



HAL
open science

Ring the alarm! Electricity markets, renewables, and the pandemic

David Benatia

► **To cite this version:**

David Benatia. Ring the alarm! Electricity markets, renewables, and the pandemic. Energy Economics, 2022, 106, pp.105755. <10.1016/j.eneco.2021.105755>. <hal-03523180>

HAL Id: hal-03523180

<https://hal.science/hal-03523180v1>

Submitted on 8 Jan 2024

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire HAL, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons CC BY-NC 4.0 - Attribution - Non-commercial use - International License

Ring the Alarm!

Electricity Markets, Renewables, and the Pandemic

David Benatia*

October 25, 2021

*HEC Montréal, Département d'Économie Appliquée, 3000 Chemin de la Côte-Sainte-Catherine, Montréal, QC H3T 2A7, Canada (e-mail: david.benatia@hec.ca); and CREST (UMR 9194), ENSAE, Institut Polytechnique de Paris, 5 Avenue Henry Le Chatelier, 91120 Palaiseau, France (e-mail: david.benatia@ensae.fr). This research is supported by grants of the French National Research Agency (ANR), “*Investissements d’Avenir*” (LabEx Ecodec/ANR-11-LABX-0047) and “*Instrument de financement : Projet de Recherche Collaborative – Entreprise*” (ANR EcoREES). The authors acknowledge financial support from *Groupe des Écoles Nationales d’Économie et Statistique* (GENES) and *Laboratoire de Finance des Marchés de l’Énergie* (FiME). The author is grateful to Théotime Coudray, Natalia Fabra, Samuel Gingras, Frédéric Lantz, Rossana Riccardi, Boris Sollier, Richard J. Tol, Sergio Vergalli, two anonymous referees, and participants to the 7th Annual Electricity Price Forecasting and Modelling Forum, the 30th CREEA Conference, and the FAEE seminar.

1 Introduction

The impacts of the COVID-19 crisis on European electricity markets are reminiscent of the anticipated consequences of the ongoing energy transition. Energy efficiency improvements and increasing shares of intermittent renewables, producing at near-zero marginal costs, tend to depreciate wholesale electricity prices by reducing the market share of conventional generators. In the long-run, “too low” prices would lead to early power plant retirements and insufficient capacity investment in necessary flexible back-up technologies, which, in turn, would compromise both system reliability and efficiency. The energy transition may therefore exacerbate issues related to the “missing money problem”, and more generally market incompleteness, unless markets are able to provide adequate scarcity signals.

In this paper, we argue that the sanitary crisis underlines the weaknesses of the current design of electricity markets in the face of ambitious environmental objectives. First, we develop a method to quantify the impacts of the COVID-19 crisis on inter-connected electricity markets, and decompose the revenue loss for producers, retailers and grid operators with respect to their anticipation. We study different counterfactual scenarios, including one where the pandemic had occurred assuming renewable capacity was at the European Union’s 2030 target. We also discuss observed market outcomes during the crisis in light of the energy transition. The empirical analysis focuses on the French electricity market. This market was one of the most affected in Europe due to the abundance of low-cost energy from nuclear plants combined with the drastic nationwide containment measures implemented by the government.

On March 16th 2020, French President Macron announced a nationwide lockdown as a measure to slow down the COVID-19 epidemic in France. This lockdown remained in force until May 11th. Around the same period, almost all European countries have enacted similar containment measures. Those measures have had important impacts on European power systems. The main short-term consequences have been the significant reductions in electricity consumption. [CRE \(2020a\)](#) reports a 15% reduction during the first lockdown in France compared to 2019. Renewable and nuclear energies were the two major production sources during this episode while security of supply was ensured by the flexibility of nuclear and hydro power plants. Fossil-fuel generation was

reduced by 53% (CRE, 2020a) in comparison to 2019. This slump in power consumption, combined with very low commodity prices caused by a depressed world energy consumption, and abundant near-zero marginal cost production from renewables, has resulted in unexpectedly low spot power prices. The crisis has also modified the nuclear maintenance and refueling calendars in France, leading to anticipations of lower nuclear power production until 2022 (CRE, 2020a).

As part of the *Clean energy for all Europeans package* adopted in 2019 (European Commission, 2019), France’s 2030 *National Energy and Climate Plan* aims for 33% renewable energy in its total energy mix (NECP, 2020). It implies that domestic power generation from renewable sources is set to increase from 21% in 2019 to 40% by 2030. The bulk of this increase will have to come from wind and solar power given the limited potential for new hydro power plants. At the same time, the share of nuclear energy is set to decrease from 71% to 50% (RTE, 2019). In Europe, the share of electricity produced by renewable energy sources is expected to increase from 25% to more than 50% by 2030. The *Clean energy for all Europeans package* includes directives to design future highly renewable electricity markets. The EU Commission essentially proposes an energy-only market design with increased cross-border trade, along with additional market-based incentives for flexibility resources (e.g. energy storage and ancillary service providers, etc.). This design may, unfortunately, fall short in providing the adequate signals to guarantee long-term reliability and efficiency (Newbery et al., 2018).

Contributions and main results. This paper has three main contributions. First, we evaluate the impacts of the pandemic on electricity demand, polluting emissions and generation by technology in France using a machine-learning approach. Second, we combine a structural econometric model and our machine learning predictions to disentangle the respective short-term effects of demand reductions and depressed fuel prices on wholesale prices in the day-ahead market while accounting for endogenous cross-border electricity trade. Third, the estimates are used to assess losses in revenues for suppliers, retailers and grid operators. We conclude the paper with a discussion about market design adjustments for the energy transition.

Our results show that load patterns have been significantly modified and electricity

consumption has reduced by around 12% between March 16, 2020 and May 31, 2020.¹ These demand reductions led to important modifications of the supply mix. Fossil-fuel generation has dropped to historically low levels. Nuclear power plants have been used, jointly with hydro plants, to balance fluctuations in demand and renewable output, thanks to their manoeuvrability. The greater share of low carbon production, together with decreased demand, have driven CO2 emissions down by 28% during this period.² We also remark that load forecast errors have surged for a limited time period after the enactment of containment measures.

The combination of demand reductions, caused by the lockdown, and low commodity prices, led to a reduction of average wholesale electricity prices from 27.6 €/MWh to 15.3 €/MWh. We find that about 50% of this price decrease can be attributed to low fuel prices. The aggregate decrease in day-ahead market value is found at 1.3 billion € (B€), that is -47%. The impacts of the crisis might have been larger for France than for other European countries due to the abundance of low-cost nuclear power and intermittent renewables. As evidence of this claim, we find that net exports have increased by 4.7 TWh (+50%) in total during this period, despite the existence of similar containment measures in neighboring countries.³ A counterfactual scenario under the 2030 renewable target of 40% is considered for France. It reveals that a shock comparable to the pandemic in a highly renewable electricity market would have resulted in even lower prices, down to an average of 8.5 €/MWh, and nearly 50% larger market impacts.

Gross revenue losses for producers and retailers depend on each actor's respective hedging position, which are not observable. The actual impacts lie in-between two hypothetical scenarios. If retailers had their entire expected demand covered by futures contracts, then they would have borne nearly all market losses whereas some suppliers would have made a profit thanks to the crisis. Indeed, hedging acts against price risk but not against volume risk like the large demand reductions observed during the crisis. Reversely, if retailers had no hedging contracts at all, then they would have obtained slightly larger revenues while suppliers would have borne all losses – with the largest

¹Relative changes are calculated with respect to their (estimated) counterfactual level assuming the pandemic had not occurred.

²RTE (2020b) evaluates this reduction at around 35% for April only.

³The market impacts in other systems are beyond the scope of this paper.

impact for the nuclear power producers. In addition, we find that the distribution grid operator has lost above 80 million € (M€) in net revenues, that is roughly 2.5% of the operator’s annual revenues from network charges (CRE, 2020c). The losses for the transmission grid operator are expected to be of similar magnitude. Operators are nevertheless fully compensated for those losses by the regulator (CRE, 2021a).

Not all end-users had unusually low consumption during the spring of 2020. For eastern France, INSEE (2021) finds that commercial and industrial usage reduced by up to 30% during the first lockdown whereas household consumption increased by as much as 10%. A notable fact is that the substantial, though temporary, reductions in wholesale electricity prices did not pass-through to end-users under regulated tariffs. Most consumers pay regulated rates which have increased (on average by +1.5%) following the biannual regulatory hearings in August 2020, January 2021 and August 2021, essentially due to increased transport costs (CRE, 2020b, 2021b).

Finally, we argue that observed prices and market shares by generation technology at the onset of the pandemic are informative about future market outcomes with abundant renewable power, where wholesale prices will fall in a more sustainable way. France’s 2030 renewable objectives are to increase the share of renewable power and to decrease that of nuclear power. Our structural estimates indicate a negative price effect of about -14 €/MWh, which is comparable to the above-mentioned impacts. The incompleteness of current electricity markets, as discussed later on, suggests that those prices may not provide adequate signals about the needs for dispatchable capacity in the future.

Literature. This paper is related to several strands of the literature. First, it contributes to quantify the pandemic’s consequences on energy markets. There are several papers evaluating demand reductions, forecast errors and market impacts in worldwide electricity markets, including Benatia (2020); Benatia and Gingras (2021), Ghiani et al. (2020), Leach, Rivers and Shaffer (2020), Narajewski and Ziel (2020), Percy and Mountain (2020), Ruan et al. (2020), Zhong et al. (2020), and all market impact analyses conducted by system operators (AESO, 2020; ERCOT, 2020; PJM, 2020; NYISO, 2020; RTE, 2020b). Gillingham et al. (2020) discuss how the crisis may have detrimental long-run consequences for clean energy innovation, in particular by postponing renewable

capacity investments. [Wigand et al. \(2020\)](#) show short-term evidence of such delays caused by disruptions in global supply chains, and document a significant decrease in renewable tender auction prices. At the macroeconomic level, [Cicala \(2020\)](#) makes use of measured demand reductions from European electricity systems to quantify the economic consequences of the crisis. We contribute to this literature by providing an in-depth analysis of the pandemic consequences on France’s electricity system, which was one of the main epicenters in Europe.

Second, our empirical framework is based on a machine learning approach to estimate counterfactual outcomes in a micro-economic context. This approach builds upon ideas from [Burlig et al. \(2020\)](#). Related approaches are used, among others, in [Benatia and Gingras \(2021\)](#), [Benatia and Billette de Villemeur \(2021\)](#), [Fabra, Lacuesta and Souza \(2021\)](#), and [Graf, Quaglia and Wolak \(2020\)](#). The latter argues, somehow similarly to the present paper, that realized demand reductions provide insights about the performance of future electricity markets with high penetration of renewables. Using a deep learning approach, they find substantial wholesale price decrease (-45%) in Italy and document an increase of re-dispatch costs. They conclude that the costs of maintaining grid reliability may increase with the share of intermittent renewables. The advantage of using a machine learning approach in our context is to obtain precise counterfactual predictions of hourly demand. Those predictions are in turn used as inputs in a structural model to obtain counterfactual market outcomes, including prices.

Third, our econometric model is based on economic theory. The approach of [Wolfram \(1999\)](#) is used to develop the functional form of the aggregate supply function. In addition, we endogenize cross-border exchanges by estimating the net import supply functions using an approach similar to [Bushnell, Mansur and Saravia \(2008\)](#), [Brown and Olmstead \(2017\)](#) and [Mansur \(2007\)](#). We provide justification for a different set of instrumental variables (IV) than used in the above-mentioned papers: renewable power production. Similar IVs have been used for estimating electricity demand elasticities in [Debia, Benatia and Pineau \(2018\)](#) and [Fabra et al. \(2021\)](#).

Finally, there is a burgeoning literature on electricity market design for highly-renewable markets. We summarize the most important results here, and discuss their implications in light of our analysis in the discussion section.

Electricity markets are subject to multiple market failures. The environmental externality and generators' market power are well-known failures (Fischer and Newell, 2008; Borenstein, Bushnell and Wolak, 2002). In addition, retail and wholesale prices do not fully reflect scarcity. First, retail prices are independent of hourly demand and supply variations. Ambec and Crampes (2012) use a micro-theoretic model to show that energy-only markets⁴ with large shares of intermittent renewables cannot decentralize the optimal energy mix in absence of price-elastic consumers. Second, wholesale prices are state-contingent but remain imperfect scarcity signals. The advocates of the energy-only market design argue that market price caps, used to mitigate abuse of market power, preclude firms to collect scarcity rents to recoup their investment costs, and lead to under-investment in new capacity (Hogan, 2005). This is known as the "missing money problem" (Joskow, 2008). However, Fabra (2018) shows that the existence of market power alone leads to under-investment, even without price caps. She considers, instead, that the root of under-investment is related to missing markets for capacity availability. Indeed, capacity availability generates a positive externality by contributing to system reliability, even when not used for production. In line with Cramton and Stoft (2006), she shows that addressing the missing money problem in the presence of market power requires the introduction of capacity payments unrelated to actual energy production.

Petit, Finon and Janssen (2017) note that energy prices will become more volatile and uncertain as the share of intermittent renewables increases, which will exacerbate issues related to under-investment, even in a perfect competition framework. They contribute to this literature by showing that capacity mechanisms are more efficient than scarcity pricing to reach similar levels of reliability, if investors are risk-averse. Relatedly, Levin and Botterud (2015) demonstrate that capacity payments or regulated scarcity tariffs, established to improve the scarcity signal of energy prices when demand exceeds supply, will be increasingly needed to safeguard supply security. However, the design of capacity payments requires careful considerations to achieve efficient and reliable systems (Byers, Levin and Botterud, 2018).

⁴In energy-only markets, suppliers earn revenues solely by selling their energy production to the wholesale market. In alternative market designs, suppliers can obtain additional remunerations by providing additional services, such as for grid reliability (e.g. capacity availability or ancillary services), which can be market-based or sold at regulated tariffs.

In the face of ambitious renewable objectives, there are other missing markets. [Henriot and Glachant \(2013\)](#) argue that the market design should reflect the changes brought by renewable energy deployment: lower predictability, increased short-time variations and greater spatial granularity. [Newbery et al. \(2018\)](#) consider that the associated externalities should be addressed as directly as possible: by introducing more granular prices through time and space, through locational prices and additional markets with different delivery horizons. [Leslie et al. \(2020\)](#) recommend similar adjustments, and argue that those would be sufficient for the energy-only market design to deliver efficient and reliable systems, assuming market power mitigation mechanisms are effective.

The remainder of the paper is organized as follows. Section 2 presents the French electricity sector and estimates the pandemic’s impacts on demand, forecast errors, CO2 emissions and generation by technology. Section 3 evaluates the market impacts and studies a variety of counterfactual scenarios. Section 4 discusses implications for the energy transition. Section 5 concludes the paper.

2 The French electricity sector and the pandemic

2.1 The French electricity market

The French electricity industry is subject to market competition in the generation and retail segments since the introduction of the *First* and *Second Energy Packages* of the European Union in 1996 and 2000.

The transmission and distribution segments are regulated monopolies. *Réseau de Transport d’Électricité* (RTE) is the legal entity in charge of grid reliability, system operations and the transmission network. Its counterpart for the distribution network is *Enedis*, which is in charge of the delivery to end-users (industrial, commercial and residential consumers). Their remuneration is based on a two-part tariff paid by market participants to access grid infrastructures.

The generation segment is dominated by the historical producer, *Électricité de France* (EDF), which is largely owned by the French State (84%). The company operates 90.5 GW of installed capacity in France, including the entire nuclear fleet and

around 75% of the total hydro capacity. It was formerly a vertically-integrated public monopoly with RTE and Enedis. As a dominant firm, EDF is regulated in two main ways. First, the company is contractually committed to carry out a “public service mission” for the French State for an unlimited period. Second, electricity retailers have a regulated access to the historical nuclear production of EDF through *Accès Régulé à l’Electricité Nucléaire Historique* (ARENH) in order to promote upstream and downstream competition. ARENH gives access to retailers to buy electricity generated by EDF’s nuclear power plants at a regulated access tariff of 42 €/MWh for up to a total of 100 TWh per year. The remainder, approximately 280 TWh per year of nuclear power, is remunerated at wholesale (spot and forward) prices. ARENH rights are attributed to retailers based on their respective customer base. As will be discussed later, the low prices caused by the lockdown in France have led some retailers to renege on their ARENH contracts, by arguing force majeure.

