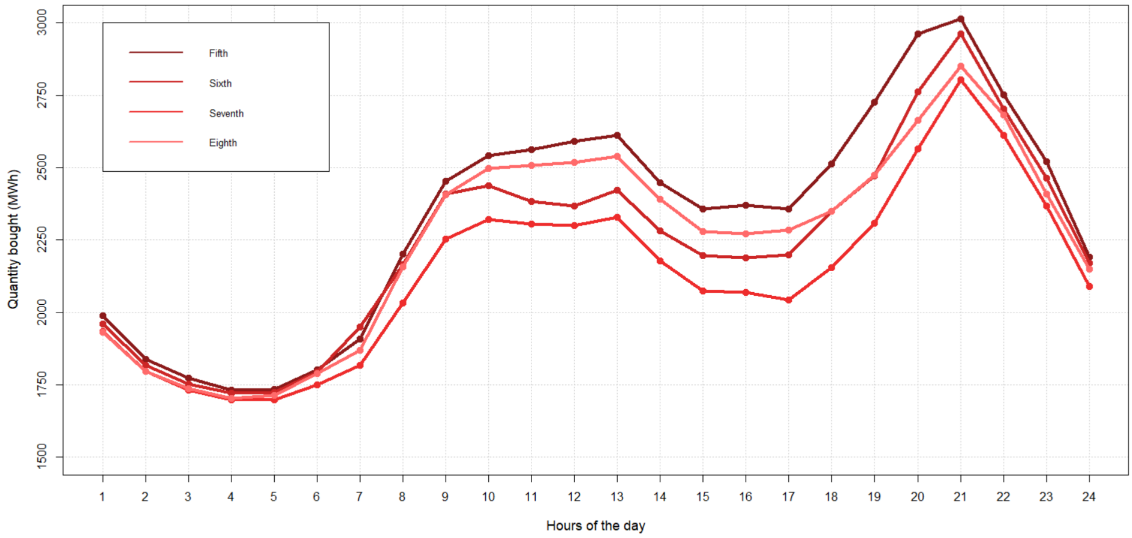
Average hourly quantities purchased over the five weeks between the end of April and the end of May in North Italy.

Figure 3.12: Average hourly quantity purchased | South Italy | First, second, third and fourth weeks



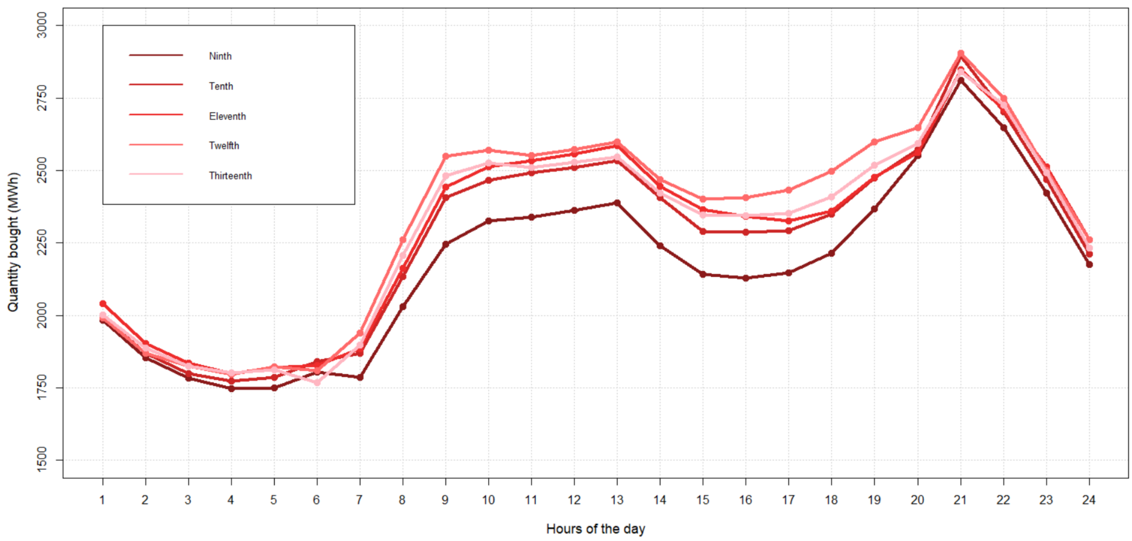
Average hourly quantities purchased over the first four weeks in March in South Italy.

Figure 3.13: Average hourly quantity purchased | South Italy | Fifth, sixth, seventh and eighth weeks



Average hourly quantities purchased over the four weeks between the end of March and the end of April in South Italy.

Figure 3.14: Average hourly quantity purchased | South Italy | Ninth, tenth, eleventh, twelfth and thirteenth weeks



Average hourly quantities purchased over the five weeks between the end of April and the end of May in South Italy.

The plots of the consumption cycles of the other geographic bidding zones are available in the appendix.

3.5 Price decrease

Restrictive measures, and more broadly the uncertainty related to the pandemic, did not affect only the quantity exchanged in the market and its patterns but also had a significant impact on price dynamics, which can be considered partially a consequence of the fall in demand. In fact a drop in demand led to a left shift of the demand curve leading to lower market clearing prices. This price fall is particularly clear from the third week of the market analysis, which highlights the effects of lockdown established gradually in the previous weeks. On Sunday, 5 April 2020, at 3 pm the national market clearing price (PUN) was zero, a phenomenon that had never occurred in the previous five years.[18] It was repeated at other hours during the month confirming the anomalous trend in prices.

To better assess the price fall two plots are set out below: Figure 3.15 presents the average weekly price of the 13 weeks under examination over the four years, and Figure 3.16 shows the percentage change between the weekly average price of the 13 weeks in 2020 under examination and the mean of the average price of the corresponding weeks in the previous three years.[19] In the first instance, what catches the eye are the large differences between the prices during the weeks of 2020 and the prices in the previous three years. The average price of the ninth week was almost 60% lower than the mean of average prices in the same period of the previous three years. Figure 3.15 shows how the prices corresponding to April and May 2020 range from 20€/MWh to 30€/MWh, whereas in the same period of 2019 the prices ranged from 45€/MWh to 60€/MWh. However, although this decrease looks critical it is

[18]This was highlighted in the article by Grossi L. and Rossetto F. in Sole24Ore, an Italian economic newspaper, and also in the RSE Report. Both links are available in the references.

[19]In other "words" the weekly percentage change in price is defined as follows:

$$\Delta P\% = \frac{(\text{Covid week} - \text{Pre-Covid week}) \times 100}{\text{Pre-Covid week}}$$

Where: Covid week $= \frac{1}{h}\sum_{i=1}^{h} p_i^{2020}$

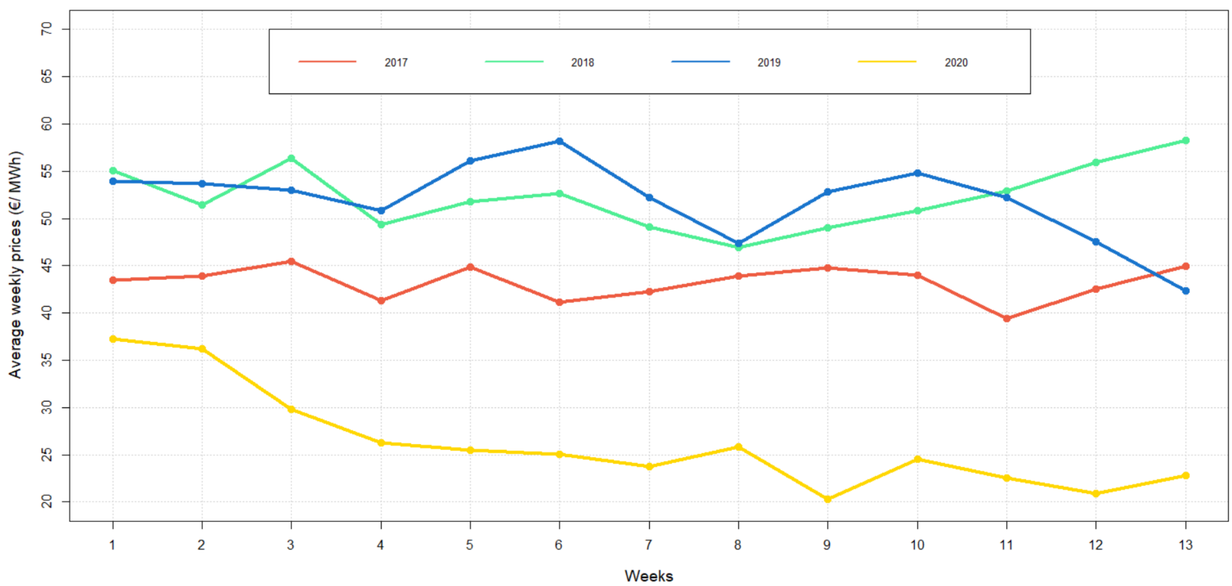
Pre-Covid week $= \frac{1}{3}(\frac{1}{h}\sum_{i=1}^{h} p_i^{2017} + \frac{1}{h}\sum_{i=1}^{h} p_i^{2018} + \frac{1}{h}\sum_{i=1}^{h} p_i^{2019})$

p is the hourly price (PUN)

h is the number of hours in a week (168 in 12 weeks, 167 in 1 week).

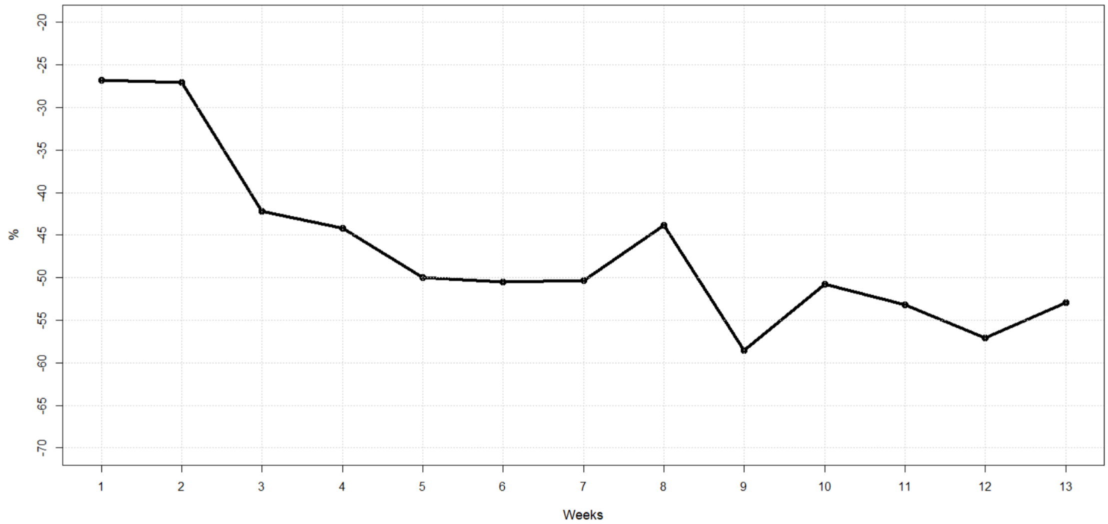
probably not the most interesting aspect. In fact, although the quantity purchased returned to the levels in previous years, price patterns were far from the regular market dynamics over the previous years. The reason could be two-fold: on the one hand marginal costs fell constantly over these months, due to the sharp decrease in the price of energy commodities, resulting in bids with very low prices, whereas on the other hand, the demand curve was able to recover fully, thus leading to a balance of low prices but larger quantities. In other words, equilibria characterized by regular quantities exchanged but with anomalous low prices are the intersection points between flatter supply curves and demand curves still slightly left shifted. Moreover, a further hypothesis could be that buyers are less willing to pay given that they are aware that suppliers had to reduce the markup in their bids.

Figure 3.15: Average weekly price (PUN) | Italy



The plot presents the average weekly price (PUN) over 13 weeks from March to May in the day-ahead market. Yellow, blue, green and red represent the corresponding weeks of 2020, 2019, 2018 and 2017, respectively.

Figure 3.16: Percentage change in average weekly price (PUN) | Italy



The plot presents the percentage change between the weekly average price in the weeks in 2020 under examination and the mean of the average price of the corresponding weeks in the previous three years.

3.5.1 Market splitting Index

The fall in demand led to a drop in market congestion and hence to very low rates of market splitting. This resulted in equal zonal prices in most of the hours during Covid-19. Therefore, if the change in the quantity demanded across the Italian geographic zones was highly heterogeneous, zonal prices converged to the same hourly value. The Market Splitting Index is defined as follows:

$$MSI_{\text{Week}} = \frac{\text{Hours}_{\text{Week}}^{\text{Market Splitting}}}{\text{Hours}_{\text{Week}}^{\text{Total}}} \tag{3.1}$$

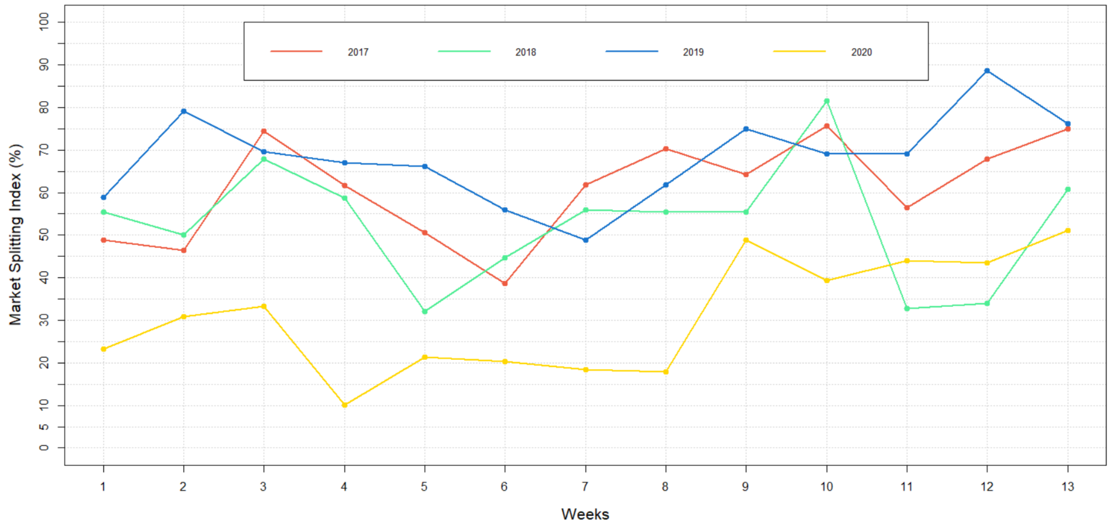
where: $\text{Hours}_{\text{Week}}^{\text{Market Splitting}}$ indicates the number of hours in the weeks where market splitting did occur, whereas $\text{Hours}_{\text{Week}}^{\text{Total}}$ indicates the total number of hours in that week.[20]

The Market Splitting Index (3.1) describes the rate of market splitting during a week. This index has a dual usefulness: it provides information about the zonal prices as well insights

[20]Note that $\text{Hours}_{\text{Week}}^{\text{Total}}$ is not always equal to 168, because of the clock change on Sunday 29 March. That week has only 167 hours coded in the data, the missing hour in the data set is 12 pm.

into market congestion and stress. Therefore it is necessary to understand the degree of market stress and utilization for a comprehensive overview of the market.

Figure 3.17: Market Splitting Index



The plot presents the average weekly market splitting index over 13 weeks from March to May in the day-ahead market. Yellow, blue, green and red represent the corresponding weeks of 2020, 2019, 2018 and 2017, respectively.

Figure 3.17 presents the market splitting index in the 13 weeks under examination over the four years. It is clear that during the lockdown the market was less stressed, thus leading to low congestion rates. From the ninth week, the number of hours where market splitting occurred increased, because of the rise in demand from the ninth week, as shown in Figure 3.1.

3.6 Econometric Analysis

Four autoregressive econometric models are used to estimate the impact of restrictive measures in response to Covid-19, both geografical (equations 3.2, 3.4) and production (equations 3.3, 3.5) lockdowns, on the zonal quantity purchased (equations 3.2, 3.3) and the PUN (equations 3.4,3.5), respectively. The models investigate the impact during the hours of the day in order to evaluate whether or not it was homogeneous, enabling a comparison between peak and off-peak hours. The models are as follows:

$$\mathbf{q}_{t,h} = \phi_0 + \phi_1\mathbf{q}_{(t-1),h} + \phi_2\mathbf{q}_{(t-2),h} + \phi_3\mathbf{q}_{(t-3),h} + \phi_4\mathbf{q}_{(t-4),h} + \phi_5\mathbf{q}_{(t-5),h} + \phi_6\mathbf{q}_{(t-6),h} + \phi_7\mathbf{q}_{(t-7),h} + \gamma_1\mathbf{D}_{1t,h} + \gamma_2\mathbf{D}_{2t,h} + \gamma_3\mathbf{D}_{3t,h} + \gamma_4\mathbf{D}_{4t,h} + \gamma_5\mathbf{D}_{5t,h} + \gamma_6\mathbf{D}_{6t,h} + \theta\mathbf{D}_{t,h}^{Geo.Lock.} + \epsilon_{t,h} \tag{3.2}$$

$$\mathbf{q}_{t,h} = \phi_0 + \phi_1\mathbf{q}_{(t-1),h} + \phi_2\mathbf{q}_{(t-2),h} + \phi_3\mathbf{q}_{(t-3),h} + \phi_4\mathbf{q}_{(t-4),h} + \phi_5\mathbf{q}_{(t-5),h} + \phi_6\mathbf{q}_{(t-6),h} + \phi_7\mathbf{q}_{(t-7),h} + \gamma_1\mathbf{D}_{1t,h} + \gamma_2\mathbf{D}_{2t,h} + \gamma_3\mathbf{D}_{3t,h} + \gamma_4\mathbf{D}_{4t,h} + \gamma_5\mathbf{D}_{5t,h} + \gamma_6\mathbf{D}_{6t,h} + \theta\mathbf{D}_{t,h}^{Prod.Lock.} + \epsilon_{t,h} \tag{3.3}$$

$$\mathbf{p}_{t,h} = \phi_0 + \phi_1\mathbf{p}_{(t-1),h} + \phi_2\mathbf{p}_{(t-2),h} + \phi_3\mathbf{p}_{(t-3),h} + \phi_4\mathbf{p}_{(t-4),h} + \phi_5\mathbf{p}_{(t-5),h} + \phi_6\mathbf{p}_{(t-6),h} + \phi_7\mathbf{p}_{(t-7),h} + \gamma_1\mathbf{D}_{1t,h} + \gamma_2\mathbf{D}_{2t,h} + \gamma_3\mathbf{D}_{3t,h} + \gamma_4\mathbf{D}_{4t,h} + \gamma_5\mathbf{D}_{5t,h} + \gamma_6\mathbf{D}_{6t,h} + \theta\mathbf{D}_{t,h}^{Geo.Lock.} + \epsilon_{t,h} \tag{3.4}$$

$$\mathbf{p}_{t,h} = \phi_0 + \phi_1\mathbf{p}_{(t-1),h} + \phi_2\mathbf{p}_{(t-2),h} + \phi_3\mathbf{p}_{(t-3),h} + \phi_4\mathbf{p}_{(t-4),h} + \phi_5\mathbf{p}_{(t-5),h} + \phi_6\mathbf{p}_{(t-6),h} + \phi_7\mathbf{p}_{(t-7),h} + \gamma_1\mathbf{D}_{1t,h} + \gamma_2\mathbf{D}_{2t,h} + \gamma_3\mathbf{D}_{3t,h} + \gamma_4\mathbf{D}_{4t,h} + \gamma_5\mathbf{D}_{5t,h} + \gamma_6\mathbf{D}_{6t,h} + \theta\mathbf{D}_{t,h}^{Prod.Lock.} + \epsilon_{t,h} \tag{3.5}$$

where:

- $\mathbf{q}_{t,h}$ and $\mathbf{p}_{t,h}$ represent the vectors of quantity purchased and the PUN at time t for hour h.
- $\mathbf{D}_{t,h}$ represents the weekly dummies at time t for hour h.
- $\mathbf{D}_{t,h}^{Geo.Lock.}$ and $\mathbf{D}_{t,h}^{Prod.Lock.}$ represent the dummies for the geografical and production lockdowns, respectively.

Furthermore, there is the following assumption: $\epsilon_{t,h} \sim N(0, \sigma_\epsilon^2)$

The appendix includes as an example the plots of ACF and PACF for the quantity, the PUN, the residuals of the model for geographical and production lockdowns at 9 am. In addition, the appendix sets out the histogram of the residuals for quantity and price both for geographical and production lockdowns. Demand and PUN ACFs and PACFs show a strong autocorrelation in the first lag and strong weekly seasonality. By contrast, the ACFs of the

residuals of models show very small autocorrelation values which lie within the confidence bands. This means that the models are able to capture the autocorrelation structure of the dependent variables.
The histograms look very symmetric. However, the histograms have fat tails: the estimation of the model could be improved by assuming a fat-tailed distribution of the disturbances.

Empirical results

The results suggest that geographical and production lockdowns had a significant impact on the quantity purchased in Italy (Figure 3.18) but not on the PUN (Figure 3.25). However, the results confirm that only in some bidding zones was there a significant impact on quantity; the estimated impact is heterogeneous across the bidding zones. North (Figure 3.19) and Centre North (Figure 3.20) show a significant impact both of geographical and production lockdowns, especially during daylight hours. The other bidding zones (Figures 3.21, 3.22, 3.23 and 3.24) seem to be affected only by geographical lockdown, and the relative impact is lower.

The results are presented in the following plots, which show the hourly relative impact of lockdown on quantity purchased, at hour h, defined as the following ratio:

$$\frac{\text{Estimated Coefficient}_h}{\text{Average Quantity}_h} \times 100$$

For the geographical lockdown, Average Quantity$_h$ is the average quantity bough in hour h computed on days in the period from 11/03/20 to 31/05/20, whereas for the production lockdown, Average Quantity$_h$ is computed from 25/03/20 to 31/05/20.

Average Quantity$_h$ is the average quantity purchased in hour h computed for days in the period from 11/03/20 to 31/05/20

Moreover, the plots also present also the related hourly p-values. P-value intervals are defined by the following colours:

* **Green**: p-value ≤ 0.01

* Yellow: $0.01 <$ p-value ≤ 0.05

* **Red**: p-value > 0.05

Figure 3.18: Italy | Relative impact of lockdown on quantity purchased

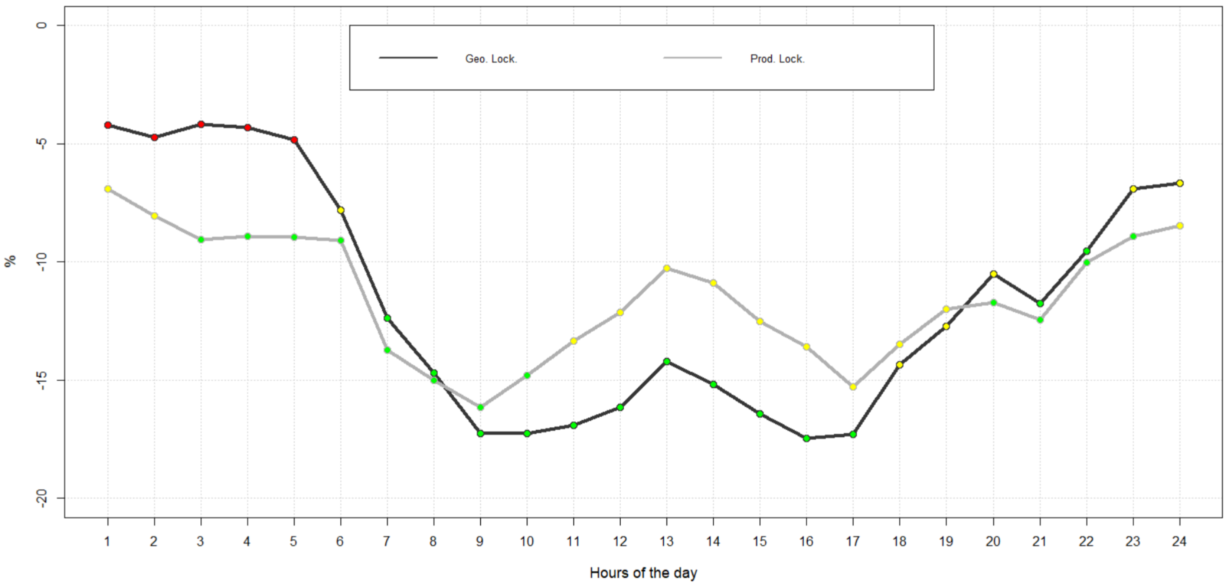


Figure 3.19: North | Relative impact of lockdown on quantity purchased

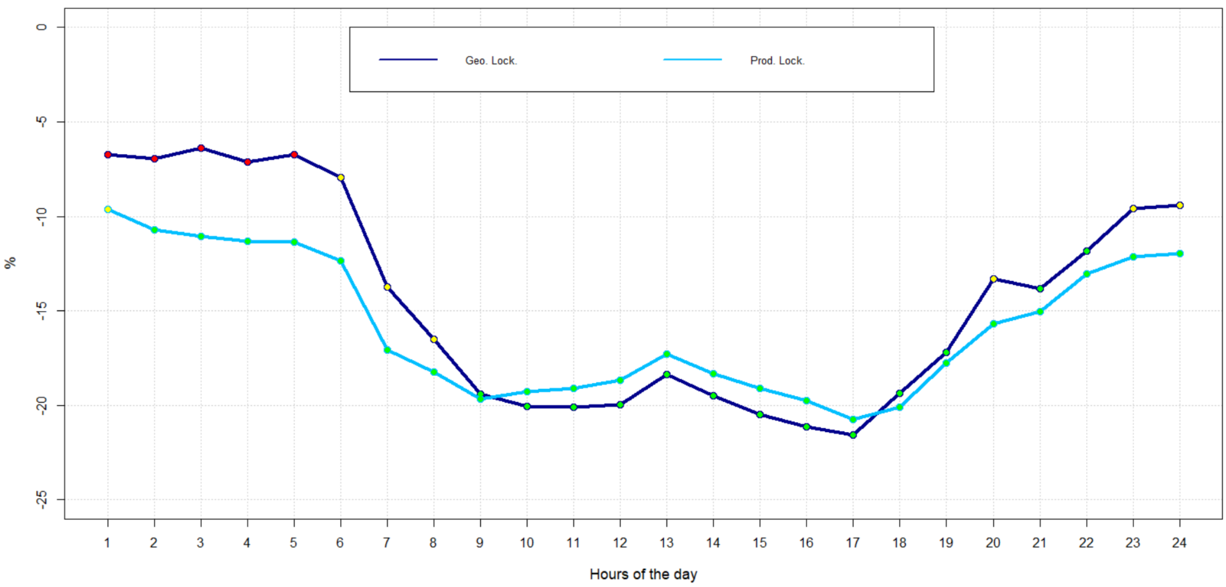


Figure 3.20: Centre North | Relative impact of lockdown on quantity purchased

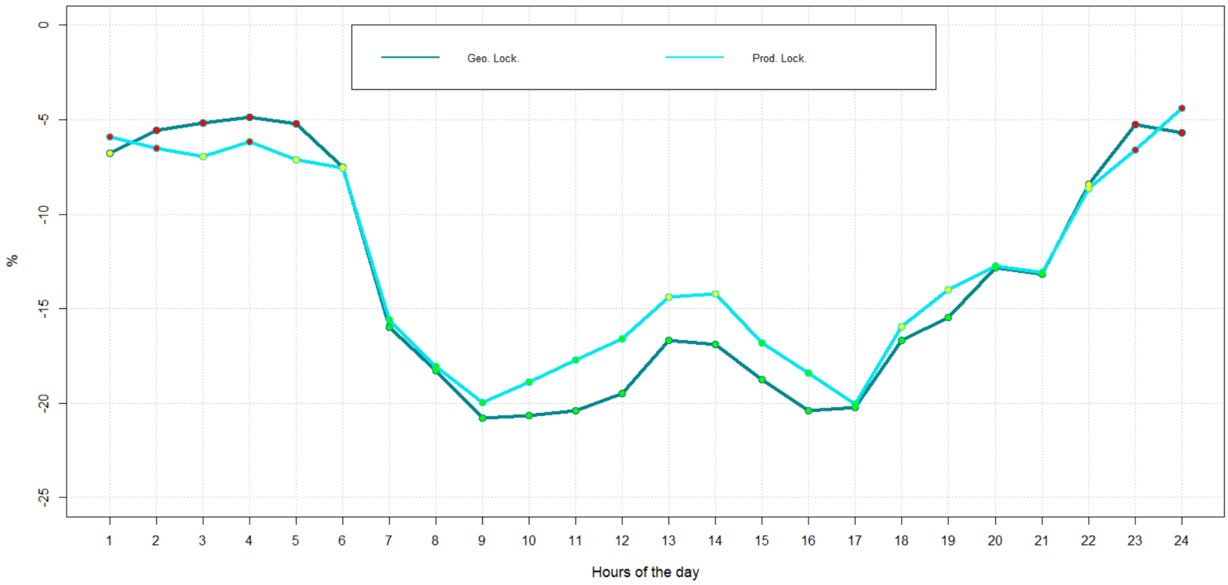


Figure 3.21: Centre South | Relative impact of lockdown on quantity purchased

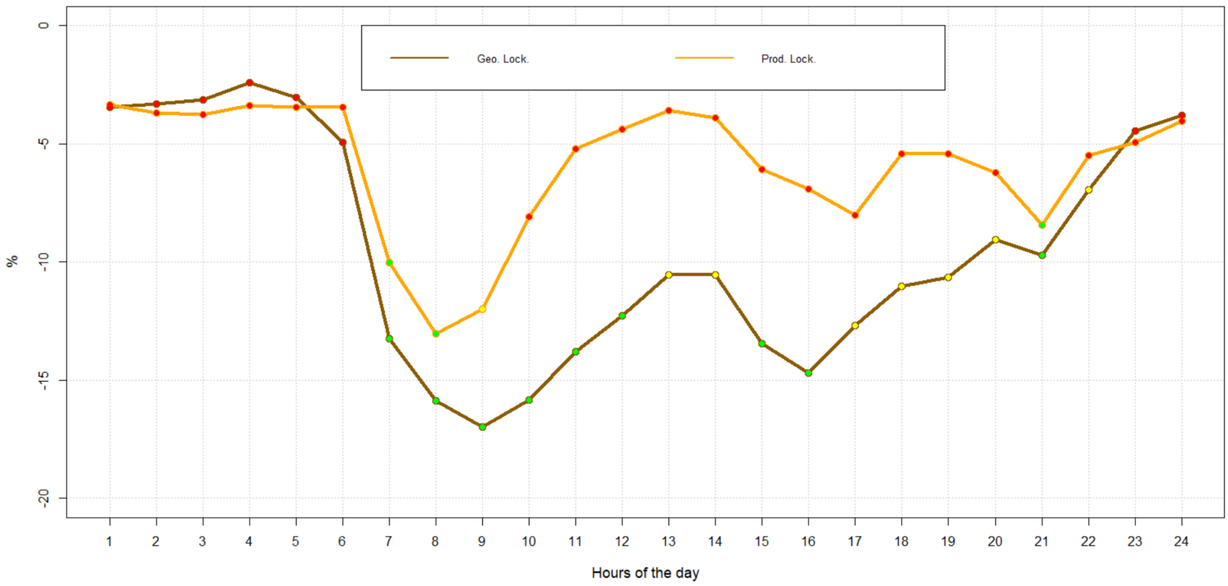


Figure 3.22: South | Relative impact of lockdown on quantity purchased

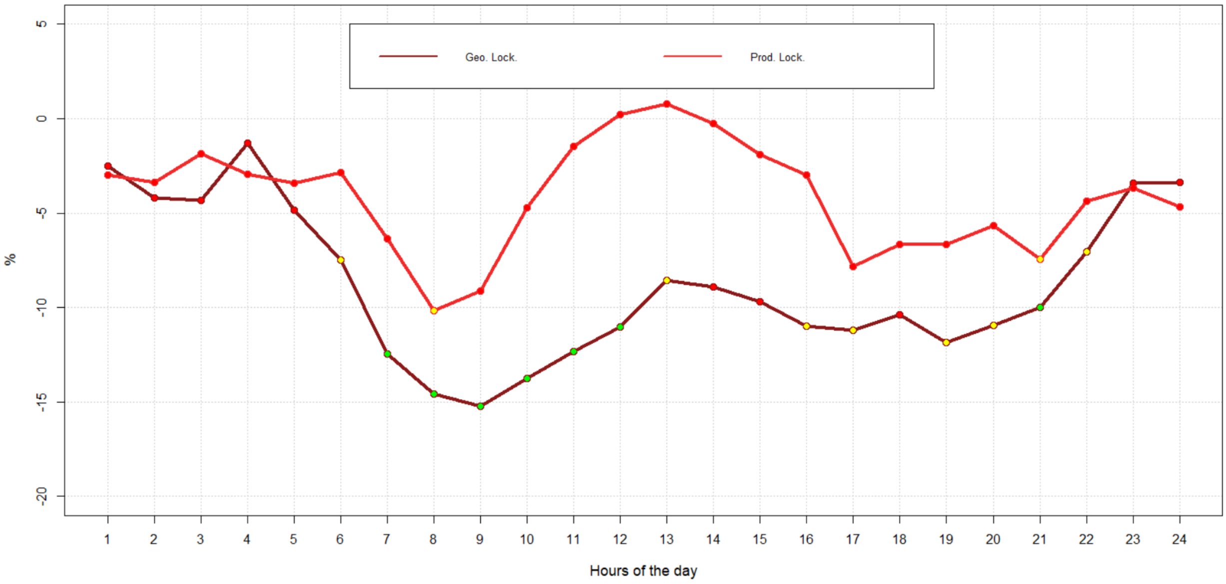


Figure 3.23: Sicily | Relative impact of lockdown on quantity purchased

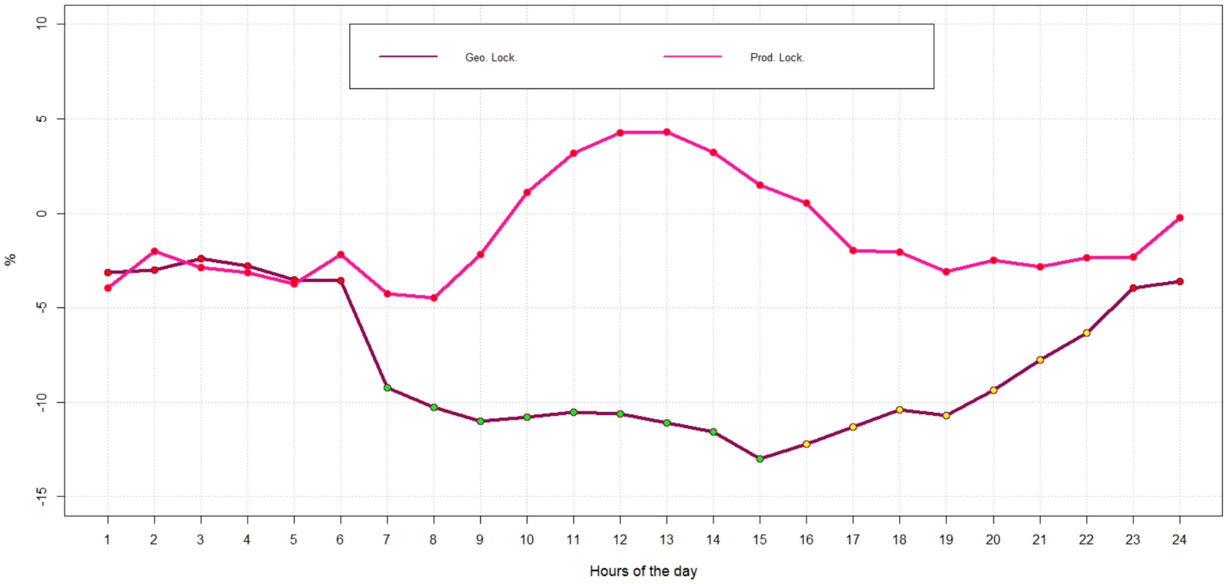


Figure 3.24: Sardinia | Relative impact of lockdown on quantity purchased

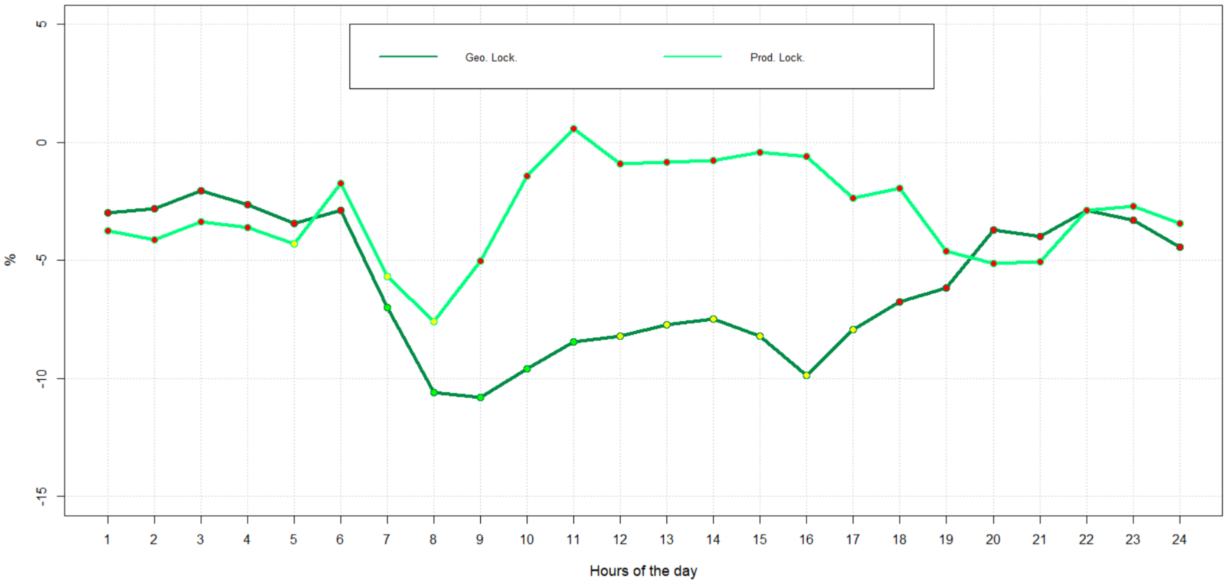
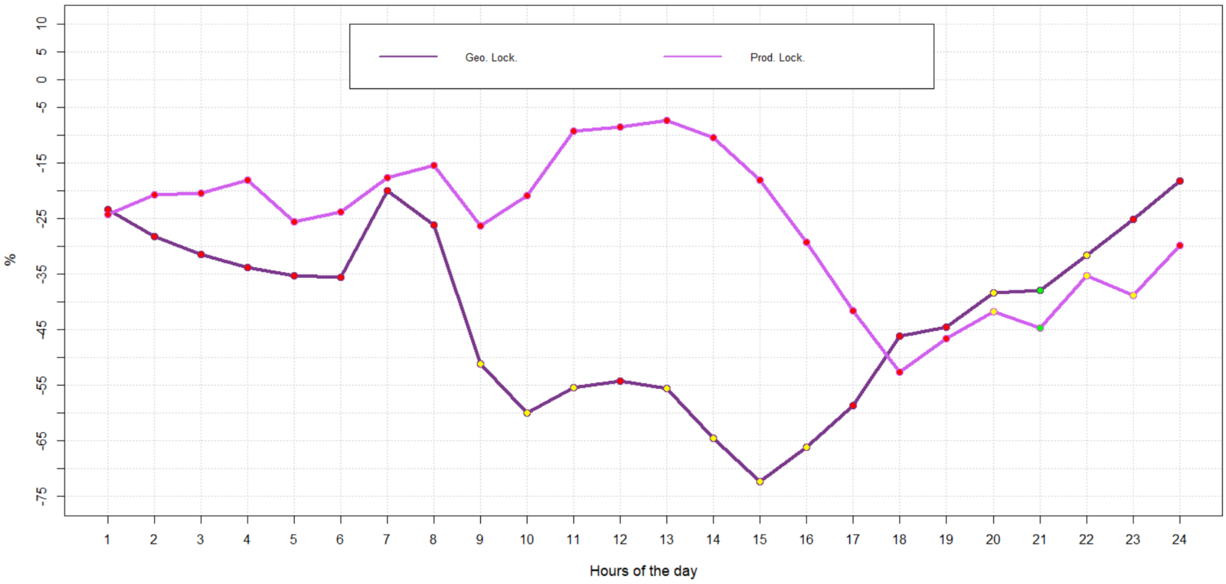


Figure 3.25: PUN | Relative impact of lockdown on quantity purchased



3.7 Change in the power generation mix

The fall in demand plus a sharp fall in prices led to a significant change in in the power generation mix. In fact, with a left shift of demand and a flatter supply curve, due to cheaper energy commodities, the hourly equilibria shifted to the bottom left causing less accepted supply offers. Therefore, only the offers with low bidding prices were accepted, thus producing electricity. In most of the cases, power plants with a bidding schedule with very low prices, coincide with renewable energy sources. In this setting, the Italian electricity market underwent, a production decrease from fossil fuel power plants, whereas on the other, production from RES remained almost unchanged. The report published by the International Energy Agency (April 2020)[21] confirmed that RES were the only energy sources that did not show a decrease in production. Indeed, their share of production rose. This was a consequence of the lack of competitiveness of all the other energy sources which were unable to see the same rate of acceptance for their offers, given that the new hourly equilibria were characterized by pairs of low quantities and prices.

