The implicit cost of carbon abatement during the COVID-19 pandemic

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March 3, 2022

Abstract

This paper provides novel estimates of the implicit cost of carbon abatement associated with the COVID-19 crisis. We compare that to the costs from renewable investments that would lead to similar abatement. Focusing on the Spanish economy and its power sector, we combine machine learning and simulation tools to construct a precise counterfactual of market performance in absence of the crisis. Results suggest that power sector CO2 emissions fell by 4.13 Million Tons (about 11.5%) during 2020 due to the pandemic, less than half of the actual year-on-year emissions reductions. Investing in renewables to achieve similar carbon abatement would yield an implicit cost of 60-65 Euro/Ton of CO2. Conversely, the pandemic caused a substantial GDP loss in Spain, relative to the extent of overall carbon abatement. The resulting cost of carbon abatement associated with the pandemic thus exceeded 7 thousand Euro/Ton.

Keywords: COVID-19, Decoupling, Carbon Emissions, Renewables.
JEL Classification: L94, Q43, Q54.

Emails: natalia.fabra@uc3m.es; aitor.lacuesta@bde.es; mateus.nogueira@uc3m.es. This work has received funding from the European Research Council (ERC) under the European Union Horizon 2020 Research and Innovation Program (Grant Agreement No 772331 ELECTRIC CHALLENGES). We would like to thank the editors, Lucas Bretschger and Simone Valente, and three anonymous referees for their constructive suggestions. We also thank the forecasting department at Bank of Spain, and in particular Alberto Urtasun, for providing growth figures of past forecasting exercises, and Red Elétrica de España (in particular, Félix Martínez). Imelda and Camila Steffens provided very useful suggestions. Finally, the paper has benefited from comments by seminar participants at the Bank of Spain, WIPE (Girona), Universidad Carlos III de Madrid, the Yale/ETH EMEE 2021 Workshop, the 2021 EAERE Conference, and the 2021 EEA Congress.

1 Introduction

Despite the dire consequences of the COVID-19 pandemic, early media reports were already alluding to a potential silver lining: reduced pollution (Forbes, 2020). Indeed, academic publications later found that carbon emissions were relatively low during 2020 (e.g. Le Quéré et al., 2020; Liu, Ciais, Deng, Lei, et al., 2020). Naturally, that carbon abatement came at a cost. Other than the loss of life and health consequences to many afflicted by viral infection, the COVID-19 pandemic also gave rise to negative economic growth rates (World Bank, 2020). The magnitude and the abrupt nature of the decrease in economic activity (and emissions) caused by the pandemic has had no parallel, compared to modern-era recessions. The pandemic therefore constitutes a unique event which can provide insight on the link between short-term economic downturns and carbon emissions. Specifically, in this paper we provide estimates of the implicit cost of carbon abatement observed during the pandemic. We benchmark those against the costs and potential abatement from investing in renewable technologies.

Since the pandemic was an unexpected shock to the economy, agents did not have enough time to optimally adjust in anticipation of the changes in behavior necessary to contain the viral spread. On the one hand, this is advantageous for our thought exercise because it implies that the short-term economic effects are observed while holding many (long-term) factors fixed.[1] On the other hand, we acknowledge that this shock impacted the various sectors of the economy asymmetrically. In particular, since some carbon-intensive sectors – such as transportation – were severely affected, the scale of carbon abatement has been significant, but so has been the reduction in economic activity. To the extent that the pandemic's effects were orthogonal to sectors' carbon intensities, the associated cost of carbon abatement might have been greater than that from, for example, a planned and "sustainable degrowth" strategy (Schneider, Kallis, and Martinez-Alier, 2010). Yet, the quantification that we provide in this paper sheds light on the orders of magnitude of the implicit cost of carbon abatement from halting economic

[1]For example, among the many factors that could not rapidly adjust, we highlight: transportation, building, and power sector infrastructures; consumers' choice of residence and occupation; industrial and retail sector physical capital investments.

growth, without changing the underlying economic structures. We compare that implicit cost to those from alternative abatement strategies that do imply structural changes with long-lasting effects: investing in power sector renewable technologies.

We place special attention on power markets because they are particularly suitable to shed light on our questions of interest, for several reasons. First, electricity generation is a major source of carbon emissions. Indeed, 30% of global CO2 emissions stem from coal-fired generation alone (IEA, 2019a), and billions of dollars are invested annually in policies aimed at reducing the power sector's footprint (UN, 2018; IEA, 2019b). Second, electricity is a key input for most activities, making it a valuable indicator of overall economic activity. During the COVID crisis, the economic contraction led to electricity demand reductions, which in turn led to substantial emissions reductions, which we assess. Finally, thanks to the highly detailed available data, electricity markets lend themselves to robust empirical analyses.

We further focus on the performance of the Spanish economy during 2020, when it faced strict lockdown movement restrictions, especially at earlier stages of the pandemic. Prior evidence suggests that these restrictions led to strong electricity demand reductions (Bover et al., 2020). Within this context, we stress the importance of building a counterfactual scenario in the absence of the pandemic, in contrast to relying on year-on-year comparisons to estimate the extent of carbon abatement *caused* by the pandemic. Prior years' emissions do not provide an accurate counterfactual as several time-variant factors would have affected emissions even in the absence of the pandemic. For instance, in the context of the Spanish electricity market, during 2020, the vast majority of coal plants were phased-out while many new renewable investments started operating. As these exit and entry decisions were made well before the pandemic, the associated emissions reductions would have also occurred in the absence of it. Furthermore, the amount of emissions in the power sector is highly sensitive to the availability of natural resources (water, wind, sun), which are subject to substantial variation across time.