The rest of the generation segment is divided into two medium-sized producers: Engie (25% of French hydro capacity and some gas turbines) and Gazel Energy (2 coal-fired power plants and some renewables), and a fringe of independent producers which operates around 5% of domestic production, mainly from renewables. Remunerations for renewable power plants are guaranteed through feed-in contracts which conditions vary across technologies and commissioning dates. Wholesale suppliers are remunerated from the wholesale market and long-term contract arrangements.⁵ This market is part of the European Power Exchange. It is organized as a sequential multi-unit auction where retailers buy wholesale energy from electricity suppliers. The day-ahead (or spot) market takes place one day prior to physical production and is used to allocate resources efficiently based on demand forecasts for the following day. The real-time (or intraday) market is operated near real-time and is essentially used to balance forecast errors and other contingencies.

In 2019, 71% of domestic electricity production came from nuclear power generators, 10% from hydro plants, 11% from other renewables (wind, solar and biomass), and only 8% from fossil fuel plants (natural gas, oil and coal). In addition, the French electricity system is interconnected with 33 European countries through 6 main interfaces (Belgium, Germany, Italy, Spain, Switzerland, and the United Kingdom). France

⁵Note that a capacity market was introduced in 2017.

is a net exporter of electricity. 473 TWh of electricity was consumed in the country in 2019 while 84 TWh was exported and 28 TWh were imported – mostly from Germany (50%) during cold winter days (RTE, 2019).

Finally, the retail segment of the industry is composed of 27 actors. Historical suppliers (Engie and EDF) covered 75% of residential demand and 55% of non-residential consumption as of March 2020. The remainder was supplied by alternative retailers (CRE, 2020*d*). 32% of the total power consumption is still under regulated tariffs accessible to consumers with less than 36 kVA. One third of the residential tariffs cover grid operation costs, one third is for energy production, and the rest covers taxes and subsidies to renewable energy.

2.2 Counterfactual demand, generation and emissions

In this section, we follow an approach similar to Benatia and Gingras (2021) to estimate the counterfactual electricity demand, emissions and generation by technology, at the *hourly* level, assuming the COVID-19 crisis had not happened. These counterfactual estimates will allow us to evaluate the hourly market impacts and revenues losses caused by the crisis once combined with the structural model in Section 3. More standard regression methods would unfortunately lead to much less precise counterfactual predictions.

The analysis focuses on the period spanning from March 2020 to May 2020, and uses data from January 2014 to May 2021. The data has been collected from ENTSO-E’s transparency platform,⁶ RTE’s Éco2mix data portal,⁷ and weather variables have been web-scraped from Reliable Prognosis.⁸ Table 1 shows means and standard deviations (in parentheses) for the main (hourly) variables of interest: actual demand (GW), forecast errors in absolute terms (MW), day-ahead price (€/MWh), and CO2 emissions (kilotons/hour). The complete dataset and pre-processing steps are detailed in Appendix A.

⁶<https://transparency.entsoe.eu/dashboard/show>.

⁷<https://data.rte-france.com/>.

⁸<https://rp5.ru>.

Table 1: Summary statistics (hourly values)

Year	Actual load	Abs. F. error	DA price	Emissions
2014	52.78 (10.84)	763.7 (631.1)	– –	2.20 (1.27)
2015	54.02 (11.60)	765.0 (677.8)	38.45 (12.99)	2.59 (1.58)
2016	54.68 (11.51)	801.0 (665.4)	36.70 (24.44)	3.15 (1.68)
2017	54.69 (12.53)	815.4 (710.4)	44.96 (20.23)	3.08 (1.87)
2018	54.28 (12.20)	858.0 (727.4)	50.20 (18.45)	2.09 (1.42)
2019	53.72 (11.53)	803.7 (681.0)	39.45 (14.02)	2.00 (1.32)
2020	50.73 (10.88)	811.2 (784.6)	32.21 (16.10)	1.76 (0.99)

Notes: This table shows (hourly) means and standard deviations (in parentheses) for realized load (in GW), forecast errors in absolute terms (in MW), day-ahead price (in €/MWh), and CO2 emissions (in kilotons/h) for France. Note that price data for 2014 is missing.

Machine learning-based counterfactual predictions. Our methodology consists in training a neural network capable of predicting the hourly electricity demand under business-as-usual conditions, but without relying on recent realizations or other variables which may have been affected by the crisis. The objective is to construct a credible counterfactual demand assuming containment measures had not been implemented. It must be clear that we do not propose a forecasting model. Instead, we focus on the discrepancies between actual realizations and counterfactual estimates which we interpret as the causal effects of the crisis on electricity demand.

This causal interpretation relies on two main assumptions. First, demand is perfectly price-inelastic. This assumption is standard for electricity demand as it is largely considered as highly price-inelastic, and it allows to use machine learning prediction techniques to predict the counterfactual demand function without addressing the price sensitivity of demand and subsequent endogeneity issues. Second, there is no omitted variable correlated with both the timing of the crisis and variations in past, contemporaneous, or future electricity demand. It implies that, for instance, there was no

anticipatory changes in behavior. The sanitary crisis being exogenous to the economy, this assumption should be satisfied unless important predictors, such as weather variables, are omitted from the model, or if observations too close to the lockdown period are included in the estimation sample. For that reason, the prediction model will be trained using the 52704 hourly observations from January 1st, 2014 to February 28th, 2020.

The neural network model, hereafter denoted FNet, has a set of 188 predictors, all exogenous to the crisis, including:

- 95 hourly weather variables: dew point temperature, humidity, pressure, precipitation, temperature, visibility, wind gusts, and wind speed measured near the largest airports located in Bordeaux, Brest, Lille, Lyon, Lyon (Satolas), Marseille, Montpellier, Paris (Orly), Paris (CDG), Perpignan, Rennes, Strasbourg, Toulouse.⁹
- 46 daily weather variables: minimum and maximum temperature (26 variables) and dew point temperature (20 variables) measured at airports.
- 47 time variables: binary variables for hours of the day, days of the week, months of the year, a linear time trend and bank holidays occurring between March to May.¹⁰

The algorithm is a two-layer feed-forward network with a single-hidden layer and 5 neurons. We minimize the risks of overfitting in two ways. First, entire days (of 24 hourly observations) are randomly attributed to two samples: a fitting set (90%), and a testing set (10%). This step is useful because hourly observations within a day can be very similar hence (hourly) random splitting could lead to overfitting. Second, we implement a cross-fitting strategy (Jacob, 2020). The fitting set is split randomly in the same way into 10 even folds, and the model is trained 10 times using each fold sequentially as the validation set and the 9 others as the training set.¹¹ The model's

⁹Note that some weather variables were not included because they had too many missing values.

¹⁰Included holidays are those taking place between March and June: Ascension, Fête du travail, Armistice, Pâques, Pentecôte, and Fête de la musique. All other observations associated with holidays (e.g. Christmas, New Year's eve, etc.) are dropped from the sample for a total of 9 days per year.

¹¹It is trained by minimizing the Mean-Squared-Errors (MSE) criterion using the Levenberg-Marquardt backpropagation algorithm in MATLAB.

predictions correspond to the median over the 10 separate models, and its performance is evaluated on the testing set which is never used for training or validation. The algorithm is finally used to predict hourly demand from March 1st, 2020 to May 31st, 2020.

The same approach is used to predict counterfactual hourly CO2 emissions, generation from thermal plants fueled by oil, coal, gas and biomass, and nuclear generation. The data covers a shorter period from January 1st, 2018 to May 31st, 2020. Generation and emissions largely depend on capacity availability and cross-border exchanges, hence we include additional variables: wind and solar power forecasts in Belgium, France, Germany, Switzerland, Spain, and United Kingdom (15 variables), actual wind and solar generation in France (2 variables), cross-border transfer capacities with adjacent countries (8 variables), planned and forced outages at thermal, hydro and nuclear power plants in France (4 variables), and temperature measured at airports in trading countries (13 variables). In addition, we use the same hourly weather variables (95 variables) and time variables (47 variables) for France but we discard daily min and max values. The network structure, the training algorithm and the sample-splitting algorithm remain unchanged. The model includes a total of 184 variables and the sample is relatively smaller with 16656 observations.

Predictive performance and counterfactuals. The predictive performance of our algorithm (FNet) is described in Table 2 for demand and emissions. Results for generation by technology are presented in Appendix B.

For demand, the performance of FNet fairs well with respect to that of RTE’s forecasting algorithm, in terms of both mean absolute (relative) prediction errors (MAPE) and root-mean-squared prediction errors (RMSE).¹² During the first two weeks before the lockdown on March 16th, the two algorithms perform equivalently than for the test set. For example, FNet exhibits a 1.6% and 2.7% MAPE, which are of similar magnitudes than the 2.3% MAPE for the test set. However, the MAPE surges to 15.3% for FNet and 5% for RTE right after the lockdown came into force.

¹²Recall that FNet is not a forecasting algorithm. It is trained using observations prior to March 1st, 2020 and predicted for March, April and May 2020. It does not use lagged realizations of the load but actual weather realizations to form predictions. The comparison to RTE’s algorithm is only useful to get a benchmark for the distribution of errors.

Table 2: Predictive performance

	Demand				Emissions	
	MAPE (%)		RMSE		MAPE (%)	RMSE
	FNet	RTE	FNet	RTE	FNet	FNet
Test set	2.3	1.5	1.66	1.05	20.2	0.46
03/02-03/08	1.6	1.3	1.20	1.02	20.0	0.69
03/09-03/15	2.7	1.5	1.94	1.06	16.2	0.45
03/16-03/22	15.3	5.0	7.90	3.60	42.5	0.66
03/23-03/29	17.7	3.1	9.42	1.96	86.8	1.27
03/30-04/05	11.4	2.0	6.64	1.53	67.4	0.80
04/06-04/12	14.7	1.9	6.56	1.03	104.1	0.53
04/13-04/19	17.9	2.9	7.53	1.49	73.6	0.39
04/20-04/26	14.8	1.5	6.31	0.79	71.1	0.40
04/27-05/04	14.3	1.4	6.64	0.75	49.9	0.32
05/05-05/10	12.0	1.9	5.00	0.97	54.0	0.37
05/11-05/18	9.2	1.7	4.56	0.96	38.1	0.28
05/19-05/24	9.7	1.7	4.09	0.84	27.2	0.28
05/25-05/31	7.6	1.9	3.24	0.94	25.7	0.31

Notes: This table shows the performance of our prediction model (FNet) and RTE’s forecasting algorithm on the test set and for all weeks from March to May 2020. Figures B.1 and B.2 in Appendix B compares actual and counterfactual demand/emissions distributions.

The forecasting errors of RTE’s algorithm are shown in Figure 1 along with FNet’s prediction errors.¹³ RTE’s errors reduced down to usual levels within 5 weeks, and the MAPE remained well below 5%, which is evidence that RTE has adapted quickly to the structural break created by containment measures, unlike other electricity system operators like New York (Benatia and Gingras, 2021).

¹³Plotted values are moving-averages over 48 hours.

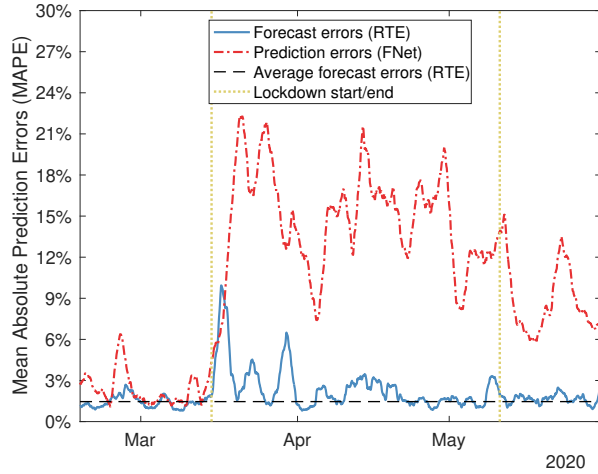
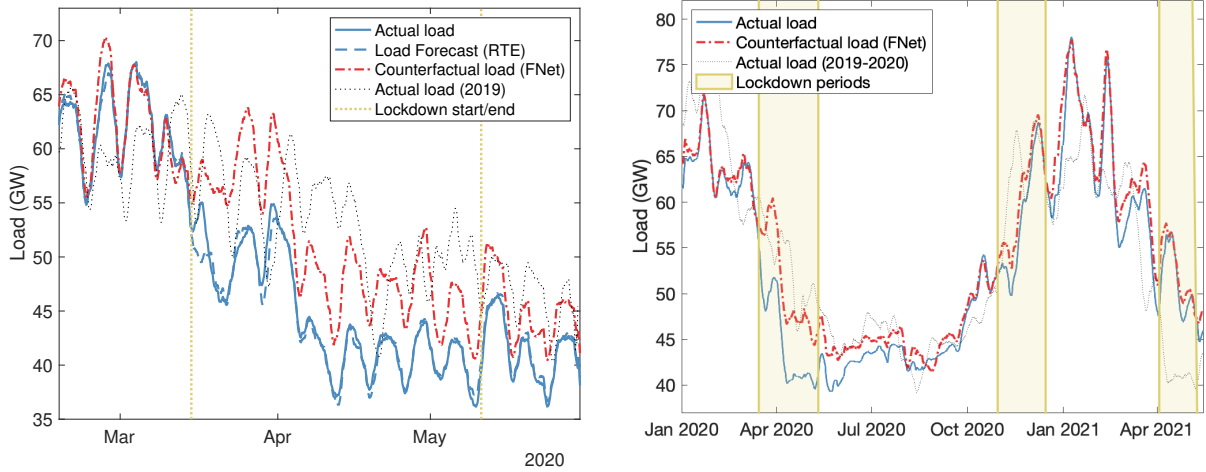


Figure 1: Mean Absolute Prediction Errors (%)

Although forecast errors quickly attenuated, demand remained away from its usual levels. The MAPE for FNet was much larger than 5% from March to May, and the predicted counterfactual demand under business-as-usual conditions is found consistently larger than realized levels. Figure 2a plots 48-hours moving-averages of actual load and predictions from mid-February 2020 to May 2020, and Figure 2b shows moving-averages over 7 days from January 2020 to May 2021. We find that the demand reductions caused by the pandemic were the largest during the first lockdown episode, probably because it was tied to more drastic sanitary measures and police controls than the subsequent episodes.



(a) Feb 18, 2020 to May 31, 2020

(b) Jan 2020 to May 2021

Figure 2: Actual load and predictions

The performance of FNet to predict CO₂ emissions is not as good. Nevertheless, we observe a sharp increase in MAPE from about 20% on the test set to above 40% during the period under study. Figure 3 shows the extent to which the crisis caused a reduction in CO₂ emissions (48-hours moving-average). The majority of emissions reductions seem to have occurred during the first weeks of the lockdown.

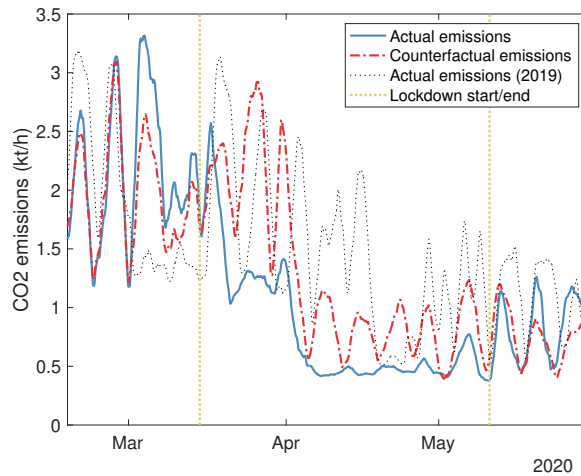


Figure 3: CO₂ emissions

Finally, the counterfactual generations by technology (48-hours moving-average)

are reported in Figure 4. The test set yields a MAPE 14% and 2.3% for thermal and nuclear generation, respectively.¹⁴ We find systematic downward deviations of thermal and nuclear generations after the lockdown was enacted. Thermal production was considerably reduced from mid-March to early May. Interestingly, its level was kept nearly constant at record lows because of the small residual demand. The equilibrium between supply and demand was instead assured by the load-following capabilities of nuclear and hydro plants. Figure 4b shows that the fluctuations of nuclear generation have been unusually large during this period.