Therefore, during the weeks under examination, the market underwent an increase in the share of electricity produced from renewable and a decrease of the share generated by fossil fuel power plants. According to TSO data, in most of these weeks the fossil fuel share was less than 50% of the total generation, with an average value of 48%, ranging from a minimum of 42% to a maximum of 58%. In contrast, during the corresponding weeks of 2019 the average fossil fuel share of the mix of energy sources was 54%, ranging from a minimum of 43% to a maximum of 63%. Renewable energy sources increased their share: shifting from an average of 33% in the 2019 weeks to 38% in the corresponding weeks of 2020. The remaining share came from self consumption (See Figures 3.26 and 3.27).
Further information regarding total generation, broken down into energy sources, is available in the appendix (see Table C.1). Moreover, in the appendix, Figures from C.13 to C.25 present the weekly comparison of mix of energy sources shares over the thirteen weeks.

3.7.1 Marginal Technology Index

The remarkable change in market dynamics, in particular regarding mix of energy sources and price, substantially altered the marginal technologies that traditionally set the prices. Figures 3.28 and 3.29 present the MTI (Marginal Technology Index) during the thirteen weeks under examination in the years 2019 and 2020. Several elements catch the eye and need to be highlighted. First of all, renewable energy sources set the price in many more hours in 2020 than in 2019 weeks, with an average share of 21% and 15%, respectively. In contrast, the hours where the coal was price setter underwent a sharp decrease, shifting from an average

[21] Link available in the references.

share of 15% in 2019 weeks to 5% in 2020 weeks. Gas-fired power plant also underwent a critical fall in MTI, shifting from 61%, in the weeks of this year, to 52% in the weeks of this year. Furthermore, the decrease of fossil fuel during the 2020 weeks was even larger than is apparent because "Other" includes oil, other natural gas generation (not the CCGT), and some other energy sources not indicated in the dataset of the Italian NEMO. "Other" decreased from an average value of 6% in the 2019 weeks to 3% in the 2020 weeks. However, the increase in the RES share does not offset the decrease in fossil fuel. Imported electricity made up the difference: market coupling and foreign virtual zones had a very significant role in setting the price in the 2020 weeks. Given that most of the electricity imported comes from France and from nuclear power plants, the reason could be the low marginal costs of nuclear energy. This hypothesis is perfectly in line with the low price during the pandemic.

3.7.2 Does decarbonization move faster or slower?

Probably, this is one of the core questions at the centre of the debate between energy market experts. Covid-19 affected the entire energy commodity market leading to anomalous implications such as the negative price of the WTI in April. In this context, it is not clear what the future of fossil fuel energy sources will be. On the one hand, there are no doubts regarding the future of coal, which is rapidly and definitively doomed,[22] but, on the other hand, the future of gas does not look so obvious. Many experts, and policy makers, believe that gas will be the "bridge" from fossil fuel to renewable generation, thereby leading the energy transition; the fact that many utilities are investing in new gas-fired power plants, for example Edison[23] and Enel[24], seems to confirm this. However, some utility companies are willing to bypass the "bridge" of natural gas and go straight to green generation.[25]

Conti (2020) writes as follows *"A key question is whether this situation will permanently alter the role of gas in the energy sector and lead to irreversible changes. On this question, there's no agreement among the experts."*.

However, it is reasonable to think that the role of gas in the future will depend on the energy market structure of each country. Indeed, in countries (e.g. Italy) with a significant penetration of CCGT power plants and the absence of nuclear power plants, gas may have a leading

[22] Many utilities worldwide announced the closure of many coal power plants during pandemic. Read for example the cases of Austria, Spain and Sweden.

[23] See the following article for further details.

[24] See the following article for further details.

[25] See the US case

role in the future. On the contrary, in countries with significant nuclear capacity, there could be a strong incentive to bypassing the gas “bridge” and investing directly in renewable energy sources. For these reasons, the future of gas is strongly linked to national market structures and policies, so it is unlikely to have a homogeneous future.

A further element to highlight is the massive green investments that took place during pandemic. In fact, investing in renewable energy sources seems to be the contemporary Keynesian way to stimulate the economy after the sharp fall in national GDPs worldwide. This plan will definitely boost the energy transition and reduce carbon emission.

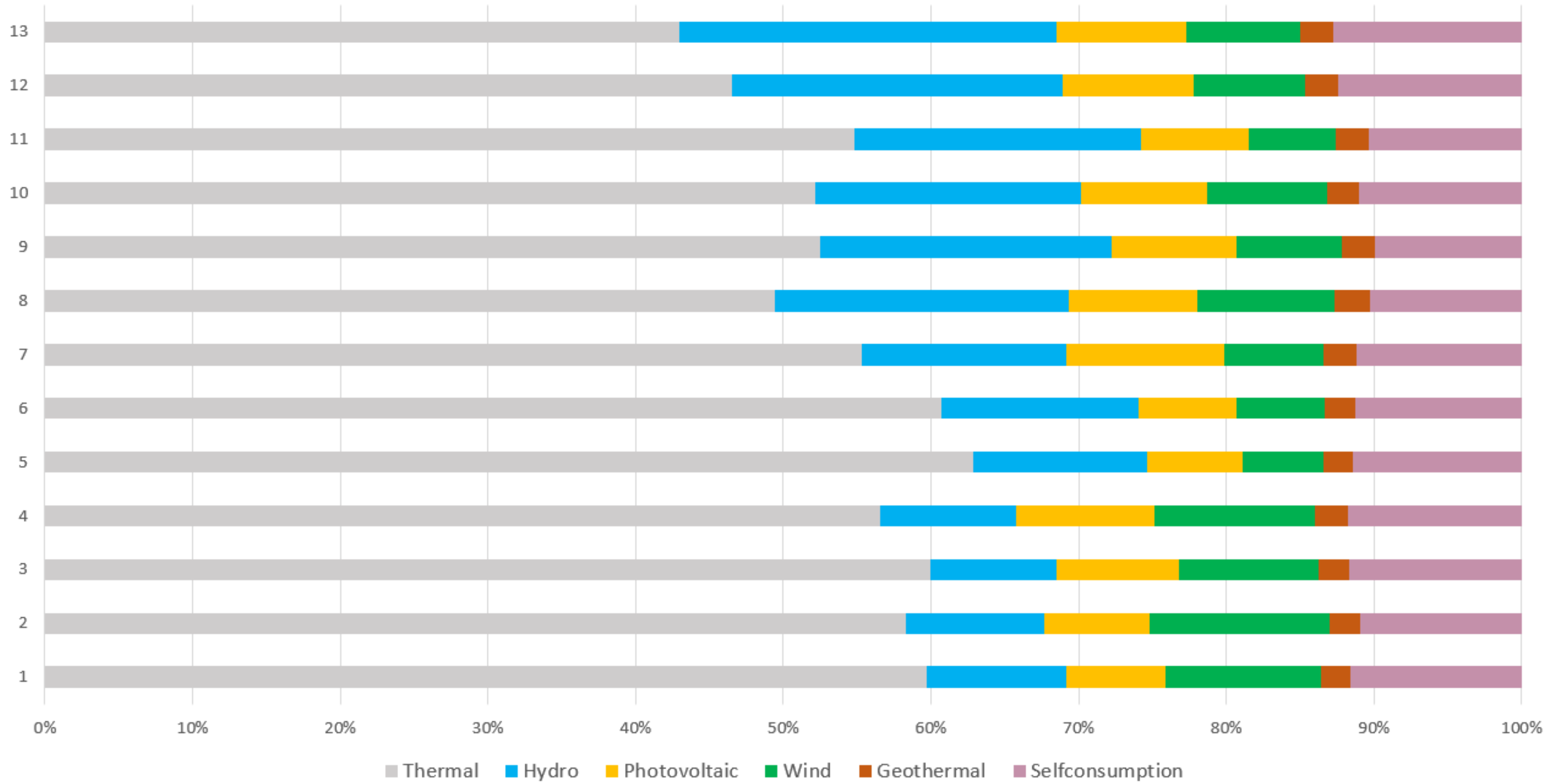
Therefore, although the question remains, due to the role that natural gas will play in the following years, it seems that decarbonization is moving faster thanks to the rapid phasing out of coal and the massive investments in renewable energy sources.

3.8 Conclusion

Restrictive measures in response to Covid-19 had a very significant effect on the overall economy and on the electricity markets. Lockdowns initially led to a fall in demand, which had a ripple effect causing further anomalous market dynamics, i.e.: price decrease, less market splitting, a change in the power generation mix and in MTI. In particular, the market saw brilliant performance by renewable energy sources, with significant increase in their share of energy generation. In contrast, fossil fuel production dropped and coal set the price in very few hours during the 2020 weeks. Some of these effects were temporary and others appear to be persistent. A negative market shock, as in this case, can provide very useful lessons and provide the opportunity to study some market dynamics, which normally are unobservable.

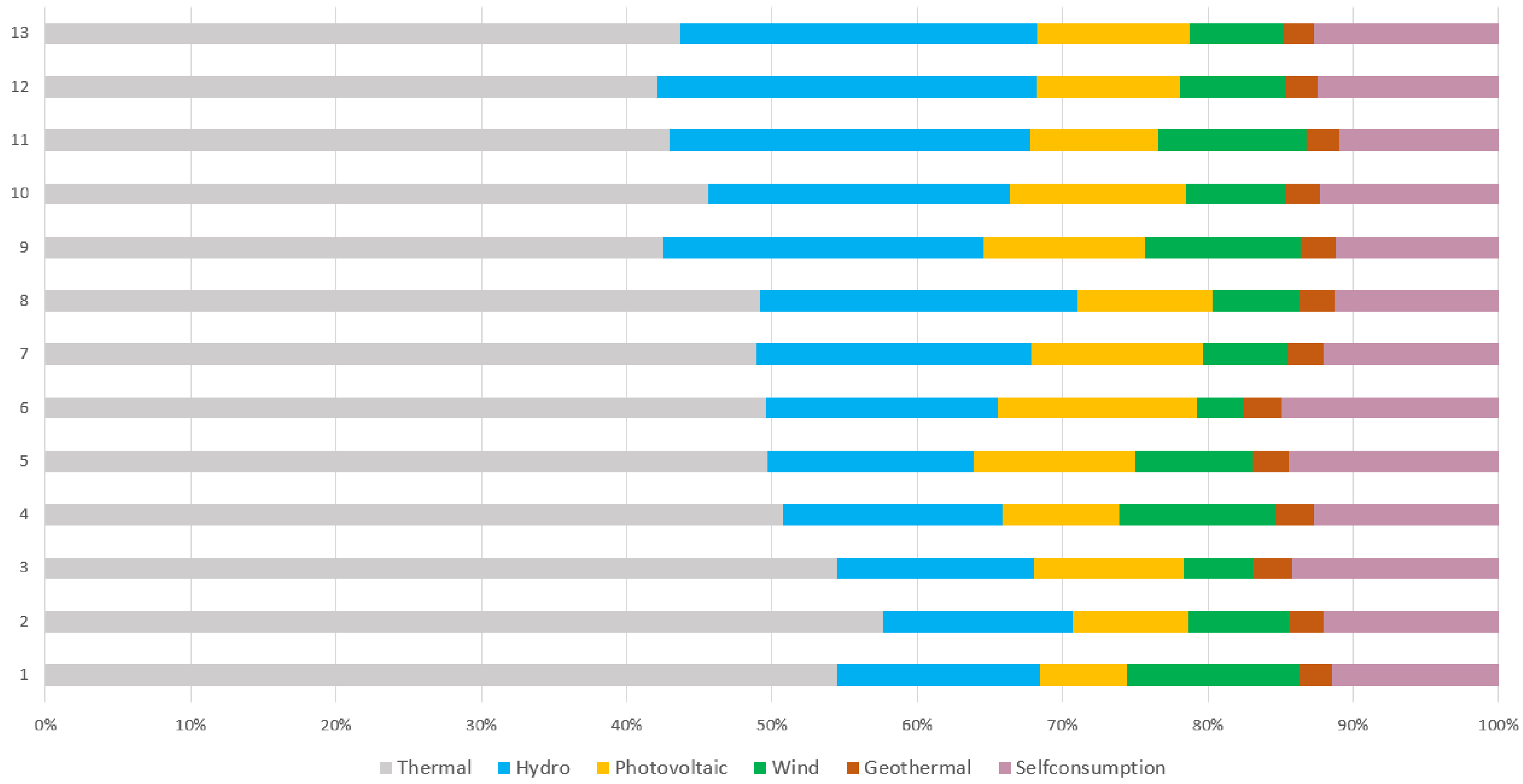
This chapter aims to provide a complete overview on the effects of lockdown on the the Italian electricity market. It is important to understand the changes in market dynamics across the geographic bidding zones, and more broadly at a national level, because it enables an assessment of the crisis and identification of the right policies and State subsidies. Indeed, the amount of electricity exchanged in the market can be used as a satisfactory proxy for revenues, thus the change in consumption can provide a general idea of the change in turnover. This useful evidence should be taken into account by policy makers to decide the best way to allocate financial resources.

Figure 3.26: Shares of the mix of energy sources | Italy | 2019



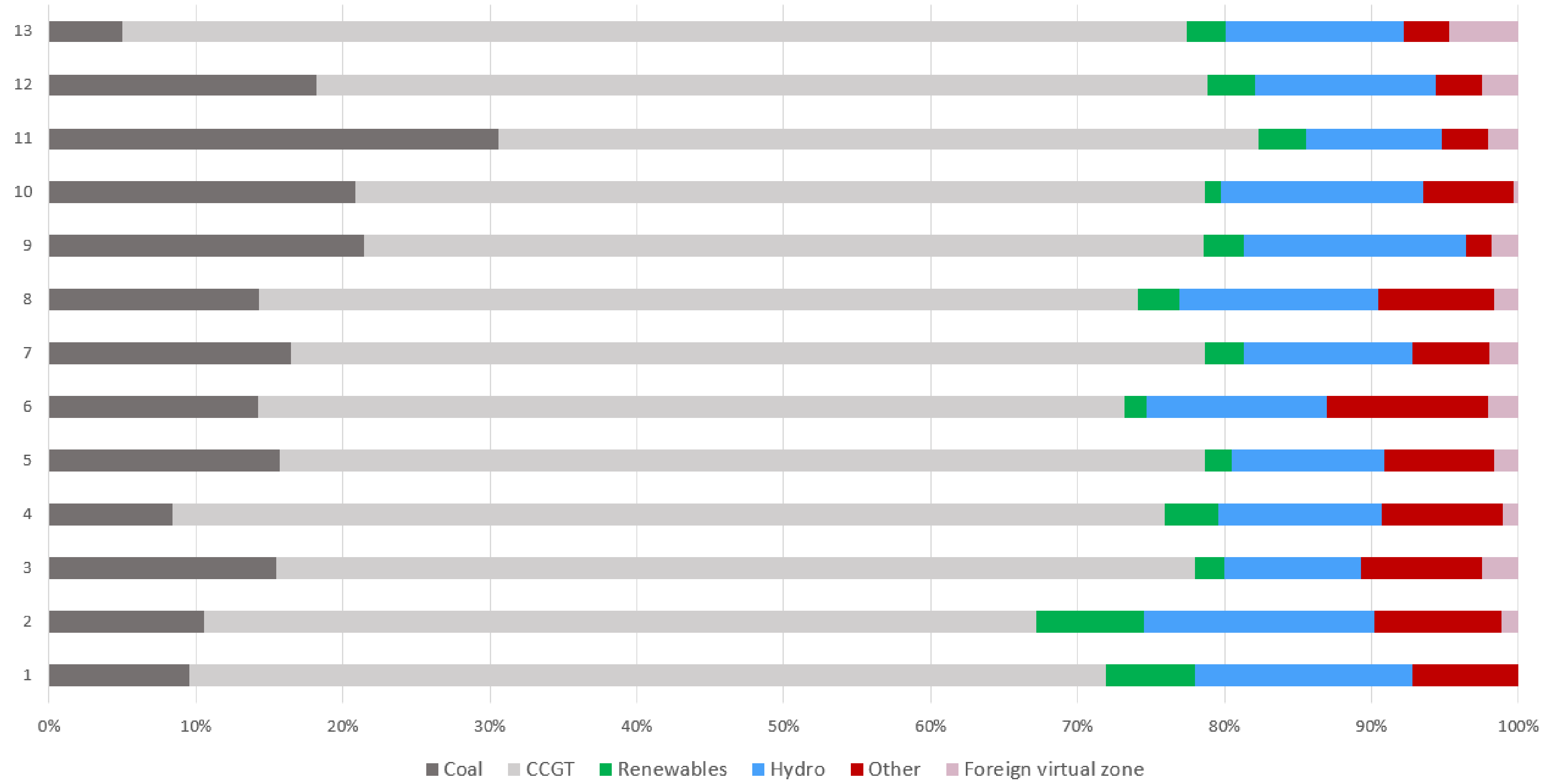
The plot presents the shares of the mix of energy sources in Italy from January to May 2019.

Figure 3.27: Shares of the mix of energy sources | Italy | 2020



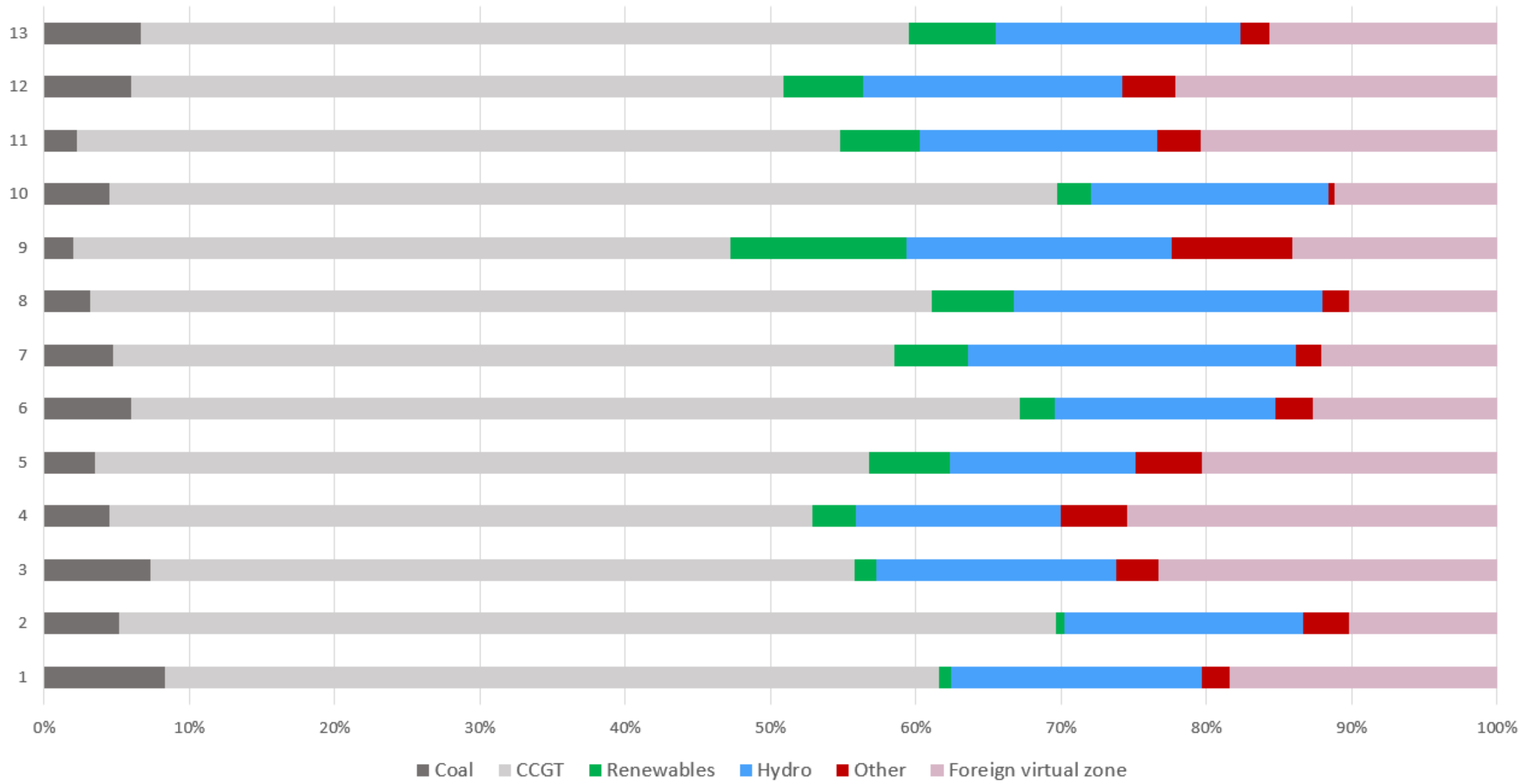
The plot presents the shares of the mix of energy sources in Italy from January to May 2020.

Figure 3.28: Marginal technology index | Italy | 2019



The plot presents the marginal technology index in Italy in the thirteen weeks under analysis during 2019.

Figure 3.29: Marginal technology index | Italy | 2020



The plot presents the marginal technology index in Italy in the thirteen weeks under analysis during 2020.

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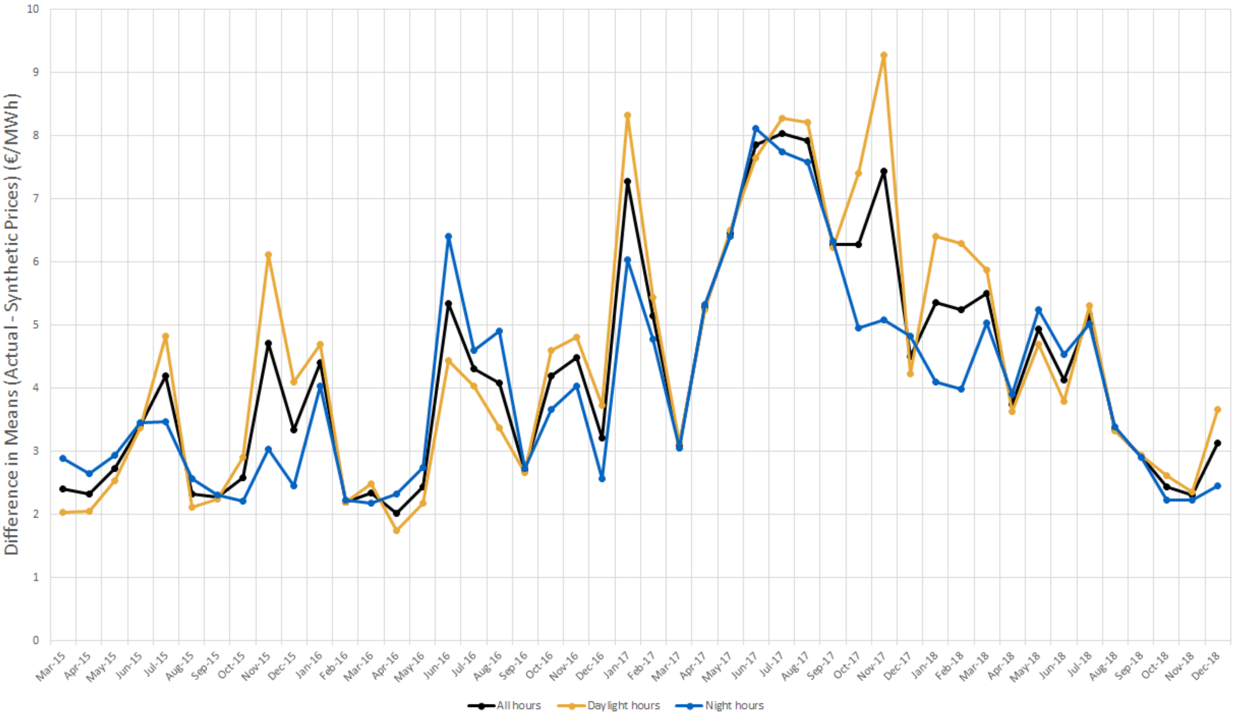
Appendix

Appendix A

Figure A.1: Prices



The differences between the monthly actual and synthetic means for different blocks of hours are reported. The black line represents the values estimated on all the hours of the day, the yellow line represents the values estimated on the daylight hours (8am - 8pm), the blue line represents the values estimated on the night hours (9pm-7am).

Table A.1: 2015 Results

Period	$\text{Mean}_{Tot}^{A.P.}$	$\text{Mean}_{Tot}^{S.P.}$	Diff_{Tot}^{P}	$\text{Mean}_{Day}^{A.P.}$	$\text{Mean}_{Day}^{S.P.}$	Diff_{Day}^{P}	$\text{Mean}_{Night}^{A.P.}$	$\text{Mean}_{Night}^{S.P.}$	Diff_{Night}^{P}	$\text{Mean}_{Tot}^{A.Q.}$	$\text{Mean}_{Tot}^{S.Q.}$	Diff_{Tot}^{Q}	CSL_{Tot}	CSL_{Tot}^{Rel}
Jan	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Feb	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Mar	50	47.59	2.41	53.69	51.66	2.03	45.51	42.63	2.88	32982.84	33109.65	-126.81	56 mln	4.53
Apr	47.88	45.56	2.32	47.18	45.13	2.05	48.73	46.09	2.64	30752.92	30854.31	-101.39	47 mln	4.54
May	47.06	44.34	2.72	46.75	44.22	2.53	47.43	44.49	2.94	30447.27	30567.53	-120.26	60 mln	5.58
Jun	48.58	45.18	3.4	49.13	45.76	3.37	47.94	44.49	3.45	32757.09	32925.55	-168.46	80 mln	6.89
Jul	67.15	62.95	4.2	68.69	63.87	4.82	65.33	61.86	3.47	37632.68	37835.61	-202.93	126 mln	6.53
Aug	53.14	50.81	2.33	52.18	50.06	2.12	54.27	51.7	2.57	30172.98	30261.28	-88.3	55 mln	4.56
Sep	49.32	47.05	2.27	51.63	49.38	2.25	46.58	44.28	2.3	33692.97	33822.41	-129.44	56 mln	4.63
Oct	47.56	44.98	2.58	51.54	48.64	2.9	42.81	40.6	2.21	32374.67	32540.35	-165.68	64 mln	5.52
Nov	53.65	48.94	4.71	60.41	54.29	6.12	45.56	42.53	3.03	33016.03	33248.29	-232.26	123 mln	9.27
Dec	55.17	51.83	3.34	60.89	56.8	4.09	48.42	45.96	2.46	32529.6	32735.95	-206.35	87 mln	6.28
2015	52	48.96	3.04	54.25	51.02	3.23	49.31	46.52	2.79	32640.88	32795.13	-154.25	0.760 bln	5.92

A. = Actual, S.= Synthetic, P. = Price, Q. = Quantity.

Table A.2: 2016 Results

Period	$\text{Mean}^{A.P.}_{Tot}$	$\text{Mean}^{S.P.}_{Tot}$	Diff^{P}_{Tot}	$\text{Mean}^{A.P.}_{Day}$	$\text{Mean}^{S.P.}_{Day}$	Diff^{P}_{Day}	$\text{Mean}^{A.P.}_{Night}$	$\text{Mean}^{S.P.}_{Night}$	Diff^{P}_{Night}	$\text{Mean}^{A.Q.}_{Tot}$	$\text{Mean}^{S.Q.}_{Tot}$	Diff^{Q}_{Tot}	CSL_{Tot}	CSL^{Rel}_{Tot}
Jan	45.91	41.51	4.4	50.3	45.61	4.69	40.69	36.65	4.04	33584.11	33837.27	-253.16	112 mln	9.45
Feb	36.99	34.79	2.2	40.12	37.93	2.19	33.3	31.08	2.22	34417.37	34568.99	-151.62	52 mln	5.7
Mar	35.13	32.79	2.34	37.12	34.63	2.49	32.74	30.56	2.18	32999.98	33136.89	-136.91	58 mln	6.71
Apr	31.7	29.69	2.01	32.15	30.4	1.75	31.17	28.84	2.33	31376.54	31473.04	-96.5	43 mln	5.96
May	34.17	31.74	2.43	34.29	32.12	2.17	34.04	31.29	2.75	31196.25	31266.61	-70.36	55 mln	6.84
Jun	36.43	31.09	5.34	36.92	32.48	4.44	35.87	29.47	6.4	32437.75	32583.73	-145.98	120 mln	14.3
Jul	42.83	38.53	4.3	43.47	39.43	4.04	42.07	37.47	4.6	36484.11	36577.24	-93.13	121 mln	10.23
Aug	36.97	32.89	4.08	36.75	33.38	3.37	37.22	32.32	4.9	30255.19	30360.99	-105.8	90 mln	10.71
Sep	41.56	38.87	2.69	43.03	40.37	2.66	39.82	37.09	2.73	33566.13	33642.99	-76.86	66 mln	6.62
Oct	51.97	47.78	4.19	55.56	50.96	4.6	47.47	43.8	3.67	32603.97	32719.73	-115.76	103 mln	8.35
Nov	56.55	52.07	4.48	61.36	56.55	4.81	50.5	46.46	4.04	34122.58	34194.3	-71.72	109 mln	8.03
Dec	54.68	51.47	3.21	58.29	54.57	3.72	50.18	47.61	2.57	33875.29	33943.94	-68.65	82 mln	6.17
2016	41.95	38.49	3.46	44.06	40.65	3.41	39.43	35.89	3.54	33067.07	33183.03	-115.96	1.016 bln	8.24

A. = Actual, S.= Synthetic, P. = Price, Q. = Quantity.

Table A.3: 2017 Results

Period	$\text{Mean}^{A.P.}_{Tot}$	$\text{Mean}^{S.P.}_{Tot}$	Diff^{P}_{Tot}	$\text{Mean}^{A.P.}_{Day}$	$\text{Mean}^{S.P.}_{Day}$	Diff^{P}_{Day}	$\text{Mean}^{A.P.}_{Night}$	$\text{Mean}^{S.P.}_{Night}$	Diff^{P}_{Night}	$\text{Mean}^{A.Q.}_{Tot}$	$\text{Mean}^{S.Q.}_{Tot}$	Diff^{Q}_{Tot}	CSL_{Tot}	CSL^{Rel}_{Tot}
Jan	68.18	60.9	7.28	75.65	67.32	8.33	59.27	53.24	6.03	35064.4	35245.41	-181.01	199 mln	10.89
Feb	54.93	49.78	5.15	58.95	53.51	5.44	49.81	45.03	4.78	34913.02	35084.78	-171.76	115 mln	9.3
Mar	44.24	41.14	3.1	46.03	42.9	3.13	42.05	39	3.05	33180.27	33283.97	-103.7	76 mln	7.04
Apr	42.8	37.52	5.28	42.83	37.58	5.25	42.77	37.45	5.32	30147.86	30274.72	-126.86	114 mln	12.43
May	42.7	36.24	6.46	43.19	36.69	6.5	42.13	35.72	6.41	31264.05	31334.77	-70.72	147 mln	14.83
Jun	47.47	39.61	7.86	48.53	40.89	7.64	46.23	38.11	8.12	34985.48	35046.54	-61.06	193 mln	15.82
Jul	49.11	41.08	8.03	49.47	41.2	8.27	48.7	40.95	7.75	37087.09	37189.2	-102.11	225 mln	16.38
Aug	54.03	46.11	7.92	54.75	46.54	8.21	53.19	45.61	7.58	32594	32688.36	-94.36	218 mln	16.01
Sep	47.87	41.59	6.28	49.4	43.18	6.22	46.07	39.74	6.33	32970.17	33120.23	-150.06	147 mln	12.78
Oct	54.93	48.65	6.28	58.77	51.36	7.41	50.4	45.45	4.95	32014.48	32326.36	-311.88	161 mln	12
Nov	64.42	56.99	7.43	71.48	62.21	9.27	55.5	50.41	5.09	34198.62	34467.63	-269.01	185 mln	12.17
Dec	63.24	58.74	4.5	69.34	65.12	4.22	55.84	51.01	4.83	33384.54	33571.06	-186.52	105 mln	6.73
2017	52.74	46.43	6.31	55.64	48.98	6.66	49.27	43.38	5.89	33473.45	33624.95	-151.5	1.89 bln	12.09

A. = Actual, S.= Synthetic, P. = Price, Q. = Quantity.

Table A.4: 2018 Results

Period	$\text{Mean}^{A.P.}_{Tot}$	$\text{Mean}^{S.P.}_{Tot}$	Diff^{P}_{Tot}	$\text{Mean}^{A.P.}_{Day}$	$\text{Mean}^{S.P.}_{Day}$	Diff^{P}_{Day}	$\text{Mean}^{A.P.}_{Night}$	$\text{Mean}^{S.P.}_{Night}$	Diff^{P}_{Night}	$\text{Mean}^{A.Q.}_{Tot}$	$\text{Mean}^{S.Q.}_{Tot}$	Diff^{Q}_{Tot}	CSL_{Tot}	CSL^{Rel}_{Tot}
Jan	48.71	43.36	5.35	54.23	47.82	6.41	42.17	38.08	4.09	34515.9	34766.71	-250.81	143 mln	11.26
Feb	56.39	51.14	5.25	61.15	54.86	6.29	50.65	46.66	3.99	35955.3	36219.65	-264.35	133 mln	9.72
Mar	56.79	51.29	5.5	60.84	54.97	5.87	51.8	46.77	5.03	34551.61	34755.83	-204.22	144 mln	9.87
Apr	49.56	45.81	3.75	50.02	46.39	3.63	49.03	45.13	3.9	30791.98	30842.7	-50.72	84 mln	7.62
May	53.83	48.89	4.94	55.45	50.76	4.69	51.9	46.66	5.24	32214.92	32285.93	-71.01	121 mln	9.23
Jun	57.49	53.36	4.13	58.13	54.34	3.79	56.73	52.2	4.53	34347.5	34398.34	-50.84	99 mln	6.94
Jul	62.29	57.13	5.16	62.6	57.3	5.3	61.94	56.92	5.02	36972.43	37081.57	-109.14	139 mln	8.12
Aug	66.53	63.19	3.34	66.57	63.25	3.32	66.49	63.11	3.38	32595.03	32645.91	-50.88	83 mln	5.21
Sep	74.83	71.91	2.92	75.83	72.89	2.94	73.67	70.77	2.9	33674.19	33701.52	-27.33	73 mln	4.01
Oct	73.23	70.79	2.44	76.82	74.21	2.61	68.93	66.7	2.23	33206.61	33310.3	-103.69	60 mln	3.36
Nov	66.52	64.22	2.3	71.84	69.48	2.36	59.65	57.43	2.22	34115.21	34161.64	-46.43	52 mln	3.38
Dec	64.9	61.77	3.13	69.55	65.88	3.67	59.15	56.7	2.45	33581.71	33651.17	-69.46	81 mln	5.1
2018	60.92	56.9	4.02	63.6	59.36	4.24	57.73	53.96	3.77	33867.46	33975.27	-107.81	1.21 bln	6.74

A. = Actual, S.= Synthetic, P. = Price, Q. = Quantity.

Appendix B

B.1 Revenues computational details

B.1.1 Actual revenues for firm i at hour h

Given the hourly actual market clearing price P_A^h and the actual quantity exchanged Q_A^h, suppliers' bids are ordered through the merit order criterion and only those with a price below P_A^h are considered. Moreover, only the cumulative sum below Q_A^h is considered. Given this truncated supply curve, actual revenues of operator i ($R_A^{i,h}$) are computed as follows:

$$R_A^{i,h} = S^{i,h} \times P_A^h$$

where: $S^{i,h}$ represents the cumulative sum of bids submitted by operator i, at hour h, having a bid price below P_A.