Accordingly, we build our measure of avoided emissions in the power sector by running simulations of market performance under realized and counterfactual demand values, holding all else equal. The simulations are based on a model developed by De Frutos and Fabra (2012), which incorporates technological and institutional features of electricity markets, and allows for strategic bidding behaviour by electricity companies. The model solves for the Nash equilibria in discrete supply functions, which determine market clearing prices and quantities. Simulations with counterfactual demand thus provide a clear picture of the carbon intensity had the crisis not occurred.

A key input of the simulations thus regards the estimation of the electricity demand reductions attributable to the COVID-19 crisis, for which we build on prior literature using machine learning methods (Burlig et al., 2020; Christensen et al., 2021). We use high-frequency energy data, weather variables, and date/time fixed effects from 2015-2019 to train a highly flexible model to predict counterfactual demand in 2020 in the absence of the pandemic. Our estimates are more accurate than those from more conventional approaches, particularly so if we focus on the hourly predictions, which is the frequency at which the market power simulations have to be conducted. For instance, in comparison to Santiago et al. (2021), we take into account nonlinear relationships between energy demand and weather variations, which allows us to predict more accurate counterfactuals. Further, to assess the predictive accuracy of our model, we implement a cross-validation approach that is adequate for time series data. Specifically, we use forward chaining cross-validation errors as a proxy for *out-of-sample* errors (Hyndman and Athanasopoulos, 2018).[2]

Our results reveal that reductions in electricity demand were stronger during periods in which stricter lockdown measures were in place, and during certain hours of the day.[3] We highlight changes in hourly electricity demand patterns – and not just the overall demand reduction – because they have a key impact on market performance and hence

[2]Prior related literature uses validation folds assigned at random (Graf, Quaglia, and Wolak, 2020; Benatia, 2020; Benatia and Gingras, 2020). The implication is that training folds may contain observations that are in the future, relative to validation folds. We argue that such approach is inconsistent with our objective of using past observations to predict future counterfactual electricity demand. Further, in Appendix B.1 we show that standard cross-validation approaches, as opposed to forward chaining, may underestimate out-of-sample errors in our setting, potentially due to serial correlation across observations.

[3]For example, during full lockdown (March 29 - April 10), demand was reduced by almost 26% at 8 am, while demand at night (9 pm - 2 am) went down by about 15%. During partial lockdowns and looser movement restrictions (April 11 - August 14), reductions ranged from 7% - 10% throughout the day.

on the extent of emissions reductions in the power sector. Another key insight is that by the last quarter of 2020 electricity demand in Spain was almost back to normal (pre-pandemic) levels.

Regarding our simulation results, we find that the difference between counterfactual and realized emissions in the Spanish power sector during 2020 ranged from 3.9 to 4.1 Million Tons of CO2, depending on assumptions regarding competitive or strategic firm behavior. This is only half of the actual power sector emissions reductions relative to the previous year, as the other half cannot be attributed to the pandemic.[4]

Our analysis for the other sectors of the Spanish economy relies on data from Carbon Monitor (Liu, Ciais, Deng, Lei, et al., 2020).[5] Although abatement was substantial in the power sector, we find that other sectors experienced even stronger emissions reductions. For example, in percentage terms, the carbon reductions in the power sector are about 10 times smaller than those from aviation, 3.1 times smaller than those from ground transport, 2.8 times smaller than those from industry, and only slightly larger than those from residential.[6] This is consistent with findings from prior literature showing that the power sector experienced relatively smaller reductions in activity during the pandemic (Le Quéré et al., 2020). Bover et al. (2020) provide one reason for this finding, which is that the reduction in electricity demand by firms was partly offset by the increase in electricity demand by households, as people spent more time at home due to the lockdown measures (see also Cicala, 2020). This finding can also be explained by differences in the emissions intensity across sectors: the power sector relies on gas plants, while other sectors rely on more polluting fossil fuels, such as oil in aviation and transport. Summing the estimates of emission reductions in all sectors, the total carbon abatement in Spain reached about 23.14 Million Tons during 2020.

[4]This is partly explained by the fact that 2020 was more humid and sunny, leading to a 24% and 68% increase in hydro and solar generation, respectively, relative to 2019 (REE, 2020b). This was accompanied by the coal phase-out and the renewables expansion.

[5]They use comparisons between 2019 and 2020 emissions, which may be less precise than the counterfactual analysis that we performed for the power sector. However, other sectors of the economy might be less vulnerable to the shortcomings highlighted above. Other sectors might be less dependent on weather variables, and there are no major exit/entry decisions affecting their emissions intensity.

[6]"Residential" here excludes electricity consumption. This category includes mostly emissions due to natural gas for heating.