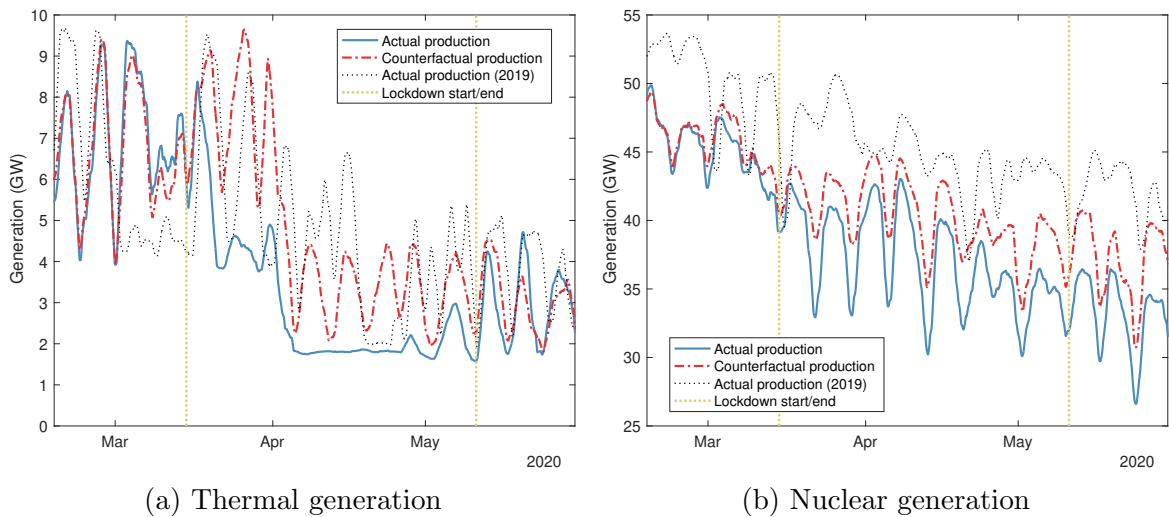


Figure 4: Actual and predicted generation (FNET)

Reduced demand and new load patterns. Weekly demand and emissions reductions during the lockdown were substantial. They are estimated as the aggregated differences by week between realized demand and its counterfactual had the crisis not occurred. Table B.2 in Appendix B the weekly estimates and standard errors (in parentheses). The largest reduction in electricity consumption occurred during the first and second weeks of the lockdown with -1228 GWh (-12.9%) and -1502 GWh (15%) of weekly demand. At the same time, emissions dropped by 62 and 179 kilotons (46%). From March 16th to May 31st, consumption was 10.6 TWh smaller than usual, that is about 12%, and emissions have been 28% smaller. For comparison, [Benatia and](#)

¹⁴Density plots of actual and predicted output are shown in Figures B.3 and B.4 in Appendix B.

Gingras (2021) finds that demand had reduced by about 8% over the same period in the state of New York, the initial COVID-19 epicenter in North America.

As teleworking became the new normal and public transportation was shutdown, new daily load patterns have emerged. Table 3 reports the average estimates of relative demand reduction by time of the day from March 23 to May 4, 2020. In relative terms, the largest consumption reduction occurs during the morning peak with -18.1% during weekdays and -14.1% during week-ends.

Table 3: Average daily load reductions

	Night 10PM-6AM	Morning 6AM-12PM	Afternoon 12PM-6PM	Evening 6PM-10PM
Weekdays (%)	-10.8 (1.1)	-18.1 (1.1)	-13.9 (0.9)	-13.4 (1.0)
Week-ends (%)	-9.2 (1.2)	-14.1 (1.4)	-10.0 (1.2)	-9.7 (1.2)

Notes: This table shows average load reductions in relative terms caused by lockdown measures, separately for weekdays and weekends. Standard errors, taking account of the correlation of hourly errors within a day, are reported in parentheses.

The consumption timing has also changed. Figures 5a and 5b show the average hourly loads (actual and counterfactual) for weekdays and week-ends. Lockdown measures shaved the morning and evening peaks during weekdays. During week-ends, morning consumption increased more sharply than usual, suggesting that sheltering measures have affected sleeping and consumption patterns.

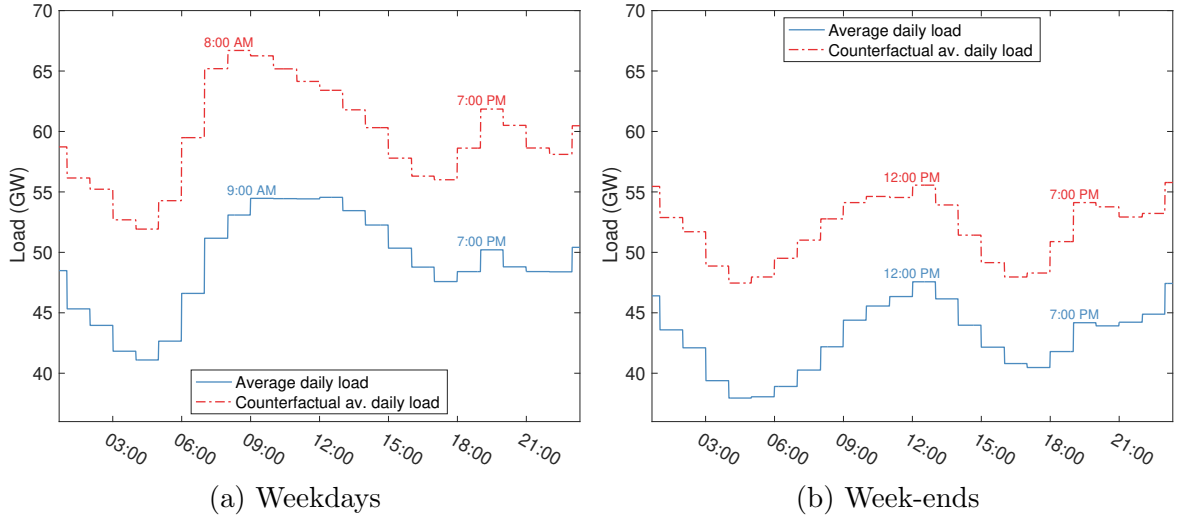


Figure 5: Daily load patterns

3 Measuring market impacts

In this section, we develop a methodology to estimate the impacts of demand reductions and natural gas price reductions on the day-ahead market. This approach follows similar steps than [Benatia and Gingras \(2021\)](#) for New York. Our principal contribution is that we fully address the endogeneity of prices by accounting for endogeneous cross-border exchanges with adjacent electricity systems. Market-coupling is a key component of European electricity markets as prices are settled altogether in a common dispatch algorithm. It is therefore crucial to account for cross-border exchanges.

Summary statistics of the main variables used in this analysis are presented in [Table 4](#). In this section, we separately estimate the net import function and domestic supply function for France using the pre-pandemic sample spanning from January 2018 to February 2020.

Table 4: Summary statistics (Jan 2018 to Feb 2020)

	Price	NetImp	NatGas	Q	N	Wind	Out.
Mean	43.96	-7.05	17.52	12.35	44.50	3.62	1.55
Std	17.21	4.10	6.00	5.23	6.21	2.71	1.42
1st percentile	6.02	-14.70	8.63	2.59	32.51	0.52	0.00
99th percentile	88.18	4.36	29.53	25.99	57.16	12.10	5.73

Notes: This table shows (hourly) means, standard deviations, 99th percentiles and 1st percentiles of the Day-ahead price (€/MWh), net imports (GW), natural gas price (€/MWh), domestic production net of wind, solar and nuclear production denoted by Q (GW), nuclear power production denoted by N (GW), domestic wind power forecast (GW), and nuclear capacity under forced outage (GW).

3.1 Net import curve

The European electricity market is a zonal market with multiple trading zones, each covering an entire country or spreading over a larger region, and with limited exchange capacities between zones. The French electricity system consists in a single trading zone interconnected to the rest of the European system through interfaces with Belgium, Germany, Italy, Spain, Switzerland, and the United Kingdom.

We aim at estimating the net import function, that is how net imports of electricity in France vary with the local day-ahead price. In order to simplify the analysis, we focus on the aggregate net imports across all six interfaces. Our methodology is inspired by previous papers in the economics literature, e.g. [Brown and Olmstead \(2017\)](#).

Specification. Let I_t be the net imports at time t , P_t be the day-ahead (DA) price in France, and Z_t be exogenous covariates in other countries. In a general equilibrium model, I_t results from a system of price equations subject to constraints on exchange capacities. We follow a partial equilibrium approach by focusing only on France. We specify the net import curve as the linear function of prices given by

$$I_t = \beta_I P_t + \gamma_I Z_t + \varepsilon_t, \quad (1)$$

where ε_t is a mean-zero error term, and the parameters of interest are β_I and γ_I .

β_I captures the effect of an increase in the local spot price (i.e. in France) on net

imports. It corresponds to the slope of the net imports curve. We expect this parameter to be positive: as the local price increases it is more likely that foreign countries find profitable to export to France. Reversely, as the price decreases, other countries may find profitable to import electricity produced in France, which would increase exports (hence reduce net imports) in France.

$\gamma_I Z_t$ measures the extent to which other countries are willing to export to France, and France is willing to import, accounting only for foreign demand and supply conditions and independently of the French price. It corresponds to the intercept of the net imports curve. This term is important to obtain credible counterfactual prices because other countries have also been affected by the crisis. More specifically, their demand for electricity produced in France may have differed from business-as-usual not only because of the effect of the crisis on the French price, but also due to its effects on their local demand.

The variables in Z_t include: 7 temperature variables measured at airports in Barcelona, Brussels, Frankfurt, Geneva, London, Paris (CDG) and Turin; 14 variables for renewable power forecasts (solar, onshore wind and offshore wind) in Belgium, Germany, Spain, Switzerland and the United Kingdom, and solar power forecast in France;¹⁵ 8 variables measuring expected interconnection capacity limits with Italy, Spain, Switzerland and the United Kingdom (in both directions).¹⁶ In addition, we include a set of 57 time dummies for hours of the day, days of the week, months, bank holidays in France and a linear time trend, leading to a total of 87 control variables in addition to the endogenous price variable.

Identification. The identification of β_I and γ_I requires that the error ε_t be uncorrelated with P_t and Z_t . The former condition is violated since P_t is simultaneously determined with I_t in equilibrium. To solve this endogeneity problem, we pursue an instrumental variable (IV) approach. A valid IV affects I_t only through P_t , the local price. We opt for wind power forecast in France which affects the (day-ahead) price in France through the merit-order effect, but does not affect (or is not correlated with) demand or supply conditions in other countries – as long as one controls for foreign re-

¹⁵Data on renewable forecasts for Italy has too many missing in our sample.

¹⁶This information is not available for Belgium and Germany because there is no direct current interconnection.

newable power production and weather conditions. We consider it to be more suitable than local weather conditions for instrumentation because temperature, for example, is likely to be strongly correlated across countries. Thus, using local weather as an instrument while controlling for foreign weather conditions would leave little identifying variations. In comparison, domestic wind power production is less predictable and tends to be much less correlated to foreign weather and renewable outputs.

Estimation. Model (1) is estimated using least-squares and two-step (linear) IV-GMM on hourly observations from January 1, 2018 to February 28, 2020. The weighting matrix used for those estimations corresponds to the Newey-West covariance matrix robust to arbitrary autocorrelation and heteroskedasticity with automated lag selection (14 hourly lags).

Table 5 shows the estimation results of three regressions. The first column reports the estimates of (1) without correcting for the endogeneity of P_t . The second column shows the estimates of the first-stage, that is the regression of P_t onto wind power forecast in France $Wind.FR$ and Z_t . The third column reports the coefficients of (1) while using $Wind.FR$ as an IV for P_t . We show only the 10 most significant coefficients associated with exogenous (and non-deterministic) covariates, as measured by their t-statistic from the IV regression.

The IV regressions yields a significantly larger coefficient for P_t than least-squares, revealing a downward endogeneity bias. The first-stage results validate $Wind.FR$ as a good IV, in the sense that it is strongly correlated with P_t , conditionally on covariates. Its coefficient is negative, which is in line with the well-known result that wind power tends to depreciate prices.¹⁷

The most significant covariates, neglecting time controls, are transmission capacities with the United Kingdom and Italy, and renewable power production in foreign countries. For instance, more solar power generation in Germany is associated with larger net imports in France. Remark that we do not need to identify these coefficients individually because we only care about the (aggregate) intercept term $\gamma_I Z_t$.

¹⁷Formal hypothesis testing based on the generalized rank tests of Kleibergen and Paap (2006) yields a p-value below 0.001 against the null hypothesis of under-identification and a maximum Wald test size distortion caused by weak identification between 15% and 20% (F-test = 8.1, 20% quantile = 6.7).

Table 5: Estimates of the net import function

	(LS) Net Imports	(FS) Price	(IV) Net Imports
<i>Price (Endog.)</i>	0.09 (0.01)		0.77 (0.25)
<i>Wind.FR (IV)</i>		-0.48 (0.16)	
<i>TC.FR.UK</i>	0.90 (0.16)	-0.88 (0.33)	1.41 (0.32)
<i>TC.UK.FR</i>	-1.24 (0.15)	-0.24 (0.28)	-0.98 (0.23)
<i>TC.FR.IT</i>	-0.54 (0.08)	0.80 (0.31)	-1.09 (0.31)
<i>Solar.DE</i>	1.29 (0.19)	-0.79 (0.68)	1.83 (0.53)
<i>Solar.BE</i>	0.72 (0.15)	-1.45 (0.51)	1.72 (0.51)
<i>Solar.FR</i>	-1.03 (0.20)	0.90 (0.66)	-1.81 (0.55)
<i>Solar.CH</i>	0.57 (0.14)	-1.55 (0.50)	1.64 (0.52)
<i>WindOff.UK</i>	0.59 (0.14)	-4.76 (0.53)	3.86 (1.24)
<i>WindOns.ES</i>	0.28 (0.07)	-1.25 (0.29)	1.30 (0.43)
<i>WindOns.DE</i>	0.73 (0.10)	-0.36 (0.40)	0.94 (0.31)
<i>WindOns.UK</i>	-0.28 (0.09)	2.78 (0.34)	-2.19 (0.73)
Dummies	Hours/Weekdays/Months/Years/Holidays		
# Covariates	88	88	88
Obs	18818	18818	18818
RMSE	2.5	9.9	7.3

Notes: This table reports regression results for the net import function specified in (1) using ordinary least-squares (LS), the first-stage of P_t onto *Wind.FR* as IV (FS) and linear IV-GMM of (1) (IV). Standard errors are computed using the Newey-West covariance estimator with automated lag selection. They are robust to arbitrary heteroskedasticity and autocorrelation. Covariates include weather variables, transfer capacities with foreign countries, renewable production forecasts by trading country, and dummies for hours of the day, days of the week, months, bank holidays in France and a linear time trend. The last row reports the root-mean-squared-error (RMSE).

3.2 Day-ahead market

The day-ahead prices across Europe are computed by a single algorithm maximizing the overall welfare.¹⁸ The algorithm, called “Euphemia”, calculates prices for each zone, for each hour of the following day, as well as implicitly allocating auction-based-cross-border capacities. The prevailing hourly price, for a given zone, corresponds approximately to the price bid of the generation unit called into operation with the highest-accepted bid price. Under perfect competition, this price coincides with the unit’s marginal cost of production. In practice, price bids include mark-ups or mark-downs depending on the firm’s forward position and ability to exercise market power.

Let us specify the aggregate supply as

$$P_t = \beta_Q Q_t + \beta_N N_t + \delta N G_t + \rho Z_t + \xi_t. \quad (2)$$

which is a linear function of thermal and hydro production Q_t , nuclear production N_t , natural gas prices NG_t , additional covariates Z_t , and a zero-mean error term ξ_t . This specification corresponds to a piecewise linear supply function with two technologies: nuclear plants N_t , and thermal and hydro plants $Q_t = D_t - N_t - I_t - R_t$, with D_t being demand, I_t being net imports and R_t being domestic renewable output. The exogenous covariates Z_t are the same as in (1).

Model (2) admits a structural interpretation following Wolfram (1999). The average of the first-order condition of firm-level profit-maximization problems across firms yields the industry-level supply relationship $P_t = \alpha MC$ where MC denote the industry-level marginal cost function and α is a behavioral parameter depending on the degree of competition. A piecewise linear specification for MC directly yields (2), where parameters implicitly depend on the degree of competition. We remain agnostic about the degree of competition, which does not matter for this paper’s main objective, and thereby neglect the identification of α .

Identification. The identification of β_Q and β_N suffers from the simultaneity of P_t with Q_t and N_t . On the one hand, the realized price depends on the respective

¹⁸The public description of the Single Price Coupling Algorithm is available at <http://www.nemo-committee.eu/publications>.

production of Q_t and N_t , and the volume of net imports I_t through the equilibrium mechanism: an increase of production implies a larger price. On the other hand, strategic players form expectations about the price upon choosing their bids. Thus Q_t and N_t are endogenous if market bids vary with expectations about the equilibrium (day-ahead) price.

We instrument Q_t and N_t with domestic wind power forecasts (*Wind.FR*) and nuclear capacity under forced outages (*Outages*). Both are considered as valid IV because they affect the equilibrium price only indirectly through their effects on conventional generation from thermal, hydro and nuclear plants. More specifically, wind power generation depends on random weather realizations and is produced at near-zero marginal cost and benefits from priority dispatch. Therefore an increase in (hourly) wind power production leads to an exogenous reduction of conventional generation in equilibrium, everything else kept constant. Similarly, forced outages of nuclear plant are caused by unexpected exogenous technological factors. These outages reduce the availability of domestic nuclear capacity and therefore result in an increased price due to a temporarily lower nuclear production. Unlike planned nuclear outages, forced outages provide more exogenous sources of variations because they have limited effects on market strategies due to their unexpected nature.