Example:

An example is provided in Figure B.1. The actual equilibrium $\{P_A; Q_A\}$ is the intersection point between demand (in blue) and actual supply (in black and red). The accepted bids submitted by generators are represented by the continuous line of supply, whereas the dotted line indicates rejected bids. Bids submitted by operator i are in red. Therefore, revenues of operator i are computed as the product between P_A and the quantity represented by the continuous red segment.

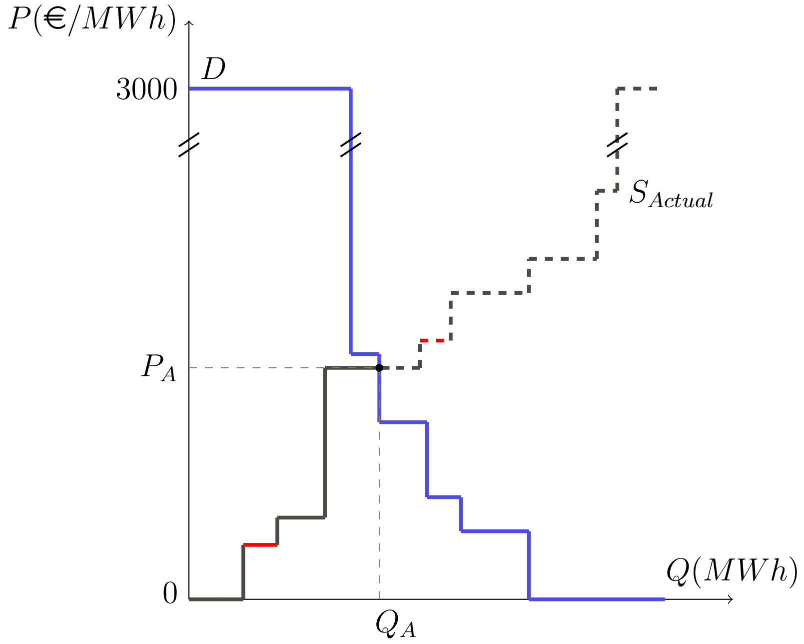
B.1.2 Synthetic revenues for firm i at hour h

Given the hourly synthetic market clearing price P_S^h and the synthetic quantity exchanged Q_S^h, suppliers' bids are ordered through the merit order criterion and only those with a price below P_S^h are considered. Moreover, only the cumulative sum below Q_S^h is considered. Given this truncated supply curve, synthetic revenues of operator i ($R_S^{i,h}$) are computed as follows:

$$R_S^{i,h} = S^{i,h} \times P_S^h + Q^{AC,h} \times P_S^h$$

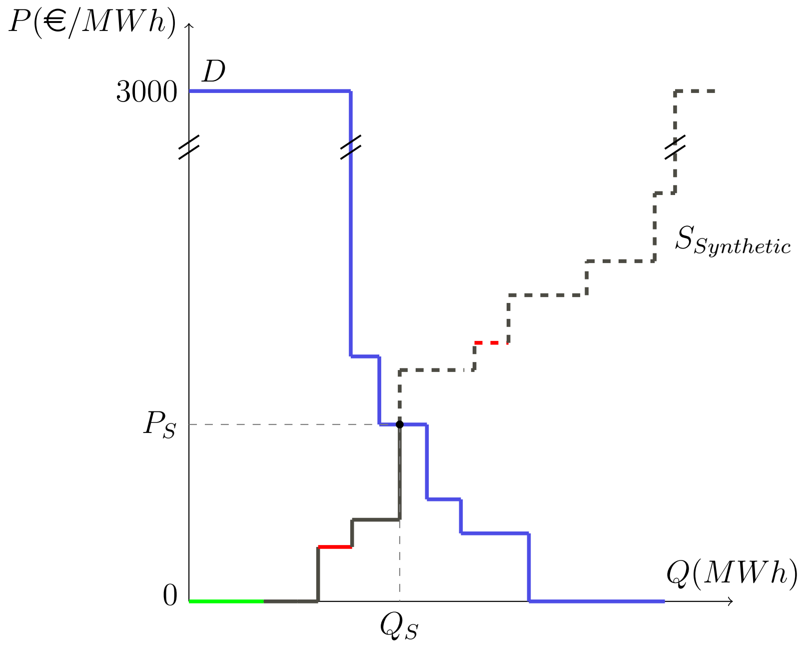
where: $S^{i,h}$ represents the cumulative sum of bids submitted by operator i, at hour h, having a bid price below P_S.
$Q^{AC,h}$ represents the additional capacity which has been offered in the counterfactual scenario at hour h.
This way, it is possible to assume that each operator, at every hour, employed a capacity withholding strategy and to verify for which operators this assumption is likely to hold. In other words, $Q^{AC,h}$ represents the capacity potentially withheld in the actual scenario. If operator i at hour h employed a capacity withholding strategy (withholding $Q^{AC,h}$) then its profits in the actual case should be higher than those in the synthetic scenario, where for operator i was more profitable to offer this additional quantity. It is possible to create a counterfactual scenario for each operator where its synthetic revenues are computed.
Example:
An example is provided in Figure B.2. Synthetic equilibrium $\{P_S; Q_S\}$ is the intersection point between demand (in blue) and synthetic supply (in black, red and green). The accepted bids submitted by generators are represented by the continuous line of supply, whereas the dotted line indicates the rejected bids. Bids submitted by operator i ($S^{i,h}$) are drawn in red whereas in green is represented the additional capacity offered in the market at hour h ($Q^{AC,h}$). Therefore, the revenues of operator i, at hour h, are computed as the product between P_S and the quantity represented by the continuous red segment plus the product between P_S and $Q^{AC,h}$, represented by the continuous green segment.

Figure B.1: Actual Case



D:Demand; S_{Actual}: Actual Supply; P_A: Actual Price;; Q_A: Actual Quantity.

Figure B.2: Synthetic Case



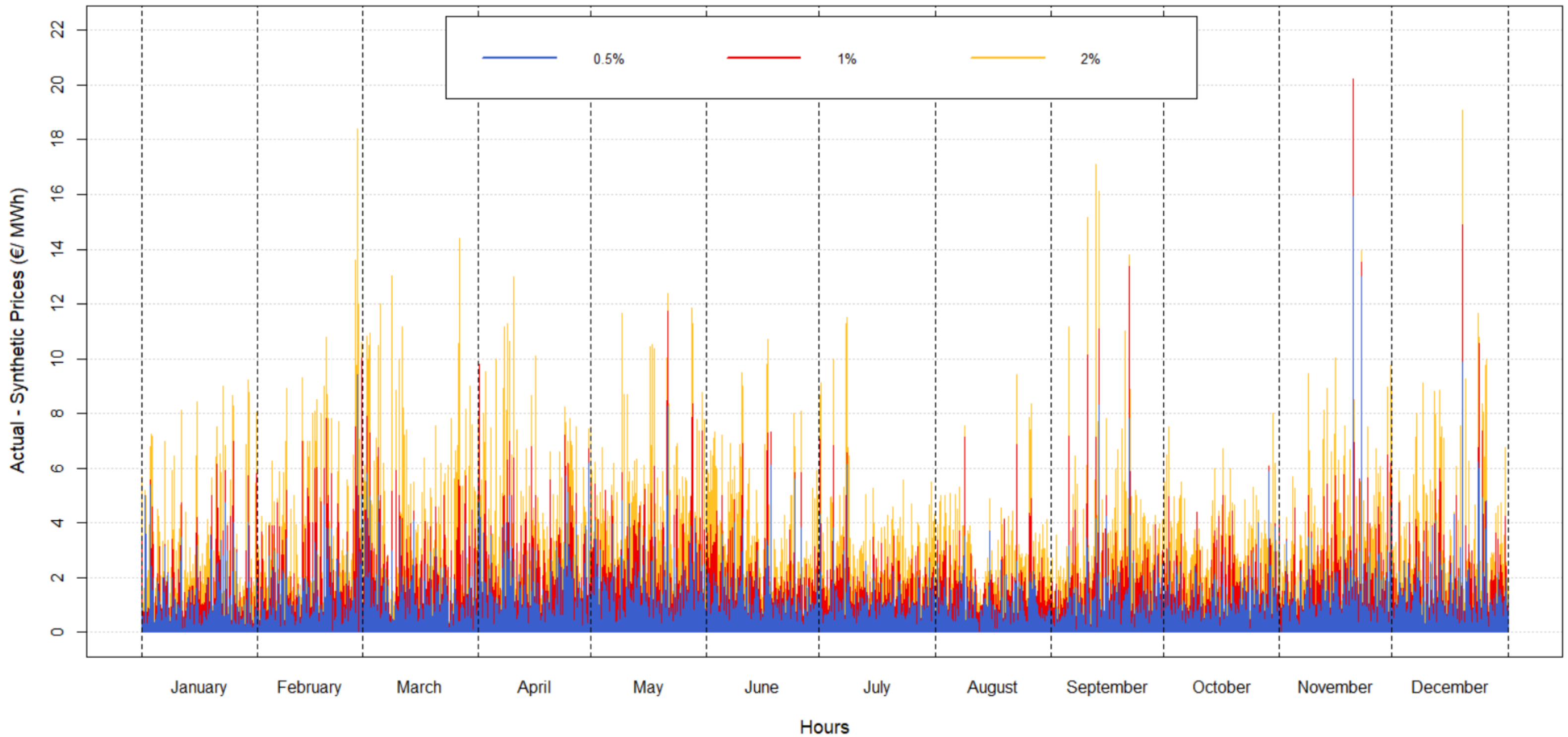
D:Demand; $S_{Synthetic}$: Synthetic Supply; P_S: Synthetic Price;; Q_S: Synthetic Quantity.

B.1.3 Number of observations in actual and synthetic scenarios: explanatory example

Let us assume the following case as explanatory example of this:
Actual scenario - *The market clearing price is 10 €/ MWh and the quantity exchanged in the market is 20 MWh, which is sold by two operators: operator A sells 19 MWh, whereas operator B sells 1 MWh. Operator B is the price setter, thanks to its bid of 3 MWh at price 10 €/MWh, but only 1 MWh is sold. The accepted bid of operator A, with the highest price, is a pair containing Q = 5 MWh and P = 10 €/MWh. However, the bid of supplier A at price 10 €/MWh is to the left of the bid of supplier B at price 10 €/MWh because of the merit order criterion. In other words, the accepted bids of operator A are always to the left of the bid of operator B in the supply curve. According to this scenario, there are 2 operators who achieved revenues.*
Synthetic scenario - *Assume now we add 1 MWh of extra capacity to the supply schedule at price 0 €/MWh; supply shifts to the right. A new synthetic equilibrium is achieved, obtained as the intersection point between demand and synthetic supply. Also in this case, the price is 10 €/MWh and the quantity exchanged is 20 MWh. According to this scenario, there is only 1 operator who achieved revenues. In other words, the extra capacity, added to the supply schedule, pushed out operator B.*

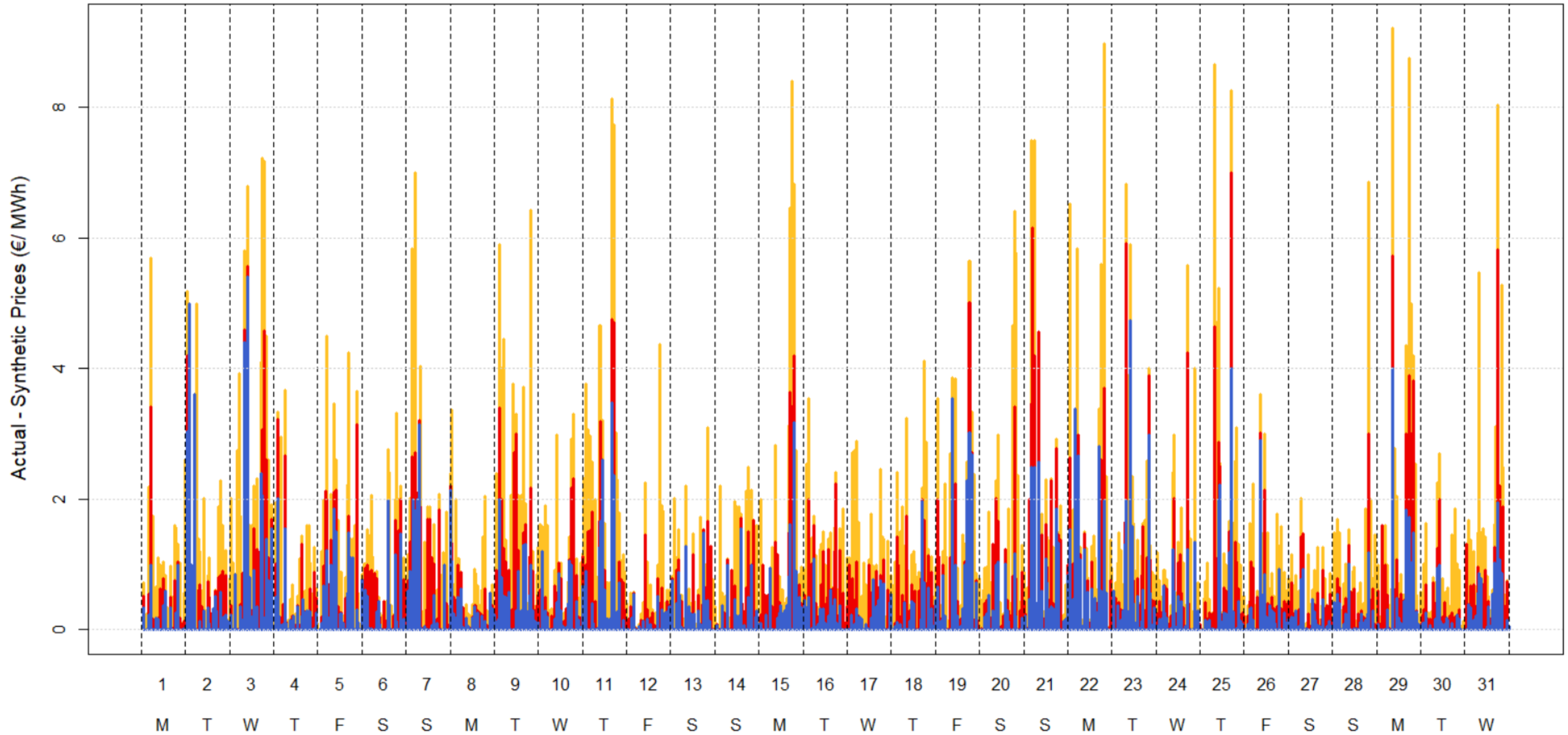
B.2 Actual Prices vs Synthetic Prices

Figure B.3: 2018 | Differences between Actual and Synthetic Prices



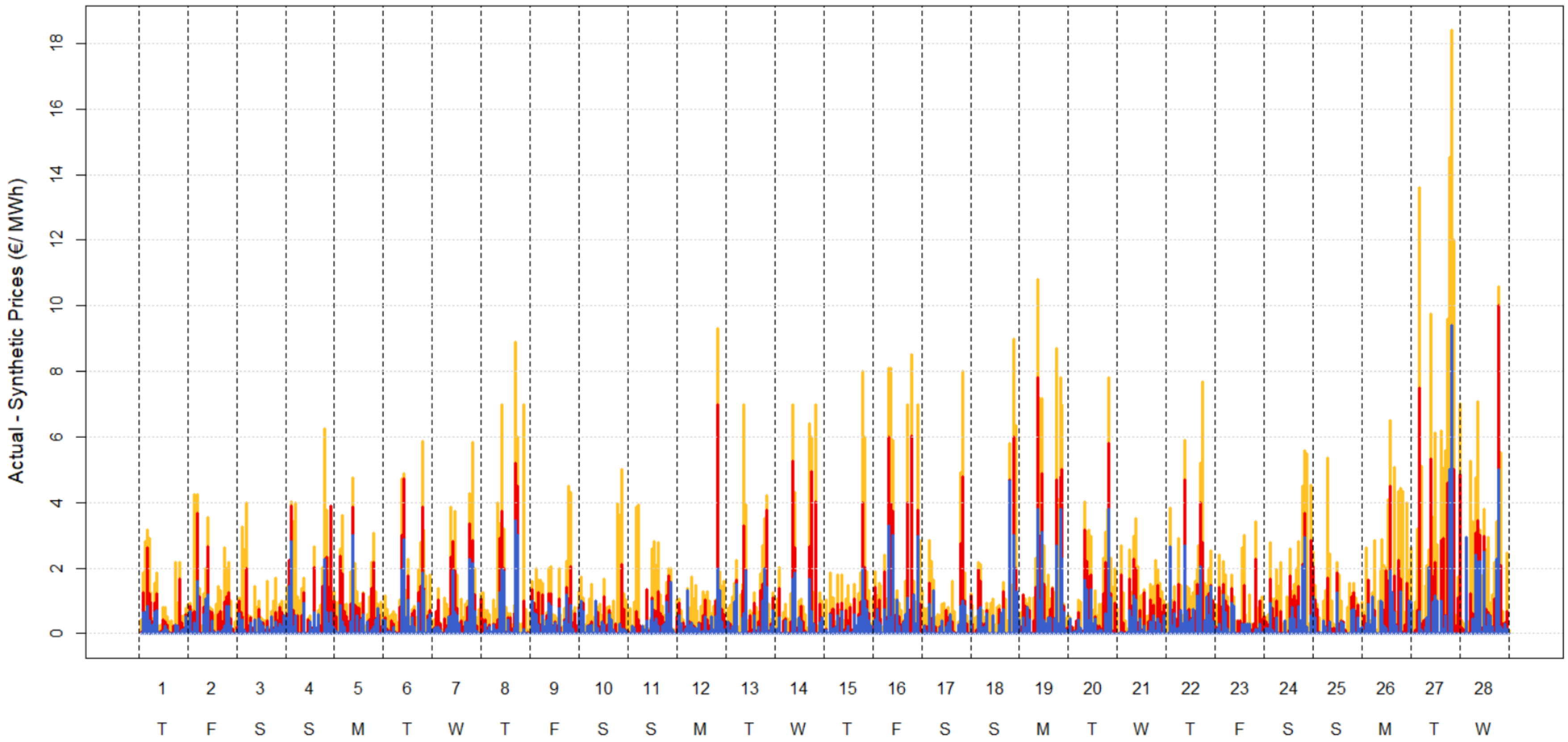
The plot illustrates the difference between actual and synthetic prices during 2018. In yellow the differences between actual and synthetic at 2%, in red at 1% and in blue at 0.5%. As already discussed, by increasing the percentage of extra capacity we obtain a fall in synthetic prices. For such reasons, higher percentages mean higher differences. Where the colour corresponding to a lower percentage overlap the one corresponding to a higher percentage it means that the discrepancy is the same.

Figure B.4: January 2018 | Actual - Synthetic Prices



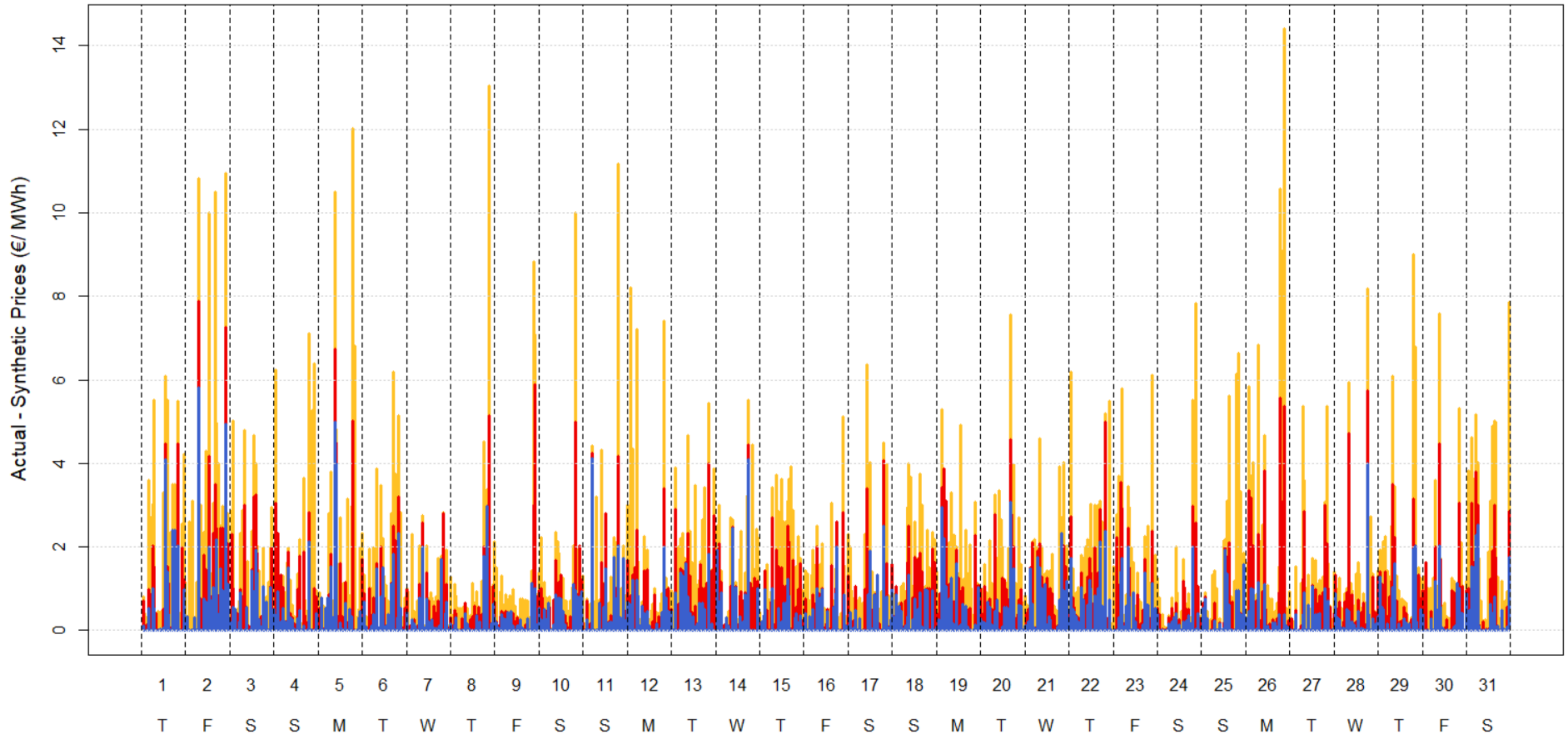
The plot illustrates the difference between actual and synthetic prices during January 2018. In yellow the differences between actual and synthetic at 2%, in red at 1% and in blue at 0.5%. As already discussed, by increasing the percentage of extra capacity we obtain a fall in synthetic prices. For such reasons, higher percentages mean higher differences. Where the colour corresponding to a lower percentage overlap the one corresponding to a higher percentage it means that the discrepancy is the same.

Figure B.5: February 2018 | Actual - Synthetic Prices



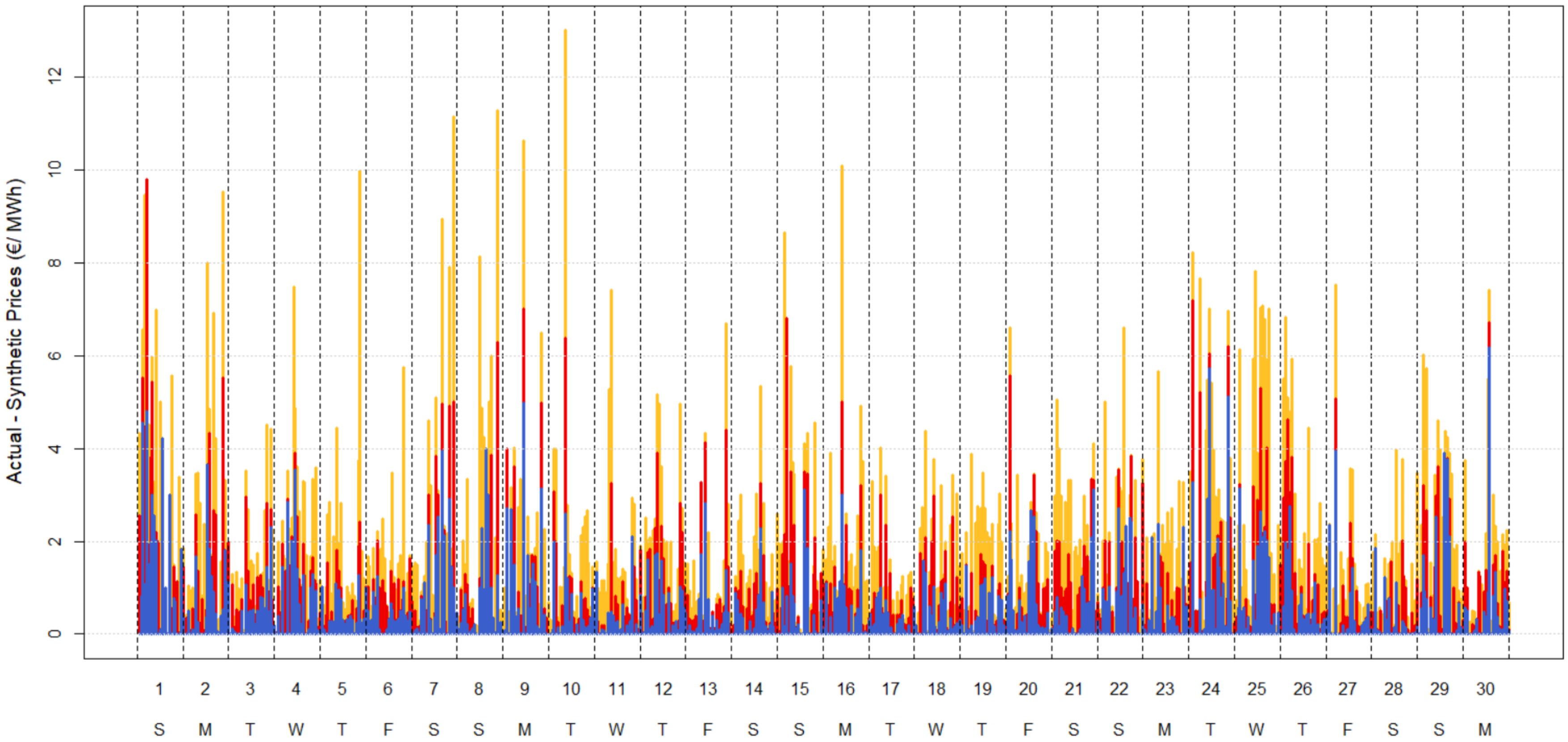
The plot illustrates the difference between actual and synthetic prices during February 2018. In yellow the differences between actual and synthetic at 2%, in red at 1% and in blue at 0.5%. As already discussed, by increasing the percentage of extra capacity we obtain a fall in synthetic prices. For such reasons, higher percentages mean higher differences. Where the colour corresponding to a lower percentage overlap the one corresponding to a higher percentage it means that the discrepancy is the same.

Figure B.6: March 2018 | Actual - Synthetic Prices



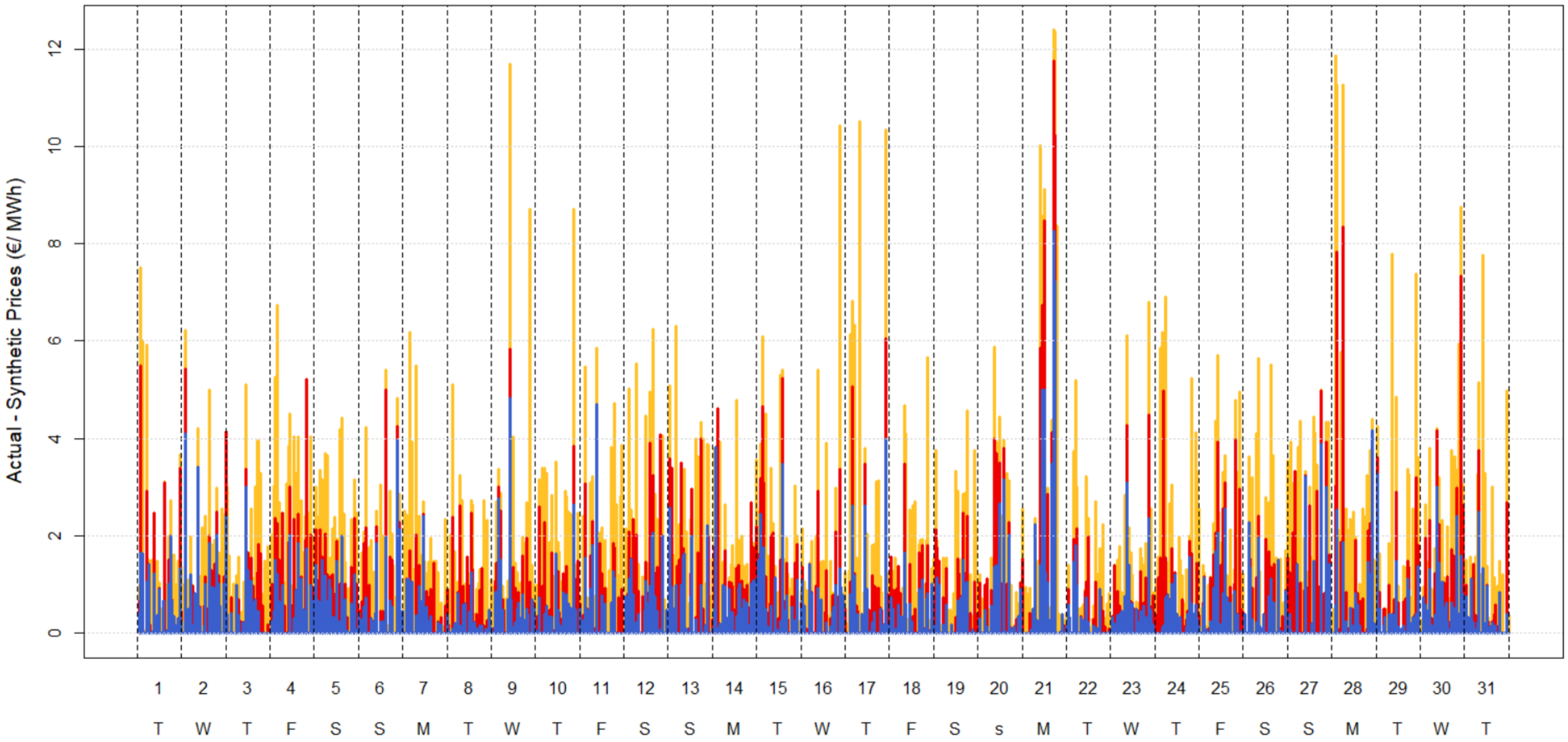
The plot illustrates the difference between actual and synthetic prices during March 2018. In yellow the differences between actual and synthetic at 2%, in red at 1% and in blue at 0.5%. As already discussed, by increasing the percentage of extra capacity we obtain a fall in synthetic prices. For such reasons, higher percentages mean higher differences. Where the colour corresponding to a lower percentage overlap the one corresponding to a higher percentage it means that the discrepancy is the same.