To compute the implicit cost of carbon abatement during the pandemic, we take into account the associated reduction in economic activity. Hence, another key input is the estimation of the short-run GDP loss caused by the crisis. For this, we again rely on counterfactual projections. In particular, we use growth rate forecasts that were produced by the Bank of Spain in November 2019, thus without knowledge of the forthcoming pandemic. Comparing those to observed data, we find that GDP loss was about 169.37 Billion Euros (13.1%). The resulting implicit cost of carbon abatement reaches an astonishing 7,319 Euro/Ton. We highlight that, in contrast with our results from the power sector, GDP levels were still far from normality by the end of 2020.

Finally, to benchmark the abatement cost associated with the pandemic, we compute the costs of reducing emissions by investing in power sector renewables. For this purpose, we run further simulations of the Spanish power market to understand the amount of renewable investments necessary to achieve the same emission reductions as those observed in the power sector during the pandemic.[7] We explore two options regarding the composition of the additional investments – all solar PV or all onshore wind. We find that solar PV and wind capacity would have had to increase by 90% or 10% respectively, in order to achieve the same emissions reductions as those caused by the pandemic. Using the most recent cost estimates provided by IRENA (2020) for Spain, we compute the costs of such investments (including both initial investments as well as the operation and maintenance costs), and compare those to the avoided emissions. The resulting implicit cost of carbon is in the range 60-65 Euro/Ton,[8] which is well below our estimate for the pandemic.

Admittedly, our analysis omits some of the costs and benefits of carbon abatement. In particular, we do not take into account the long-run costs of the GDP loss caused by the pandemic, including the social costs associated with reduced potential output, lower labour productivity and increased unemployment (ECB, 2020; World Bank, 2020;

[7] Clearly, other strategies for abatement could be considered as well. For example, a least-cost decoupling strategy would resort to a combination of policies, including investments in energy efficiency, storage, and transmission and distribution, among many others. Here we focus on renewable investments for concreteness and because of their relevance.

[8] These costs are in line with estimates from Callaway, Fowlie, and McCormick (2018) for the state of California.

Baqaee and Farhi, 2020) plus the political backlash that would likely follow. For this reason, our estimate for the pandemic could be considered as a lower bound. In contrast, our analysis does not compute the economic benefits of renewable investments. Indeed, evidence shows that the low carbon investments trigger economic growth through their multiplier effects.[9] For instance, according to IRENA (2020), replacing 500 GWs of coal capacity with solar and wind would cut annual power system costs by up to USD 23 Billion per year, providing an economic stimulus worth USD 940 Billion, or around 1% of global GDP. In turn, through learning economies, this could trigger further cost declines for future investments (Gillingham and Stock, 2018; Borenstein, 2012). Nevertheless, it is also fair to say that investments in renewables would eventually trigger further costs that are not included in this analysis, such as the strengthening of power grids and storage facilities.

In sum, our analysis shows that the pandemic indeed triggered significant carbon abatement. However, that abatement may have been short-lived (especially for the power sector), and was associated with high costs. The economic losses were substantial, and are expected to be felt for years to come. This highlights the prominence of alternative abatement strategies, such as power sector renewables, which could help decoupling growth from emissions.

The remainder of the paper is structured as follows. In section 2 we provide a simple theory-based framework to assess the link between the pandemic, economic activity and carbon emissions. In section 3 we measure the impact of the COVID-19 crisis on the Spanish power sector; in particular, on electricity demand and carbon emissions. In section 4 we provide evidence regarding the impact on carbon abatement in other polluting sectors of the Spanish economy. In section 5 we estimate counterfactual GDP which, combined with results from previous sections, allows us to compute and compare the implicit cost of carbon abatement during the pandemic versus the one obtained under renewables investments. Section 6 concludes, and the Appendix provides further details and robustness checks on the methodologies used.

[9] Several papers have documented the positive impact of renewable investments on growth. See Bhattacharya et al. (2016) or Narayan and Doytch (2017), and the UK's Office for National Statistics (2019).

2 A Simple Framework to Decompose Emissions

In order to explore the link between economic activity and energy-related factors, we first derive a simple theory-based decomposition of carbon emissions. Our analysis combines elements in Barrera-Santana et al. (2021) and Bretschger (2021).[10]

Consider a neoclassical aggregate production function, augmented with energy use, E_t:

$$Y_t = A_t L_t^{\alpha} K_t^{\beta} E_t^{1-\alpha-\beta}$$

where t is time, A is total factor productivity, L is labour and K is capital. We assume decreasing marginal returns of each input, i.e., $0 < \alpha, \beta < 1$, with constant returns to scale for labour, capital and energy.[11] Furthermore, we assume that energy production requires capital according to the expression $E_t = K_t/\upsilon_t$, where υ_t is a measure of technological progress (the higher it is, the less capital is needed to produce one unit of energy). Using this, we can rewrite aggregate production as a function of technological progress (embedded in the expression $A_t\upsilon_t^{\beta}$), energy intensity (i.e., how much energy is consumed per unit of output, E_t/Y_t) and labour:

$$Y_t = \left(A_t \upsilon_t^{\beta}\right)^{1/\alpha} \left(\frac{E_t}{Y_t}\right)^{\frac{1-\alpha}{\alpha}} L_t. \tag{1}$$

Following Stokey (1998), we assume that carbon emissions are proportional to production,

$$CO2_t = \phi\left(z_t\right) Y_t \tag{2}$$

where z_t parameterizes the dirtiness of the energy mix (the higher it is, the higher is the emission rate). The function $\phi\left(z_t\right)$ is increasing in z_t, possibly in a non-linear fashion.