Estimation. Model (2) is estimated using the same approach as model (1). Table 6 shows the estimation results of five regressions. The first column (LS) neglects the endogeneity issue. The second column (FS1) shows the estimates of the first-stage for Q_t . The third column (FS2) shows the estimates of the first-stage for N_t . The fourth column (IV1) reports the coefficients of (2) when accounting for the endogeneity of Q_t but not that of N_t . The last column (IV2) instruments for both Q_t and N_t . We report only the 8 most significant coefficients associated with exogenous (non-deterministic) covariates, as measured by their t-statistic from the last regression (IV2).

Table 6: Regression results DAM

	(LS) Price	(FS1) Q	(FS2) N	(IV1) Price	(IV2) Price
Q_t (<i>End.</i>)	1.07 (0.08)			2.33 (0.36)	2.24 (0.30)
N_t (<i>End.</i>)	0.77 (0.06)			1.08 (0.11)	1.19 (0.25)
<i>Wind.FR</i> (<i>IV</i>)		-0.32 (0.04)	-0.18 (0.05)		
<i>Outages</i> (<i>IV</i>)		0.35 (0.03)	-0.55 (0.04)		
<i>Nat. Gas Price</i>	2.04 (0.09)	-0.07 (0.03)	0.12 (0.02)	2.10 (0.12)	2.08 (0.11)
<i>WindOff.BE</i>	-2.34 (0.50)	-0.17 (0.14)	-0.36 (0.17)	-2.07 (0.52)	-2.03 (0.51)
<i>TC.FR.IT</i>	-1.21 (0.34)	0.40 (0.11)	-0.55 (0.13)	-1.59 (0.40)	-1.47 (0.42)
<i>TC.UK.FR</i>	0.70 (0.23)	-0.30 (0.07)	0.44 (0.08)	0.97 (0.27)	0.89 (0.28)
<i>TC.FR.UK</i>	-0.46 (0.20)	0.28 (0.05)	-0.21 (0.07)	-0.78 (0.24)	-0.73 (0.23)
<i>Solar.UK</i>	-0.77 (0.18)	-0.02 (0.06)	0.07 (0.08)	-0.47 (0.20)	-0.48 (0.20)
<i>TC.ES.FR</i>	-0.65 (0.18)	0.10 (0.06)	-0.15 (0.07)	-0.49 (0.20)	-0.47 (0.20)
<i>WindOns.DE</i>	-1.18 (0.36)	-0.13 (0.12)	-0.34 (0.13)	-0.88 (0.40)	-0.86 (0.40)
<i>WindOns.ES</i>	-2.12 (0.30)	-0.26 (0.12)	-0.04 (0.14)	-0.86 (0.44)	-0.88 (0.42)
Dummies	Hours/Weekdays/Months/Years/Holidays				
# Covariates	90	90	90	90	90
Obs	18818	18818	18818	18818	18818
RMSE	7.5	2.1	2.3	7.9	7.9

Notes: This table reports regression results for the supply function specified in (2) using ordinary least-squares (LS), first-stages of Q_t (FS1) and N_t (FS2), linear IV-GMM of (2) where only Q_t is instrumented (IV1), and where both Q_t and N_t are instrumented (IV2). Standard errors are computed using the Newey-West covariance estimator with automated lag selection. They are robust to arbitrary heteroskedasticity and autocorrelation. Covariates include weather variables, transfer capacities with foreign countries, renewable production forecasts by trading country, and dummies for hours of the day, days of the week, months, bank holidays in France and a linear time trend. The last row reports the root-mean-squared-error (RMSE).

The first-stage regressions (FS1) and (FS2) confirm that both Q_t and N_t are substituted by wind power. Forced outages of nuclear capacity reduces nuclear production but increases thermal and hydro production. All four coefficients are statistically significant and have the expected signs.¹⁹

The estimated coefficients for Q_t and N_t in (IV1) and (IV2) are not statistically different. This result suggests that nuclear production is not endogenous to the day-ahead price, unlike Q_t , implying that the nuclear producer (EDF) is not acting strategically in the day-ahead market. It might be explained by EDF's tendency to sell the vast majority of its nuclear production through forward contracts.

Our preferred estimates are given by (IV2). The coefficients for Q_t and N_t in the IV regression are larger than when neglecting endogeneity, although this difference is not statistically significant for N_t . Furthermore, the coefficient associated with N_t is smaller than that of Q_t . Nuclear plants have typically smaller marginal costs than other conventional plants. The estimated aggregate supply function hence becomes steeper as domestic generation increases and more expensive units enter into production. Natural gas prices also turn out to have a significantly positive effect on prices by shifting the supply curve upwards.

Finally, several control variables measuring transmission capacities and renewable forecasts in foreign countries are found to be significantly correlated with prices. For instance, wind power production in Belgium is negatively correlated with the domestic price, probably because it decreases domestic production by increasing net imports, everything else kept constant. Remark that identifying those parameters is unnecessary for our analysis.

3.3 Counterfactual scenarios

In this section, we investigate 4 counterfactual scenarios. The first 3 scenarios are focused on the short-run effects of the crisis. Scenario 1 evaluates the impacts of the electricity demand reductions. Scenario 2 measures the impacts of low natural gas prices. Scenario 3 combines the above two effects into the main counterfactual of

¹⁹Formal hypothesis testing based on the generalized rank tests of [Kleibergen and Paap \(2006\)](#) yields a p-value below 0.0001 against the null hypothesis of under-identification and a maximum Wald test size distortion caused by weak identification below 10% (F-test = 71.6, 10% quantile = 7.03).

interest. Scenario 4 is used to draw insights about the sustainability of the current industry in the longer run by assuming that the pandemic had occurred in the highly-renewable electricity system planned for 2030.

For clarity, we use the standard notations of the potential outcomes framework, where variables indexed by (1) have received the treatment and those indexed by (0) have not. Note that the “treatment” under study varies across scenarios.

Counterfactual scenario 1 (CF1): No Demand Reductions. First, we study the impact of demand reductions using our estimates of the counterfactual demand obtained in Section 2. The counterfactual day-ahead price $\hat{P}_t(0)$ assuming that demand reductions due to containment measures had not occurred is given by

$$\hat{P}_t(0) = P_t(1) + \hat{\beta}_Q [\hat{Q}_t(0) - Q_t(1)] + \hat{\beta}_N [\hat{N}_t(0) - N_t(1)], \quad (3)$$

where $P_t(1)$, $Q_t(1)$, and $N_t(1)$ are the observed realizations during the pandemic and

$$\hat{Q}_t(0) = \hat{D}_t(0) - \hat{N}_t(0) - \hat{I}_t(0) - R_t, \quad (4)$$

is the counterfactual generation from thermal and hydro plants given: 1. the predicted counterfactual demand $\hat{D}_t(0)$, 2. the predicted counterfactual nuclear production $\hat{N}_t(0)$, and 3. the endogenous net imports as defined by

$$\hat{I}_t(0) = \hat{\beta}_I \hat{P}_t(0) + \hat{\gamma}_I Z_t, \quad (5)$$

subject to aggregate transmission capacity limits $I_t^U \geq \hat{I}_t(0) \geq I_t^L$, defined as the sum of transmission capacity limit across interfaces.²⁰ Although rarely binding in practice, these constraints are useful to have meaningful predictions for aggregate net imports. We solve for $\hat{P}_t(0)$ for each hour between March and May 2020 using linear grid search.

Counterfactual scenario 2 (CF2): No Natural Gas Price Reductions. Second, we study the impact of the natural gas price reductions by assuming a coun-

²⁰Due to the lack of controllable direct current interconnections, interface limits with Belgium and Germany are approximated by the 1st and 99th quantiles of observed exchanges in the estimation sample.

terfactual price equal to 10.2 €/MWh, the average price in January-February 2020, corresponding to an average increase of 6 €/MWh compared to actual prices from March to May 2020. All other variables are kept unchanged. Figure 6 shows the time-series of natural gas prices $NG_t(1)$ and its counterfactual $\widehat{NG}_t(0)$. The counterfactual price is given by

$$\widehat{P}_t(0) = P_t(1) + \hat{\beta}_Q [\widehat{Q}_t(0) - Q_t(1)] + \hat{\delta} [\widehat{NG}_t(0) - NG_t(1)], \quad (6)$$

where $\widehat{Q}_t(0)$ depends on the price through endogenous exchanges with trading countries $\widehat{I}_t(0)$, as defined above. Demand is kept at observed levels during the crisis in this scenario. As a consequence, the nuclear production is unchanged because it essentially varies with expected domestic demand.

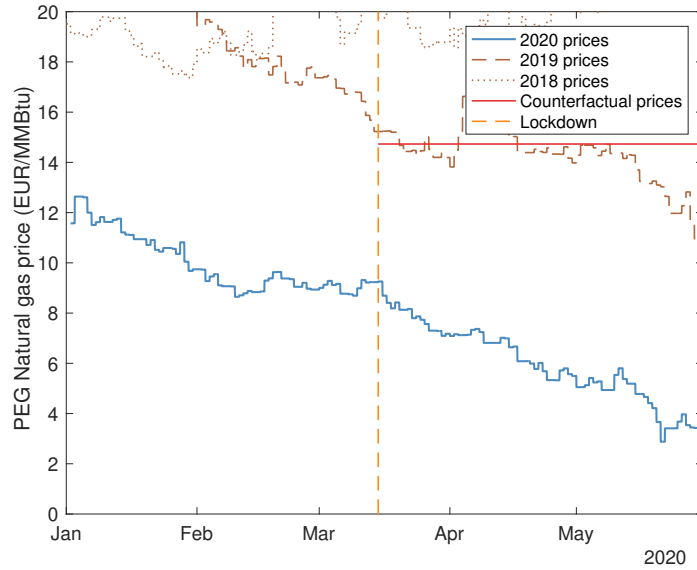


Figure 6: Natural gas prices

Counterfactual scenario 3 (CF3): Neither Demand Nor N.Gas Reductions.

In this scenario, we combine (3) and (6) to obtain the counterfactual price assuming the crisis did not affect energy markets, neither through demand nor through commodity prices. The counterfactual price is defined as

$$\widehat{P}_t(0) = P_t(1) + \hat{\beta}_Q \left[\widehat{Q}_t(0) - Q_t(1) \right] + \hat{\beta}_N \left[\widehat{N}_t(0) - N_t(1) \right] + \hat{\delta} \left[\widehat{NG}_t(0) - NG_t(1) \right], \quad (7)$$

where $\widehat{Q}_t(0)$ again depends on the price through the net import function.

Counterfactual scenario 4 (CF4): COVID-19 pandemic in 2030. What would have been the consequences of the crisis if Europe had already reached its ambitious renewable targets set for 2030? Answering this question should shed light on the sustainability of future highly-renewable electricity markets in the face of disruptive events. In this scenario, demand and fuel prices are held at the realized “crisis level”, i.e. $D_t(0) = D_t(1)$ and $NG_t(0) = NG_t(1)$.

In 2030, all European countries would have increased their renewable capacity and so increasing exports would not be an available option for France to integrate its domestic renewable power. We formalize this idea by assuming cross-border exchanges to remain as observed, i.e. $I_t(0) = I_t(1)$. As will be shown, it corresponds to an already large amount of exports compared to usual levels. Since this is a partial equilibrium model where foreign countries are not explicitly modelled, and cross-border transfer capacities are held as observed, this assumption allows to prevent exports from increasing further as a consequence of even lower local prices.

France’s objective for 2030 is to have 40% of domestic generation from renewable sources and 50% from nuclear energy. From January to May 2020, renewable and nuclear energy accounted for, respectively 25.4% and 68.1% of domestic production. We hence assume wind and solar power to increase from 10.9% to 25.5% of total generation while keeping hydro and biomass generation fixed at 14.5%. Keeping domestic production constant, the counterfactual generation from wind and solar plants is hence given by $\widehat{R}_t(0) = R_t(1) \times 25.5/10.9$. At the same time, nuclear generation is assumed to reduce down by 18.1 points to its counterfactual value $\widehat{N}_t(0) = N_t(1) \times 50/68.1$.²¹ The counterfactual price is hence given by

²¹We acknowledge that there are many alternative and more realistic way to construct such counterfactual series but this is beyond the scope of this paper.

$$\widehat{P}_t(0) = P_t(1) + \hat{\beta}_Q \left[\widehat{Q}_t(0) - Q_t(1) \right] + \hat{\beta}_N \left[\widehat{N}_t(0) - N_t(1) \right], \quad (8)$$

where $\widehat{Q}_t(0) = D_t(0) - \widehat{N}_t(0) - I_t(0) - \widehat{R}_t(0)$ is not endogenous since $I_t(0) = I_t(1)$ by assumption.

3.4 Price impacts and net imports

The counterfactual prices are calculated together with their corresponding net imports, for all hours from March 1 to May 31, 2020. Those predictions are in turn used to compute the gross value of the day-ahead market in each scenario.

Day-ahead prices. Hourly price impacts are calculated as

$$\Delta P = P_t(1) - \widehat{P}_t(0), \quad (9)$$

that is a negative value indicates that the observed prices were (on average) lower than their corresponding counterfactual levels in scenarios 1 to 3. To better understand the joint impact of the pandemic and increased penetration of renewables, we replace $P_t(1)$ by the counterfactual prices in absence of the pandemic (CF3) to evaluate impacts in CF4. Weekly average price impacts are reported in Table 7 for all five scenarios.

Table 7: Average price impacts (€/MWh)

	(CF1) No Dem. Red.	(CF2) No Gas. Red.	(CF3) No D/G Red.	(CF4) More Renew.
03/16-03/22	-10.02	-6.00	-11.47	-16.84
03/23-03/29	-13.39	-9.26	-15.39	-28.59
03/30-04/05	-9.99	-8.58	-12.31	-21.45
04/06-04/12	-7.95	-6.03	-10.39	-11.89
04/13-04/19	-8.55	-6.75	-11.40	-17.17
04/20-04/26	-7.00	-6.85	-10.47	-12.77
04/27-05/04	-8.65	-8.66	-12.31	-21.56
05/05-05/10	-7.17	-8.62	-11.03	-14.03
05/11-05/18	-7.86	-10.33	-11.95	-23.00
05/19-05/24	-9.73	-12.99	-14.93	-19.98
05/25-05/31	-8.35	-13.23	-13.85	-23.12
Average	-8.97	-8.85	-12.32	-19.13

Notes: This table shows weekly average price impacts in €/MWh after March 16th, 2020, when the lockdown was implemented in France. We report estimates for the four counterfactual scenarios presented earlier. The averages across all hours are given in the last row.

The average DA price observed during this period was about 15.3 €/MWh. Containment measures alone are found to have caused an average price decrease of about 9 €/MWh (CF1). The strongest price impacts occurred during the first weeks of the lockdown where demand reductions were the largest. The price of natural gas has also had a significant impact. We find that, on average, prices would have been nearly 8.9 €/MWh higher in absence of fuel price reductions (CF2). This effect is larger in May since the fuel price gradually decreased from February onward. Combining both effects yields an average price impact of the crisis of about 12.3 €/MWh (CF3), i.e. a decrease above 45% with respect to the average counterfactual price of 27.6 €/MWh had no crisis occurred. The results from (CF1) and (CF2) imply that roughly half of the average effect of the pandemic can be attributed to demand reductions, and the other half was caused by low fuel prices.

In the scenario with increased penetration of renewables (CF4), the consequences of the crisis are even stronger. Prices would have been reduced by an extra 6.8 €/MWh down to an average of 8.5 €/MWh. Therefore, increasing the deployment of renewable energy without market design adjustments dampens the economic sustainability of the

system, not only by reducing average prices in normal conditions but also by making it less resilient to highly disruptive events.