Figure B.7: April 2018 | Actual - Synthetic Prices



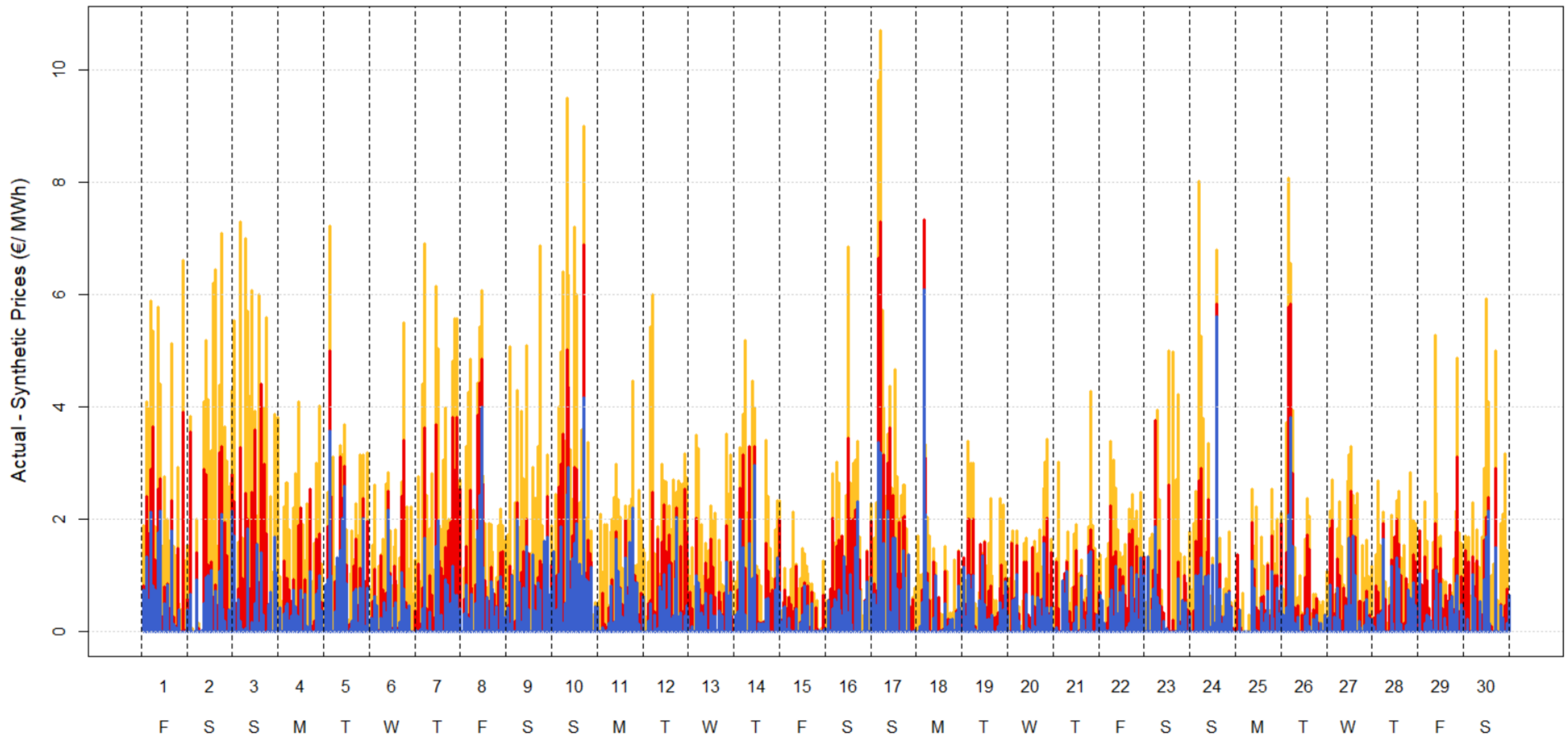
The plot illustrates the difference between actual and synthetic prices during April 2018. In yellow the differences between actual and synthetic at 2%, in red at 1% and in blue at 0.5%. As already discussed, by increasing the percentage of extra capacity we obtain a fall in synthetic prices. For such reasons, higher percentages mean higher differences. Where the colour corresponding to a lower percentage overlap the one corresponding to a higher percentage it means that the discrepancy is the same.

Figure B.8: May 2018 | Actual - Synthetic Prices



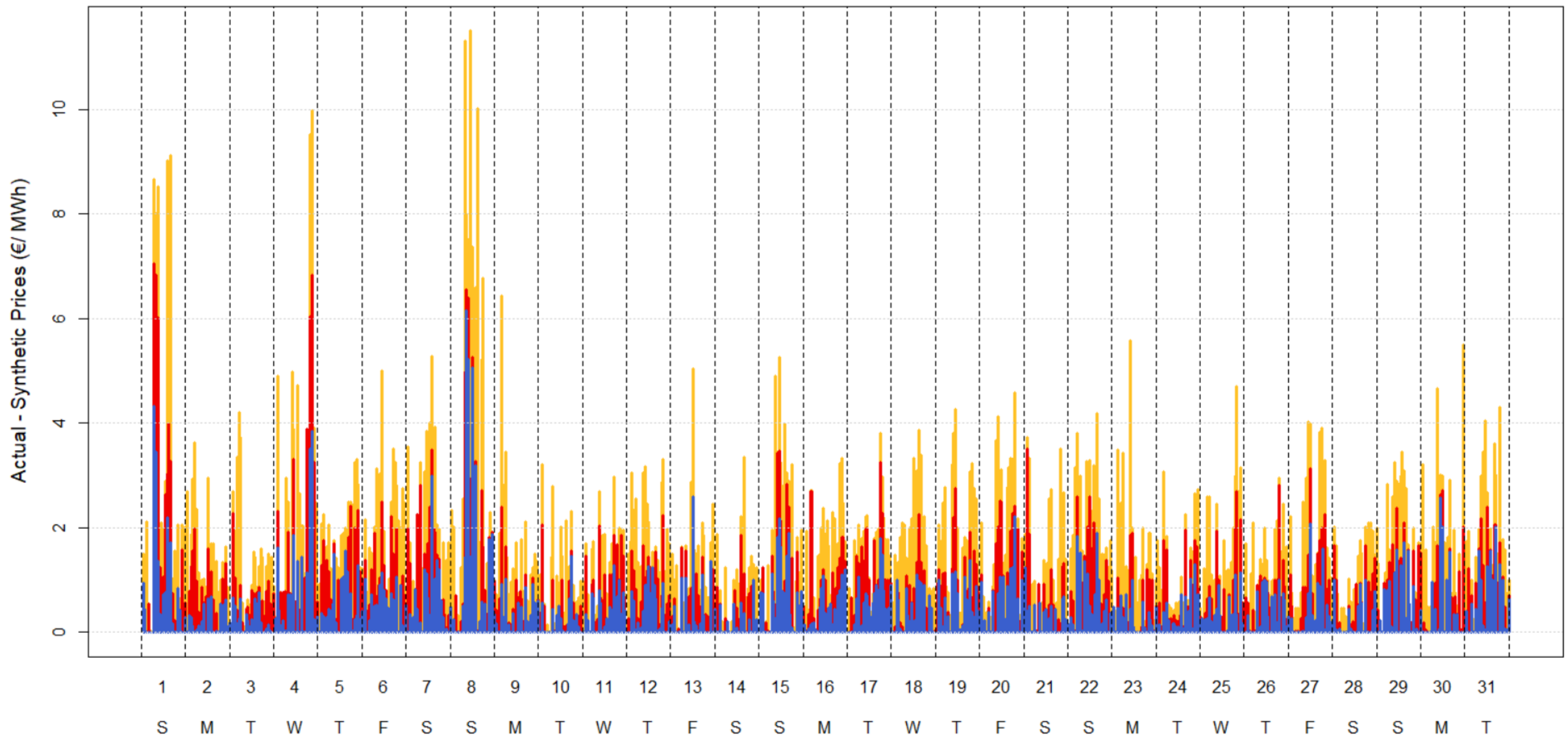
The plot illustrates the difference between actual and synthetic prices during May 2018. In yellow the differences between actual and synthetic at 2%, in red at 1% and in blue at 0.5%. As already discussed, by increasing the percentage of extra capacity we obtain a fall in synthetic prices. For such reasons, higher percentages mean higher differences. Where the colour corresponding to a lower percentage overlap the one corresponding to a higher percentage it means that the discrepancy is the same.

Figure B.9: June 2018 | Actual - Synthetic Prices



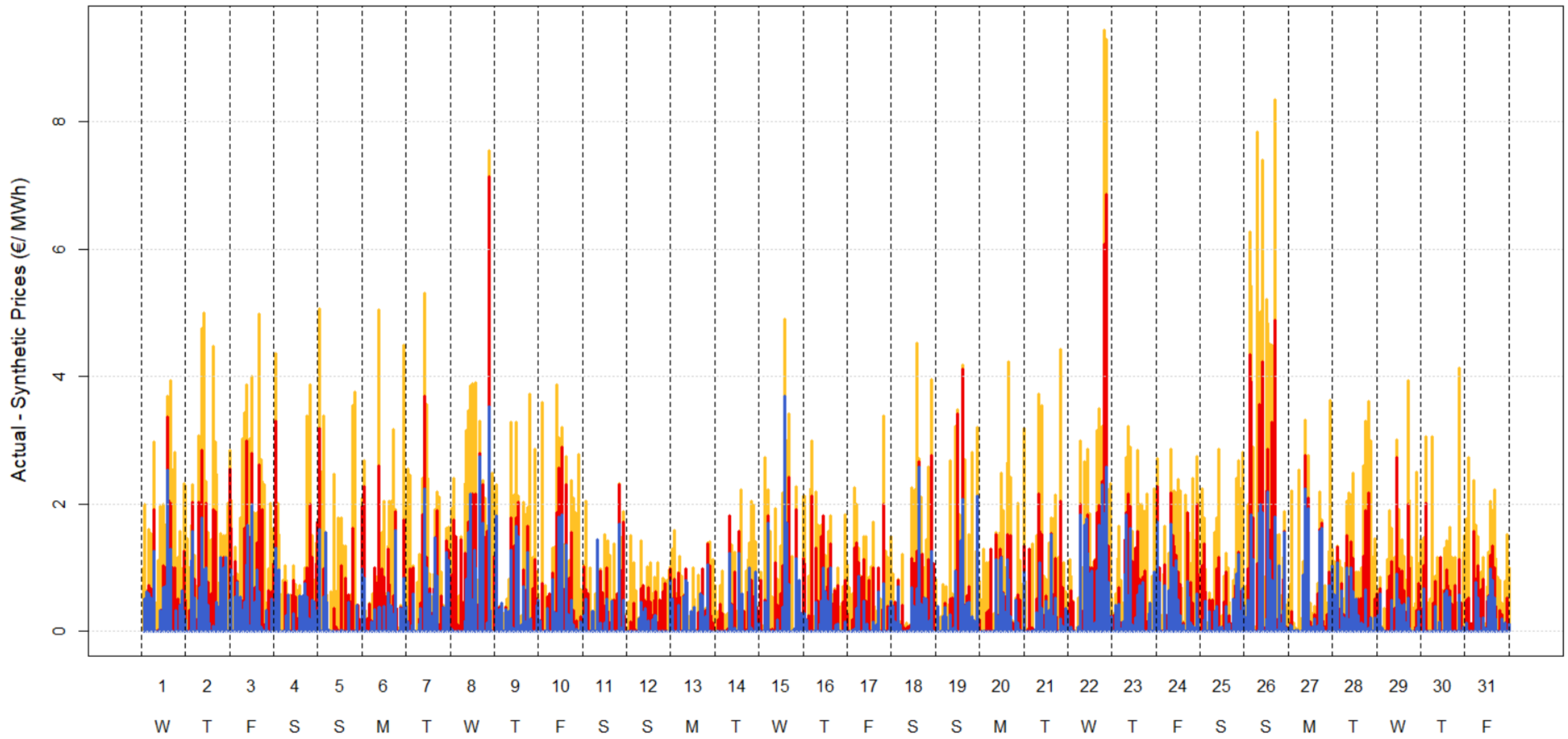
The plot illustrates the difference between actual and synthetic prices during June 2018. In yellow the differences between actual and synthetic at 2%, in red at 1% and in blue at 0.5%. As already discussed, by increasing the percentage of extra capacity we obtain a fall in synthetic prices. For such reasons, higher percentages mean higher differences. Where the colour corresponding to a lower percentage overlap the one corresponding to a higher percentage it means that the discrepancy is the same.

Figure B.10: July 2018 | Actual - Synthetic Prices



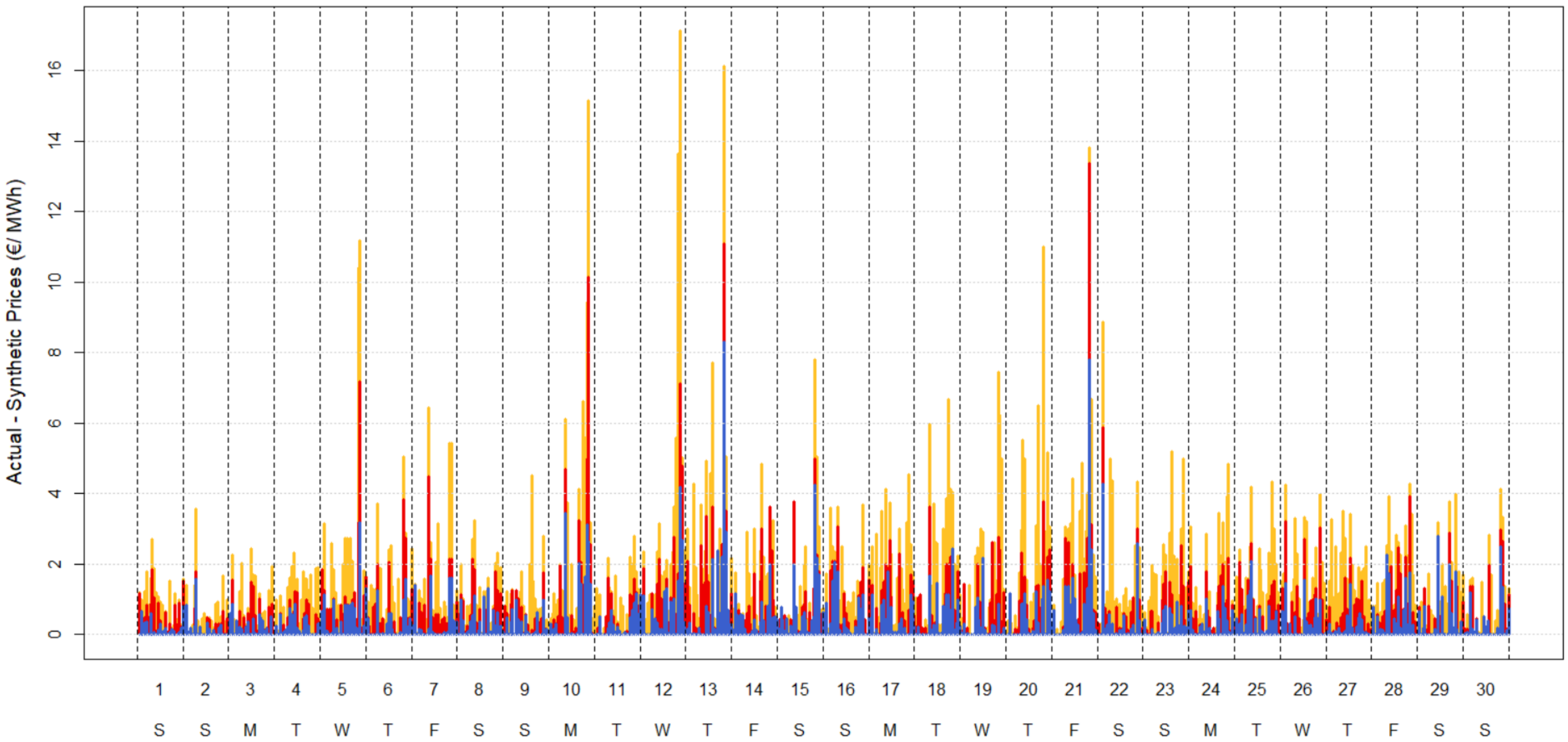
The plot illustrates the difference between actual and synthetic prices during July 2018. In yellow the differences between actual and synthetic at 2%, in red at 1% and in blue at 0.5%. As already discussed, by increasing the percentage of extra capacity we obtain a fall in synthetic prices. For such reasons, higher percentages mean higher differences. Where the colour corresponding to a lower percentage overlap the one corresponding to a higher percentage it means that the discrepancy is the same.

Figure B.11: August 2018 | Actual - Synthetic Prices



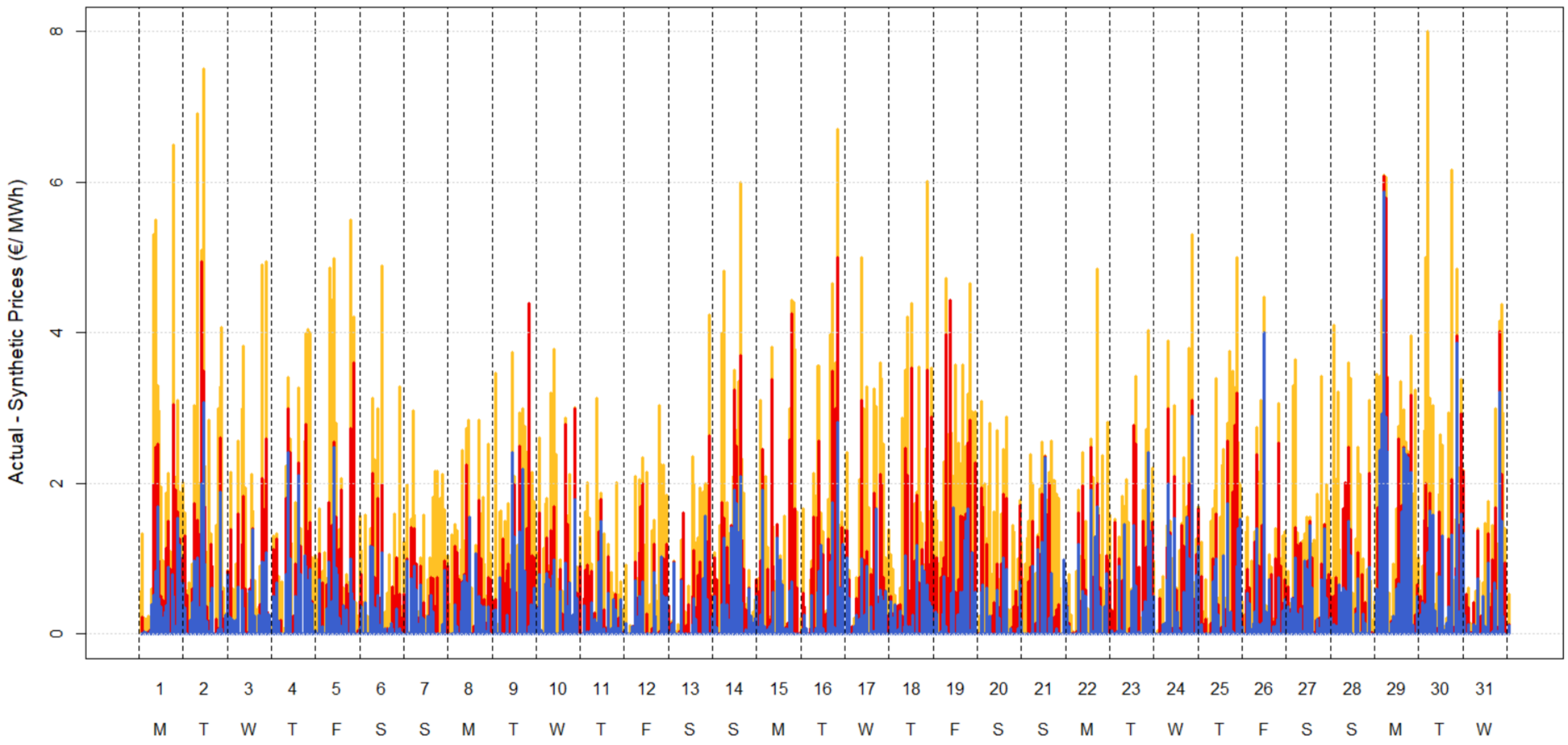
The plot illustrates the difference between actual and synthetic prices during August 2018. In yellow the differences between actual and synthetic at 2%, in red at 1% and in blue at 0.5%. As already discussed, by increasing the percentage of extra capacity we obtain a fall in synthetic prices. For such reasons, higher percentages mean higher differences. Where the colour corresponding to a lower percentage overlap the one corresponding to a higher percentage it means that the discrepancy is the same.

Figure B.12: September 2018 | Actual - Synthetic Prices



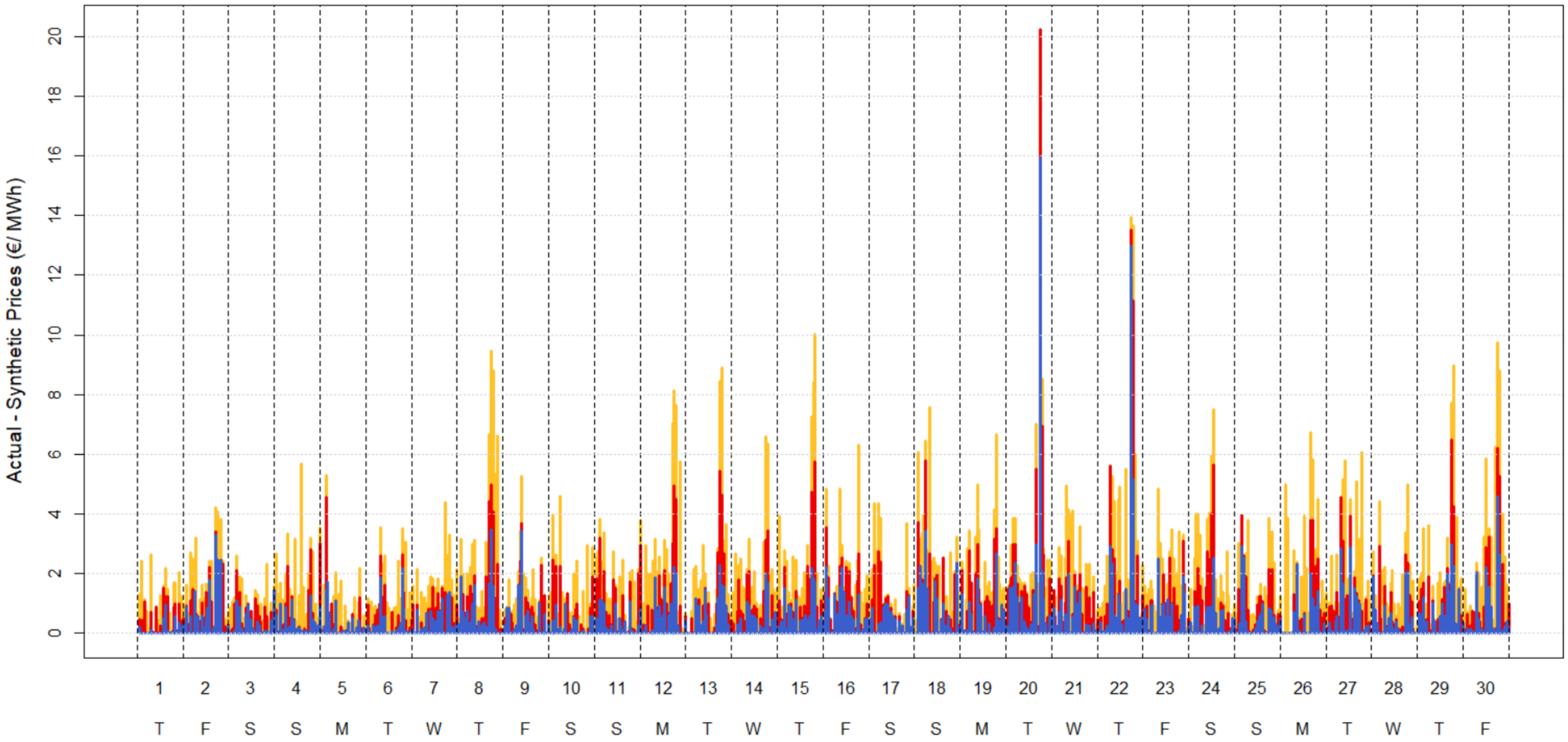
The plot illustrates the difference between actual and synthetic prices during September 2018. In yellow the differences between actual and synthetic at 2%, in red at 1% and in blue at 0.5%. As already discussed, by increasing the percentage of extra capacity we obtain a fall in synthetic prices. For such reasons, higher percentages mean higher differences. Where the colour corresponding to a lower percentage overlap the one corresponding to a higher percentage it means that the discrepancy is the same.

Figure B.13: October 2018 | Actual - Synthetic Prices



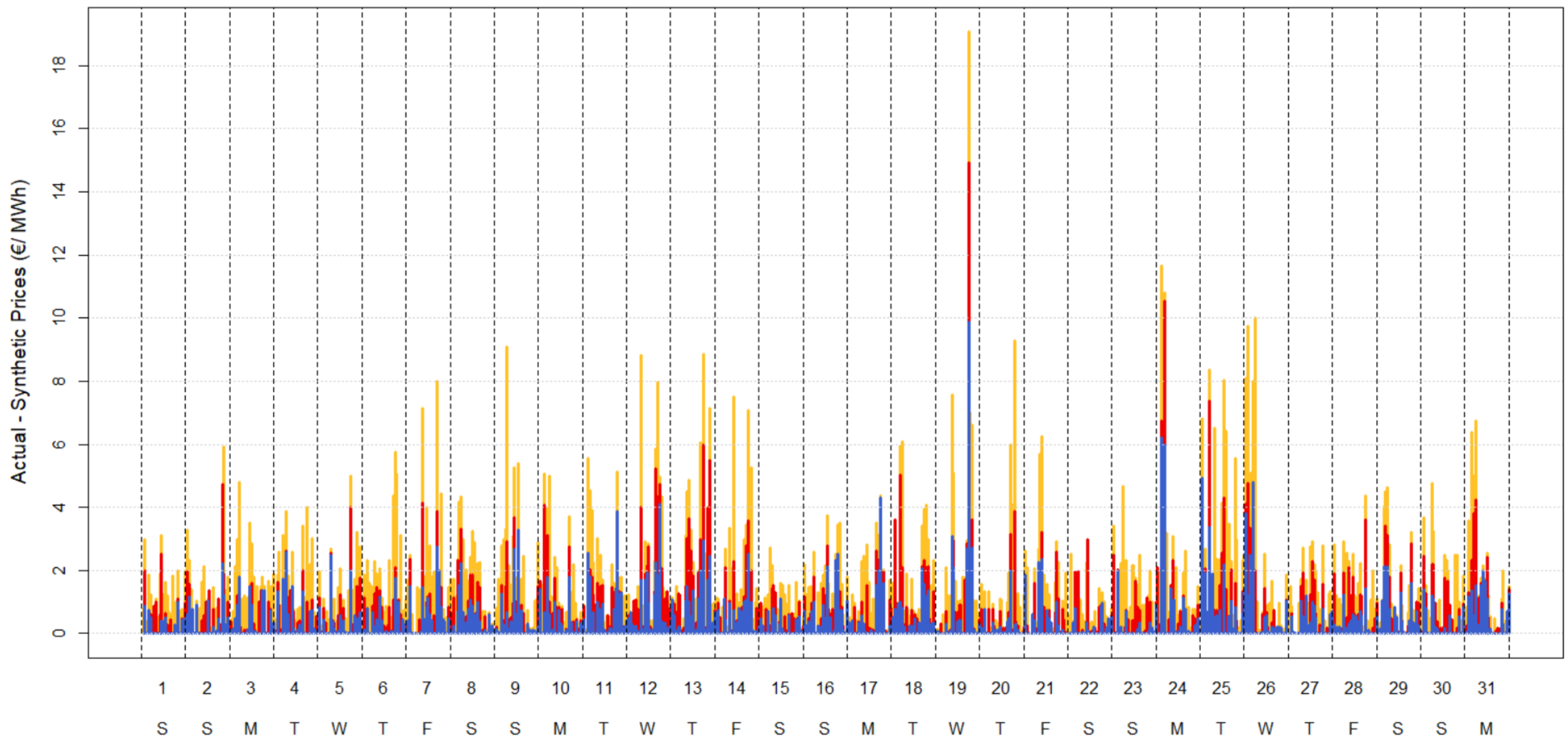
The plot illustrates the difference between actual and synthetic prices during October 2018. In yellow the differences between actual and synthetic at 2%, in red at 1% and in blue at 0.5%. As already discussed, by increasing the percentage of extra capacity we obtain a fall in synthetic prices. For such reasons, higher percentages mean higher differences. Where the colour corresponding to a lower percentage overlap the one corresponding to a higher percentage it means that the discrepancy is the same.

Figure B.14: November 2018 | Actual - Synthetic Prices



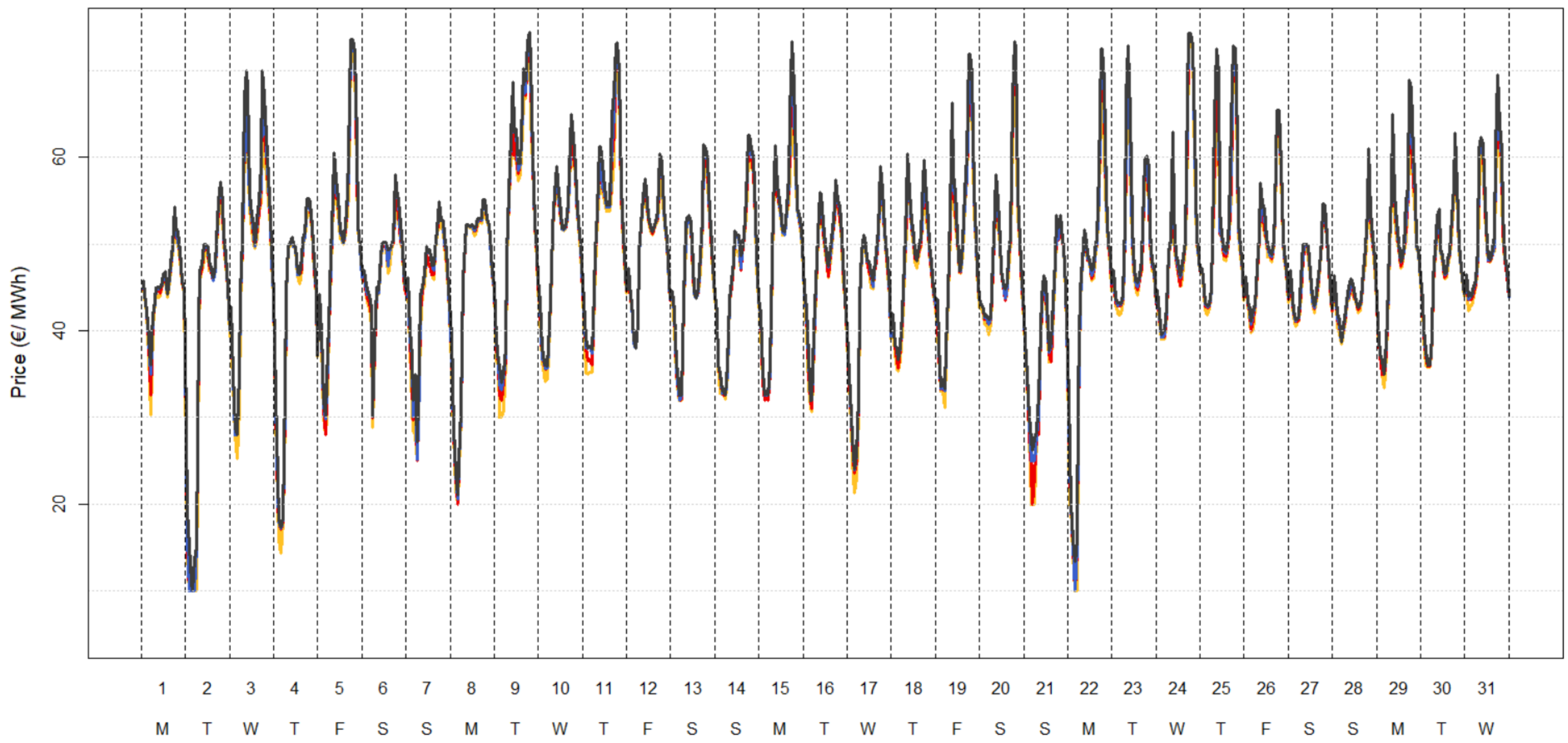
The plot illustrates the difference between actual and synthetic prices during November 2018. In yellow the differences between actual and synthetic at 2%, in red at 1% and in blue at 0.5%. As already discussed, by increasing the percentage of extra capacity we obtain a fall in synthetic prices. For such reasons, higher percentages mean higher differences. Where the colour corresponding to a lower percentage overlap the one corresponding to a higher percentage it means that the discrepancy is the same.

Figure B.15: December 2018 | Actual - Synthetic Prices



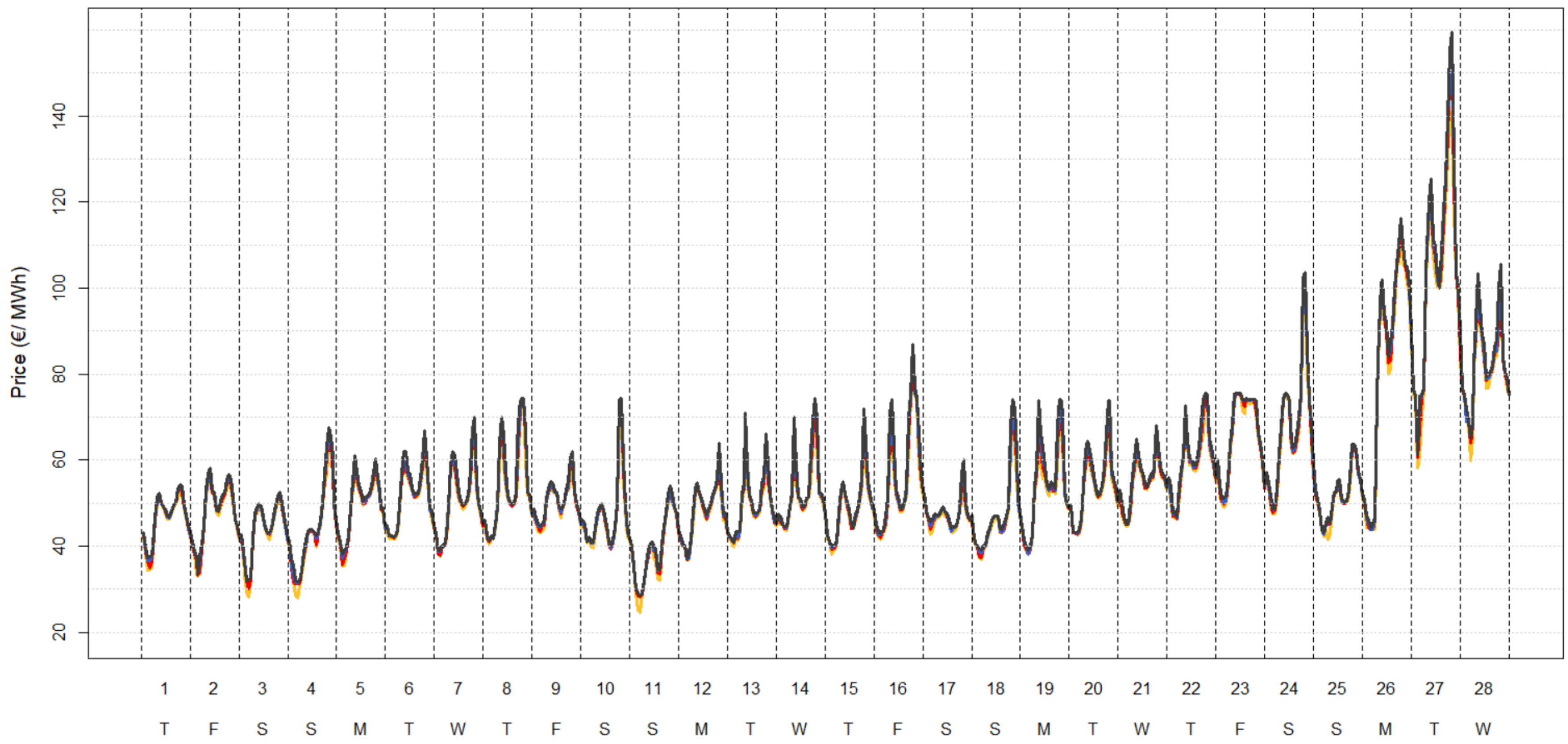
The plot illustrates the difference between actual and synthetic prices during December 2018. In yellow the differences between actual and synthetic at 2%, in red at 1% and in blue at 0.5%. As already discussed, by increasing the percentage of extra capacity we obtain a fall in synthetic prices. For such reasons, higher percentages mean higher differences. Where the colour corresponding to a lower percentage overlap the one corresponding to a higher percentage it means that the discrepancy is the same.