Using (1), we can further express carbon emissions as

$$CO2_t = \left(A_t \upsilon_t^{\beta}\right)^{1/\alpha} \left(\frac{E_t}{Y_t}\right)^{\frac{1-\alpha}{\alpha}} \left(\frac{\phi\left(z_t\right) Y_t}{E_t}\right) \left(\frac{L_t}{Y_t}\right) E_t$$

[10] Other useful references are Hassler, Krusell, and Olovsson (2021) and Bretschger and Karydas (2019) for unified frameworks to analyze the economics of climate change.

[11] Hassler, Krusell, and Olovsson (2021) find that unitary elasticity is a reasonable assumption for periods as long as ten years.

where $\phi(z_t) Y_t / E_t$ is a measure of carbon intensity (i.e., how much carbon is emitted per unit of energy consumed) and L_t / Y_t is a measure of labour intensity (i.e., how much labour is employed per unit of output produced).

Last, solving for E_t in (1) and re-arranging, we can recover the following expression for carbon emissions

$$CO2_t = Y_t \left(\frac{E_t}{Y_t}\right)^{\gamma_1} \left(\frac{\phi(z_t) Y_t}{E_t}\right) \left(\frac{L_t}{Y_t}\right)^{\gamma_2} \left(A_t v_t^{\beta}\right)^{\gamma_3} \tag{3}$$

where $\gamma_1 = \frac{1-\alpha}{\alpha}$, and $\gamma_2 = \frac{1-2\alpha}{1-\alpha}$and $\gamma_3 = \frac{1-2\alpha}{\alpha(1-\alpha)}$.

This expression provides a useful framework to disentangle the impacts of the pandemic on total emissions. It makes it clear that emissions depend on economic activity (Y_t), energy intensity (E_t/Y_t), carbon intensity ($\phi(z_t) Y_t/E_t$), labour intensity (L_t/Y_t) and technological progress (embedded in $A_t v_t^{\beta}$).

The impact of the pandemic. We can make use of equation (3) to assess the impact of the pandemic on carbon emissions. A direct impact has been to reduce economic activity Y_t, which has contributed to pushing down emissions. To the extent that the pandemic has also reduced E_t and L_t, equation (3) suggests that the pandemic might have also acted indirectly through energy intensity, carbon intensity, and labour intensity. However, the sign of these cross effects is in principle unclear. First, with Y_t and E_t moving in the same direction, it is possible that energy intensity has gone up or down during the pandemic. Second, the characteristics of the energy mix z_t determine whether a reduction in E_t translates in lower or higher carbon intensity. This, coupled with the asymmetries in the shocks and carbon intensities of the various sectors (European Commission, 2021), suggest that the impact of the pandemic on carbon intensity might have gone either way. Third, changes in labour intensity might have had a positive or negative impact on emissions, depending on the substitution patterns between labour and other inputs (note that the coefficient on labour intensity γ_2 is positive for $\alpha < 1/2$ or negative otherwise). Furthermore, while it is plausible that the pandemic might have also affected total factor productivity A_t, it is reasonable to assume that technological progress v_t has remained constant given the short-run nature of the shock.[12] In this paper, we aim to quantify the *short-run* combined direct and indirect effects of reduced economic activity on carbon abatement, whatever the sign of the latter effects is.

We compute the difference between actual and counterfactual (i.e., in the absence of the pandemic) emissions, and actual and counterfactual GDP during 2020.[13] To compare them, we use the ratio of these differences as a measure of the implicit cost of carbon abatement associated with the pandemic. This metric captures the direct effect of the pandemic on economic activity and emissions, as well as the indirect effects through changes in energy intensity, carbon intensity, labour, and total factor productivity. To the contrary, we do not assess the long-run effects of the shock on future economic activity or emissions.[14]

As mentioned above, the pandemic not only led to reduced economic activity overall, but also impacted sectors asymmetrically. While some energy-related sectors were particularly affected by the lockdown measures, the impact on other sectors was milder. For instance, travel restrictions halted aviation and significantly reduced ground transportation, and while the industry's power demand fell, this was partly compensated by the increase in households' electricity consumption (Bover et al., 2020). To the extent that this sectoral reallocation was not part of a planned carbon abatement strategy, the pandemic's implicit cost of carbon has probably been higher than optimal. Yet, the emissions reductions from the pandemic might have been greater than those from a planned degrowth strategy. This is because some of the less energy-efficient and most carbon intensive sectors of the economy have been the ones most severely affected by the pandemic,

[12]In the long-run, Gillingham, Knittel, et al. (2020) argue that the pandemic may have adverse long-run consequences on innovation by postponing renewable capacity investments.

[13]We acknowledge that GDP does not necessarily capture all of the costs associated with the pandemic. Also, one may argue that GDP is not a comprehensive measure of well-being. However, while it is clear that GDP leaves out some welfare-enhancing activities, it is also true that GDP is positively correlated with most metrics that capture important notions of well-being, such as education, life expectancy, reduced child mortality, women's employment, and others. For a discussion on this issue, see Milanovici (2021).