Figure 7a shows the actual and counterfactual prices in CF3. It reveals that the occurrences of negative prices would have been much less frequent had the crisis not occurred. Figure 7b shows the actual and counterfactual net imports in CF3. We find that containment measures and low commodity prices have decreased net imports by 4.7 TWh over the period under study. It corresponds to a 50% increase of exports. During April 2020 alone, France has increased its exports by 2.5 TWh because of the low price environment. This increase is found to be significantly smaller during the second half of May 2020.²²

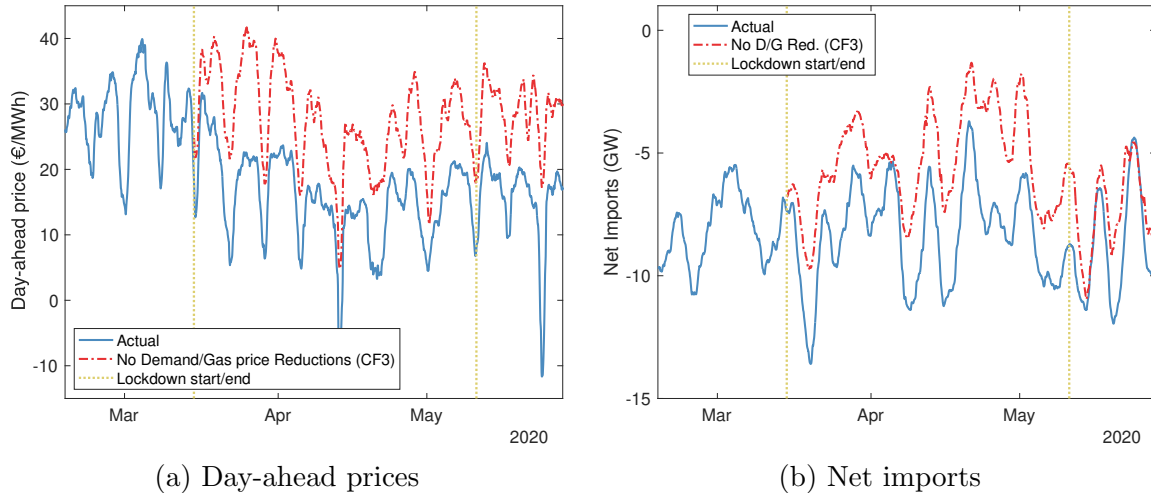


Figure 7: Actual and counterfactual series (48-hour moving averages)

3.5 Consequences for producers, retailers and grid operators

The previous results provide the necessary basis to compute the economic consequences for producers, retailers and grid operators.

²²Weekly average impacts for net imports are reported in Table B.3 in Appendix B for all five scenarios.

Day-ahead market values. The value of the day-ahead market in every hour t corresponds to the producers' gross revenues. It is defined as

$$Value_t^{DA} = P_t^{DA} \times D_t^{DA}. \quad (10)$$

Table 8 reports the actual day-ahead market value and its counterfactual values in each scenario. The total market value realized from March 16th to May 31st is 1.5 B€ (Observed). Therefore, the joint effects of containment measures and fuel price drop are found to have caused a 47% decrease in gross value from 2.9 B€ (CF3). The marginal effects of sheltering measures and fuel prices are of similar magnitude (CF1 and CF2). The *2030 scenario* reveals that gross revenues would have been down to 960 M€, hence an extra 600 M€ reduction, had renewable penetration been twice as large as today (CF4).

Table 8: Weekly day-ahead market values (M€)

	(Observed)	(CF1)	(CF2)	(CF3)	(CF4)
	Actual	No D. Red.	No G. Red.	No D/G Red.	More R.
03/16-03/22	221	348	282	358	189
03/23-03/29	177	349	274	363	62
03/30-04/05	188	316	275	332	111
04/06-04/12	126	215	177	231	127
04/13-04/19	88	175	141	193	43
04/20-04/26	98	168	147	188	91
04/27-05/04	104	199	175	220	28
05/05-05/10	147	229	216	250	131
05/11-05/18	154	248	245	274	56
05/19-05/24	113	207	209	236	75
05/25-05/31	123	213	228	246	48
Total	1539	2666	2370	2889	960

Notes: This table shows the total weekly day-ahead market value in M€ for each counterfactual scenario after the lockdown. The last row reports the total values over the period.

Market impacts across technologies. We decompose revenues loss by technology focusing on CF3, for which our counterfactual generations by technology are the most plausible. Let us denote the observed production of thermal, nuclear and hydro plants

by $T(1)$, $N(1)$ and $H(1)$, respectively, and their counterfactual values by $\widehat{T}(0)$, $\widehat{N}(0)$ and $\widehat{H}(0)$. Recall that renewable power remains unchanged $R(0) = R(1)$ in CF3.

For internal consistency, the equilibrium between the counterfactual demand $\widehat{D}^{DA}(0)$ and the sum of productions and net imports $\widehat{I}_{it}(0)$ for any scenario i must hold in each hour t . Thus, for each scenario i , we calculate the counterfactual hydro generation as $\widehat{H}_{it}(0) = \widehat{D}_t^{DA}(0) - \widehat{N}_t(0) - \widehat{T}_t(0) - \widehat{I}_{it}(0)$, where $\widehat{D}_t^{DA}(0)$, $\widehat{N}_t(0)$, and $\widehat{T}_t(0)$ are predicted with FNet, and $\widehat{I}_{it}(0)$ is obtained when calculating counterfactual prices.²³

We consider the revenue of a producer, without hedging positions, to be the production volume times the difference between the day-ahead price and the production cost K_t^X , where $X \in \{T, H, N, R\}$ denotes the technology. For gas-fired thermal plants, the production cost is assumed to be $K_t^T = \rho(\alpha NG_t + \beta C_t^{carbon})$ with NG_t denoting the gas price and $C_t^{carbon} = 20 \text{ €}$ being the carbon price.²⁴ We calibrate the parameters $\alpha = \frac{1}{0.52}$ and $\beta = 0.43$, which denote the heat rate and emissions rate of the gas power plant, respectively (CRE, 2018). This marginal cost is then multiplied by $\rho = 0.65$, which corresponds to the share of gas-fired generation in the thermal mix.

In absence of hedging, the revenues loss L_{it}^T at time t in scenario i for thermal producers is

$$L_{it}^T = T_t(1) (P_t^{DA}(1) - K_t^T(1)) - \widehat{T}_{it}(0) (\widehat{P}_{it}^{DA}(0) - \widehat{K}_{it}^T(0)), \quad (11)$$

with $\widehat{K}_{it}(0)$ and $K_t(1)$ the counterfactual and observed production cost.

Assuming hydro plants' production cost to be zero, the revenues loss for is simply

$$L_{it}^H = P_t^{DA}(1)H_t(1) - \widehat{P}_{it}^{DA}(0)\widehat{H}_{it}(0). \quad (12)$$

For nuclear production, we consider a constant production cost $K_t^N = 12 \text{ €/MWh}$ (Alasseur and Féron, 2018) and focus on the revenue variation not related to the ARENH mechanism. We subtract the ARENH volume V_t^{ARENH} auctioned at the end

²³The weekly changes for demand, net imports and each technology are summarized in Table B.4 in Appendix B.

²⁴This carbon price corresponds to the mean EU ETS's allowance emission price during the period (last accessed on October 2021 at <https://www.investing.com/commodities/carbon-emissions-historical-data>).

of 2019 from the production to obtain

$$L_{it}^N = (N_t(1) - V_t^{ARENH})(P_t^{DA}(1) - K_t^N) - (\widehat{N}_{it}(0) - V_t^{ARENH})(\widehat{P}_{it}^{DA}(0) - K_t^N). \quad (13)$$

Considering that the global yearly ARENH volume contracted for 2020 is 100TWh, we set $V_t^{ARENH} = 21.09\text{TWh}$ as the proportion of 100TWh corresponding to the 11 weeks under study.

The change in revenues for renewable producers exposed to markets, and not benefiting from any subsidies, only comes from the price decrease given $R(0) = R(1)$. Assuming that all intermittent renewable producers are in this situation provides the upper bound on revenue variation defined as $L_{it}^R = \left(P_t^{DA}(1) - \widehat{P}_{it}^{DA}(0)\right) R_t(1)$.

Hedging contracts. Let us now consider the role of hedging. We assume that it consists in a constant volume Δ^X during the whole period. The revenues loss \bar{L}_{it}^X is then defined as

$$\bar{L}_{it}^X = L_{it}^X - \Delta^X(P_t^{DA}(1) - \widehat{P}_{it}^{DA}(0)). \quad (14)$$

In the numerical results, we consider a hedging position $\Delta_i^X = E_t[X_{it}(0)]$ equal to the expected production over the period under study. The average production in CF3 corresponds to what rational producers would have anticipated upon choosing their hedging positions before the risk of a pandemic has materialized. One can thus rewrite equation (14) into

$$\begin{aligned} \bar{L}_{it}^X = & \left(X_t(1) - \widehat{X}_{it}(0)\right) \left(\widehat{P}_{it}^{DA}(0) - \widehat{K}_t^X(0)\right) - X_t(1) \left(K_t^X(1) - \widehat{K}_t^X(0)\right) \\ & - (\Delta^X - X_t(1)) \left(P_t^{DA}(1) - \widehat{P}_{it}^{DA}(0)\right). \end{aligned} \quad (15)$$

The first term corresponds to the loss with respect to the expected revenue caused by the output reduction. The second term corresponds to the loss due to changes in the production costs. This term is assumed to be zero for all producers except for the gas power plant, for which this term is negative because the gas price is lower leading to a reduced impacts on revenues. The last term is related to the combination of price and volume risks associated with the spread between the expected production volume Δ^X and its realization $X_t(1)$. In the case of the COVID-19 crisis, this last term is

almost always negative because production was significantly lower than anticipated for most producers, and the price difference $\left(P_t^{DA}(1) - \widehat{P}_{it}^{DA}(0)\right)$ is negative. For hydro producers, however, production has increased by 3 TWh (+10%).²⁵

Table 9 shows aggregate estimates of revenues impacts with respect to the expected revenue before the crisis for CF3. In absolute terms, the nuclear producer has suffered the most with losses above 600 M€ (column 2) in absence of hedging.²⁶ This figure corresponds to roughly 4.3% of 2019 revenues for the nuclear producer. For the other technologies, the losses are estimated at -1.5% for thermal producers, -3.6% for hydro producers and -8% for intermittent renewable producers. The latter estimate largely exaggerates the real consequences for renewable producers because it assumes that all plants are directly exposed to the market and receive no subsidies. This is bound to happen in a very close future, but applies today only for the oldest wind power plants.

Both gas price and demand reductions have contributed to reduce revenues for nuclear and hydro producers assuming they were completely exposed to spot prices. The gas price contraction has counterbalanced the reduction of demand and hence of production for thermal producers. They are nevertheless much less resilient to important financial disruptions because they operate on much smaller scale.

Producers are bound to hedge their future production using derivative contracts. Accounting for future contracts leads to very different impacts of the COVID crisis on their revenues. All producers would have managed to secure their expected revenue under complete hedging of average future production.²⁷ They might even have earned slightly more because the difference between the realised and expected spot prices is so high that the last term in (14) counterbalances the impact of the diminution of production. This shows the importance and efficiency of hedging to secure future revenues even with the simple hedging strategy considered here. In that particular case, hedging manages to counterbalance the price risk but also the volume risk. This would have been different if the crisis had led to a contraction of production combined with an increase of spot prices.

²⁵This finding is confirmed by RTE (2020a) which reports a 8.4% annual increase of hydro power production in 2020 compared to 2019, whereas all other sources had significantly lower production.

²⁶Table B.5 reports weekly values under zero hedging.

²⁷Table B.6 reports weekly values under complete hedging.

Table 9: Total revenues impacts by technology (M€)

	No Dem/N.Gas Red. (CF3)				
	Thermal.	Nuclear	Hydro	Renew.	Retail
No Hedging	-34.3	-645.3	-86.6	-136.2	80.7
Hedging	1.0	12.2	55.8	0.3	-1063.5

Notes: This table shows the aggregate revenues changes by generation technology in M€ in CF3, i.e. assuming away demand and fuel price reductions. Hedging contracts are estimated at the average counterfactual production in this scenario, which is considered business-as-usual.

Retailers. Consider a retailer selling electricity at a fixed tariff C . Let us denote by $\widehat{S}_t(0)$ and $S_t(1)$ the counterfactual and observed retailer's sales to end-users for a given hour t . The revenues impacts of the retailer without hedging are

$$\begin{aligned}
 L_t^S &= S_t(1) (C - P_t(1)) - \widehat{S}_t(0) (C - \widehat{P}_t^{DA}(0)) \\
 &= (S_t(1) - \widehat{S}_t(0)) (C - \widehat{P}_t^{DA}(0)) - S_t(1) (P_t(1) - \widehat{P}_t^{DA}(0))
 \end{aligned} \tag{16}$$

where the first term represents the volume risk and the revenue loss due to a volume contraction. The second term represents the price risk, which in this case becomes an opportunity to reduce the revenue losses because buying power on the spot market is much less expensive than expected.

If we assume that the retailer has fully hedged its expected volume at Δ^S at the average price F , its revenues losses at time t for scenario i are

$$\begin{aligned}
 \bar{L}_t^S &= -\widehat{S}_{it}(0)(C - \widehat{P}_{it}^{DA}(0)) - \Delta^S (\widehat{P}_{it}^{DA}(0) - F) \\
 &\quad + S_t(1) (C - P_t(1)) + \Delta^S (P_t(1) - F) \\
 &= (S_t(1) - \widehat{S}_{it}(0)) (C - \widehat{P}_{it}^{DA}(0)) + (\Delta^S - S_t(1)) (P_t(1) - \widehat{P}_{it}^{DA}(0)).
 \end{aligned} \tag{17}$$

The first term comes from an unexpected consumption contraction, whereas the second term represents the fact that the retailer has to sell the remaining volume $(\Delta^S - S_t(1))$ bought at the price F on the day-ahead market at the (lower) price $P_t(1)$. If the retailer is risk averse, then the hedging volume was close to the expected consumption, i.e. $\Delta^S = S_t(1)$, and the second term is negative $\widehat{P}_{it}(0) \geq P_t(1)$. Contrary to producers,

the additional hedging term increases the revenues losses for retailers, due to spot price reductions caused by the COVID-19 crisis.

Let $C = 115.71$ €/MWh be the retail price in France,²⁸ and $F = 50.8$ €/MWh be the average price of future contracts late 2019 for year 2020.²⁹ As reported in Table 9, the total revenue impacts for retailers between March 16, 2020 to May 31, 2020 is +81 M€ in absence of hedging compared to -1.1 B€ assuming they had taken hedging positions based on pre-crisis expectations.

This finding explains why some retailers have reneged on ARENH contracts by arguing force majeure,³⁰ hence reshuffling market losses among market participants.³¹ Indeed, retailers' expectations about future spot prices and consumption from March onward could not anticipate the COVID-19 crisis with certainty at the time ARENH contracts were signed in December 2019. The full available volume of ARENH was sold to retailers at 42 €/MWh based on market expectations, including about fuel prices. During the lockdown, however, the power demand dropped considerably below the 2019 expectations and retailers had extra volumes they had to sell back on the spot market at an average price of 15 €/MWh. Given the hedging price $F = 42$ €/MWh and the realized price of 15 €/MWh, and considering the ARENH volume Δ^S to be $100 \text{ TWh} \times 11 \text{ weeks}/365 \text{ days} = 21.1 \text{ TWh}$, the ARENH contracts correspond to a financial issue of 571 M€ for retailers for the first lockdown episode. This is around one half of the financial impacts evaluated above. For comparison, the net income of Total Direct Energie, one of the leading alternative retailer in France, was around 52 M€ in 2017.³²

²⁸The retail price is evaluated considering the average retail price for households at 179.91 €/MWh, the average industrial retail price at 81.15 €/MWh, and a ratio of 35% of total power consumption for households (<https://www.statista.com/statistics/418087/electricity-prices-for-households-in-france/> and <https://www.statista.com/statistics/595816/electricity-industry-price-france/>).

²⁹Values were obtained from the European Energy Exchange (<https://www.eex.com>).

³⁰Reuters: *Total among companies seeking force majeure on EDF contracts: sources*, April 6, 2020 (<https://www.reuters.com/article/us-edf-nuclearpower-idUSKBN2101B7>).

³¹Whether the “force majeure” claim is legitimate is a matter for the law and thereby beyond the scope of this paper.

³²Direct Energie: *Annual Financial Report 2017* (https://total.direct-energie.com/fileadmin/Digital/Groupe/PDF/Rapport_annuels/2017/en/Annual_financial_report_2017.pdf).

Grid operators: distribution networks. The cost structure of Enedis, the entity in charge of the distribution network in France, has variable and fixed components. CRE (2019) evaluates that approximately 1/3 of their annual costs comes from variable expenses (network losses and access rights to the transmission network) and 2/3 from fixed costs (infrastructure management). In 2018, Enedis’ expenses were evaluated at 13.5 B€, of which 3.6 B€ for transmission grid access rights (called “TURPE HTB”) and 1 B€ in compensation of network losses. Based on this evaluation, we can decompose the 2018 revenue of the distribution operator into: 76% of fixed costs; 26.5% of transmission grid access rights which are proportional to the global consumption; and 7.5% of network losses which we consider proportional to the product of the consumption and the spot price.