Figure B.16: January 2018 | Actual and Synthetic Prices



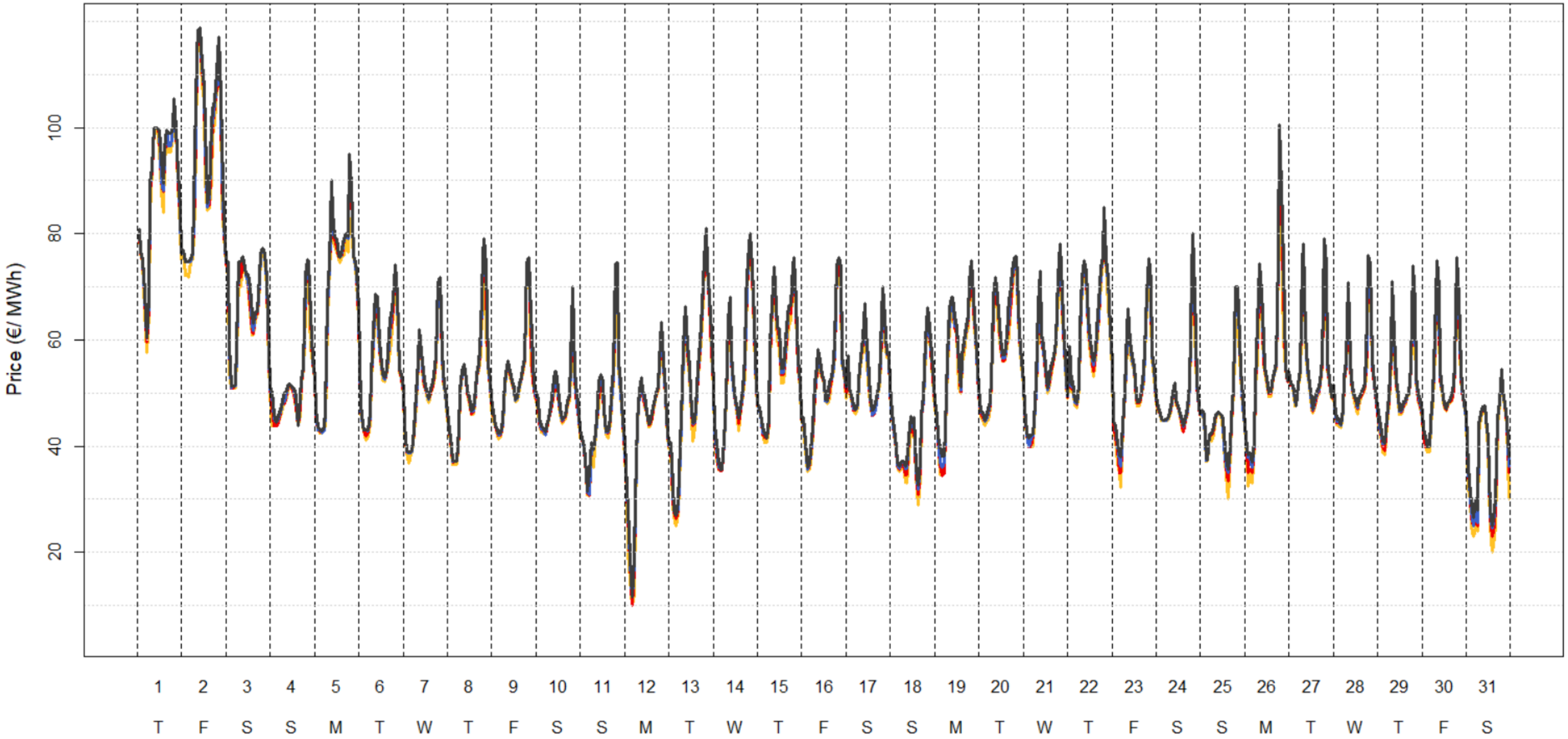
The plot illustrates the actual and synthetic prices during January 2018. In black actual unconstrained prices, in yellow synthetic prices at 2%, in red at 1% and in blue at 0.5%. As already discussed, by increasing the percentage of extra capacity we obtain a fall in synthetic prices. For such reasons, higher percentages mean higher differences.

Figure B.17: February 2018 | Actual and Synthetic Prices



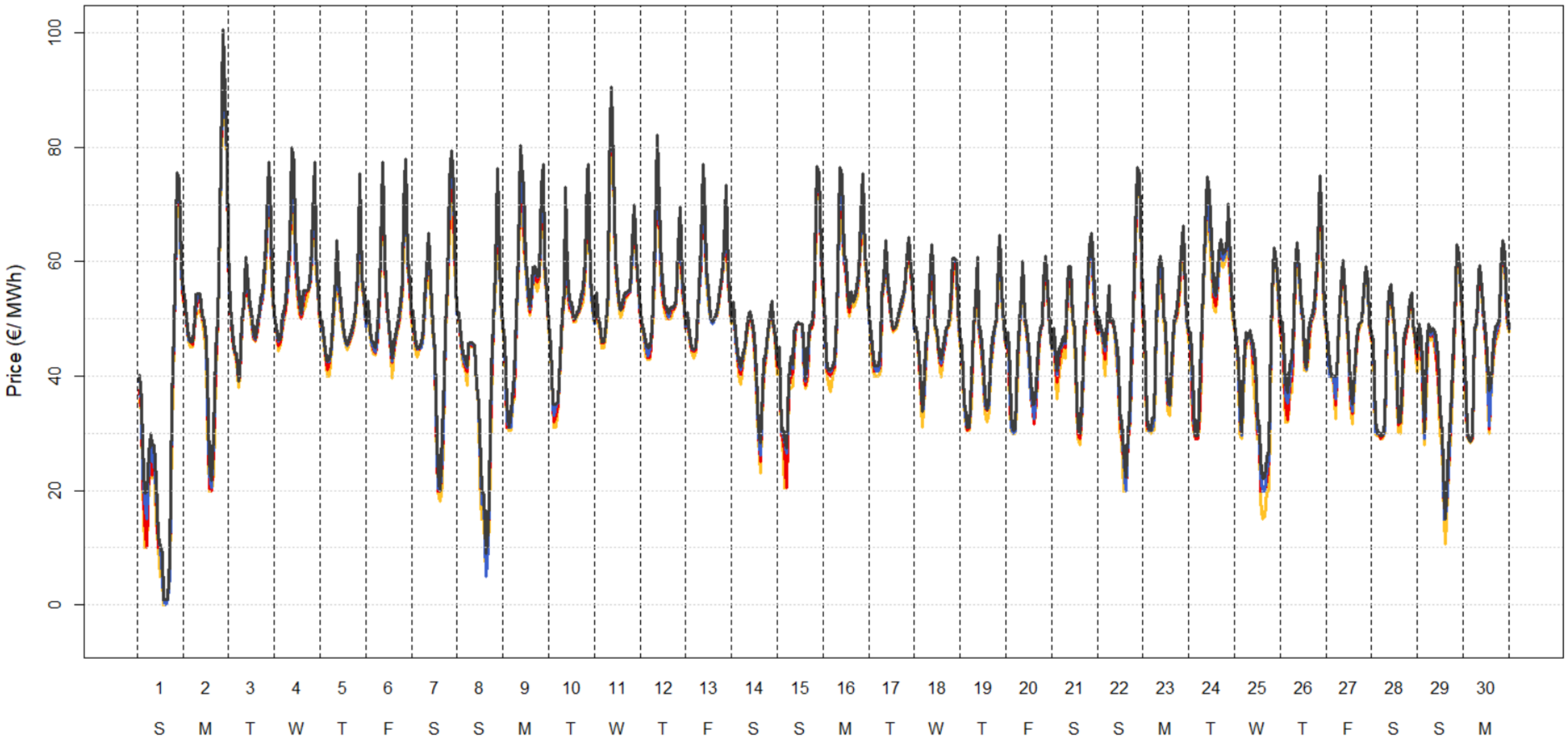
The plot illustrates the actual and synthetic prices during February 2018. In black actual unconstrained prices, in yellow synthetic prices at 2%, in red at 1% and in blue at 0.5%. As already discussed, by increasing the percentage of extra capacity we obtain a fall in synthetic prices. For such reasons, higher percentages mean higher differences.

Figure B.18: March 2018 | Actual and Synthetic Prices



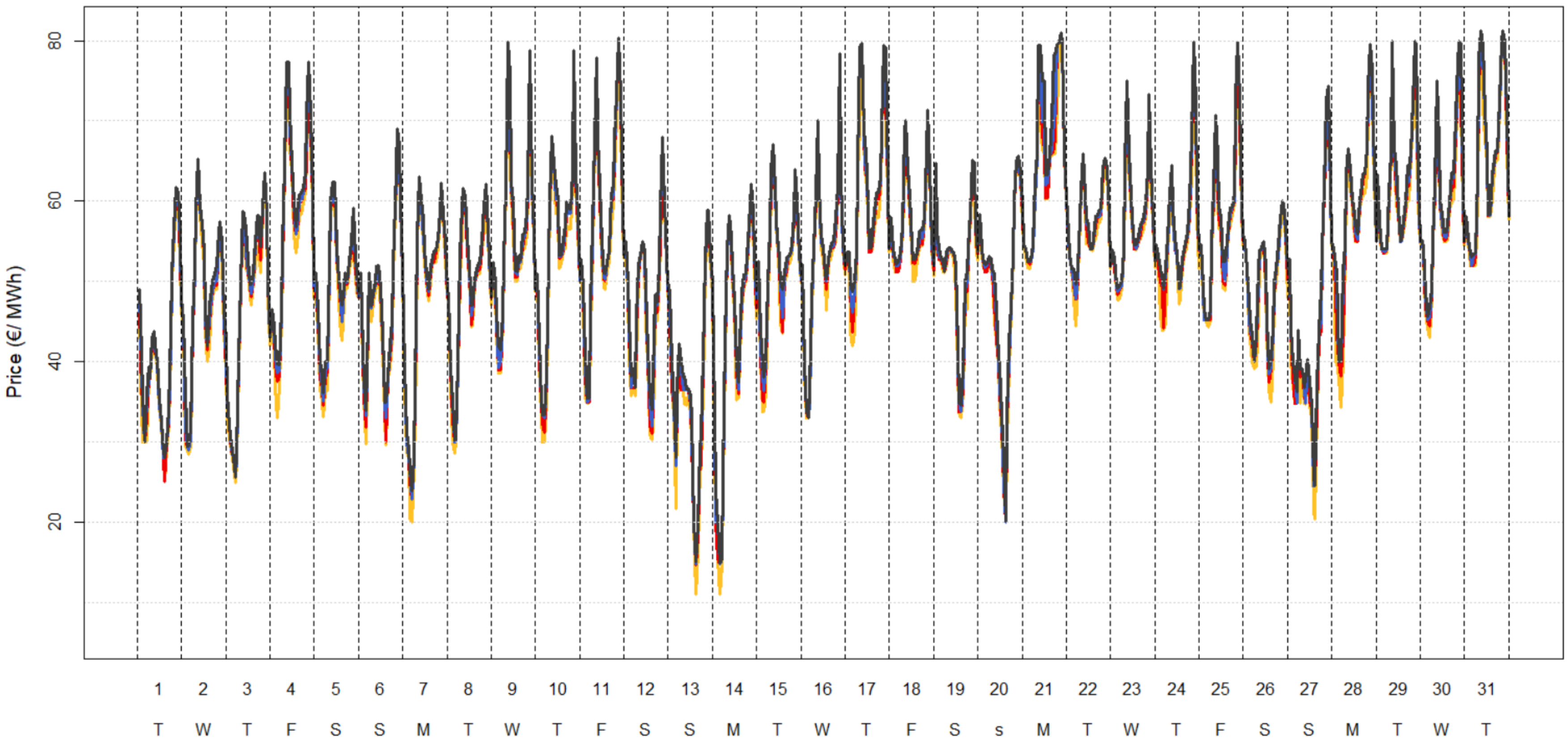
The plot illustrates the actual and synthetic prices during March 2018. In black actual unconstrained prices, in yellow synthetic prices at 2%, in red at 1% and in blue at 0.5%. As already discussed, by increasing the percentage of extra capacity we obtain a fall in synthetic prices. For such reasons, higher percentages mean higher differences.

Figure B.19: April 2018 | Actual and Synthetic Prices



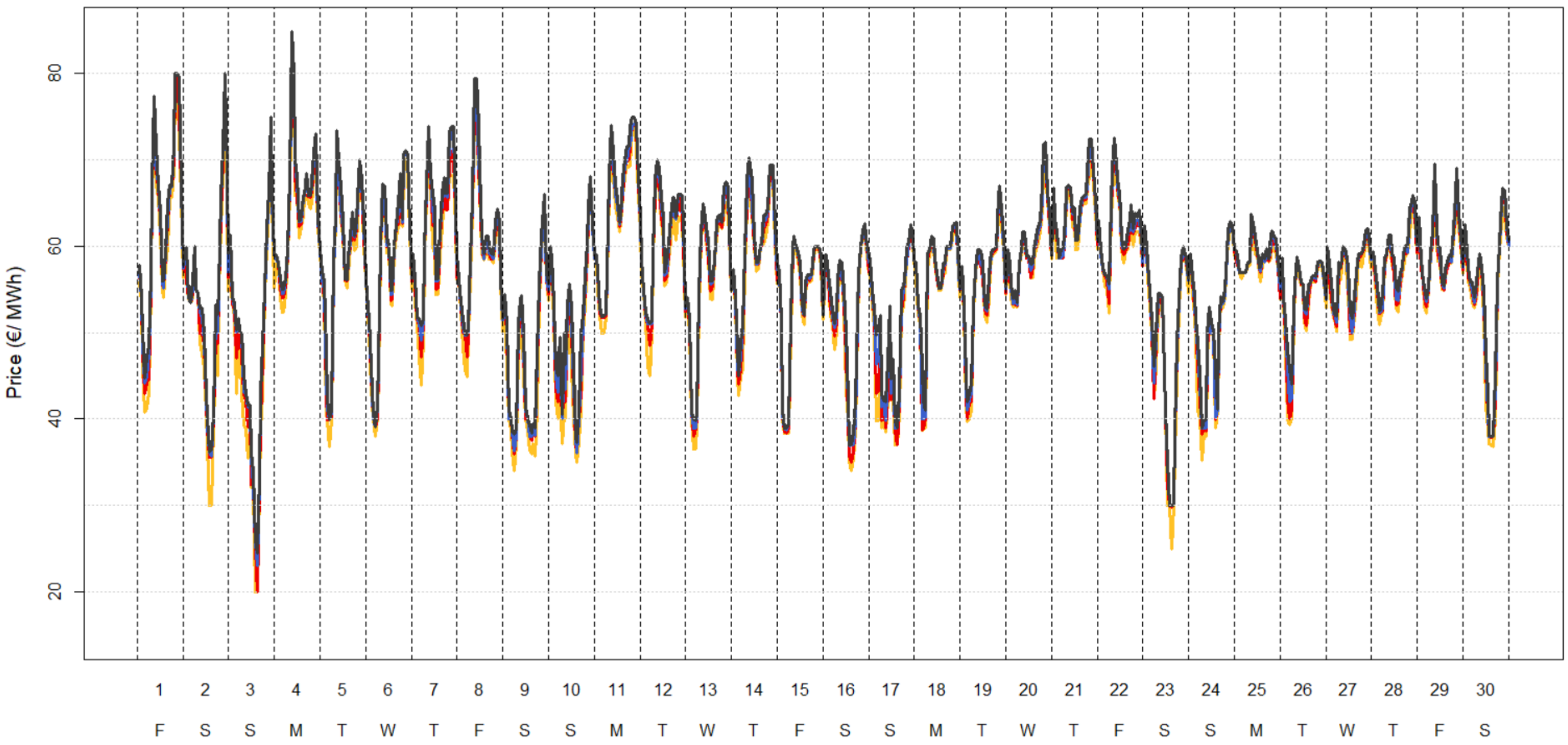
The plot illustrates the actual and synthetic prices during April 2018. In black actual unconstrained prices, in yellow synthetic prices at 2%, in red at 1% and in blue at 0.5%. As already discussed, by increasing the percentage of extra capacity we obtain a fall in synthetic prices. For such reasons, higher percentages mean higher differences.

Figure B.20: May 2018 | Actual and Synthetic Prices



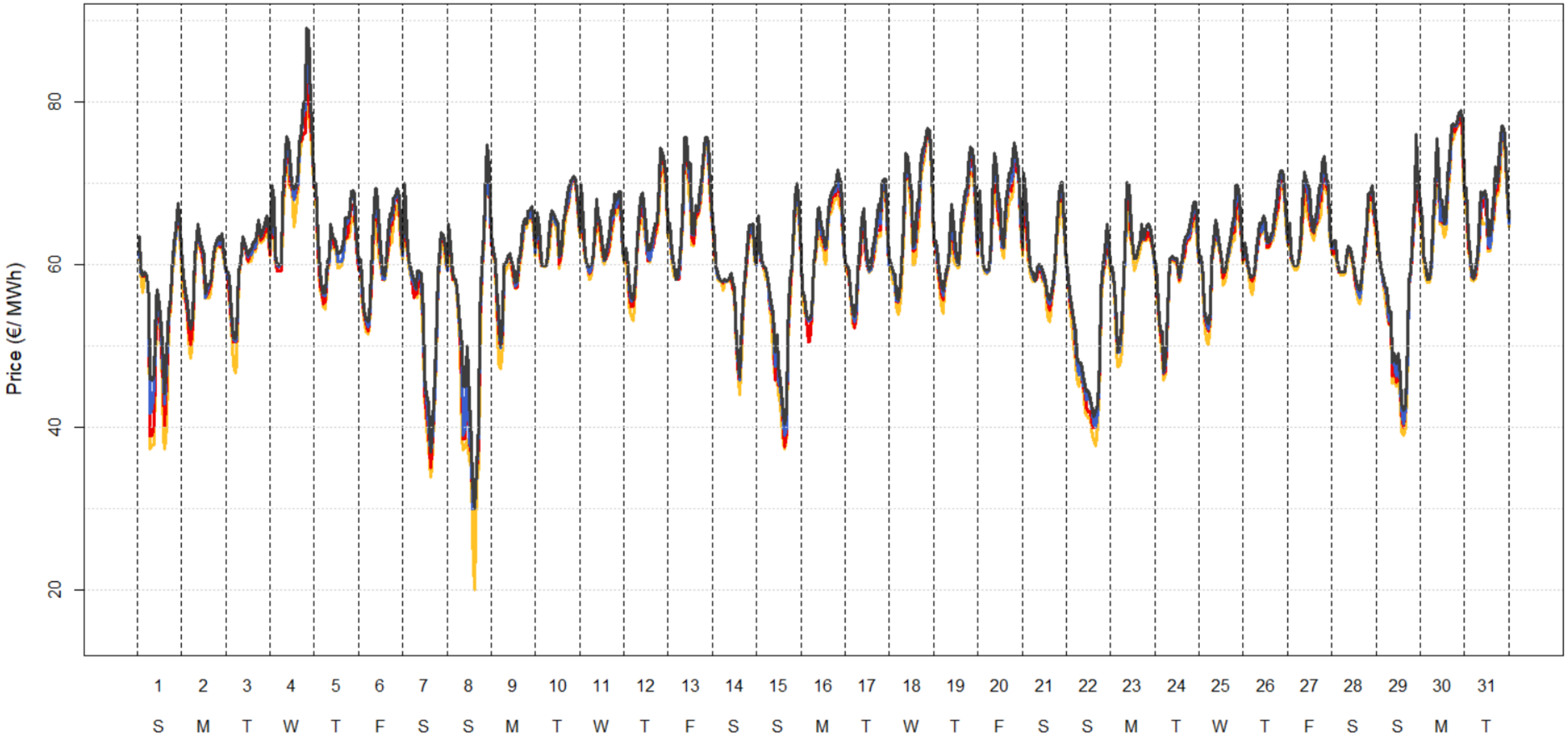
The plot illustrates the actual and synthetic prices during May 2018. In black actual unconstrained prices, in yellow synthetic prices at 2%, in red at 1% and in blue at 0.5%. As already discussed, by increasing the percentage of extra capacity we obtain a fall in synthetic prices. For such reasons, higher percentages mean higher differences.

Figure B.21: June 2018 | Actual and Synthetic Prices



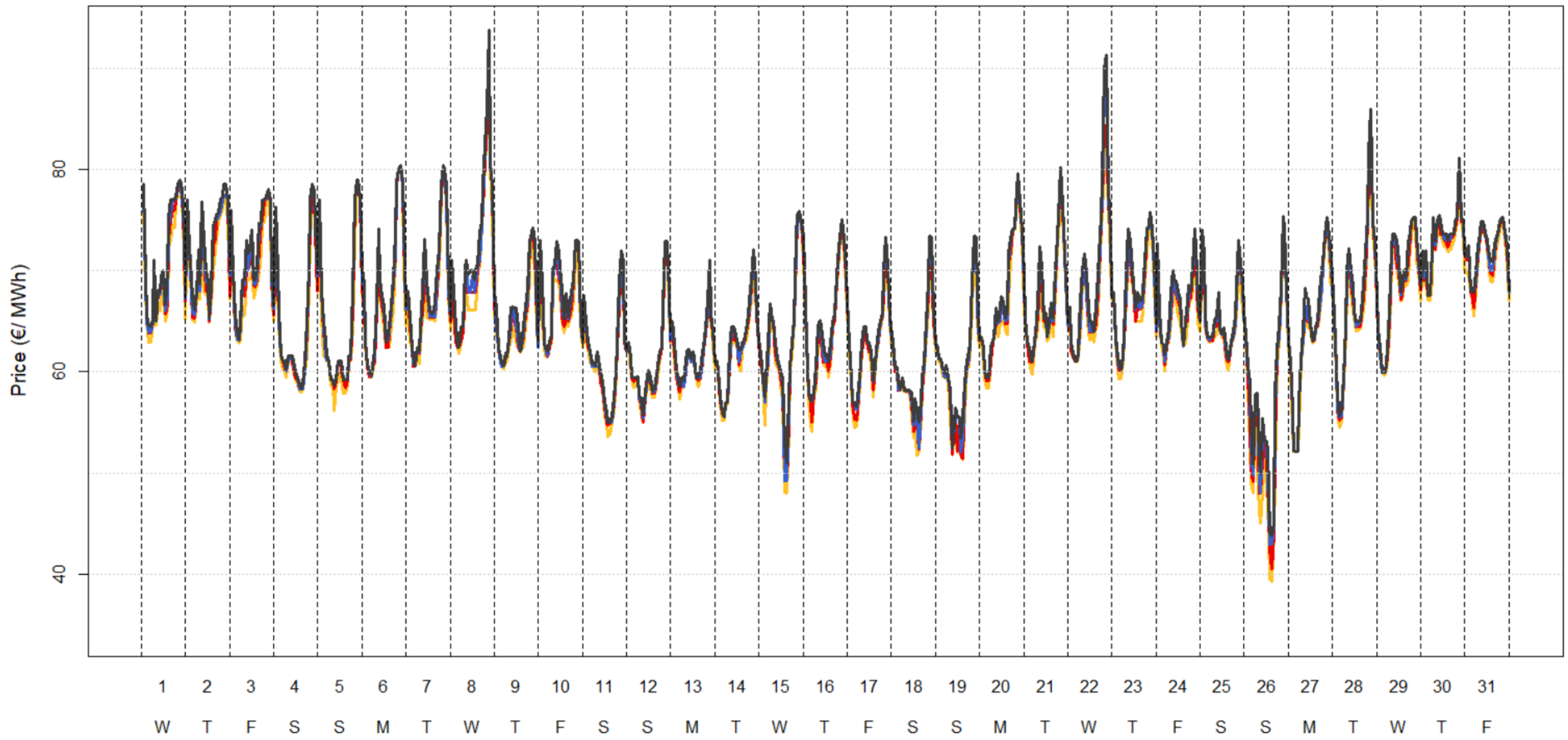
The plot illustrates the actual and synthetic prices during June 2018. In black actual unconstrained prices, in yellow synthetic prices at 2%, in red at 1% and in blue at 0.5%. As already discussed, by increasing the percentage of extra capacity we obtain a fall in synthetic prices. For such reasons, higher percentages mean higher differences.

Figure B.22: July 2018 | Actual and Synthetic Prices



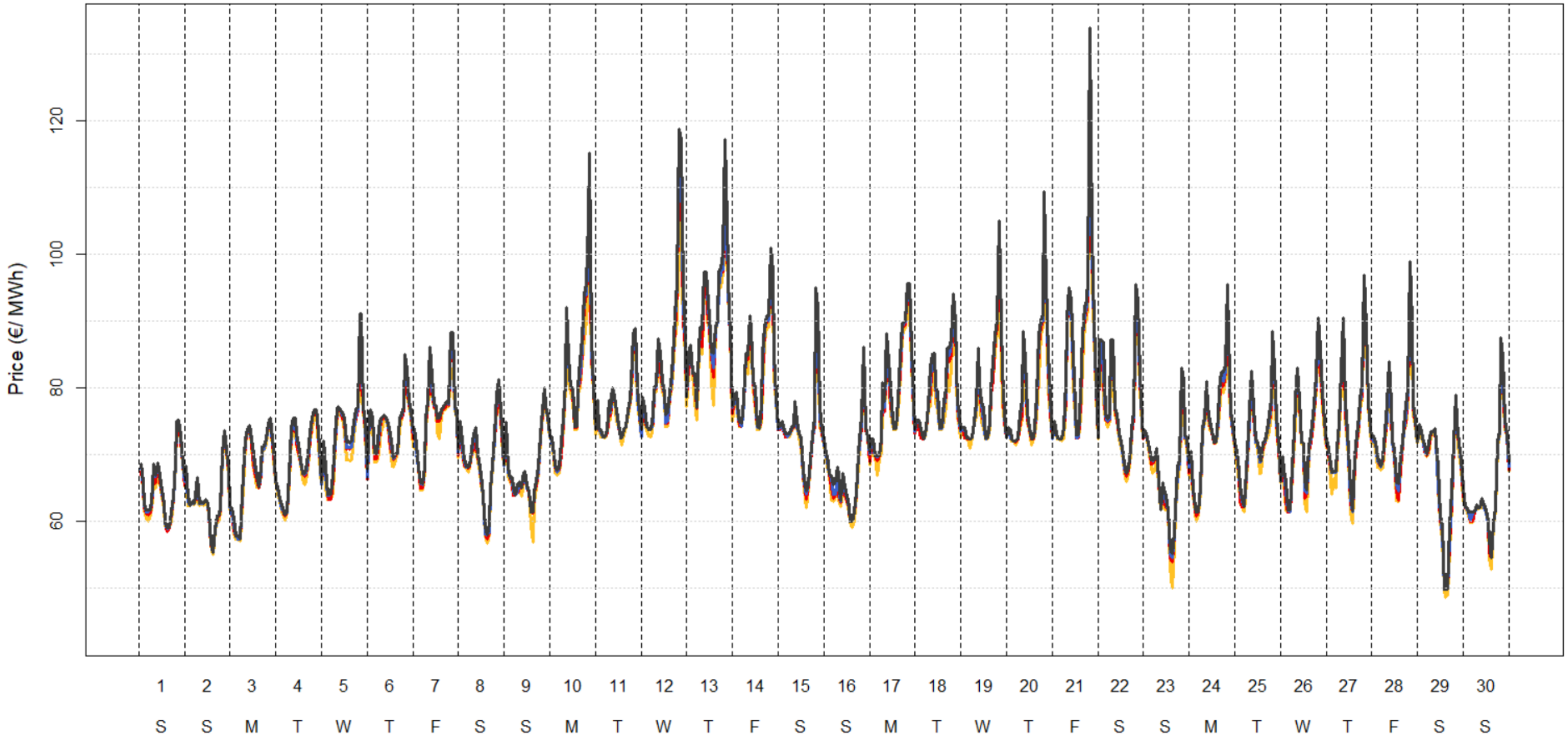
The plot illustrates the actual and synthetic prices during July 2018. In black actual unconstrained prices, in yellow synthetic prices at 2%, in red at 1% and in blue at 0.5%. As already discussed, by increasing the percentage of extra capacity we obtain a fall in synthetic prices. For such reasons, higher percentages mean higher differences.

Figure B.23: August 2018 | Actual and Synthetic Prices



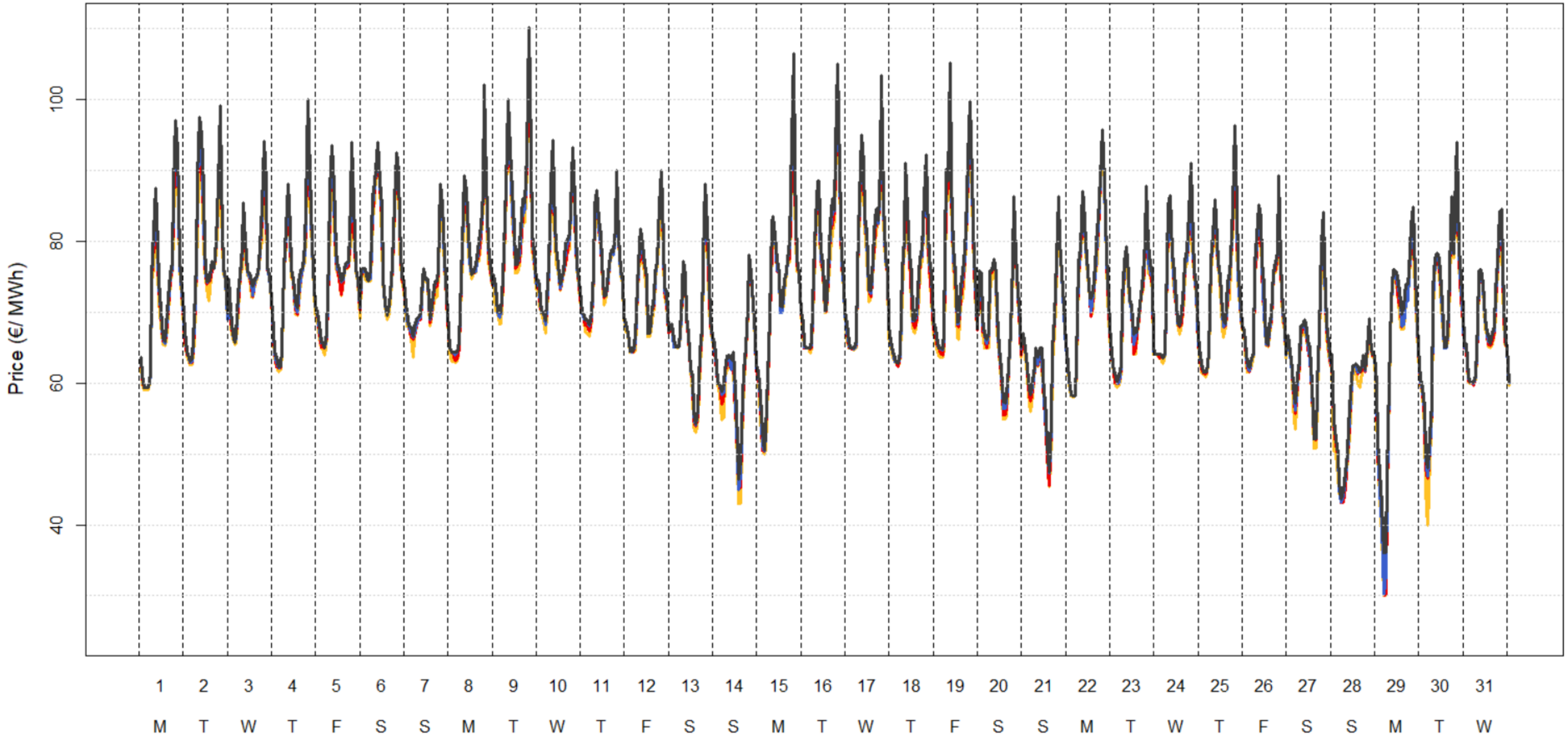
The plot illustrates the actual and synthetic prices during August 2018. In black actual unconstrained prices, in yellow synthetic prices at 2%, in red at 1% and in blue at 0.5%. As already discussed, by increasing the percentage of extra capacity we obtain a fall in synthetic prices. For such reasons, higher percentages mean higher differences.

Figure B.24: September 2018 | Actual and Synthetic Prices



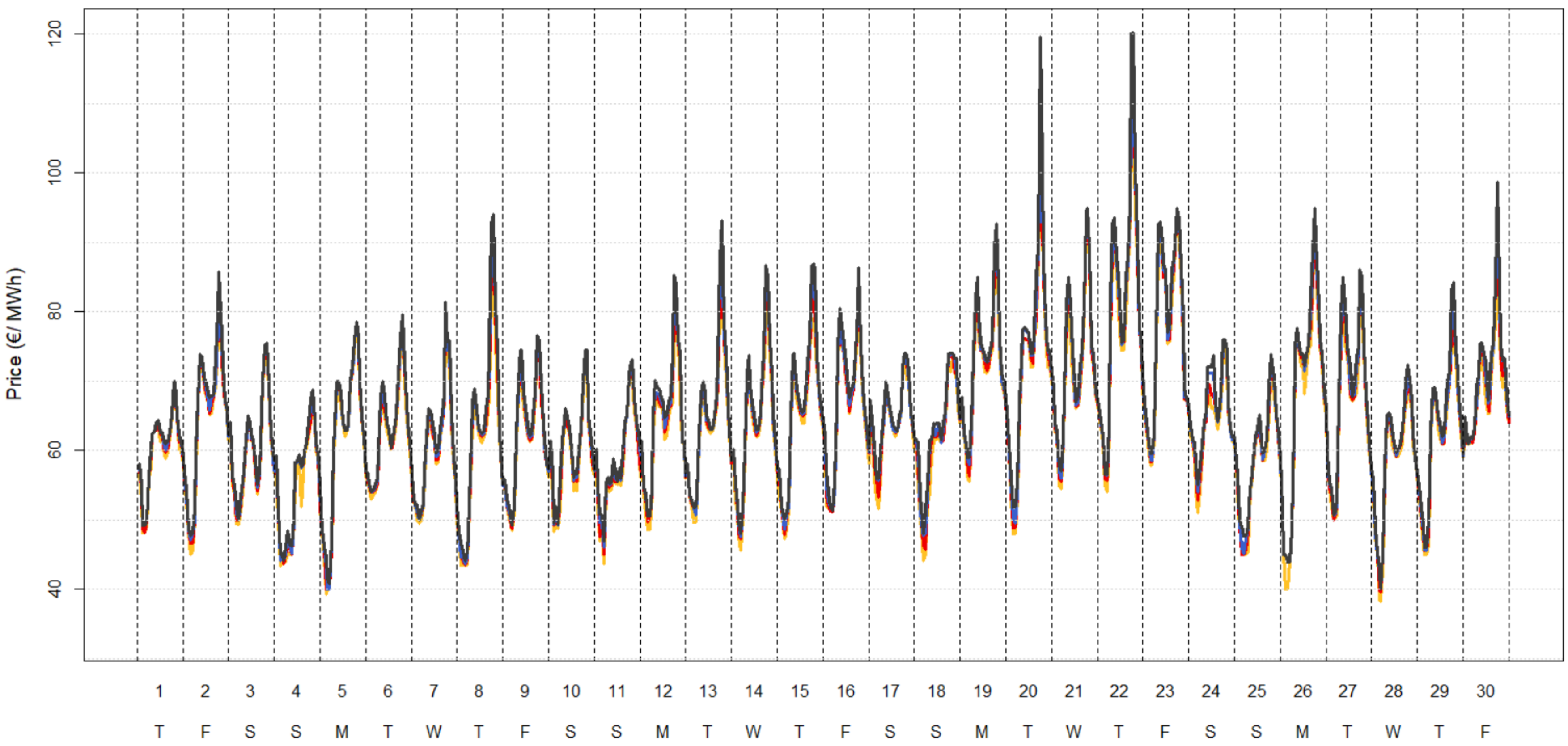
The plot illustrates the actual and synthetic prices during September 2018. In black actual unconstrained prices, in yellow synthetic prices at 2%, in red at 1% and in blue at 0.5%. As already discussed, by increasing the percentage of extra capacity we obtain a fall in synthetic prices. For such reasons, higher percentages mean higher differences.