[14]Consistent with our results in this paper, the International Energy Agency (2021) reports a rebound in emissions, after the temporary decline during 2020. As the executive director of the IEA reported, 'our numbers show we are returning to carbon-intensive business-as-usual.' Conversely, the effects on economic activity seem to be more persistent (IMF, 2021).

e.g., aviation and ground transportation.[15]

In order to provide a benchmark for the implicit cost of carbon abatement during the pandemic, in this paper we also compute the implicit cost of reducing carbon emissions through investments in power sector renewables. This reduces z_t in expression (2), which in turn reduces the carbon intensity term in expression (3). In words, investing in renewables implies that the power sector's carbon intensity goes down, which pushes emissions down. If renewable investments do not crowd out other sources of economic activity (i.e., consumption and investment in other activities), then emissions reductions can be achieved without sacrificing economic growth.

The ratio between the emissions reductions and the costs of the renewable investments thus measures the implicit cost of carbon abatement through renewable investments. This metric captures the direct effect of renewables on carbon emissions and investment costs, but omits their indirect effects through changes in economic activity in the short and in the long-run. If these indirect effects are positive overall, this metric provides an upper bound on the implicit cost of carbon abatement of the renewables strategy.[16]

We devote the next sections to provide details both on our empirical assessment of the effects of the pandemic, as well as on the benchmark exercise of investment in renewables.

3 Methods and Results for the Power Sector

We start with a careful evaluation of the impact of the COVID-19 crisis on the power sector in Spain. Specifically, we are interested in measuring the electricity demand reductions caused by the movement restrictions and the overall reduction in economic activity, which in turn led to carbon abatement. For this purpose, we first implement an event study approach with machine learning to predict counterfactual demand in the

[15] See Table 4 below.

[16] For instance, in a simple dynamic model, Bretschger and Karydas (2019) show that abatement implies that economic growth starts from a lower level, but it reaches a higher steady state due to reduced pollution and damages.

absence of the crisis. Next, we simulate and compare the equilibrium outcomes in the Spanish electricity market under realized demand versus the estimated counterfactual demand. This allows us to compute, among other variables of interest, the avoided emissions in the power sector.

3.1 Approach for Predicting Counterfactual Electricity Demand

In order to understand the impact of the COVID-19 crisis on electricity demand, a first step is to predict *counterfactual* demand in the absence of the pandemic. Building on the Neyman-Rubin potential outcomes framework (Neyman, 1923; Rubin, 1974), let $E_t(p)$ denote electricity demand at time t and at potential states p. Let $p = 1$ for outcomes that were affected by the pandemic, and $p = 0$ for outcomes in the absence of the crisis. We also assume that there exists a vector of covariates $\mathbf{X}_t(p)$, with realizations that may also depend on p. Let $t = pre$ denote time periods before the pandemic, while $t = post$ denotes time periods during the pandemic. The counterfactual potential outcome that we aim to identify can then be defined as $E_{post}(0)$, which is by definition unobservable.

Our proposal is to use pre-pandemic data to predict $E_{post}(0)$ based on the vector of covariates $\mathbf{X}_t(p)$. The first necessary assumption is that electricity consumption behavior did not change in anticipation of the pandemic. Therefore the outcomes that we observe for the periods before the pandemic (E_{pre}) are assumed to be equal to the potential outcomes in case the pandemic had never happened. Formally, that can be stated as follows.

Assumption 1: No anticipatory effects.

$$E_{pre} = E_{pre}(0) \ . \tag{Asm. 1}$$

Asm. 1 is common for event studies. In the context of this paper, a violation of this assumption implies that pre-pandemic outcomes (at least in part) cannot be used to understand counterfactual consumption, because such outcomes would have already been affected by the pandemic.

Similarly, another assumption is that the covariates $\mathbf{X}_t$ are independent of the pandemic itself:

Assumption 2: Covariates are independent of treatment (the pandemic).

$$\mathbf{X}_t(0) = \mathbf{X}_t(1) = \mathbf{X}_t \ . \tag{Asm. 2}$$

Note that if Asm. 2 does not hold, then the researcher would have to implement yet another counterfactual prediction procedure (to predict the counterfactual realizations of the covariates). In practice, one could force Asm. 2 to hold by using only exogenous covariates such as weather and date/time fixed effects.

Now let the relationship between covariates and demand in absence of the pandemic be defined as follows:

$$\begin{gathered} E_{pre}(0) = g(\mathbf{X}_{pre}(0)) + \varepsilon_{pre} \\ \text{such that } \ \mathbb{E}[E_{pre}(0)|\mathbf{X}_{pre}(0)] = g(\mathbf{X}_{pre}(0)) \ . \end{gathered} \tag{4}$$

Under Asm. 1 and Asm. 2, we can rewrite equation (4) as:

$$\begin{gathered} E_{pre} = g(\mathbf{X}_{pre}) + \varepsilon_{pre} \\ \text{such that } \ \mathbb{E}[E_{pre}|\mathbf{X}_{pre}] = g(\mathbf{X}_{pre}) \ . \end{gathered} \tag{4'}$$

We also assume that the relationship between $E_t(0)$ and the covariates would not have changed over time. This is our key identifying assumption, which allows us to rewrite equation (4) also for post-pandemic time periods, as follows.