The costs can be written as follows:

$$\text{costs} = \text{fixed costs} + \underbrace{c_1 \sum_t D_t}_{\text{access rights}} + \underbrace{c_2 \sum_t P_t D_t}_{\text{losses}} \quad (18)$$

Using 2018 figures, we can estimate $c_1 = 7.5 \text{ €/MWh}$ and $c_2 = 4.2 \times 10^{-2}$. Both the transmission grid access rights and the network losses diminished due to demand and price reductions caused by the crisis. The diminution of costs is therefore the sum of:

- transmission grid access reduction : considering the estimated demand decrease to be on average 10590 GWh and c_1 , the reduction is 79.4 M€;
- network losses reduction : considering the estimated market values decrease to be 1350 M€ and c_2 , the reduction is 56.7 M€.

The revenues of the distribution grid operator come from a two-part tariff with a variable component proportional to the realized energy consumption. Reversely to the cost structure, the revenue structure is such that only 27% of the annual revenues is fixed while 73% are variable. It implies that a diminution of the variable part mechanically induces a diminution of net revenues for the distribution grid operator.

The revenues can be written as follows:

$$\text{revenues} = \text{fixed part} + r_1 \underbrace{\sum_t D_t}_{\text{variable part}}. \quad (19)$$

Assuming that the revenues are equal to the costs and using 2018 values, we recover the parameter $r_1 = 20.7 \text{ €/MWh}$. Therefore, the revenue contraction implied by the reduction of demand of 10590 GWh is 219.2 M€.

As a result, the global impact for the distribution grid operator is a global reduction of its net revenue of $219.2 - 79.4 - 56.7 = 83.1 \text{ M€}$. It is explained by the inverse ratios of fixed over variable components for costs and revenues. Sufficient information to evaluate the financial impact of the crisis on the transmission grid operator (RTE) was not available but we can expect a negative impact. Operators are nevertheless fully compensated through future rate hikes following regulatory hearings.

Those results show that the crisis had enormous short-term consequences for wholesale market participants in the French electricity sector. As stated in the introduction, end-users have not been affected by wholesale price variations due to regulated tariffs. Moreover, demand variations have been heterogeneous across consumer segments. We argue that temporary price reductions did not pass on to consumers mainly because the crisis had generated significant losses for transmission and distribution operators which the regulator had to compensate by raising tariffs ex-post.

In the next section, we draw a parallel between the observed market outcomes during the crisis and future outcomes that will prevail through the energy transition.

4 Discussion

The empirical results document how unprecedented demand reductions and low fuel prices, both caused by the crisis, have resulted in historically low wholesale electricity prices in France. In addition, containment measures have dramatically affected load patterns and thereby temporarily increased uncertainty around demand net of renewable production. The COVID-19 crisis is undoubtedly an extreme event, which negative impacts was mitigated (exacerbated) for producers (retailers) who had taken

hedging positions in 2019, i.e. when the future prices under “pre-crisis” expectations did not reflect the pandemic’s impacts.

More generally, we argue that the observed market outcomes during the crisis are informative about the future with abundant renewable power in which (wholesale) spot and futures prices will fall in a more sustainable way, and become more volatile. Unfortunately, those prices might be “too low” to guarantee grid reliability by generating enough investments in necessary capacity in absence of market design adjustments. Today’s main concern arising from the missing money problem (Joskow, 2008) and missing markets (Newbery et al., 2018) is the risk of under-investment in *flexible* plants which are necessary to guarantee supply reliability in systems with large amounts of intermittent renewable power.

At the onset of the crisis, demand decreased by 12% and became (temporarily) more difficult to forecast, which introduced additional uncertainty around the demand net of renewable output. This context is somehow comparable to France’s 2030 renewable scenario which plans an increase of 19 percentage points of domestic generation from renewable sources, and a reduction of 21 points from nuclear power, with respect to 2019, assuming demand is maintained at today’s pre-crisis levels. To illustrate this point, let us consider the average hourly domestic power generation was 62 GW in 2019. Achieving 2030 objectives implies that 13 GW of nuclear power must be substituted each hour by, on average, a combination of renewable sources (11.8 GW) and thermal production (1.2 GW). The average price effect implied by our structural estimates is therefore

$$\hat{\beta}_Q \times [+1, 200MW] + \hat{\beta}_N \times [-13, 000MW] \approx -14 \text{ €/MWh}, \quad (20)$$

which is comparable to the price impacts estimated for the crisis. This result occurs because substituting nuclear power with renewable power tends to reduce prices for two reasons. First, wind and solar plants have near-zero marginal costs, unlike nuclear plants. Second, the nuclear producer acts similarly to a regulated monopoly by selling its production around its average costs, as evidenced by ARENH contracts (42 €/MWh) compared to marginal cost estimates (12 €/MWh).

Figure 8a shows the distributions of energy prices observed during the crisis and

their counterfactual values in CF3. This comparison reveals that the realized prices were lower and more volatile than usual, often taking values close to zero or even negative. The levelized cost of electricity (LCOE) for CCGT and combustion turbines entering service in 2025 as projected by [EIA \(2020\)](#) are also shown. The LCOE is a measure of average costs by technology under assumptions about capacity factors, capital costs, and operations and maintenance costs. Realized prices are found almost always below both projected LCOEs, implying both technologies would be largely unprofitable in this market. In addition, [Figure 8b](#) shows thermal generation during the crisis and its counterfactual values under business-as-usual conditions. The realized average output from thermal plants was 2.8 GW, implying a 13% capacity factor ([RTE, 2020a](#)). This production level only requires 5.6 GW of installed thermal capacity, nearly 4 times less than actual capacity in France, assuming the plants have a 50% capacity factor on average. In comparison, the projected LCOEs in [EIA \(2020\)](#) assume a 87% capacity factor for CCGT and 30% for combustion turbines.

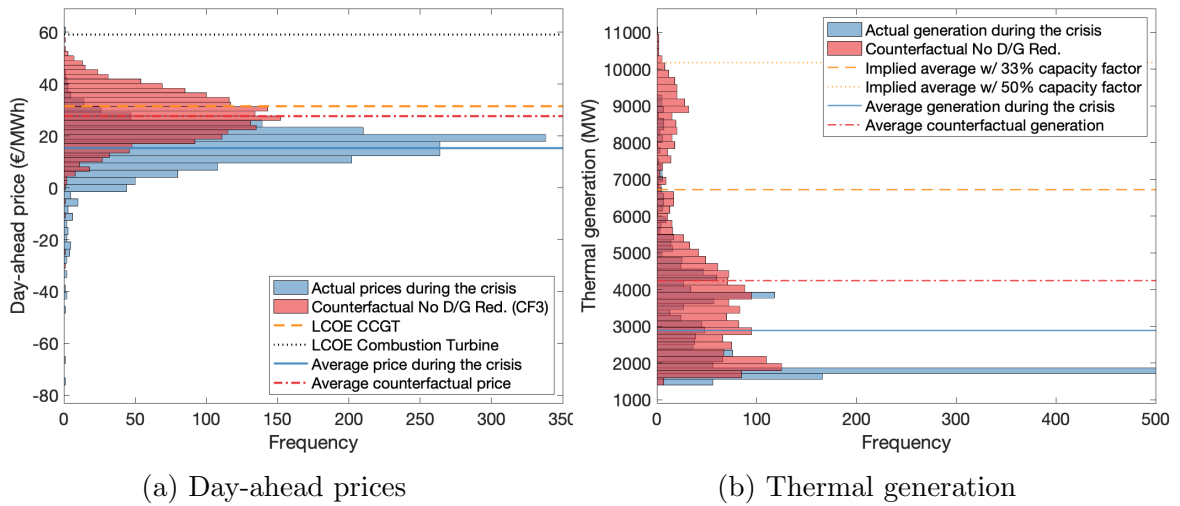


Figure 8: Histograms of actual and counterfactual outcomes

The combination of low prices and small capacity factors should drive thermal producers to exit the market in the long run. Those results show that the energy transition would likely lead to many early retirements of thermal plants along with a dramatic reduction of investment in necessary flexible capacity if: 1) there is no

additional remuneration for flexibility and capacity availability, and 2) demand remain relatively stable at pre-crisis levels.

Although informative about potential future outcomes, the realized market outcomes during the crisis cannot be interpreted as a long-run equilibrium with large renewable deployment. Instead, it is a market in disequilibrium where prices will adjust as producers will enter or exit the market (Green and Léautier, 2017). All plants must cover their full costs in the long-run, hence prices would increase to reflect the scarcity of flexible capacity as exit occurs. Demand rationing would also occur if prices are capped for regulatory reasons and flexibility is not adequately priced.

Our literature review demonstrates that achieving an efficient and reliable high-renewable system requires to address multiple externalities, and that the current European electricity market design is insufficient in that respect (Newbery et al., 2018). Some experts consider that externalities should be corrected by introducing additional “energy markets” with prices at finer spatial and time scales (Newbery et al., 2018; Leslie et al., 2020). Others emphasize the importance of capacity payments to address the externality related to capacity availability while keeping in mind market power issues and risk-aversion (Fabra, 2018; Petit et al., 2017). In particular, Fabra (2018) discusses reliability options, which provide capacity payments but also incentivize capacity availability and address market power issues. This solution does not, however, remove the need for proper pricing of ancillary and flexibility services for short-term efficiency reasons, and to adequately incentivize investment in new capacity needed to manage highly-renewable systems.³³

It is worth considering that there are capacity and flexibility markets in several European countries, including France. However, those markets are still in a developing phase. We identify two main drawbacks. First, technologies are not discriminated according to their flexibility in the capacity auctions. Investments in flexible back-up generators, although required to balance short-term fluctuations of wind power production, are not incentivized differently than baseload power plants. Second, observed capacity prices have been highly volatile so far,³⁴ and, as such, cannot yet provide a clear signal of long-term capacity needs.

³³We thank an anonymous referee for pointing this out.

³⁴For instance, capacity prices for year 2019 collapsed to zero in two out of six auctions.

The sanitary crisis is also a portent of more risky electricity markets. Investors' expectations about future market fundamentals and regulatory policies must account for the possibility of similar events causing large demand, or fuel price, variations over sustained periods of time, such as pandemics but also climate events. Future cash flows of long-term stranded assets, like power plants, are hence subject to increasing uncertainty. The introduction of more granular prices would result in even more volatile prices and time-varying cash flows. Conversely, capacity payments and long-term contracts can contribute to mitigate revenue uncertainty, in particular related to extreme events.

5 Conclusion

The impacts of the COVID-19 crisis on the French electricity sector have been enormous. This paper has developed an empirical framework to quantify the effects of the crisis on demand, forecast errors, and market outcomes, accounting for cross-border trade with all adjacent countries. Our results document large demand reductions (-12%) and wholesale price drops (-45%) leading to gross revenue losses for market participants at 1.3 B€ (-47%), and net revenue losses for the distribution network operator at 80 M€. Retailers have probably borne the vast majority of the market losses, assuming all participants had forward contracts to cover their expected “pre-crisis” demand and supply volumes. These losses have been, however, redistributed in great majority to the historical vertically-integrated producer, following the renegeing of regulated supply contracts by retailers.³⁵

More generally, the consequences of the crisis are evocative of the anticipated consequences of the ongoing energy transition: low energy prices and increased uncertainty caused by the large deployment of intermittent renewables. European electricity markets will experience similarly low and volatile prices along with decreasing market shares for fossil-fuel and nuclear generators going through 2030. In the long-run, the

³⁵Moreover, an analysis over a longer time horizon would probably show different results. The pandemic has deeply affected the maintenance schedule of nuclear plants, leading to significant reduction of available nuclear capacity during winter. The spot prices will therefore be higher than usual. Retailers should hence be able to pocket the difference between the spot price and that of the regulated contracts.

energy transition may exacerbate reliability issues related the “missing money problem” and missing markets. We argue that capacity payments can be useful to guarantee capacity adequacy, provided that they discriminate across technologies with respect to their contribution to system reliability, and offer stable long-term signals.

There are other important considerations not studied in this paper, in particular related to market power. Intermittent renewable plants will have larger shares in electricity auctions and will be marginal more frequently going through 2030. In theory, market power in electricity markets come from generators with positive probabilities to be marginal ([Ausubel et al., 2014](#)). Following [Fabra and Llobet \(2020\)](#), the energy transition will thus lead to a new competitive paradigm in electricity markets. We believe that empirical studies of strategic behaviors in European electricity markets during the crisis may provide important insights in that respect.

References

- AESO.** 2020. “Impacts of the COVID-19 Pandemic and Low Oil Prices on Alberta’s Power System.” AESO. <https://www.aeso.ca/assets/Uploads/Pandemic-Low-Oil-Analysis-Summary-April-20-Final.pdf>, accessed May 2020.
- Alasseur, Clémence, and Olivier Féron.** 2018. “Structural Price Model for Coupled Electricity Markets.” *Energy Economics*, 75: 104–1199.
- Ambec, Stefan, and Claude Crampes.** 2012. “Electricity Provision with Intermittent Sources of Energy.” *Resource and Energy Economics*, 34(3): 319–336.
- Ausubel, Lawrence M, Peter Cramton, Marek Pycia, Marzena Rostek, and Marek Weretka.** 2014. “Demand Reduction and Inefficiency in Multi-unit Auctions.” *The Review of Economic Studies*, 81(4): 1366–1400.
- Benatia, David.** 2020. “Electricity Markets under Lockdown: Insights from New York.” *Energy Forum*.
- Benatia, David, and Samuel Gingras.** 2021. “Reaching New Lows? The Pandemic’s Consequences for Electricity Markets.” *USAEE Working Paper No. 20-454*.
- Benatia, David, and Étienne Billette de Villemeur.** 2021. “Strategic Reneging in Sequential Imperfect Markets.” *Center for Research in Economics and Statistics Working Paper*.
- Borenstein, Severin, James B. Bushnell, and Frank A. Wolak.** 2002. “Measuring Market Inefficiencies in California’s Restructured Wholesale Electricity Market.” *American Economic Review*, 92(5): 1376–1405.
- Brown, David P., and Derek E.H. Olmstead.** 2017. “Measuring Market Power and the Efficiency of Alberta’s Restructured Electricity Market: An Energy-only Market Design.” *Canadian Journal of Economics/Revue Canadienne d’Économie*, 50(3): 838–870.

- Burlig, Fiona, Christopher Knittel, David Rapson, Mar Reguant, and Catherine Wolfram.** 2020. “Machine Learning from Schools about Energy Efficiency.” *Journal of the Association of Environmental and Resource Economists*, 7(6): 1181–1217.
- Bushnell, James B., Erin T. Mansur, and Celeste Saravia.** 2008. “Vertical Arrangements, Market Structure, and Competition: An Analysis of Restructured US Electricity Markets.” *American Economic Review*, 98(1): 237–66.
- Byers, Conleigh, Todd Levin, and Audun Botterud.** 2018. “Capacity Market Design and Renewable Energy: Performance Incentives, Qualifying Capacity, and Demand Curves.” *The Electricity Journal*, 31(1): 65–74.
- Cicala, Steve.** 2020. “Early Economic Impacts of COVID-19 in Europe: A View from the Grid.” Tech. rep. Online, last accessed: May 6, 2020. University of Chicago.
- Cramton, Peter, and Steven Stoft.** 2006. “The Convergence of Market Designs for Adequate Generating Capacity.”
- CRE, Commission de Régulation de l’Énergie.** 2018. “Le Fonctionnement des Marchés de Gros de l’Électricité et du Gaz Naturel.” *Surveillance*. <https://www.cre.fr/content/download/21173/270188>.
- CRE, Commission de Régulation de l’Énergie.** 2019. “Délibération de la CRE du 25 juin 2019 portant Proposition des Tarifs Réglementés de Vente d’Électricité.” *Tarifs*. <https://www.cre.fr/Documents/Deliberations/Proposition/Proposition-des-tarifs-reglementes-de-vente-d-electricite2>.
- CRE, Commission de Régulation de l’Énergie.** 2020a. “Consommation Énergétique : les Effets du Confinement.” *Decryptages*. <https://www.cre.fr/Documents/Publications/Decryptages/decryptages-n-63-consommation-energetique-les-effets-du-confinement>.
- CRE, Commission de Régulation de l’Énergie.** 2020b. “Délibération de la CRE du 2 juillet 2020 portant Proposition des Tarifs Réglementés de

- Vente d'Électricité.” *Tarifs*. <https://www.cre.fr/Documents/Deliberations/Proposition/tarifs-reglementes-de-vente-d-electricite5>.
- CRE, Commission de Régulation de l'Énergie.** 2020*c*. “Délibération N°2020-094.” *Journal officiel électronique authentifié n° 0130 du 29/05/2020*. <https://www.legifrance.gouv.fr/download/pdf?id=1wulT1qU3IEiYGyD4fBVGKfnZhQYvseZTGXlWvrPu1M=>.
- CRE, Commission de Régulation de l'Énergie.** 2020*d*. “Les Marchés de Détail de l'Électricité et du Gaz Naturel, 1er Trimestre 2020.” <https://www.cre.fr/Documents/Publications/Observatoire-des-marches/observatoire-des-marches-de-detail-du-1e-trimestre-2020>.
- CRE, Commission de Régulation de l'Énergie.** 2021*a*. “Délibération de la Commission de Régulation de l'Énergie du 25 mars 2021 portant Communication sur les Effets pour l'Année 2020 de la Crise COVID-19 pour les Opérateurs de réseaux.” *Délibération N° 2021-105*.
- CRE, Commission de Régulation de l'Énergie.** 2021*b*. “Délibération de la CRE du 8 juillet 2021 portant Proposition des Tarifs Réglementés de Vente d'Électricité.” *Tarifs*. <https://www.cre.fr/Documents/Deliberations/Proposition/proposition-des-tarifs-reglementes-de-vente-d-electricite-1er-aout-2021>.
- Debia, Sébastien, David Benatia, and Pierre-Olivier Pineau.** 2018. “Evaluating an Interconnection Project: Do Strategic Interactions Matter?” *The Energy Journal*, 39(6).
- EIA.** 2020. “Levelized Cost and Levelized Avoided Cost of New Generation Resources in the Annual Energy Outlook 2020.” *U.S. Energy Information Administration*.
- ERCOT.** 2020. “COVID-19 Load Impact Analysis.” ERCOT. http://www.ercot.com/content/wcm/lists/200201/ERCOT_COVID-19_Analysis_FINAL.pdf, accessed May 2020.