Figure B.25: October 2018 | Actual and Synthetic Prices



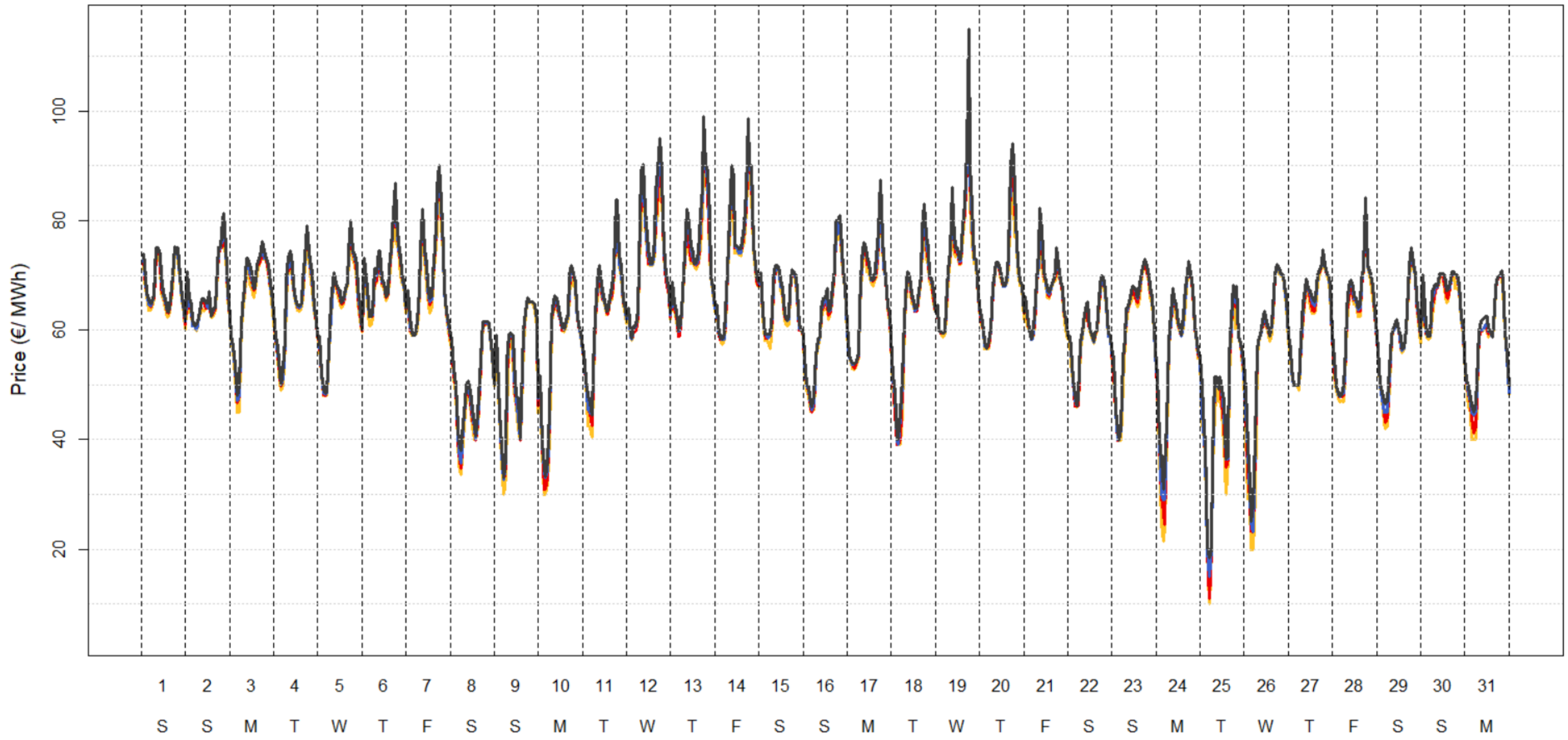
The plot illustrates the actual and synthetic prices during October 2018. In black actual unconstrained prices, in yellow synthetic prices at 2%, in red at 1% and in blue at 0.5%. As already discussed, by increasing the percentage of extra capacity we obtain a fall in synthetic prices. For such reasons, higher percentages mean higher differences.

Figure B.26: November 2018 | Actual and Synthetic Prices



The plot illustrates the actual and synthetic prices during November 2018. In black actual unconstrained prices, in yellow synthetic prices at 2%, in red at 1% and in blue at 0.5%. As already discussed, by increasing the percentage of extra capacity we obtain a fall in synthetic prices. For such reasons, higher percentages mean higher differences.

Figure B.27: December 2018 | Actual and Synthetic Prices



The plot illustrates the actual and synthetic prices during December 2018. In black actual unconstrained prices, in yellow synthetic prices at 2%, in red at 1% and in blue at 0.5%. As already discussed, by increasing the percentage of extra capacity we obtain a fall in synthetic prices. For such reasons, higher percentages mean higher differences.

Appendix C

C.1 Consumption cycles

Figure C.1: Average hourly quantity bought | Centre North Italy | First, second, third and fourth weeks

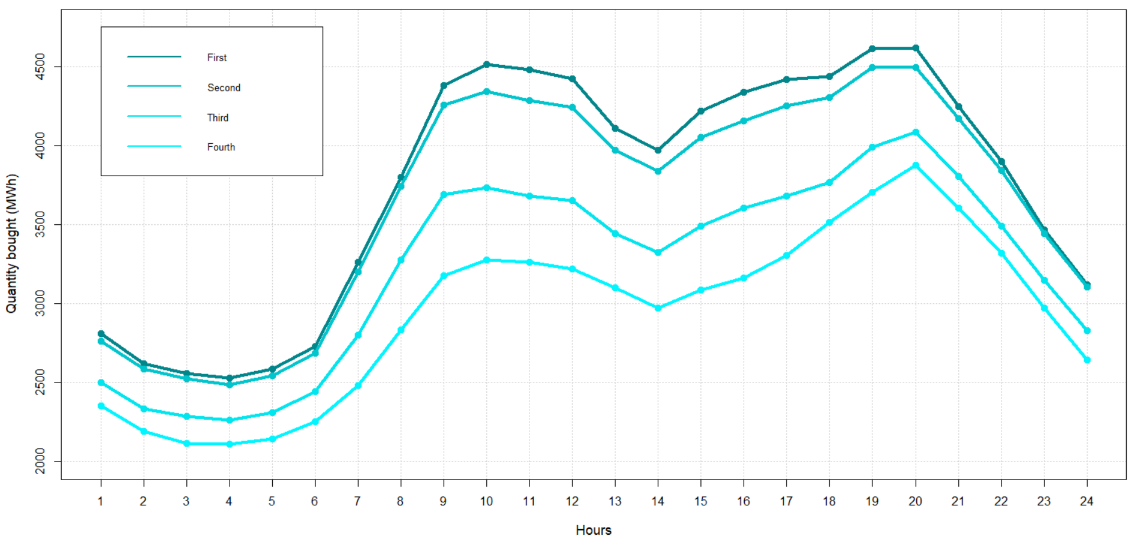


Figure C.2: Average hourly quantity bought | Centre North Italy | Fifth, sixth, seventh and eighth weeks

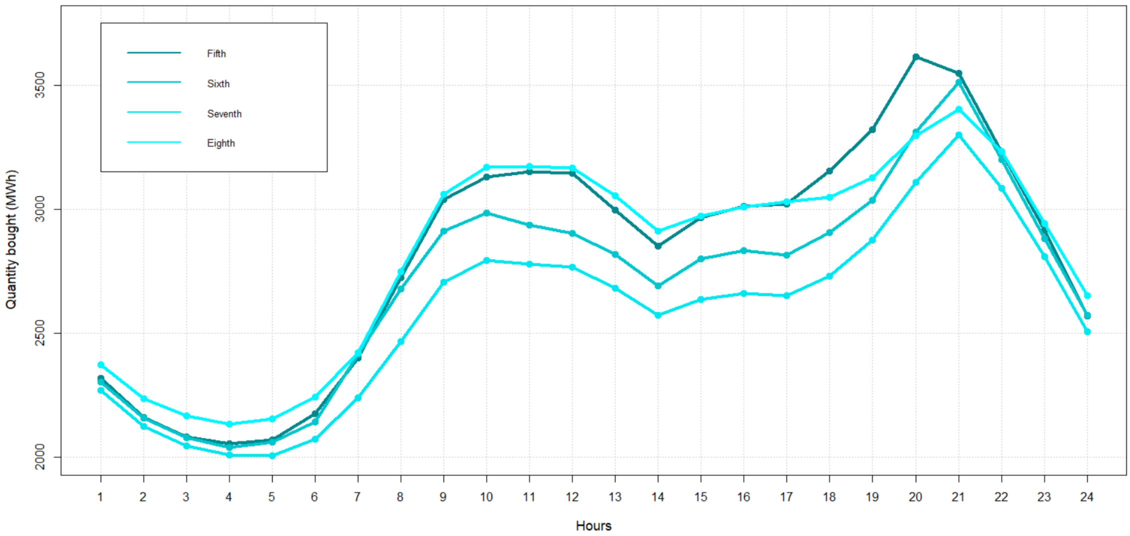


Figure C.3: Average hourly quantity bought | Centre North Italy | Ninth, tenth, eleventh, twelfth and thirteenth weeks

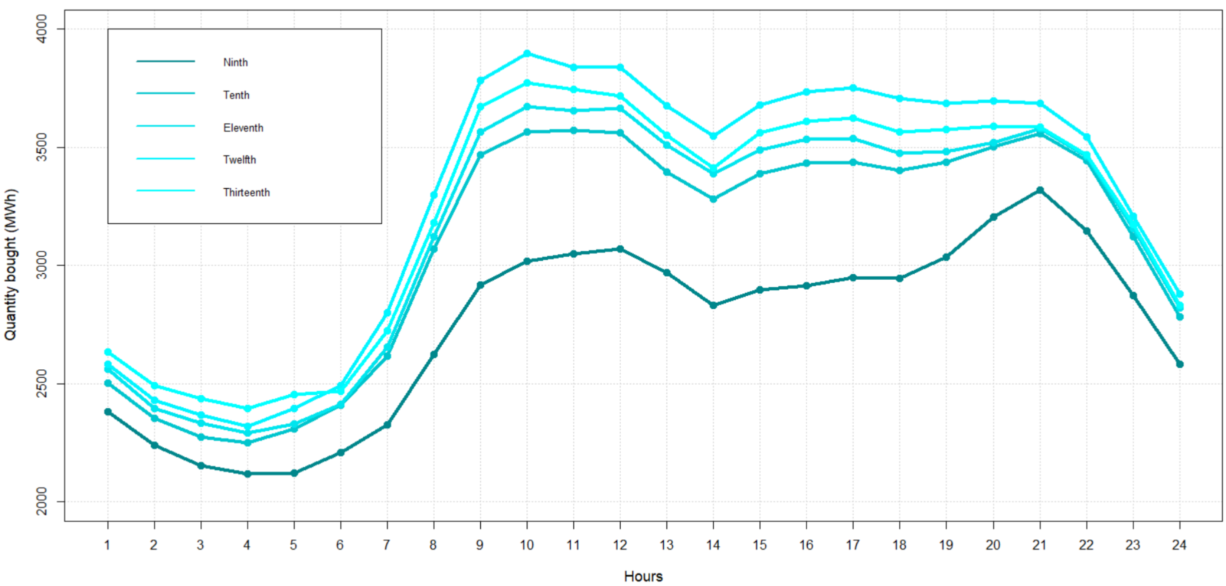


Figure C.4: Average hourly quantity bought | Centre South Italy | First, second, third and fourth weeks

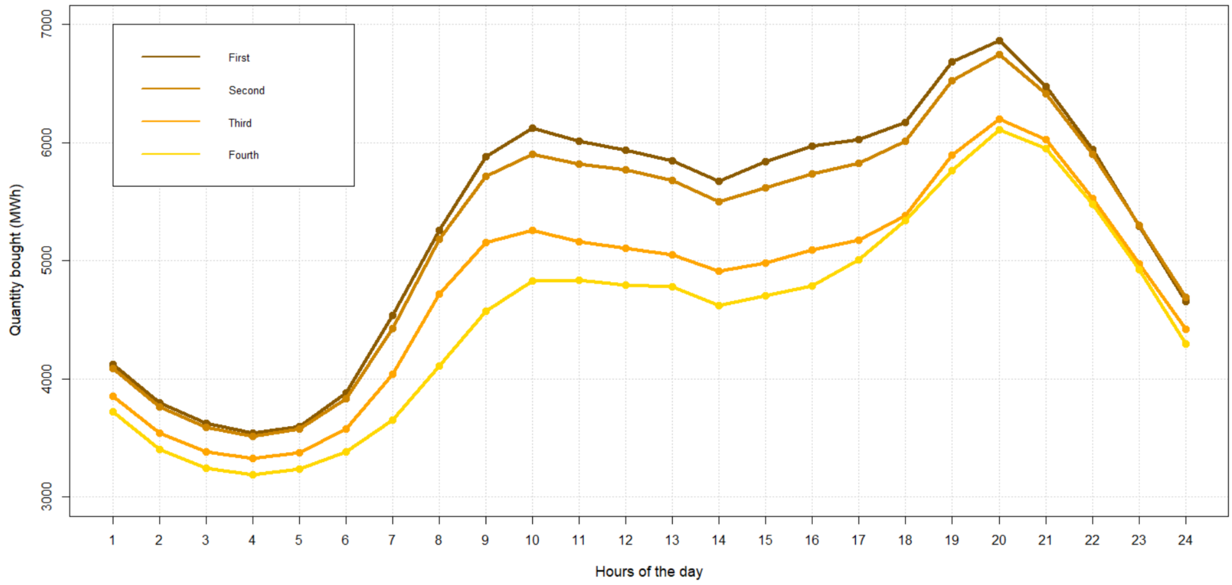


Figure C.5: Average hourly quantity bought | Centre South Italy | Fifth, sixth, seventh and eighth weeks

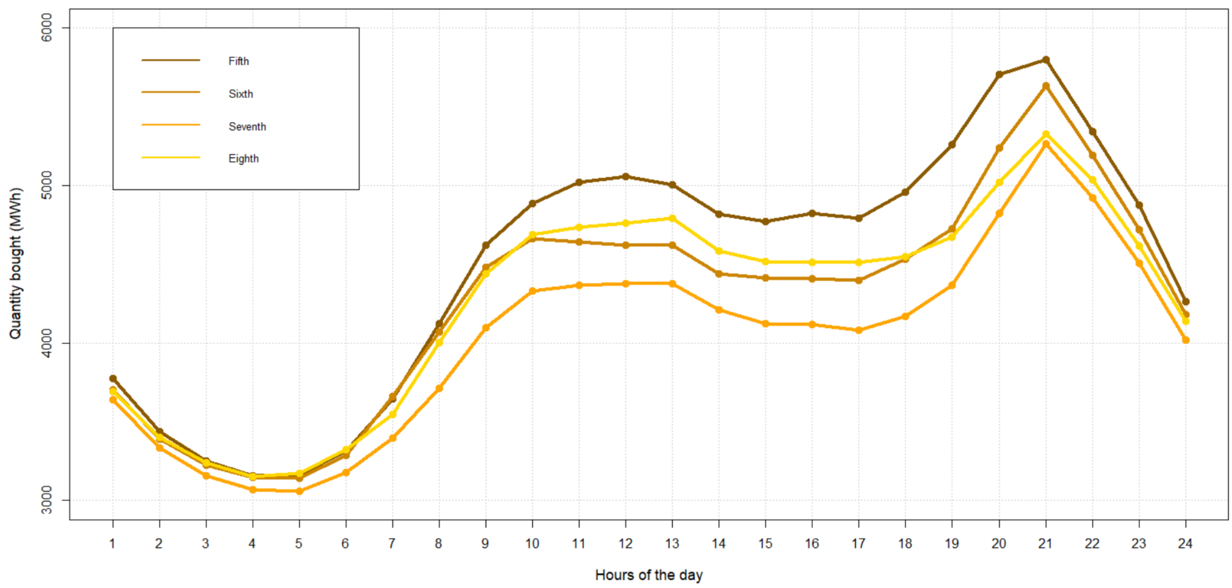


Figure C.6: Average hourly quantity bought | Centre South Italy | Ninth, tenth, eleventh, twelfth and thirteenth weeks

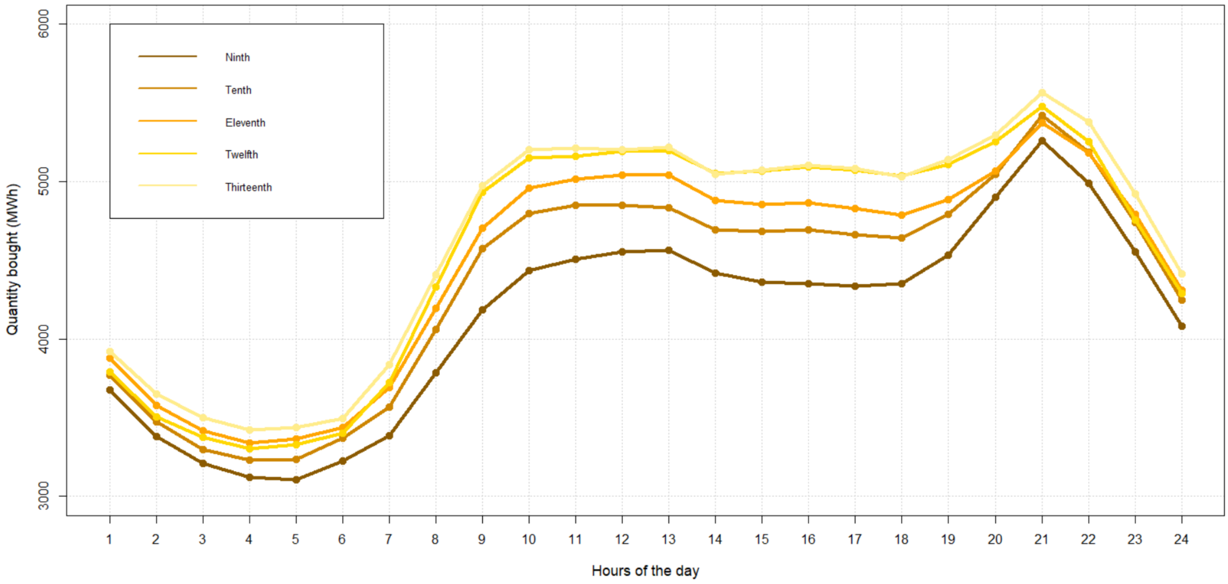


Figure C.7: Average hourly quantity bought | Sicily | First, second, third and fourth weeks

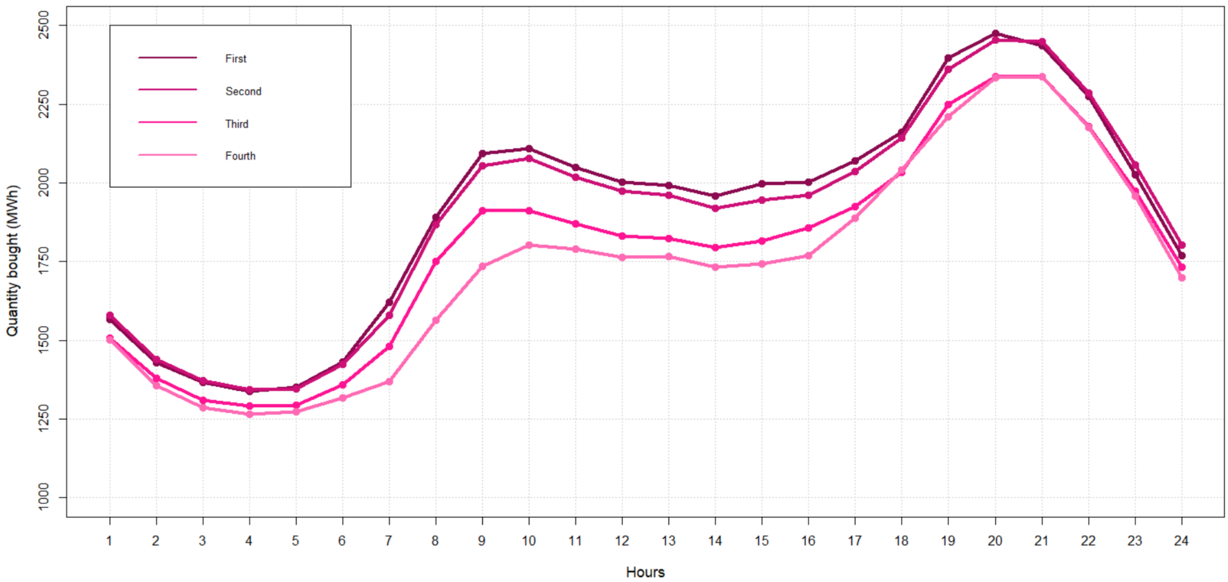


Figure C.8: Average hourly quantity bought | Sicily | Fifth, sixth, seventh and eighth weeks

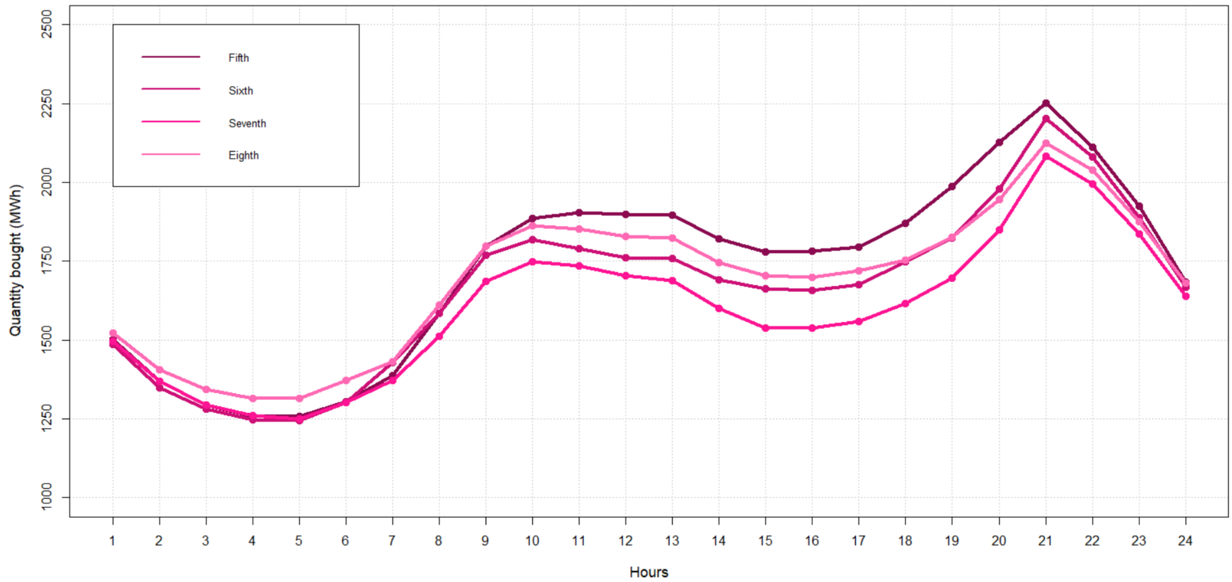


Figure C.9: Average hourly quantity bought | Sicily | Ninth, tenth, eleventh, twelfth and thirteenth weeks

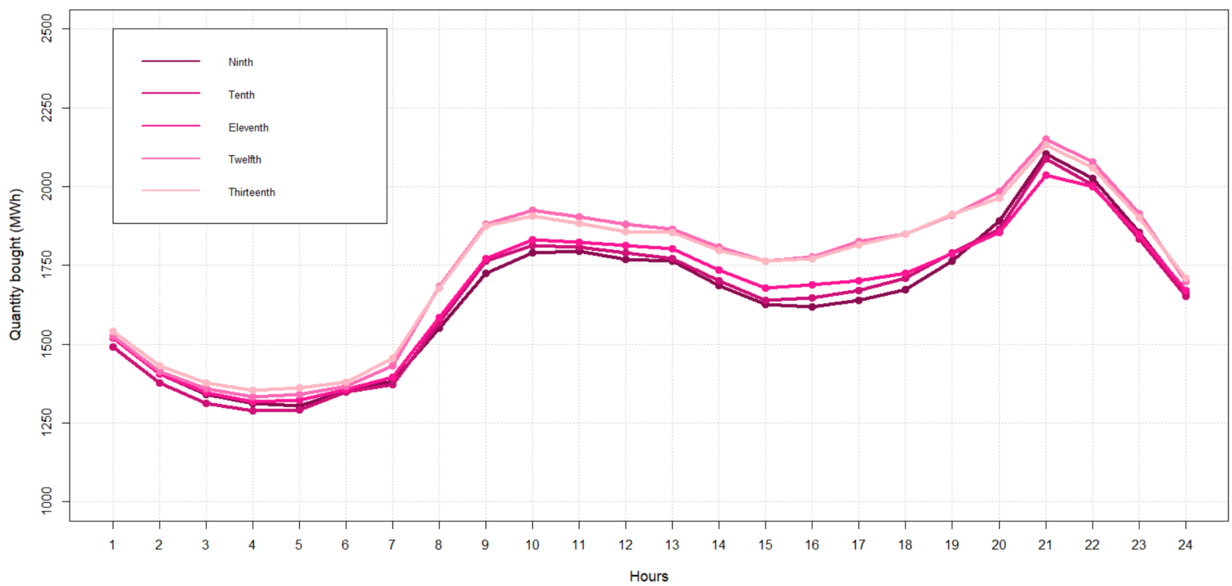


Figure C.10: Average hourly quantity bought | Sardinia | First, second, third and fourth weeks

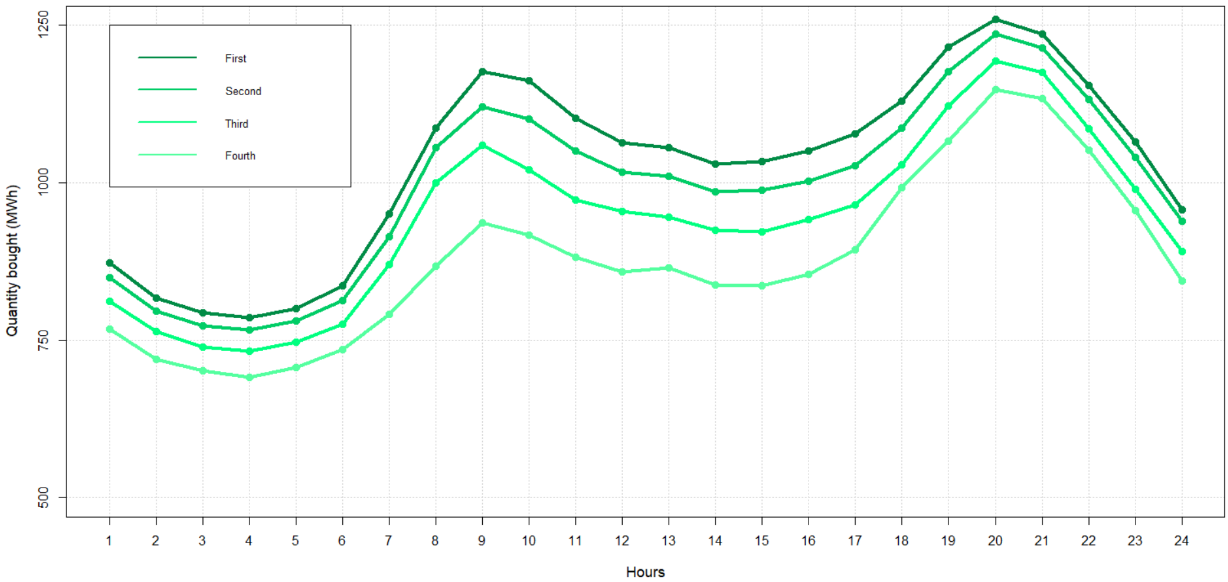


Figure C.11: Average hourly quantity bought | Sardinia | Fifth, sixth, seventh and eighth weeks

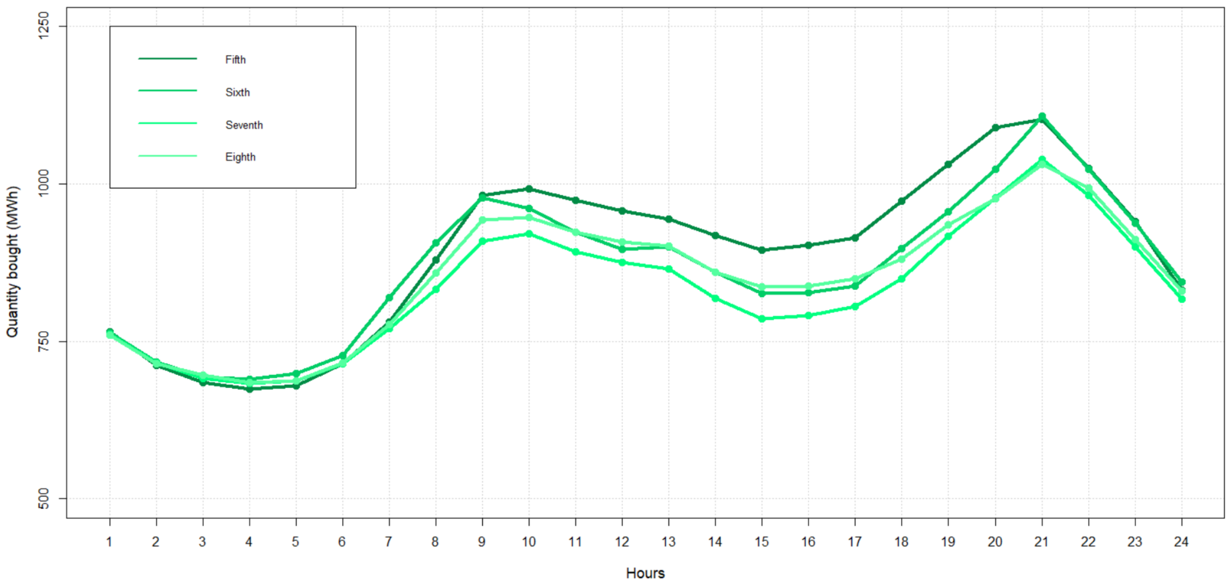
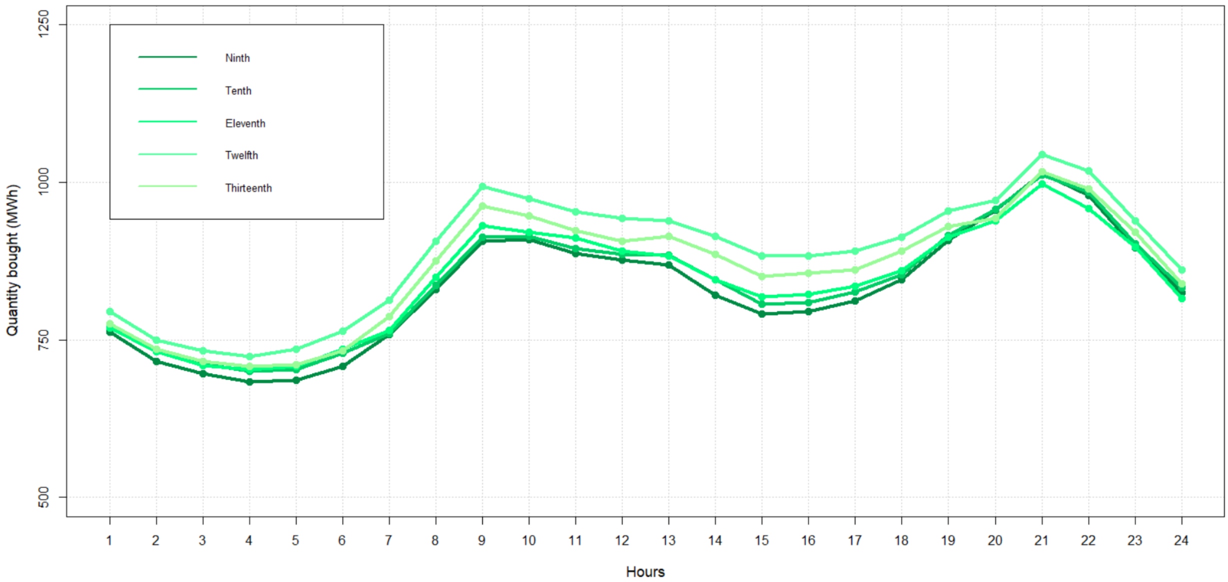


Figure C.12: Average hourly quantity bought | Sardinia | Ninth, tenth, eleventh, twelfth and thirteenth weeks



C.2 Generation mix

Table C.1: Total weekly generation (GWh) divided by energy sources | Italy

Year	Week	Thermal	Hydro	Solar	Wind	Geother.	Self Cons.
2019	First	3138.61	495.97	354.26	553.74	107.85	607.89
2019	Second	3087.77	498.16	377.56	644.43	107.21	580.95
2019	Third	3153.36	447.18	438.24	495.04	110.11	614.02
2019	Fourth	2842.64	465.07	471.3	546.48	110.33	592.55
2019	Fifth	3356.26	624.67	346.08	292.56	107.99	609.28
2019	Sixth	3254.92	715.41	353.27	319.61	110.12	606.2
2019	Seventh	2728.55	685.02	526.47	333.92	111.19	550.78
2019	Eighth	2287.22	921.54	401.17	430.18	111.19	476.64
2019	Ninth	2577.72	968.06	415.93	349.62	111.82	488.03
2019	Tenth	2636.46	908.41	430.04	412.26	109.3	555.98
2019	Eleventh	2753.85	977.07	364.82	297.56	110.58	522.7
2019	Twelfth	2334.52	1123.3	447.4	377.4	110.71	624.99
2019	Thirteenth	2149.18	1274.9	441.65	384.28	111.94	639.24
Year	Week	Thermal	Hydro	Solar	Wind	Geother.	Self Cons.
2020	First	2780.93	713.94	305.61	607.57	113.3	585.93
2020	Second	2692.86	608.7	369.53	321.21	112.65	563.32
2020	Third	2312.4	573.46	437.56	205.09	112.04	602.35
2020	Fourth	2167	647.38	343.45	459.69	112.01	542.44
2020	Fifth	2246.84	642.42	504.03	365.39	112.17	653.04
2020	Sixth	2195.99	705.53	609.68	143.86	111.67	663.15
2020	Seventh	2132.94	829.24	511.86	254.57	110.81	523.7
2020	Eighth	2261.12	1004.08	427.63	273.26	111.24	518.79
2020	Ninth	1954.86	1010.43	510.41	495.78	110.62	513.13
2020	Tenth	2170.72	986.88	576.07	329.04	108.01	585.85
2020	Eleventh	2085.83	1204.85	429.64	497.12	108.08	531.06
2020	Twelfth	2126.35	1320.8	50005	368.42	108.7	629.47
2020	Thirteenth	2254.87	1270.63	543.48	334.48	106.97	654.75

The table presents the total generation divided by the energy sources over the thirteen weeks under analysis during 2019 and 2020. *Source*: Elaboration of Italian TSO data.