Assumption 3: Stability of the counterfactual function.

$$\begin{gathered} E_{post}(0) = g(\mathbf{X}_{post}(0)) + \varepsilon_{post} \ , \\ \text{such that } \ \mathbb{E}[E_{post}(0)|\mathbf{X}_{post}(0)] = g(\mathbf{X}_{post}(0)) \ . \end{gathered} \tag{Asm. 3}$$

Asm. 3 implies that the same function $g()$ from the pre-pandemic period can be used to obtain the counterfactual electricity consumption in the post-pandemic period.

Under Asm. 1 and Asm. 2, we can rewrite Asm. 3 as:

$$\mathbb{E}[E_{post}(0)|\mathbf{X}_{post}] = g(\mathbf{X}_{post}) \ , \tag{5}$$

thus identifying our counterfactual outcome of interest.

Since $g()$ is in practice unknown, we must estimate it. We aim to do so, focusing on the context of Spain. For our outcome of interest (E_t), we have thus collected hourly aggregate electricity demand data, measured in MWh, from the Spanish electricity system operator (ESIOS, 2020), spanning from the 1st of January, 2015 to the 31st of December, 2020. To remain consistent with Asm. 2, we have collected data on a set of covariates $\mathbf{X}_t$ that are exogenous to the pandemic: weather variables and date/time fixed effects. Daily data from the universe of Spanish weather stations were collected from AEMET (2020). Those were then aggregated to the province level.[17] The following key weather variables were available: minimum, maximum and median temperature; solar radiation; precipitation; prevailing wind direction, and wind speed. In terms of date/time fixed effects, we considered: month of the year; day of the month; day of the year; week of the year; daily time trends; monthly time trends; hour of the day; and holidays. Including transformations (squares, cubes, and up to 3 lags) for the weather variables, we therefore considered a total of 1,642 variables. With these data, our estimation procedure is as follows.

$$\text{Step 1. Estimate: } E_{pre} = g(\mathbf{X}_{pre}) + \epsilon_{pre} \ \text{, where } pre \text{ denotes years 2015-2019} \ ,$$
$$\text{such that } \hat{E}_{pre} = \hat{g}(\mathbf{X}_{pre}) \ .$$
$$\text{Step 2. Predict: } \hat{E}_{2020} = \hat{g}(\mathbf{X}_{2020}) \ \text{, using data from year 2020.}$$

Therefore, we use data from 2015-2019 to build a model for counterfactual electricity demand in 2020. By using data available only prior to 2020, we argue that Asm. 1 is likely to hold, given that the timing of the pandemic and its widespread consequences were unexpected. Several models could be considered for our predictive task. Our proposal is to use a machine learning (ML) algorithm which we show has high predictive

[17]Further details about the weather data can be found in Appendix A.

accuracy. Recent literature has demonstrated that ML methods improve predictive accuracy for energy demand forecasts, since they are able to capture nonlinearities and complex interactions in the relationships between demand and available covariates.[18]

The use of machine learning is also becoming increasingly popular within causal frameworks in energy economics (Burlig et al., 2020; Christensen et al., 2021; Knittel and Stolper, 2019), potentially because it is a field in which required assumptions are particularly more likely to hold. Prior literature has shown, for example, that it is possible to accurately forecast energy demand using only exogenous covariates, such as weather realizations. Additionally, concerns about indirect effects through price changes are appeased in this setting, given that electricity demand is found to be highly inelastic to price or income variations, especially in the short-run (Csereklyei, 2020; Fabra et al., 2021). Those may be considered arguments in favor of the "stability" (Asm. 3) of the functions used to predict electricity demand. Otherwise, if demand were price-elastic, then counterfactual demand predictions would need to account for potential price changes associated with the policy/event being analyzed.

Asm. 3 from our framework is essentially untestable, given that counterfactuals are never observed. However, building on the ML literature, we propose a procedure that can provide insight regarding the stability over time of the function that relates energy demand and the covariates that we use. Namely, we implement forward chaining cross-validation (Hyndman and Athanasopoulos, 2018) to assess *out-of-sample* prediction errors of the models that we consider. We split the pre-pandemic sample into five years, and for each cross-validation iteration, we use a single year as the validation set, while all prior years are the training set. This cross-validation procedure is further illustrated in Appendix B.1. Note that this procedure implies that the size of the training set increases with each iteration. Consequently, one may expect lower errors for later years in the sample.[19] Nevertheless, we are particularly interested in assessing the *out-of-sample*

[18]Among others, see: Schneider, Dziubany, et al. (2019); Ghoddusi, Creamer, and Rafizadeh (2019); Guo et al. (2018); Robinson et al. (2017); Ahmad et al. (2014).

[19]In Appendix Table B.1 we show that, with the machine learning algorithms used in this paper, later validation years have lower errors, but with evidence of diminishing returns from additional observations. We therefore choose not to drop any years for the training set used for counterfactual predictions in 2020.

errors obtained in this way for the year of 2019, which is temporally closer to the year of the crisis and is expected to better reflect errors for the counterfactual predictions in 2020. In Appendix Figure B.3 we show that validation set errors from forward chaining are similar to errors from a held out "test" set with observations from January 1st to March 10th, 2020.

Within this general framework, we can consider many models for counterfactual predictions, not only machine learning algorithms. We then select the best-performing model based on out-of-sample errors in 2019. In the following section we present results for the models that we considered, focusing on the one that produces the lowest prediction errors.