- European Commission.** 2019. “Clean Energy for all Europeans.” *Directorate-General for Energy, European Commission*. https://ec.europa.eu/energy/topics/energy-strategy/clean-energy-all-europeans_en.
- Fabra, Natalia.** 2018. “A Primer on Capacity Mechanisms.” *Energy Economics*, 75: 323–335.
- Fabra, Natalia, Aitor Lacuesta, and Mateus Souza.** 2021. “The Implicit Cost of Carbon Abatement During the COVID-19 Pandemic.” *Technical Report 109, EnergyEcoLab*.
- Fabra, Natalia, and Gerard Llobet.** 2020. “Auctions with Unknown Capacities: Understanding Competition Among Renewables.” CEPR Discussion Paper No. DP14060.
- Fabra, Natalia, David Rapson, Mar Reguant, and Jingyuan Wang.** 2021. “Estimating the Elasticity to Real-Time Pricing: Evidence from the Spanish Electricity Market.” *AEA Papers and Proceedings*, 111: 425–29.
- Fischer, Carolyn, and Richard G Newell.** 2008. “Environmental and Technology Policies for Climate Mitigation.” *Journal of environmental economics and management*, 55(2): 142–162.
- Ghiani, Emilio, Marco Galici, Mario Mureddu, and Fabrizio Pilo.** 2020. “Impact on Electricity Consumption and Market Pricing of Energy and Ancillary Services during Pandemic of COVID-19 in Italy.” *Energies*, 13(13): 1–19.
- Gillingham, Kenneth T, Christopher R Knittel, Jing Li, Marten Ovaere, and Mar Reguant.** 2020. “The Short-run and Long-run Effects of Covid-19 on Energy and the Environment.” *Joule*, 4(7): 1337–1341.
- Graf, Christoph, Federico Quaglia, and Frank A Wolak.** 2020. “(Machine) Learning from the COVID-19 Lockdown about Electricity Market Performance with a Large Share of Renewables.” *Journal of Environmental Economics and Management*, 102398.

- Green, Richard J., and Thomas-Olivier Léautier.** 2017. “Do Costs Fall Faster than Revenues? Dynamics of Renewables Entry into Electricity Markets.” *Working Paper*.
- Henriot, Arthur, and Jean-Michel Glachant.** 2013. “Melting-Pots and Salad Bowls: The Current Debate on Electricity Market Design for Integration of Intermittent RES.” *Utilities Policy*, 27: 57–64.
- Hogan, William.** 2005. “On an “Energy only” Electricity Market Design for Resource Adequacy.”
- INSEE.** 2021. “L’Économie Tente de Résister à la Crise Sanitaire.” *Note de Conjoncture Régionale - 3e trimestre 2020*. <https://www.insee.fr/fr/statistiques/5011288#graphique-figure11>.
- Jacob, Daniel.** 2020. “Cross-fitting and averaging for machine learning estimation of heterogeneous treatment effects.” *arXiv preprint arXiv:2007.02852*.
- Joskow, Paul L.** 2008. “Capacity Payments in Imperfect Electricity Markets: Need and Design.” *Utilities Policy*, 16(3): 159 – 170. Capacity Mechanisms in Imperfect Electricity Markets.
- Kleibergen, Frank, and Richard Paap.** 2006. “Generalized Reduced Rank Tests using the Singular Value Decomposition.” *Journal of econometrics*, 133(1): 97–126.
- Leach, Andrew, Nic Rivers, and Blake Shaffer.** 2020. “Canadian Electricity Markets during the COVID-19 Pandemic: An Initial Assessment.” *Canadian Public Policy*, 46(S2): S145–S159.
- Leslie, Gordon, David I. Stern, Akshay Shanker, and Michael T. Hogan.** 2020. “Designing Electricity Markets for High Penetrations of Zero or Low Marginal Cost Intermittent Energy Sources.” USAEE Working Paper No.20-449, available at SSRN: <https://ssrn.com/abstract=3601485>.
- Levin, Todd, and Audun Botterud.** 2015. “Electricity Market Design for Generator Revenue Sufficiency with Increased Variable Generation.” *Energy Policy*, 87: 392–406.

- Mansur, Erin T.** 2007. “Do Oligopolists Pollute Less? Evidence from a Restructured Electricity Market.” *The Journal of Industrial Economics*, 55(4): 661–689.
- Narajewski, Michał, and Florian Ziel.** 2020. “Changes in Electricity Demand Pattern in Europe due to COVID-19 Shutdowns.” *Energy Forum*.
- NECP.** 2020. “France’s National Energy and Climate Plan 2030.” *European Commission*. https://ec.europa.eu/info/energy-climate-change-environment/implementation-eu-countries/energy-and-climate-governance-and-reporting/national-energy-and-climate-plans_en.
- Newbery, David, Michael G. Pollitt, Robert A. Ritz, and Wadim Strielkowski.** 2018. “Market Design for a High-Renewables European Electricity System.” *Renewable and Sustainable Energy Reviews*, 91: 695–707.
- NYISO.** 2020. “COVID-19 and the Electric Grid: Load Shifts as New Yorkers Respond to Crisis.” NYISO. <https://www.nyiso.com/-/covid-19-and-the-electric-grid-load-shifts-as-new-yorkers-respond-to-crisis>, accessed May 2020.
- Percy, Steve, and Bruce Mountain.** 2020. “Covid-19 and Social Distancing: Does It Show Up in the Demand for Electricity?” *Energy Forum*.
- Petit, Marie, Dominique Finon, and Tanguy Janssen.** 2017. “Capacity Adequacy in Power Markets facing Energy Transition: A Comparison of Scarcity Pricing and Capacity Mechanism.” *Energy Policy*, 103: 30–46.
- PJM.** 2020. “Estimated Impact of COVID-19.” PJM. <https://www.pjm.com/-/media/committees-groups/subcommittees/las/2020/20200505/20200505-item-03-covid-19-impact-update.ashx>, accessed May 2020.
- RTE.** 2019. “Bilan Électrique 2019.” Réseau Transport Électricité. https://bilan-electrique-2019.rte-france.com/wp-content/uploads/2020/02/pdf_BE2019.pdf, accessed September 2021.

- RTE.** 2020*a*. “Bilan Électrique 2020.” Réseau Transport Électricité. https://assets.rte-france.com/prod/public/2021-03/Bilan%20electrique%202020_0.pdf, accessed September 2021.
- RTE.** 2020*b*. “L’Impact de la Crise Sanitaire sur le Fonctionnement du Système Électrique.” Réseau Transport Électricité. https://www.rte-france.com/sites/default/files/impacts_de_la_crise_sanitaire_covid-19_sur_le_systeme_electrique.pdf, accessed May 2020.
- Ruan, Guangchun, Dongqi Wu, Xiangtian Zheng, S Sivaranjani, Haiwang Zhong, Chongqing Kang, Munther A Dahleh, and Le Xie.** 2020. “A Cross-Domain Approach to Analyzing the Short-run Impact of COVID-19 on the US Electricity Sector.” *JOULE-D-20-00678*.
- Wigand, F., R. Brückmann, M. Jimeno, F von Blücher, B Breitschopf, V. Anatolitis, L. Kitzing, M. Dukan, P del Rio, and O. Fitch-Roy.** 2020. “Impact of COVID-19 on Renewable Energy Auctions.” *Working Paper*.
- Wolfram, Catherine D.** 1999. “Measuring Duopoly power in the British Electricity Spot Market.” *American Economic Review*, 89(4): 805–826.
- Zhong, Haiwang, Zhenfei Tan, Yiliu He, Le Xie, and Chongqing Kang.** 2020. “Implications of COVID-19 for the Electricity Industry: A Comprehensive Review.” *CSEE Journal of Power and Energy Systems*, 6(3): 489–495.

A Data Appendix

This section describes the data. Table A.1 gives the time resolution and the sources. Note that the data used in this paper is publicly available online.³⁶ The final dataset is available on demand for replication purposes.

Table A.1: Data sources

Data	Resolution	Source
Weather data	Hourly	Reliable Prognosis
French market and load	Hourly	RTE
Capacity outages	Hourly	RTE
Renewable forecasts	Hourly	ENTSO-E's Transparency
Transmission capacities	Hourly	ENTSO-E's Transparency
Natural gas prices	Daily	European Energy Exchange

Notes:

For example, hourly weather data from weather station in Paris Orly is obtained from [https://rp5.ru/Weather_archive_in_Paris,_Orly_\(airport\),_METAR](https://rp5.ru/Weather_archive_in_Paris,_Orly_(airport),_METAR).

France's electricity market data is obtained from <https://www.rte-france.com/eco2mix/telecharger-les-indicateurs>.

Nuclear plants' outages are obtained from <https://www.services-rte.com/en/download-data-published-by-rte.html?category=generation&type=unavailabilities>.

Renewable forecasts are downloaded from <https://transparency.entsoe.eu/generation/r2/dayAheadGenerationForecastWindAndSolar/show>.

Transmission capacities are downloaded from <https://transparency.entsoe.eu/transmission-domain/ntcDay/show>.

PEG Natural gas prices have been collected by extracting .json data from <https://www.powernext.com/spot-market-data>.

The weather data contains hourly measurements from 13 weather stations in France and 13 weather stations in adjacent countries, from Jan 1, 2014 to May 31, 2021.³⁷

The weather variables include measurements of temperature, dew point temperature, humidity, pressure, precipitation, visibility, wind gusts, and wind speed. Variables for stations with above 1% of missing hourly values are discarded. Table A.2 reports the mean, standard deviations, 1st and 99th percentiles of each variables used in the

³⁶Some variables have been collected using web-crawlers.

³⁷The data is sometimes irregularly measured in time within and across stations and was reshaped in a regular panel of hourly observations using linear interpolation.

analysis. Remark that foreign weather variables outside temperature are not used, hence not reported here.

Descriptive statistics for all other variables used at some point in the analysis, but for which no summary statistics is provided in Tables 1 or 4, are given in Table A.3 below. Again, variables with above 1% missing values are discarded, that is why there are no renewable forecasts for Italy.

Table A.2: Weather variables

	Temp.	DewP.	Humi.	Pres.	Prec.	Visi.	WindG.	Winds.
Bordeaux	14.2 (6.9)	.	75.7 (18.5)	.	.	.	6.1 (3.3)	3.4 (2.0)
Brest	11.7 (4.9)	8.7 (4.6)	82.8 (13.6)	753.9 (7.5)	0.3 (1.2)	20.5 (15.5)	8.4 (4.6)	4.8 (2.7)
Lille	11.5 (6.8)	7.1 (5.3)	77.1 (16.9)	757.9 (7.4)	0.2 (0.9)	23.5 (17.0)	7.3 (4.0)	4.3 (2.5)
Lyon	13.5 (8.1)	7.0 (5.6)	.	745.7 (5.7)	0.2 (1.2)	34.9 (20.2)	6.1 (4.1)	3.2 (2.5)
Lyon/Satol	13.2 (8.0)	7.0 (5.5)	69.8 (18.7)	741.9 (5.7)	0.2 (1.3)	30.0 (17.3)	6.5 (3.8)	3.6 (2.4)
Marseille	16.1 (7.4)	8.9 (5.8)	65.3 (17.5)	759.4 (5.3)	0.1 (1.3)	34.9 (18.7)	7.8 (5.0)	4.8 (3.4)
Montpellier	15.7 (7.1)	8.8 (6.5)	66.5 (19.1)	762.1 (5.4)	0.1 (1.6)	36.3 (19.8)	7.0 (3.9)	4.3 (2.5)
Nantes	12.8 (6.4)	.	.	760.7 (6.8)	.	24.3 (16.7)	6.8 (3.6)	3.6 (2.0)
Paris/CDG	12.3 (7.1)	7.1 (5.3)	73.8 (17.8)	752.6 (6.9)	0.2 (0.9)	19.4 (10.4)	8.1 (3.7)	4.4 (2.2)
Paris/Orly	12.4 (7.2)	7.3 (5.3)	74.0 (17.8)	754.7 (6.9)	0.2 (1.0)	21.4 (10.4)	6.8 (3.5)	3.7 (2.0)
Perpignan	16.3 (6.9)	8.7 (6.1)	64.1 (18.6)	759.1 (5.4)	0.1 (1.3)	41.5 (18.5)	8.5 (5.6)	4.5 (3.1)
Rennes	12.2 (6.4)	8.3 (5.0)	79.5 (16.5)	759.5 (7.2)	0.2 (0.9)	26.3 (18.5)	6.7 (3.6)	3.6 (2.0)
Toulouse	14.4 (7.3)	.	72.4 (18.3)	750.3 (5.7)	0.1 (0.9)	28.4 (16.6)	7.1 (3.9)	4.0 (2.4)
Alcantaril (ES)	19.1 (7.3)
Barcelona (ES)	17.2 (6.5)
Berlin (DE)	10.9 (7.8)
Bologna (IT)	14.6 (8.5)
Brussels (BE)	11.1 (6.7)
Florence (IT)	15.7 (8.0)
Frankfurt (DE)	11.4 (7.7)
Geneva (CH)	11.5 (7.9)
London (UK)	12.5 (5.8)
Madrid (ES)	15.3 (9.1)
Shoreham (UK)	11.1 (5.5)
Turin (IT)	13.4 (8.2)
Zurich (CH)	10.3 (7.8)

Notes: This table provides means and standard deviations of all weather variables used in the paper.

Table A.3: Descriptive statistics for other variables

	Mean	St. Dev.	1st p.	99th p.
Demand (F)	54.51	11.81	33.50	82.73
Oil.FR (A)	0.28	0.24	0.07	1.07
Coal.FR (A)	0.41	0.56	-0.01	2.23
Nat.Gas.FR (A)	4.01	2.48	0.43	8.75
Biomass.FR (A)	1.10	0.07	0.94	1.26
Wind.FR (A)	3.80	2.94	0.29	12.05
Solar.FR (A)	1.23	1.79	-0.00	6.16
Hydro.FR (A)	6.56	3.47	-0.34	14.49
Co2rate.FR (A)	35.74	17.35	9.00	84.00
Solar.BE (F)	0.39	0.61	0.00	2.33
WindOff.BE (F)	0.52	0.45	0.01	1.51
WindOns.BE (F)	0.43	0.38	0.04	1.52
Solar.CH (F)	0.05	0.08	0.00	0.29
WindOns.CH (F)	0.01	0.01	0.00	0.03
Solar.DE (F)	4.49	7.03	0.00	25.93
WindOff.DE (F)	2.64	1.66	0.10	6.03
WindOn.DE (F)	11.40	8.83	0.87	36.43
Solar.ES (F)	1.52	1.81	0.00	5.92
WindOns.ES (F)	5.84	3.35	0.84	14.82
Solar.FR (F)	1.16	1.65	0.00	5.80
WindOns.FR (F)	3.62	2.71	0.52	12.10
Solar.UK (F)	1.25	1.91	0.00	7.40
WindOff.UK (F)	3.01	2.07	0.21	8.39
WindOns.UK (F)	4.10	2.41	0.64	9.50
TC.CH.FR	1.18	0.12	0.70	1.50
TC.FR.CH	2.75	0.30	2.29	3.20
TC.ES.FR	2.20	0.55	1.00	3.50
TC.FR.ES	2.40	0.66	1.00	3.60
TC.IT.FR	1.02	0.10	0.87	1.16
TC.FR.IT	2.43	0.67	0.37	3.39
TC.UK.FR	1.86	0.31	1.00	2.00
TC.FR.UK	1.86	0.31	1.00	2.00
Out.Nuclear (Planned)	21.55	7.56	6.26	34.85
Out.Thermal (All)	4.91	2.15	1.00	9.28
Out.Hydro (All)	4.68	1.93	1.73	8.53

Notes: This table provides mean, standard deviations, 1st and 99th percentiles for the other variables used in the analysis but not reported in the main body of the paper.