Figure C.13: Generation mix shares | Comparison between first weeks

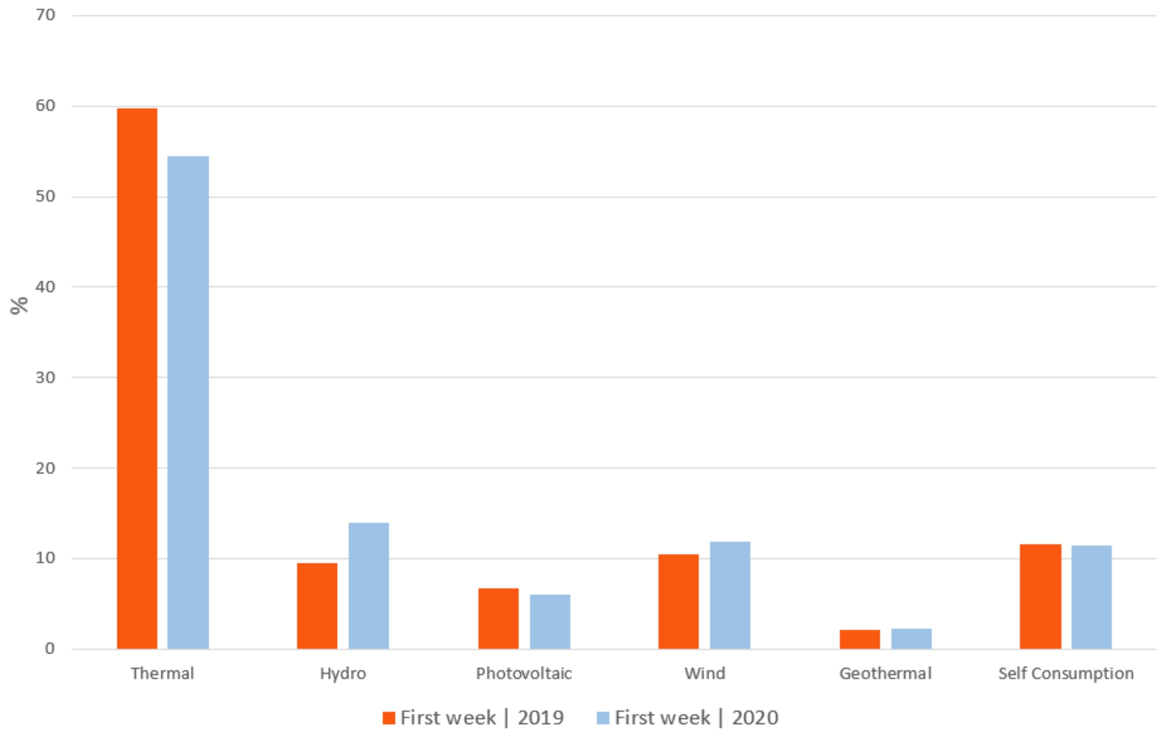


Figure C.14: Generation mix shares | Comparison between second weeks

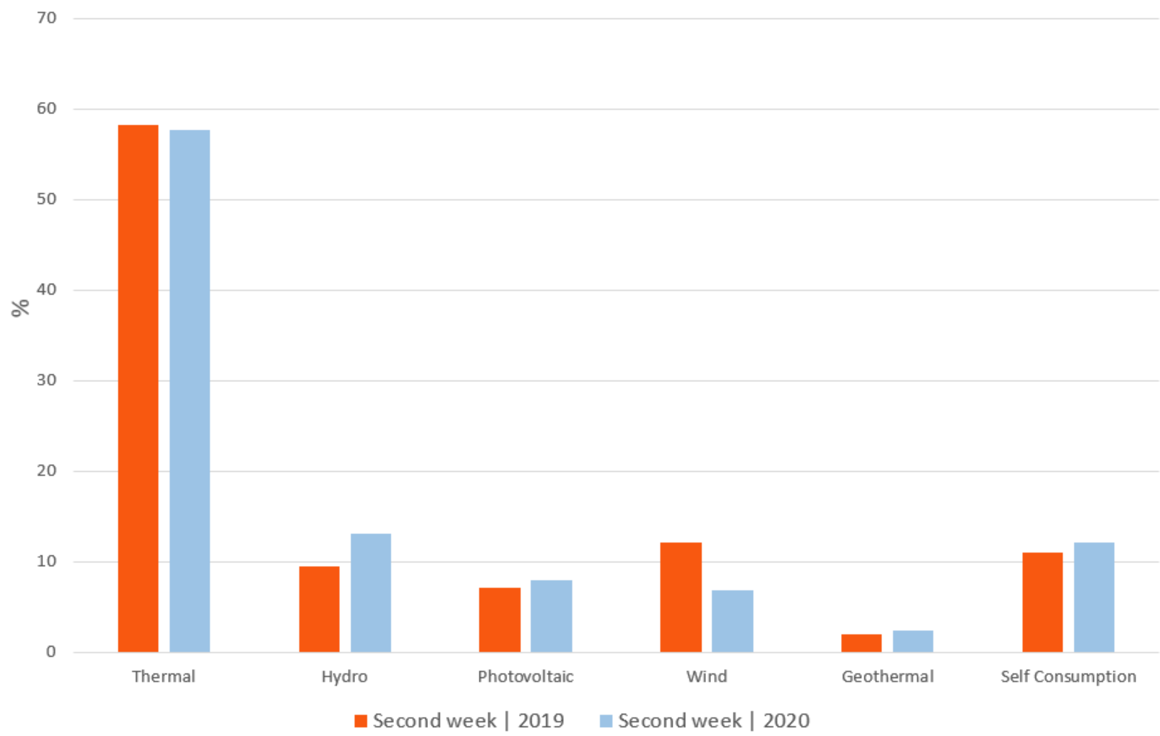


Figure C.15: Generation mix shares | Comparison between third weeks

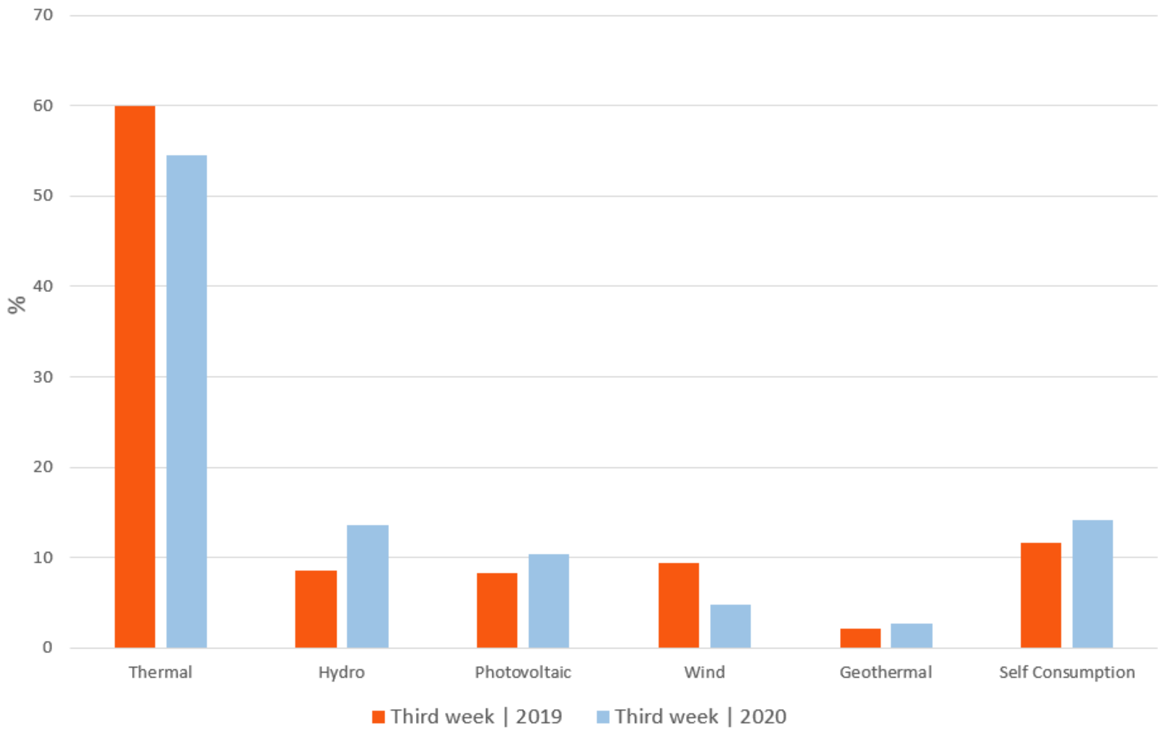


Figure C.16: Generation mix shares | Comparison between fourth weeks

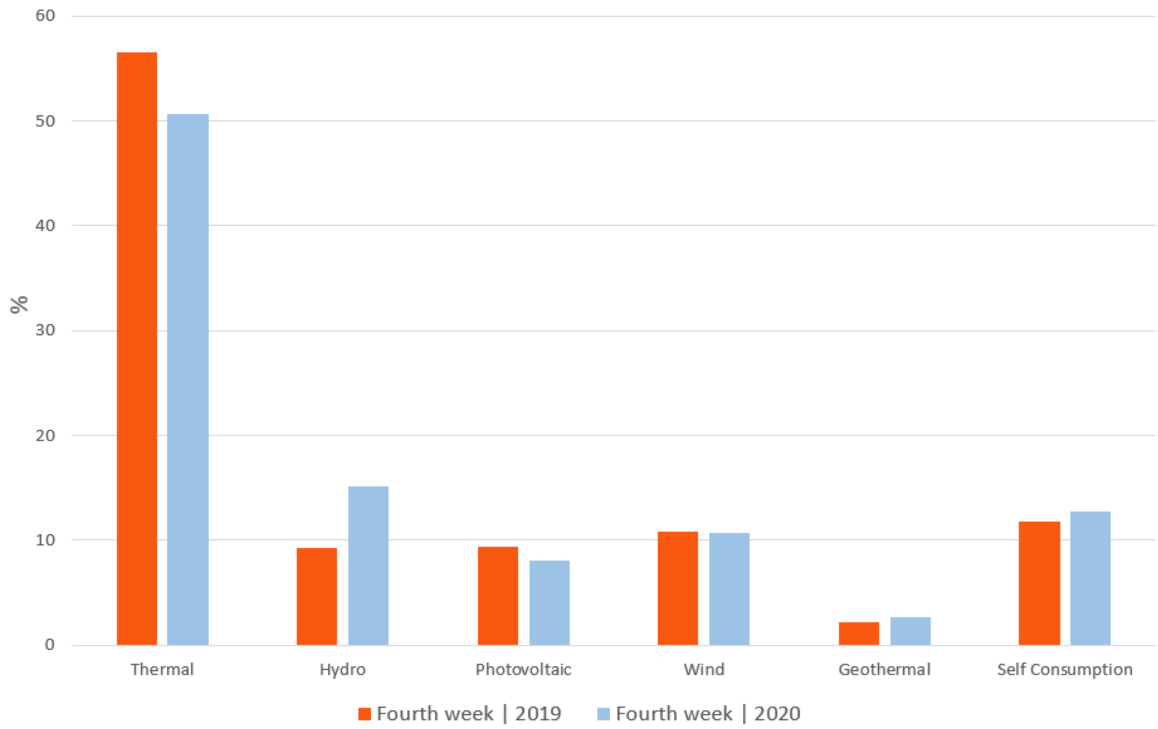


Figure C.17: Generation mix shares | Comparison between fifth weeks

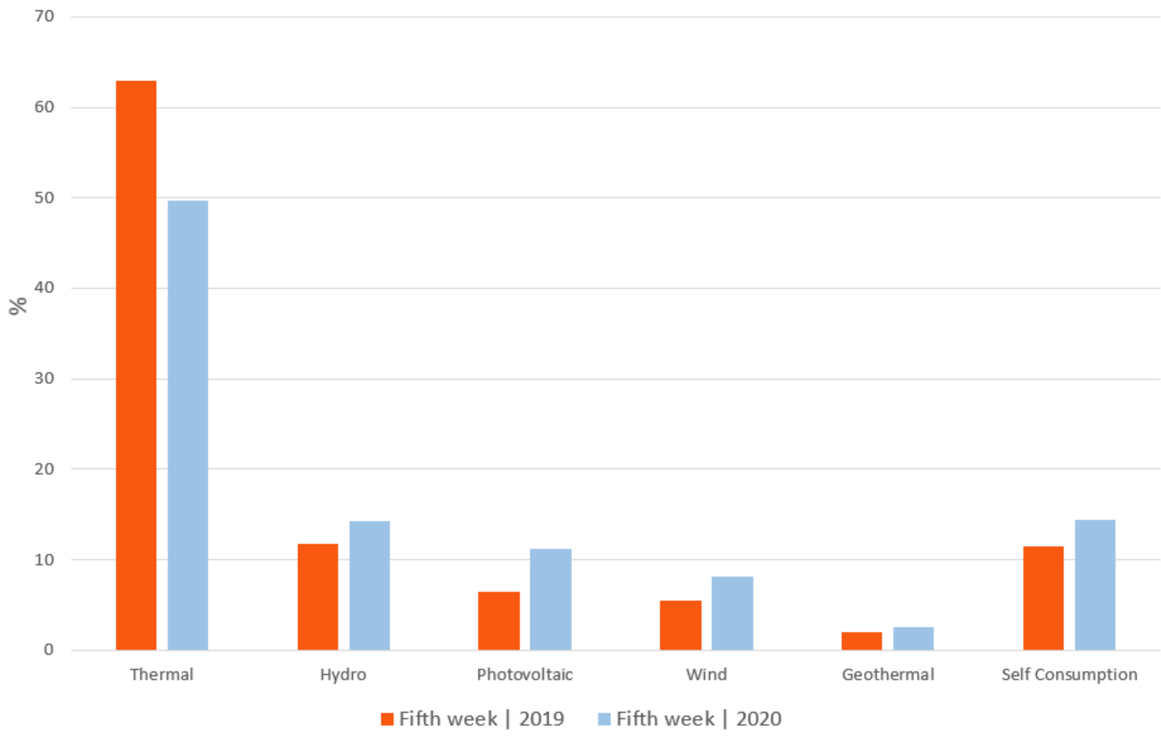


Figure C.18: Generation mix shares | Comparison between sixth weeks

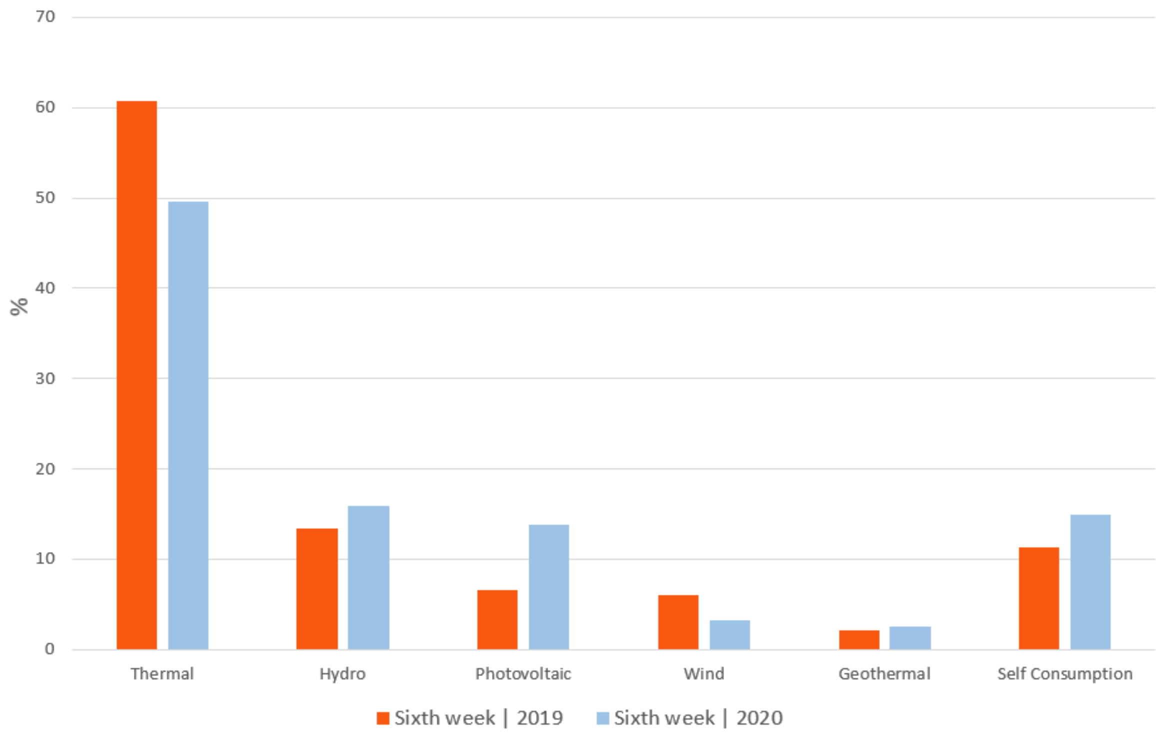


Figure C.19: Generation mix shares | Comparison between seventh weeks

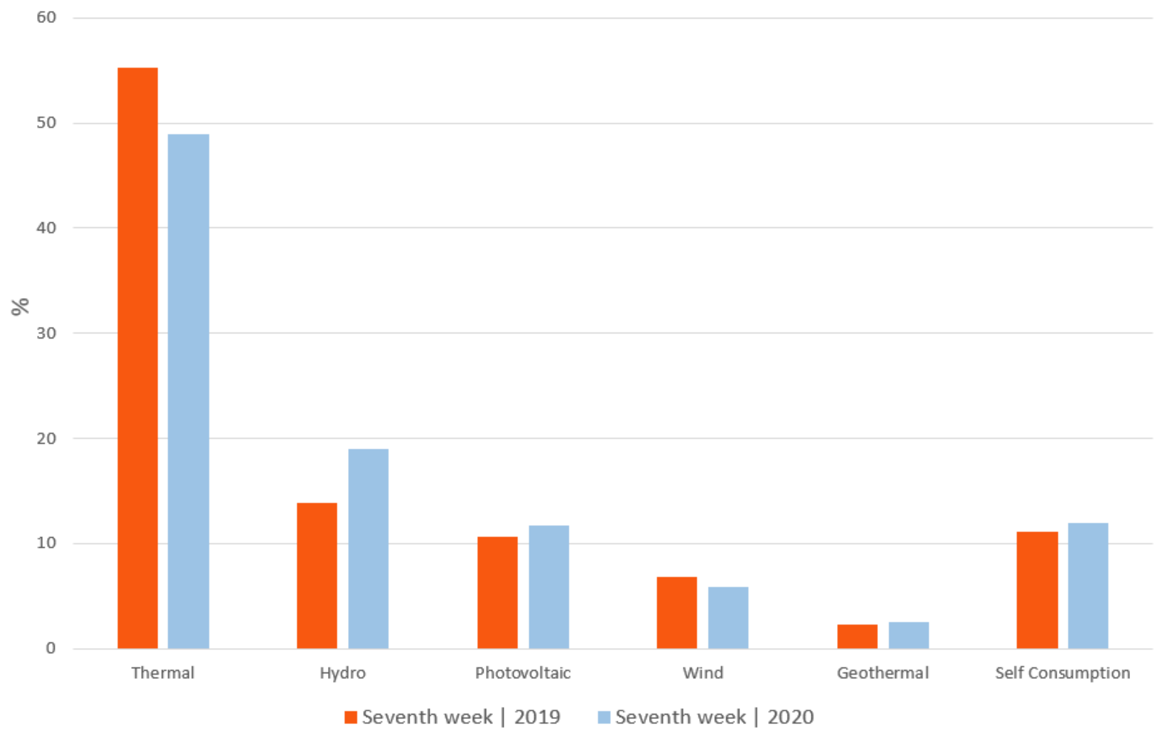


Figure C.20: Generation mix shares | Comparison between eighth weeks

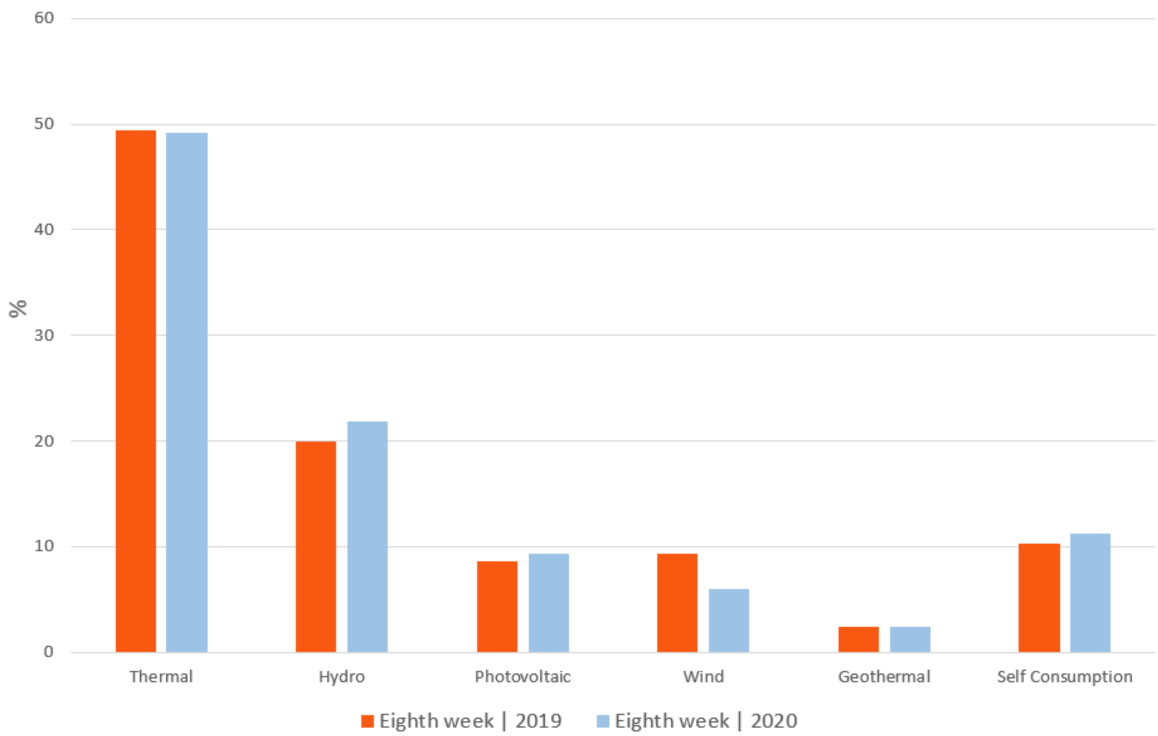


Figure C.21: Generation mix shares | Comparison between ninth weeks

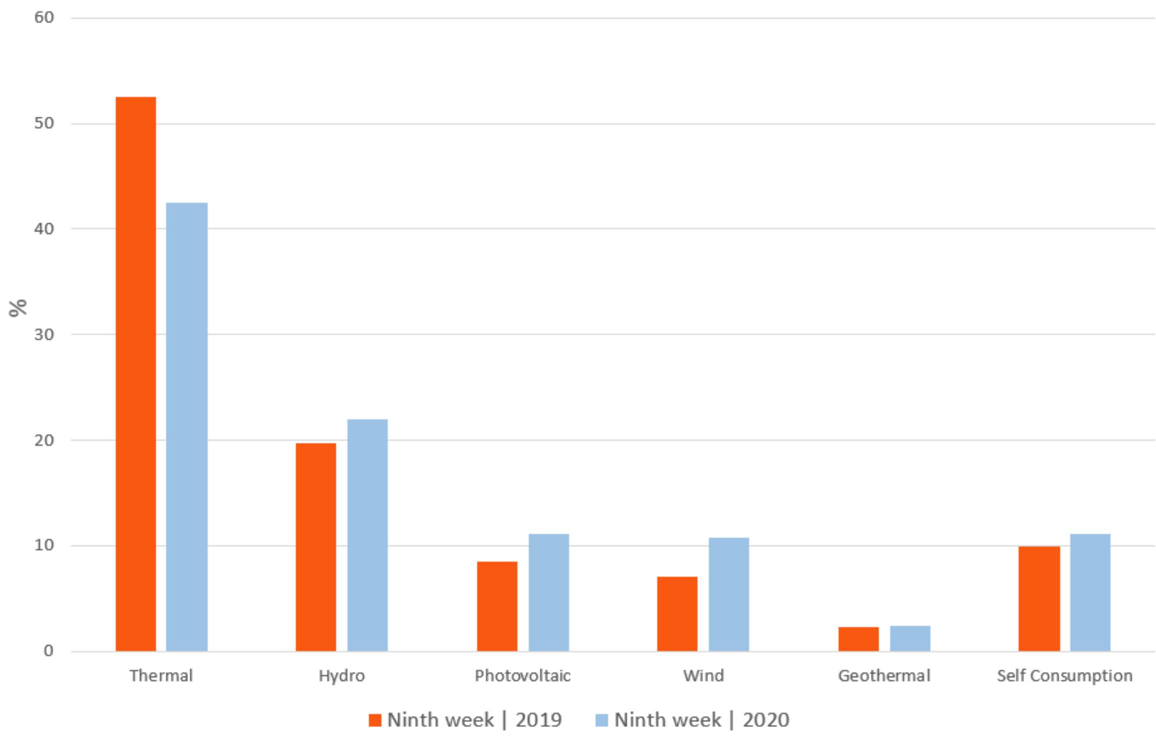


Figure C.22: Generation mix shares | Comparison between tenth weeks

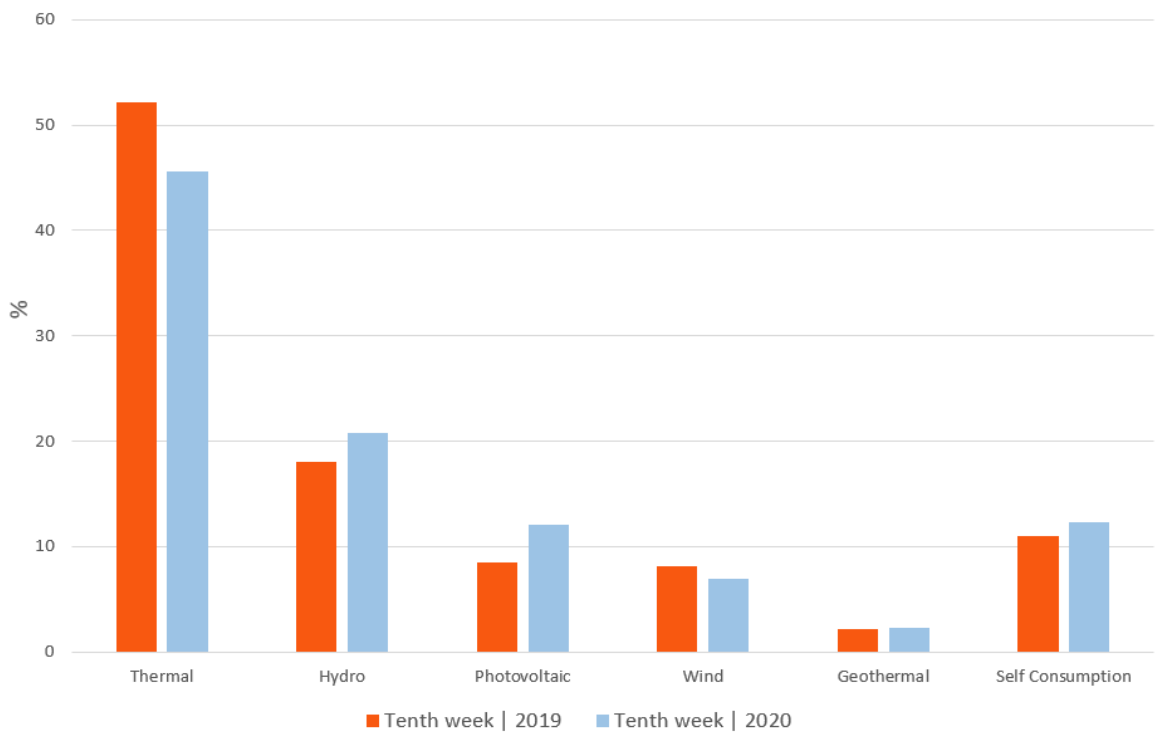


Figure C.23: Generation mix shares | Comparison between eleventh weeks

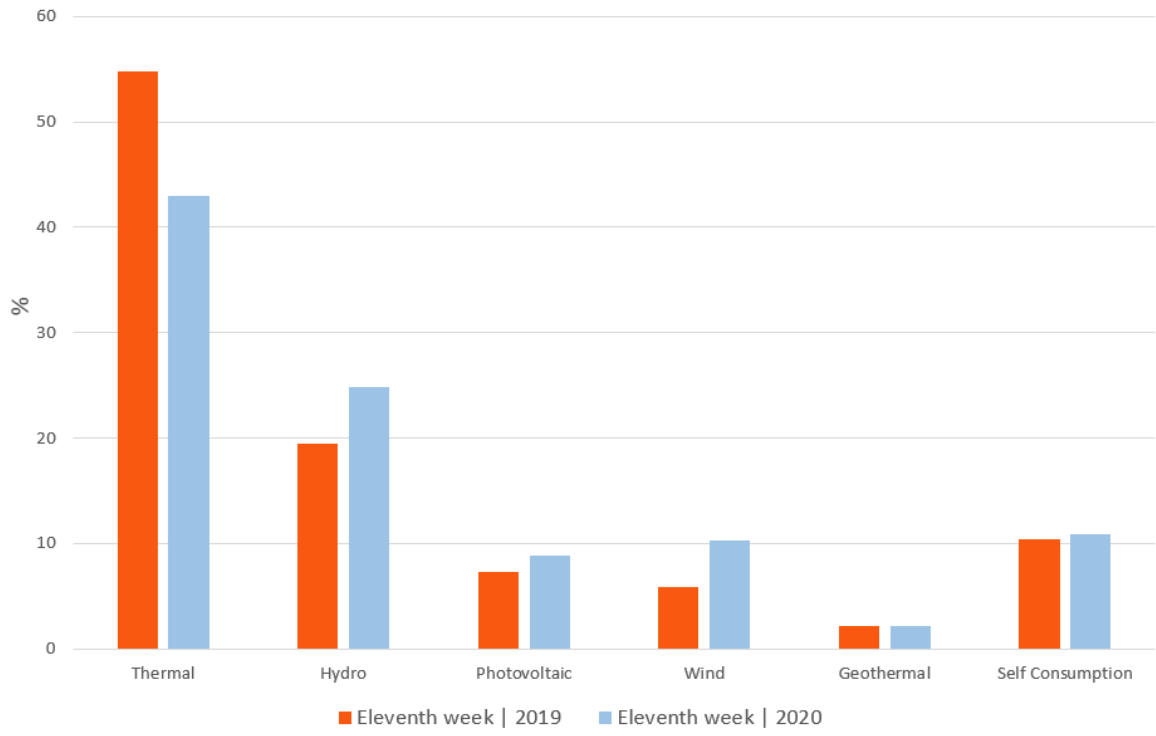


Figure C.24: Generation mix shares | Comparison between twelfth weeks

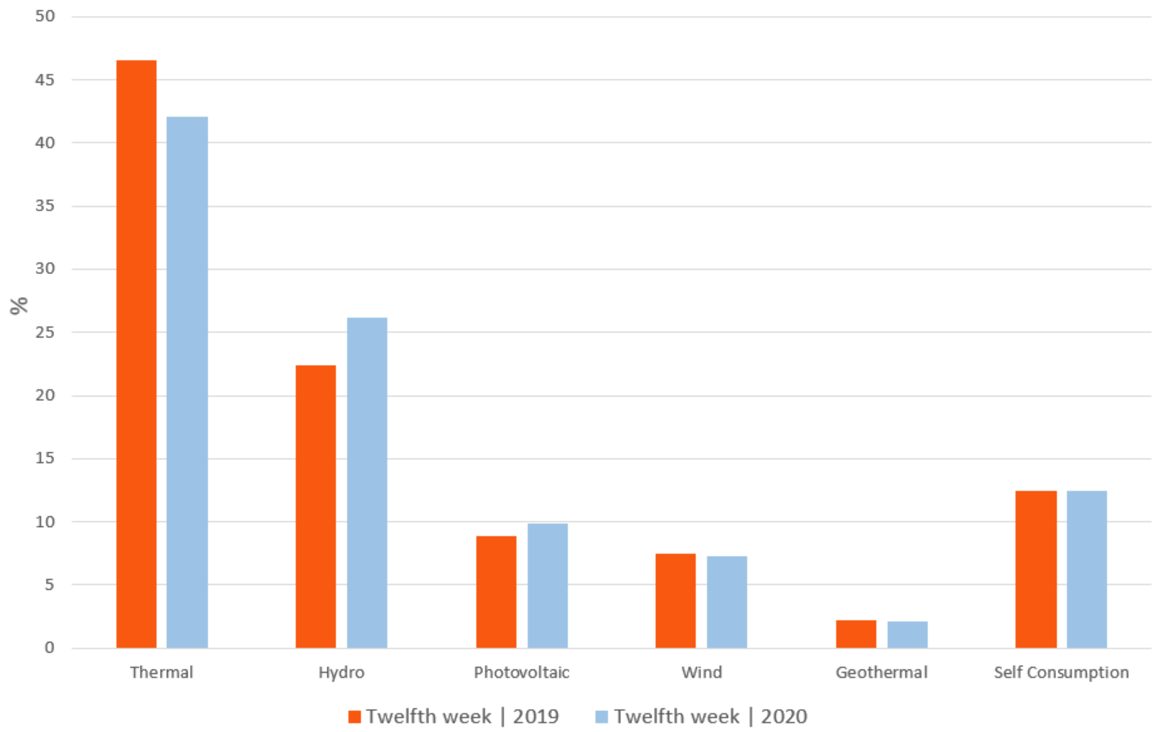
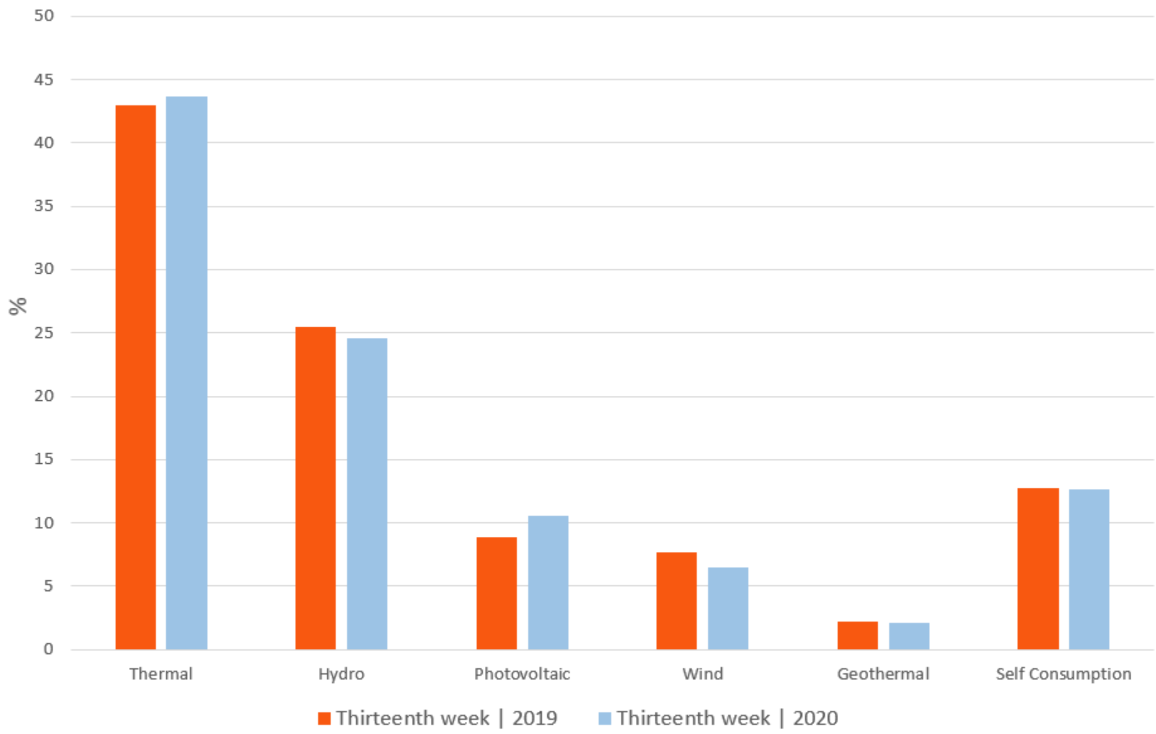


Figure C.25: Generation mix shares | Comparison between thirteenth weeks



C.3 Econometric Analysis

C.3.1 Autocorrelation functions and residual diagnostics

Figure C.26: Italy | 9am | ACF | Quantity

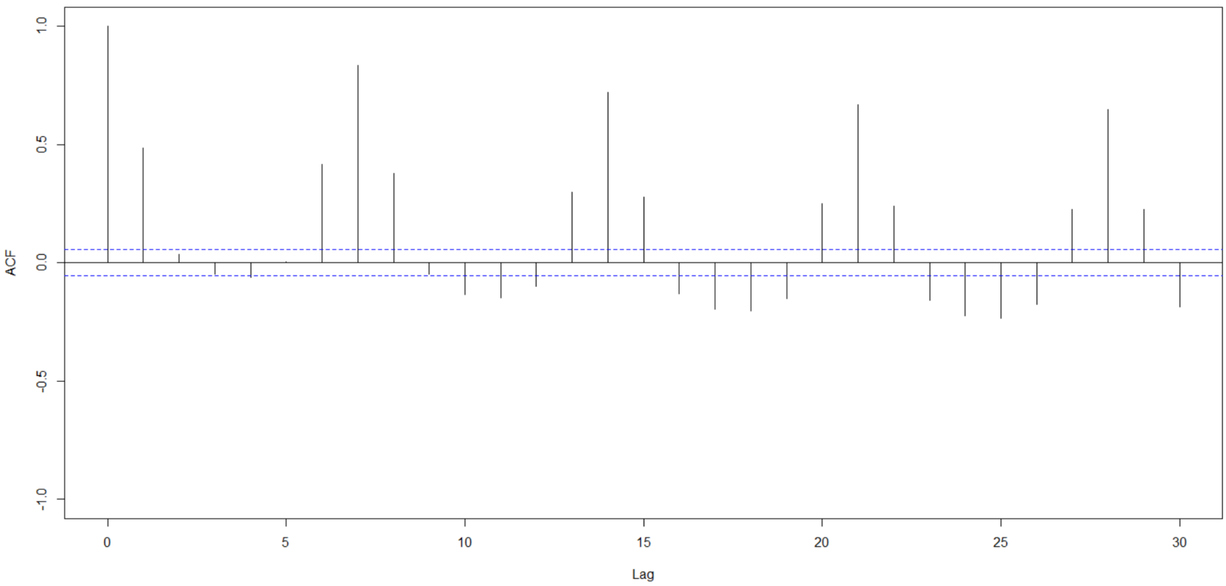


Figure C.27: Italy | 9am | PACF | Quantity

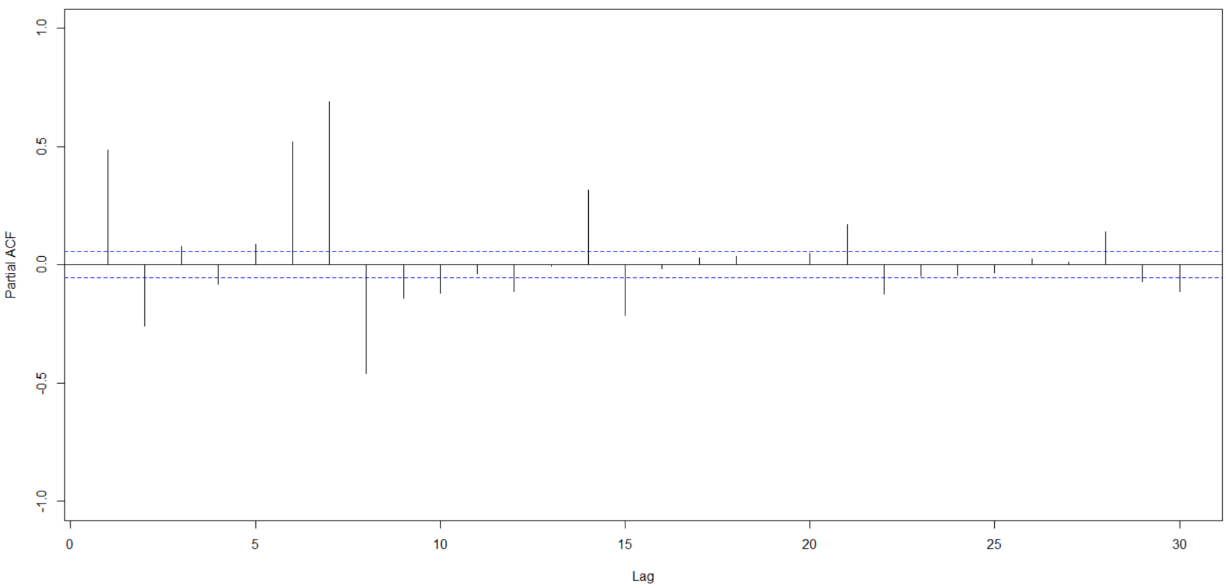


Figure C.28: Italy | 9am | ACF | Quantity Residuals Geo. Lock.