3.2 Counterfactual Prediction Results

We consider a suite of machine learning algorithms (ML) and fixed effects regression specifications (FE) to build our model for counterfactual electricity consumption. Specifically, in terms of ML we focus on Gradient Boosted Trees (GBT; Chen and Guestrin, 2016). This is a regression tree-based method that inherently allows for non-linearities and high-order interactions between variables. The algorithm starts with a simple (base) regression tree, to which complexity is added by iteratively increasing the number of trees that constitute the model.[20] Model complexity also depends on how we set the algorithm's *hyperparameters* (e.g. the total number of trees considered, the maximum depth of each tree, the number of observations in terminal nodes, and the relative importance of each new tree).

To benchmark the results from GBT, we also consider FE regressions with increasing complexity: (i) month-of-year FE; (ii) week-of-year FE; (iii) day-of-year FE; (iv) day-of-

[20]The algorithm relies on numerical optimization in function space. The optimization minimizes the expected value of a loss function based on the Euclidean distance between the observed outcome and the predicted value from a linear combination of many regression trees. Consistency properties of this algorithm are shown in Biau and Cadre (2021).

year FE plus hour-of-day FE interacted weather variables.[21] All the specifications also include the weather variables described in section 3.1 above.

Out of all that we considered, the best-performing model was a GBT with the following hyperparameters: 2,000 trees; max. tree depth of 10; min. of 20 observations in the terminal nodes of the trees; and shrinkage parameter (importance of each new tree) of 0.05. As shown in Appendix Table B.1 and Figure B.4, that model achieved an average out-of-sample error (for 2019) of -234 MWh and RMSE of 809 MWh, which represent, respectively, about 0.8% and 2.8% of the average hourly demand of 28,528 MWh. In contrast, the best-performing fixed effects regression specification achieved an average error of -616 MWh, thus 2.6 times the average error from the ML approach. The RMSE from the fixed effects approach was also substantially higher, at 1,095 MWh.

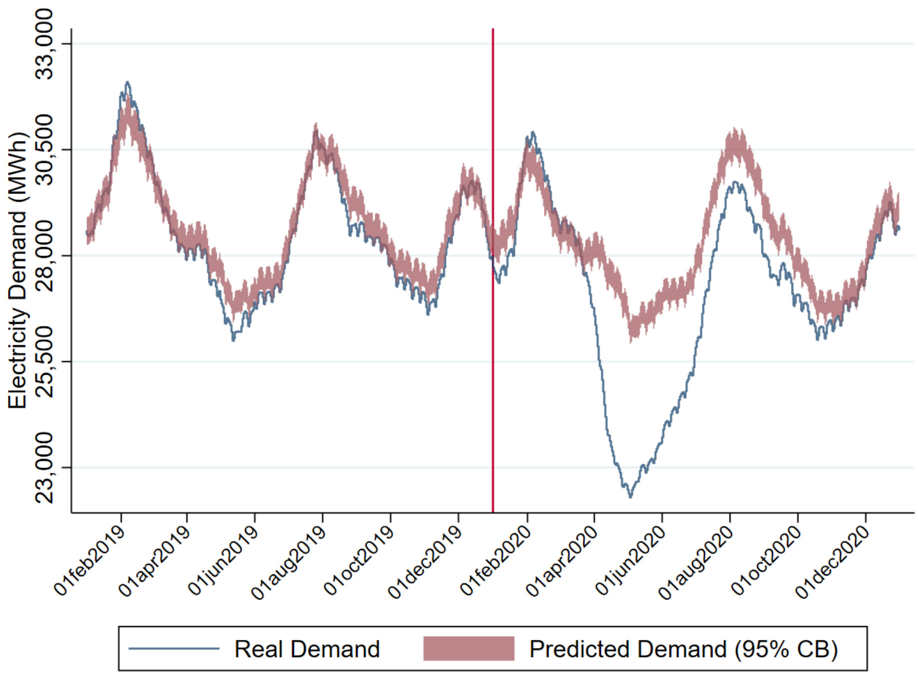
Appendix Table B.1 presents the RMSE from all models considered. Further, Appendix Figure B.4 compares the distribution of residuals obtained from an ML approach versus that from a fixed effects specification. Assessing the residuals is relevant in this prediction context, since those can reveal systematic prediction biases. We find that the FE specification produces a residuals' distribution that is shifted to the left, thus suggesting systematic overestimation of electricity demand. Conversely, the residuals' distribution from the ML approach is more closely centered around zero, such that biases are less likely.

Finally, Figure 1 compares realized (in blue) and predicted (in red) electricity demand in 2019 and 2020. We present a smoothed hourly series (for real demand) and 95% Confidence Bands (for predicted demand), based on 30-day moving averages and standard deviations. All predictions are based on the best-performing GBT describe above, and are made out-of-sample (i.e. the model was trained excluding the observations represented in the figure). The comparison of predicted and realized curves in 2019 serve as an additional check that the model performs well. Although predictions for any given hour

[21] In our view, specification (iv), also referred to as FE 4 in the Appendix, is the one which is the closest to a 'fully saturated' regression model typically considered in empirical applications in economics. Our specification (iv) includes a total of 1,029 control variables. That specification is also the most comparable to Santiago et al. (2021), who build a model based on daily averages of electricity demand (analogous to day-of-year fixed effects).

must be interpreted with caution, it can be noted that real and predicted seasonality patterns are closely matched.[22] The predictions in 2020 represent the counterfactuals (from a model without any information about the pandemic). A clear divergence of the realized and predicted curves can be noted in 2020, starting in mid-March, illustrating the effects of the pandemic. Strong reductions in electricity demand can be noted especially between April and July. However, by mid-October the curves are already overlapping, suggesting that aggregate electricity consumption returned to normal levels. In the following section we investigate the difference between the two curves in greater detail.