B Additional results

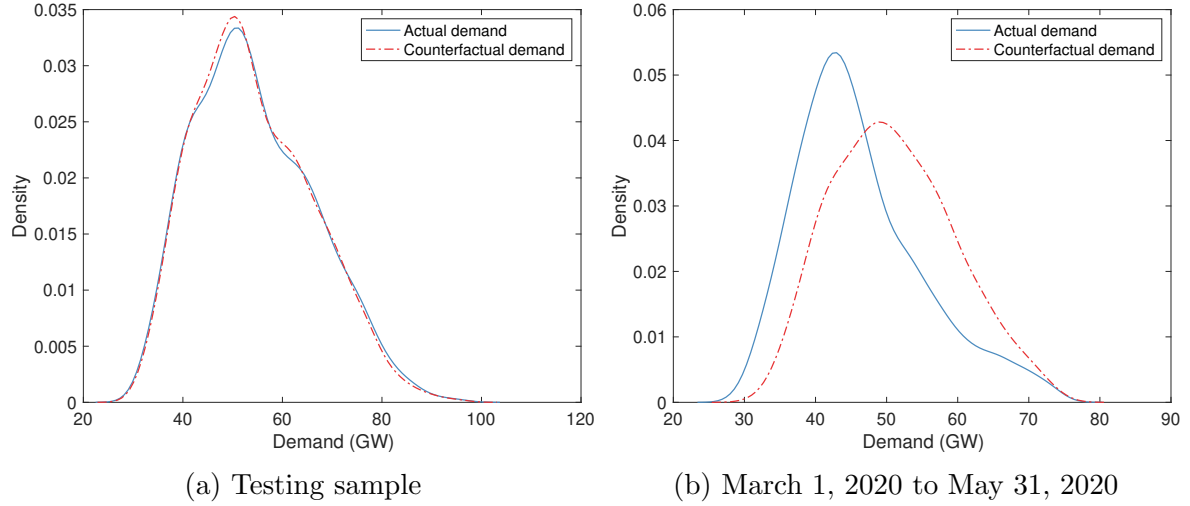


Figure B.1: Density plots of actual load and FNet predictions

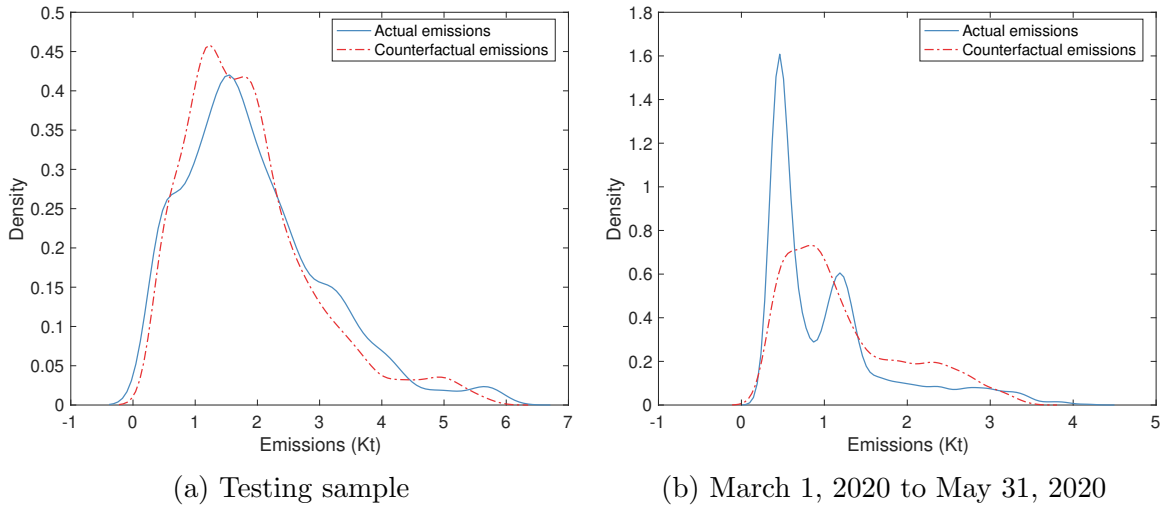


Figure B.2: Histograms of actual emissions and FNet predictions

Table B.1: Predictive performance (RMSPE)

	Thermal		Nuclear	
	MAPE	RMSE	MAPE	RMSE
Test set	14.2%	0.90	2.3%	1.28
03/02-03/08	10.0%	0.98	2.5%	1.43
03/09-03/15	13.7%	1.16	3.6%	1.97
03/16-03/22	42.2%	2.40	8.2%	3.82
03/23-03/29	82.1%	3.89	9.5%	3.98
03/30-04/05	73.8%	2.85	8.1%	3.46
04/06-04/12	89.7%	1.92	7.2%	3.10
04/13-04/19	81.4%	1.80	10.5%	3.97
04/20-04/26	89.0%	1.82	9.9%	3.78
04/27-05/04	63.9%	1.57	9.7%	3.68
05/05-05/10	48.3%	1.21	11.2%	4.08
05/11-05/18	37.8%	1.04	13.0%	4.50
05/19-05/24	21.7%	0.90	10.0%	3.57
05/25-05/31	13.5%	0.55	15.3%	5.09

Notes: This table shows predictive performance of FNet for production by technology.

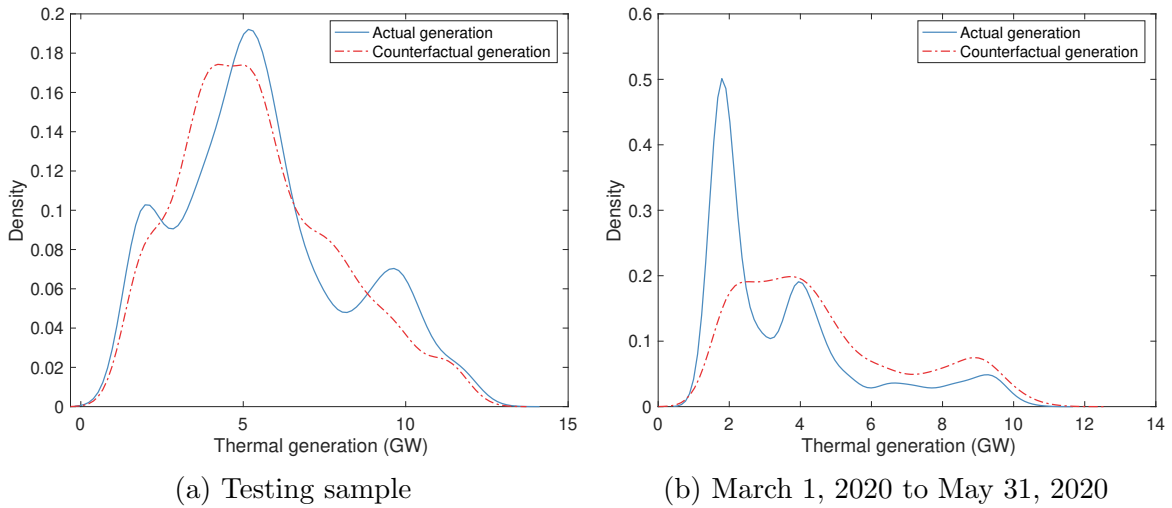


Figure B.3: Histograms of actual thermal generation and FNet predictions

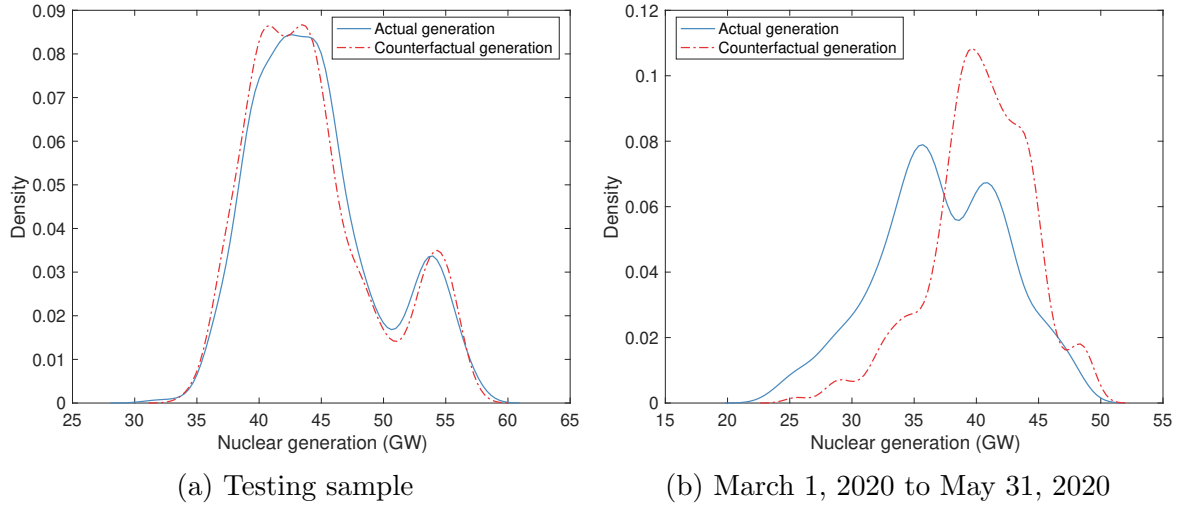


Figure B.4: Histograms of actual nuclear generation and FNet predictions

Table B.2: Weekly demand reductions (GWh)

	Demand			Emissions		
	GWh	SE	%	Kt	SE	%
03/16-03/22	-1228	(91)	-12.9	-62	(24)	-17.9
03/23-03/29	-1502	(91)	-15.1	-179	(24)	-46.4
03/30-04/05	-985	(91)	-10.4	-103	(24)	-39.8
04/06-04/12	-1024	(91)	-12.8	-73	(24)	-49.8
04/13-04/19	-1211	(91)	-15.1	-53	(24)	-41.0
04/20-04/26	-1007	(91)	-12.8	-56	(24)	-41.2
04/27-05/04	-1006	(91)	-12.7	-35	(24)	-30.7
05/05-05/10	-798	(91)	-10.7	-53	(24)	-35.4
05/11-05/18	-677	(91)	-8.5	-24	(24)	-16.8
05/19-05/24	-634	(91)	-8.7	18	(24)	16.4
05/25-05/31	-517	(91)	-7.1	42	(24)	36.6
Total	-10590		-11.7	-579		-28.4

Notes: This table shows weekly demand and emissions reductions in GWh and kilotons, respectively, predicted using FNet. Standard errors are reported in parentheses. Errors are calculated using the delta-method from FNet prediction errors on the test set. They are constant across week because the covariance matrix only accounts for error correlation across hours of a given day, hence it neglects other factors like correlation across days, or week.

Table B.3: Impacts on net imports (GWh)

	(CF1) No Dem. Red.	(CF2) No Gas. Red.	(CF3) No D/G Red.	(CF4) More Renew.
03/16-03/22	-264	158	-447	0
03/23-03/29	-232	284	-491	0
03/30-04/05	-4	168	-305	0
04/06-04/12	-217	-39	-525	0
04/13-04/19	-294	-66	-652	0
04/20-04/26	-216	-195	-664	0
04/27-05/04	-98	-96	-569	0
05/05-05/10	46	-133	-444	0
05/11-05/18	257	-16	-226	0
05/19-05/24	335	-48	-296	0
05/25-05/31	499	-37	-116	0
Total	-188	-21	-4736	0

Notes: This table shows weekly average impacts on net imports in GWh after March 16th, 2020, when the lockdown was implemented in France. We report estimates for the five counterfactual scenarios presented earlier. The total across all hours are given in the last row.

Table B.4: Changes in load, exchange, and production compared to CF3 (in TWh)

	Demand	Net Imp.	Therm.	Nuclear	Hydro
03/16-03/22	-1.23	-0.45	-0.30	-0.45	-0.03
03/23-03/29	-1.50	-0.49	-0.59	-0.57	0.15
03/30-04/05	-0.98	-0.30	-0.39	-0.49	0.21
04/06-04/12	-1.02	-0.53	-0.27	-0.45	0.22
04/13-04/19	-1.21	-0.65	-0.25	-0.59	0.28
04/20-04/26	-1.01	-0.66	-0.27	-0.57	0.49
04/27-05/04	-1.01	-0.57	-0.21	-0.55	0.32
05/05-05/10	-0.80	-0.44	-0.18	-0.65	0.48
05/11-05/18	-0.68	-0.23	-0.12	-0.73	0.41
05/19-05/24	-0.63	-0.30	0.05	-0.51	0.13
05/25-05/31	-0.52	-0.12	0.03	-0.83	0.40
Total	-10.59	-4.74	-2.51	-6.40	3.06

Notes: This table shows changes in domestic production by technology, as predicted by FNet. Standard errors are robust to serial correlation within a day.

Table B.5: Weekly revenues impacts by technology (M€)

	(CF1)				(CF3)			
	No Demand Red.				No Dem/Gas Red.			
	The.	Nuc.	Hyd.	Ren.	The.	Nuc.	Hyd.	Ren.
03/16-03/22	-11.4	-53.8	-16.4	-10.9	-8.5	-58.8	-17.8	-12.3
03/23-03/29	-16.8	-73.7	-14.9	-17.3	-12.6	-80.3	-16.2	-19.9
03/30-04/05	-10.6	-58.1	-9.7	-12.1	-7.0	-66.4	-11.1	-14.7
04/06-04/12	-3.5	-44.6	-5.2	-6.1	-1.5	-54.5	-6.4	-7.8
04/13-04/19	-2.9	-40.0	-2.2	-8.7	-0.6	-51.5	-3.6	-11.3
04/20-04/26	-2.5	-34.0	2.8	-5.4	0.5	-47.2	1.7	-7.7
04/27-05/04	-4.4	-42.8	-5.2	-9.4	-1.5	-55.2	-7.0	-13.3
05/05-05/10	-4.6	-42.0	0.1	-5.0	-1.1	-54.6	-2.0	-7.8
05/11-05/18	-4.9	-43.9	-4.0	-9.6	-1.4	-57.5	-6.9	-14.2
05/19-05/24	-3.9	-42.2	-8.8	-8.5	-0.4	-57.7	-12.9	-12.7
05/25-05/31	-4.1	-43.2	-1.2	-8.8	-0.4	-61.6	-4.3	-14.5
Total	-69.7	-518.5	-64.8	-101.8	-34.3	-645.3	-86.6	-136.2

Notes: This table shows the weekly revenues loss by generation technology in M€ for each counterfactual scenario after the lockdown. The last row reports the total values over the period.

Table B.6: Weekly revenues loss, net of hedging contracts, by technology (M€)

	(CF1)				(CF3)			
	No Demand Red.				No Dem/Gas Red.			
	The.	Nuc.	Hyd.	Ren.	The.	Nuc.	Hyd.	Ren.
03/16-03/22	-3.6	-5.2	-5.9	-0.8	-2.3	-3.1	-5.7	-0.7
03/23-03/29	-6.4	-8.7	-0.9	-3.8	-4.5	-5.6	0.0	-4.4
03/30-04/05	-2.8	-9.7	0.8	-2.1	-2.0	-6.7	1.8	-2.3
04/06-04/12	2.7	-6.0	3.1	1.9	1.9	-4.1	4.5	2.7
04/13-04/19	3.8	1.5	6.8	-0.1	2.8	3.8	8.4	0.2
04/20-04/26	2.9	-0.0	10.2	1.7	1.9	3.6	12.7	2.8
04/27-05/04	2.4	-0.8	3.9	-0.7	1.0	4.5	5.9	-0.9
05/05-05/10	0.9	-7.2	7.6	2.2	0.0	-1.1	9.6	3.3
05/11-05/18	1.2	-5.8	4.2	-1.6	0.3	0.5	5.6	-2.2
05/19-05/24	3.7	5.0	1.5	1.3	1.4	14.8	2.8	2.3
05/25-05/31	2.4	-2.7	7.5	-0.4	0.6	5.6	10.2	-0.6
Total	7.0	-39.7	38.8	-2.4	1.0	12.2	55.8	0.3

Notes: This table shows the weekly revenues loss by generation technology in M€ for each counterfactual scenario after the lockdown. The last row reports the total values over the period. Hedging contracts are estimated at the average production in scenario 3 (Lockd./Gas), which is considered business-as-usual.