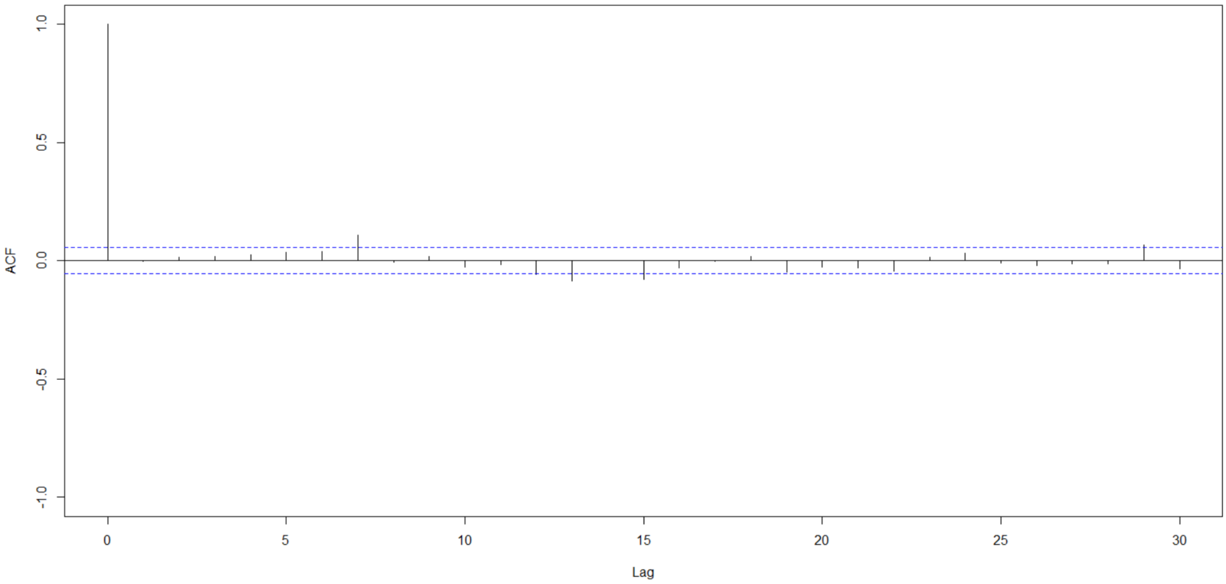


Figure C.29: Italy | 9am | PACF | Quantity Residuals Geo. Lock.

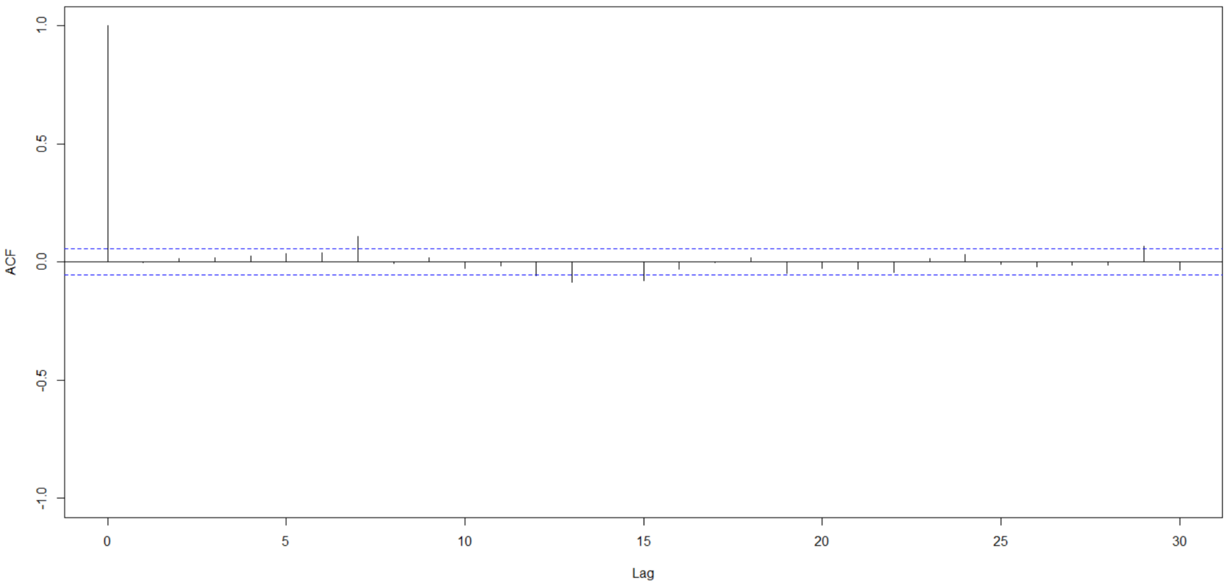


Figure C.30: Italy | 9am | ACF | Quantity Residuals Prod. Lock.

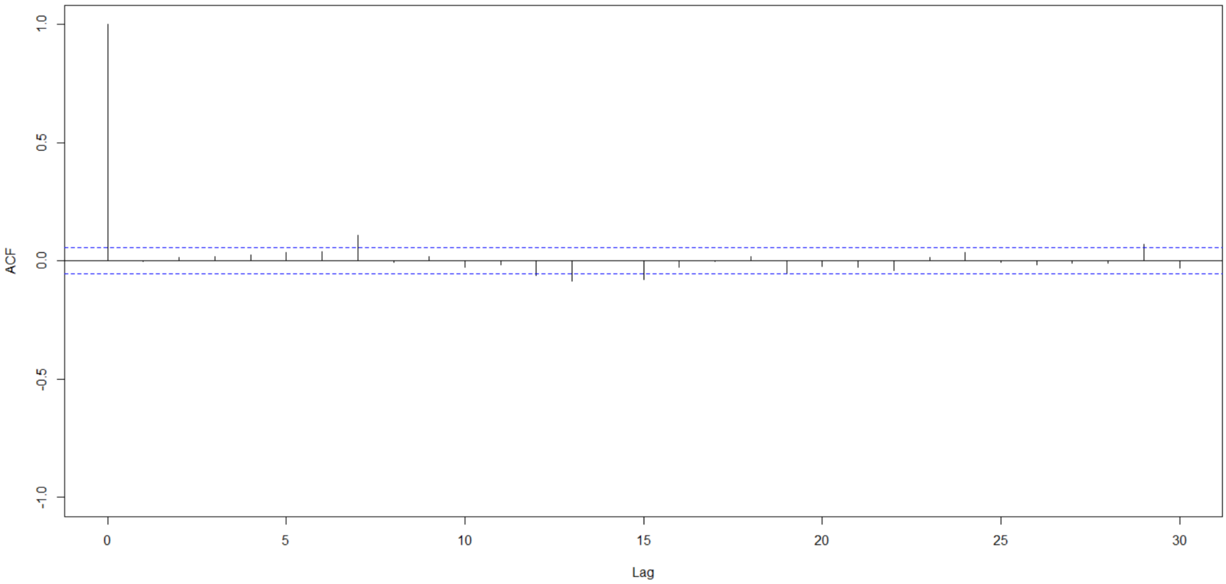


Figure C.31: Italy | 9am | PACF | Quantity Residuals Prod. Lock.

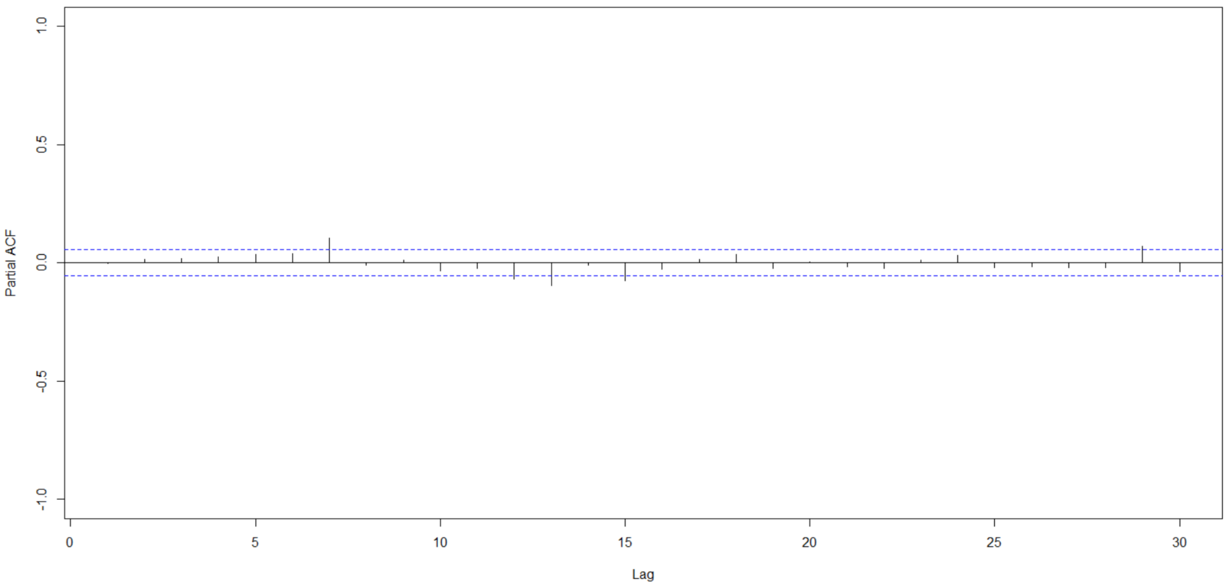


Figure C.32: Italy | 9am | Hist | Quantity Residuals Prod. Geo.

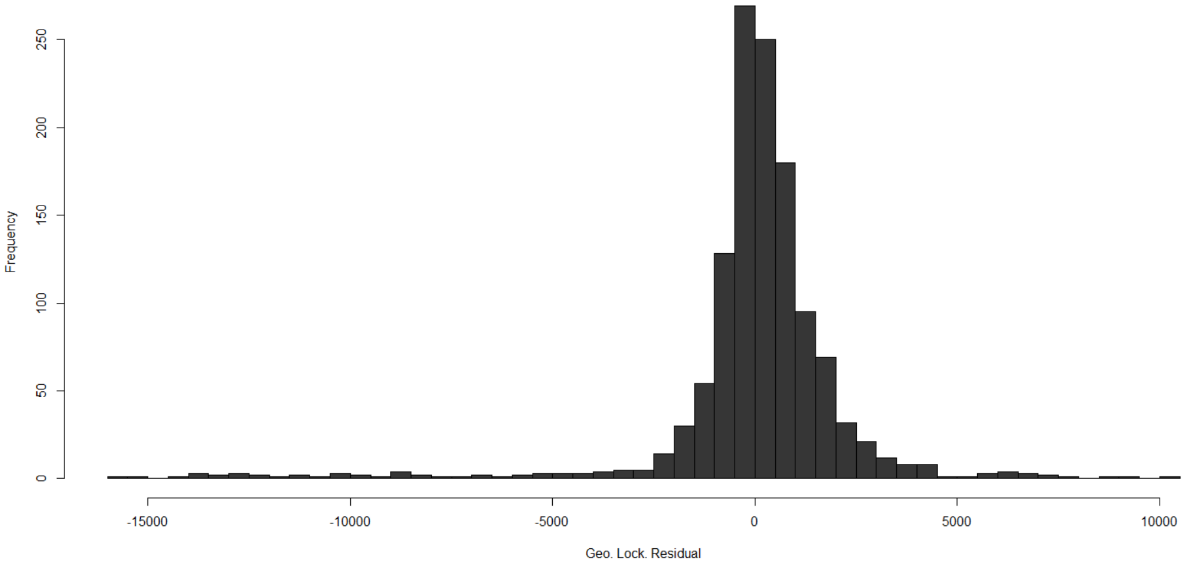


Figure C.33: Italy | 9am | Hist | Quantity Residuals Prod. Lock.

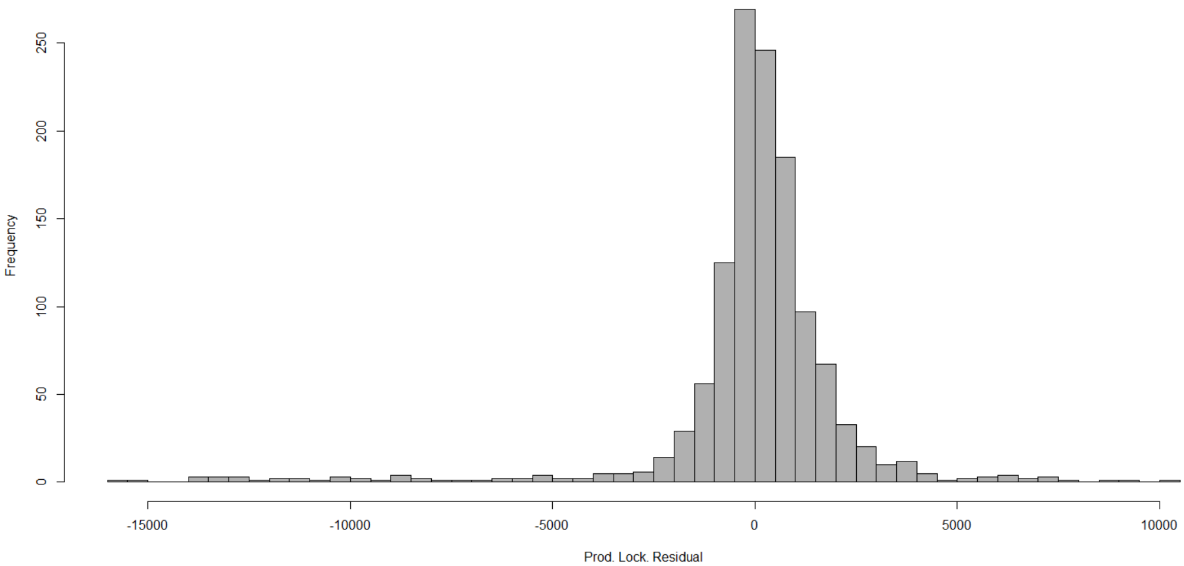


Figure C.34: Italy | 9am | ACF | PUN

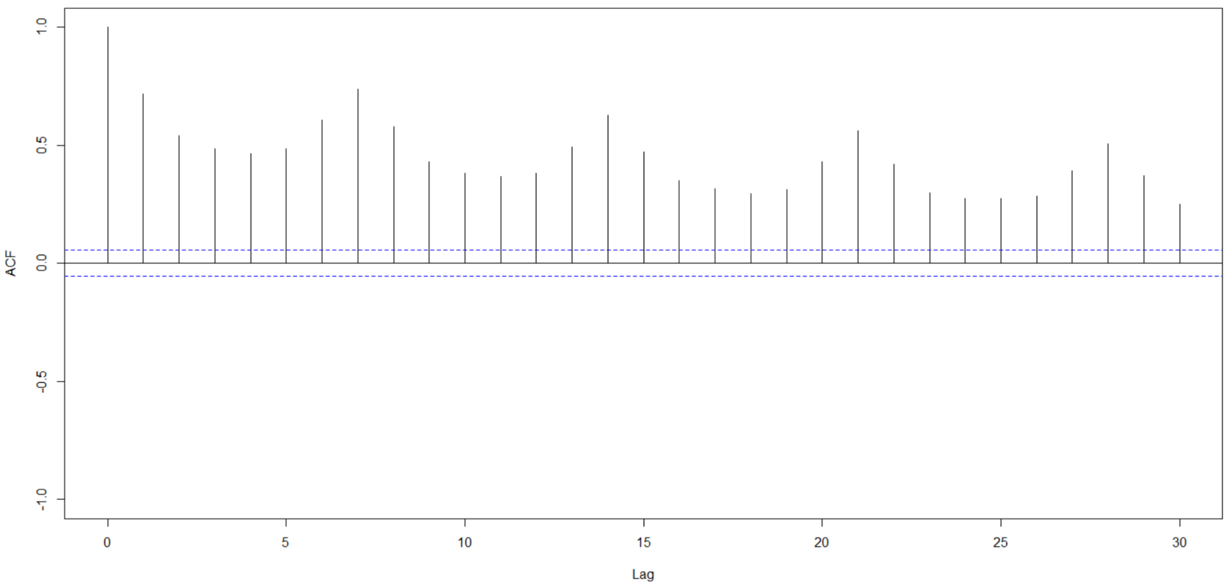


Figure C.35: Italy | 9am | PACF | PUN

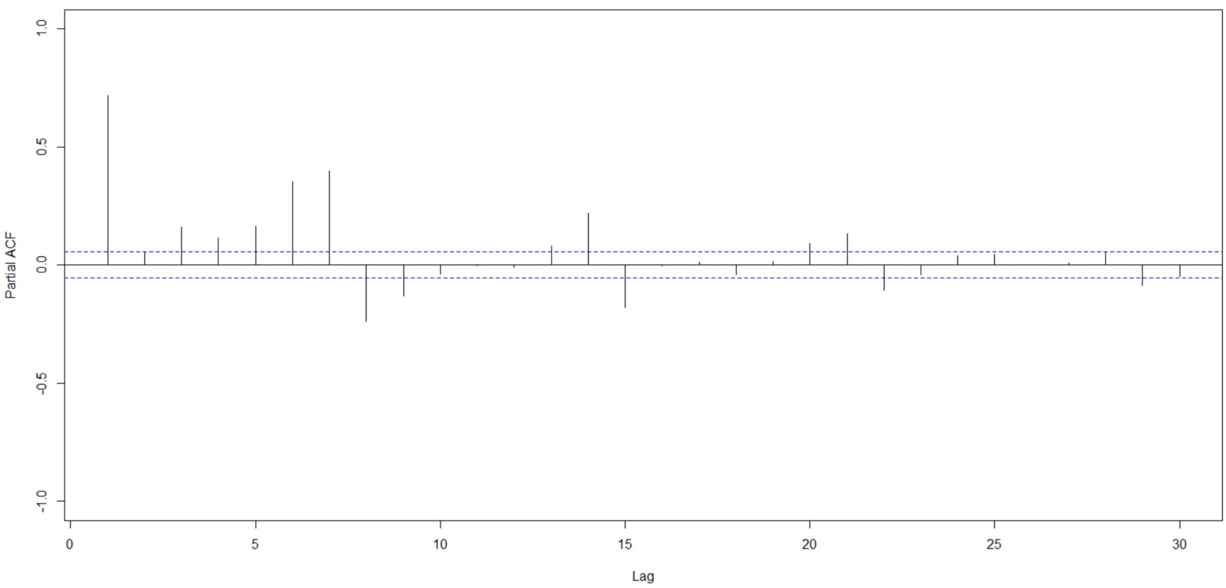


Figure C.36: Italy | 9am | ACF | PUN Residuals Geo. Lock.

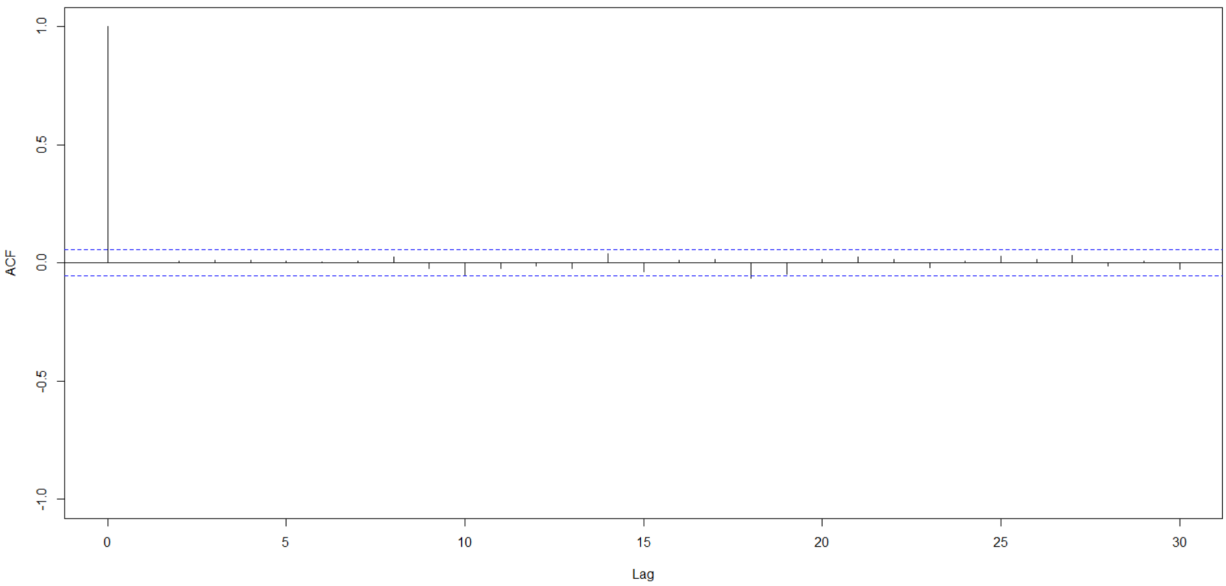


Figure C.37: Italy | 9am | PACF | PUN Residuals Geo. Lock.

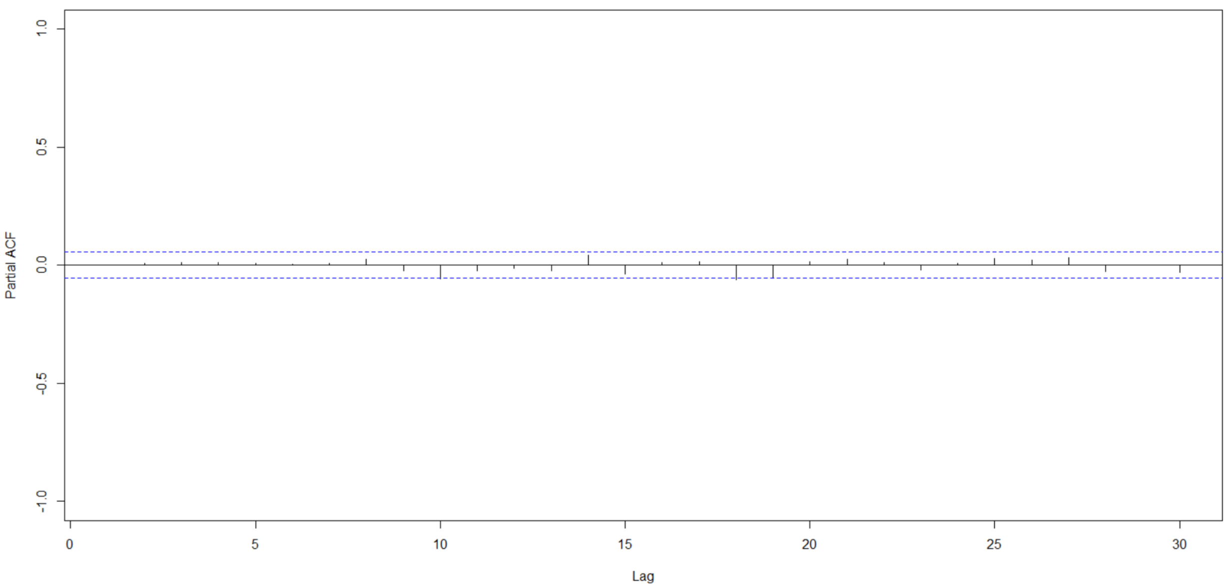


Figure C.38: Italy | 9am | ACF | PUN Residuals Prod. Lock.

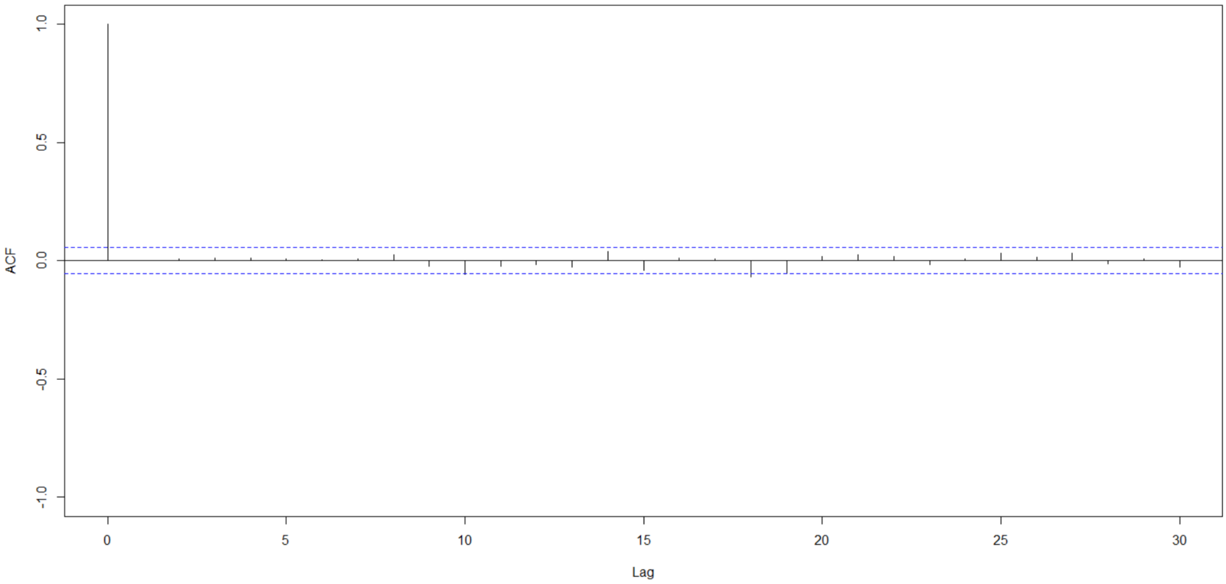


Figure C.39: Italy | 9am | PACF | PUN Residuals Prod. Lock.

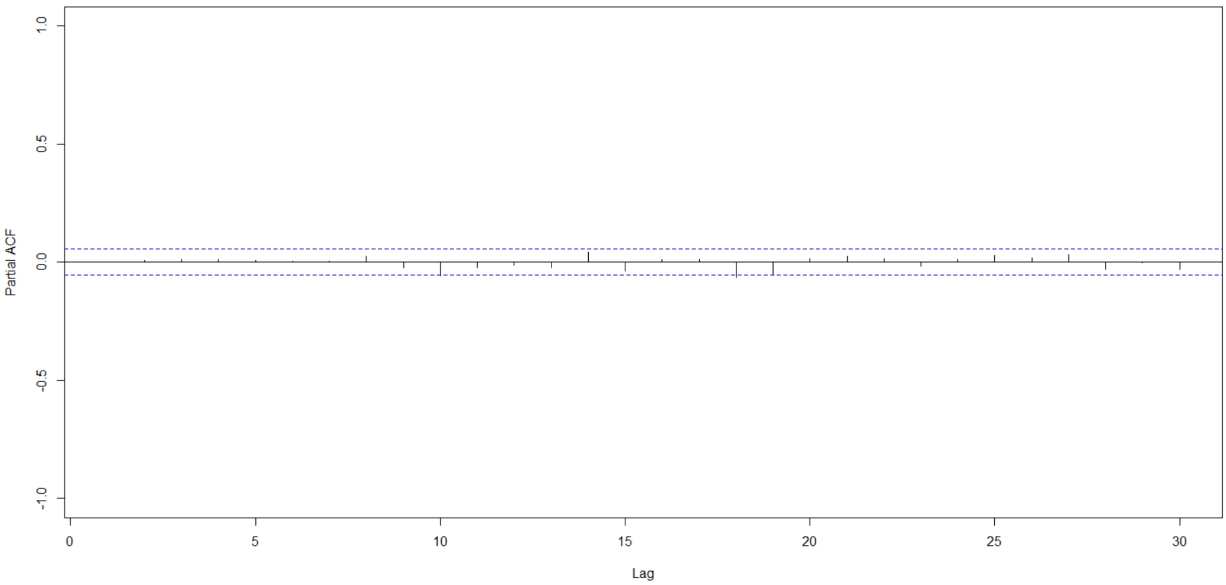


Figure C.40: Italy | 9am | Hist | PUN Residuals Prod. Geo.

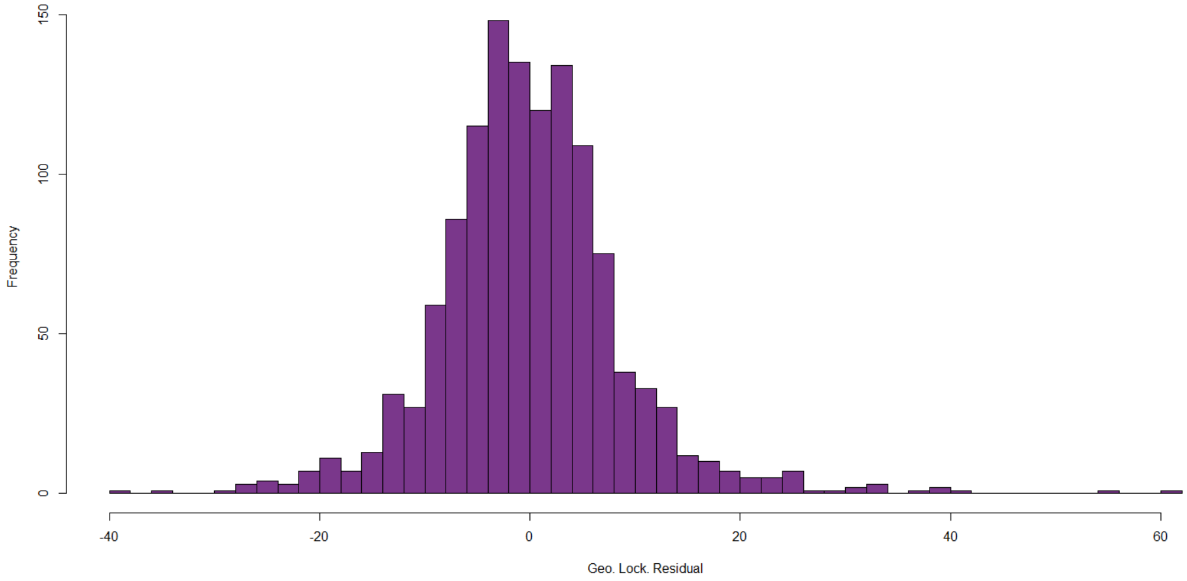
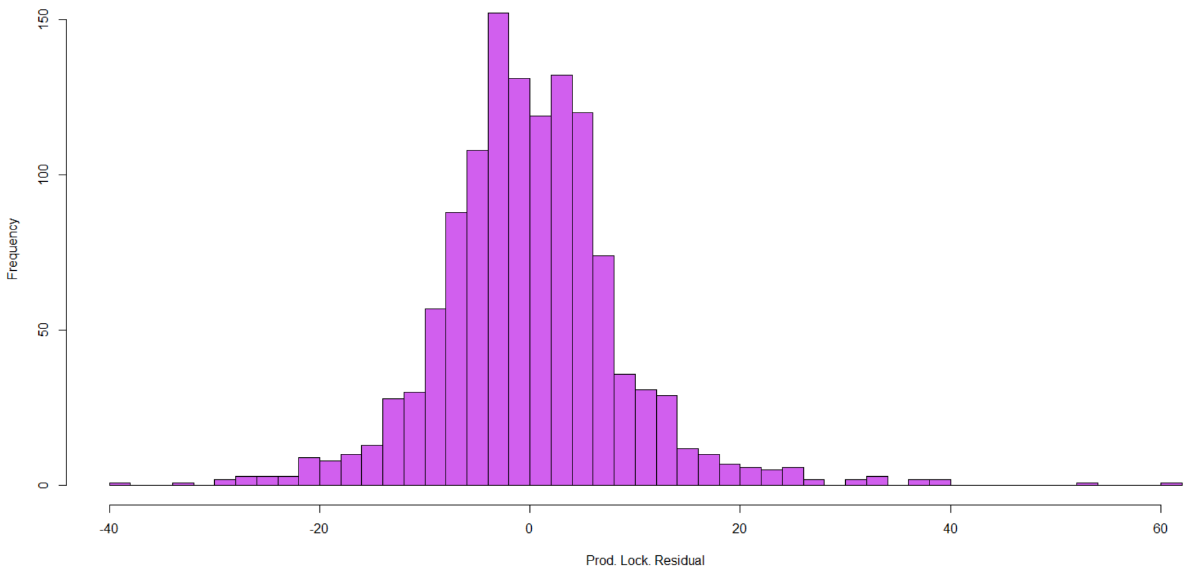


Figure C.41: Italy | 9am | Hist | PUN Residuals Prod. Lock.



C.3.2 Tables

Table C.2: Geographic lockdown | Quantity | Italy | 9am

	Estimated Coeff.	Std. Error	t.stat	p.value
$\hat{\phi}_1$	0.572	0.028	20.174	0.000
$\hat{\phi}_2$	0.045	0.032	1.380	0.168
$\hat{\phi}_3$	0.072	0.032	2.230	0.026
$\hat{\phi}_4$	-0.004	0.032	-0.126	0.900
$\hat{\phi}_5$	0.033	0.032	1.018	0.309
$\hat{\phi}_6$	0.155	0.033	4.768	0.000
$\hat{\phi}_7$	-0.008	0.029	-0.292	0.770
$\hat{\phi}_0$	25999	523.106	49.701	0.000
$\hat{\gamma}_1$	12645	197.273	64.097	0.000
$\hat{\gamma}_2$	14197	254.204	55.848	0.000
$\hat{\gamma}_3$	14453	273.957	52.756	0.000
$\hat{\gamma}_4$	14499	273.945	52.927	0.000
$\hat{\gamma}_5$	14127	254.195	55.576	0.000
$\hat{\gamma}_6$	6236	197.272	31.611	0.000
$\hat{\theta}^{Geo.Lock.}$	-5083	1459.356	-3.483	0.001

Table C.3: Production lockdown | Quantity | Italy | 9am

	Estimated Coeff.	Std. Error	t.stat	p.value
$\hat{\phi}_1$	0.574	0.028	20.283	0.000
$\hat{\phi}_2$	0.042	0.032	1.305	0.192
$\hat{\phi}_3$	0.076	0.032	2.359	0.018
$\hat{\phi}_4$	-0.002	0.032	-0.047	0.963
$\hat{\phi}_5$	0.030	0.032	0.927	0.354
$\hat{\phi}_6$	0.156	0.033	4.792	0.000
$\hat{\phi}_7$	-0.008	0.029	-0.291	0.771
$\hat{\phi}_0$	25918	540.924	47.914	0.000
$\hat{\gamma}_1$	12645	197.279	64.096	0.000
$\hat{\gamma}_2$	14198	254.168	55.859	0.000
$\hat{\gamma}_3$	14451	273.071	52.922	0.000
$\hat{\gamma}_4$	14498	273.058	53.094	0.000
$\hat{\gamma}_5$	14126	254.157	55.581	0.000
$\hat{\gamma}_6$	6235	197.277	31.607	0.000
$\hat{\theta}^{Prod.Lock.}$	-4666	1578.496	-2.956	0.003