Figure 1: Realized and Predicted Electricity Demand



Notes: This figure presents realized (in blue) and predicted (in red) hourly demand in Spain. Predictions follow the approach described in section 3.1, using Gradient Boosted Trees. To smooth out intra-day and intra-month variation, we present smoothed series and 95% Confidence Bands (CB) based on 30-day moving averages and standard deviations. The vertical red line represents the beginning of year 2020. All predictions are made out-of-sample: predictions for 2019 use a model trained with data from 2015-2018; predictions for 2020 use a model trained with data from 2015-2019.

[22] In Appendix Figure B.7 we extend the analysis of validation set errors to include 2018. With that, we show that there are no clear patterns in terms of months of the year with larger errors in the pre-pandemic period. Thus we cannot clearly identify if any months of 2020 would be particularly prone to prediction bias.

3.3 Impact of the Crisis on Electricity Demand

To assess the impact of the COVID-19 crisis on electricity demand in Spain, we follow a two-step approach. The first step is to obtain counterfactual predictions as described in the above section. The second step is to compute the differences between realized and counterfactual demand, at each time t: $b_t = E_t - \hat{E}_t$. Suppose that we want to summarize the effect of the crisis for the whole year of 2020. Then we can calculate the average:

$$\bar{b}_{2020} = \sum_{t \in 2020} (E_{2020} - \hat{E}_{2020}) \Big/ N_{2020} \ , \tag{6}$$

where $\bar{b}_{2020}$ will be our estimate, in MWh, of the average effect of the crisis in 2020; E_{2020} is realized electricity demand for all hours of the year; $\hat{E}_{2020}$ is counterfactual predicted demand; and N_{2020} is the total number of hours in the year. The estimate can also be transformed to percentage terms by taking $\bar{b}_{2020}$ and dividing it by the average counterfactual in the same period.

Note that our measure of the change in demand is obtained by taking the difference between an observed and a predicted variable. When summarizing those effects, we should therefore take into account the true variability in the data, as well as the uncertainty and errors from the predictive step. We propose to use the prediction errors from validation samples to adjust the variance associated with our estimates. We define the variance of our estimates as follows:

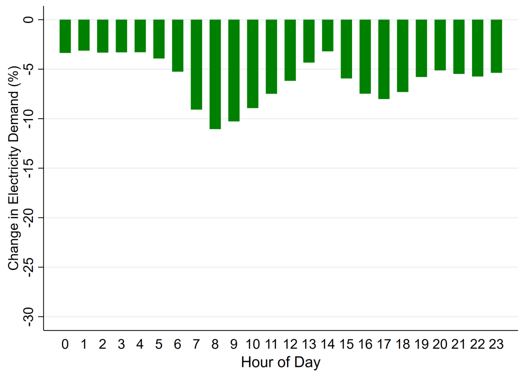
$$\sigma_e^2 = \sigma_b^2 + \sigma_{cv}^2 \ , \tag{7}$$

where σ_b^2 is the variance of b_t for a given subsample, and σ_{cv}^2 is the variance of the prediction errors for a comparable *validation* subsample. For example, if we want to summarize the effects for the whole year of 2020, then the comparable validation subsample would be the whole year of 2019. Alternatively, if we want to summarize effects only for the summer, then the comparable validation subsample should also be comprised only of observations during the summer. We can use σ_e^2 to calculate standard errors and confidence intervals for our estimates. In Appendix B.5 we provide more details about inference. One key assumption is that the two variance components are independent (Heskes, 1996).

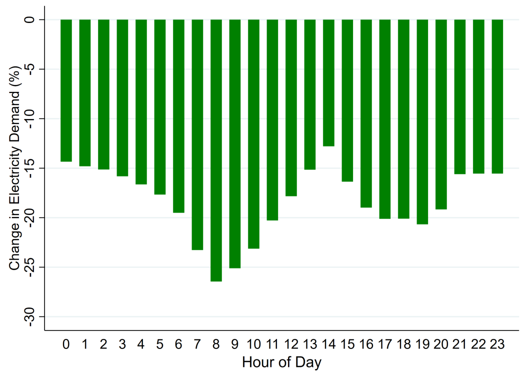
Considering observations from March 2020 until the end of the year, we find that the pandemic was associated with an average reduction of 1,513.69 MWh in electricity demand in Spain, with a 95% confidence interval of [1,472.16 1,555.21] MWh. That represents a reduction of about 5.39%, compared to the average counterfactual consumption during the same period. To investigate if the lockdowns were associated with a change in intraday demand patterns, we plot average percent reductions by hour of the day. Those results are presented in Figure 2. We also disaggregate them into four periods with varying stringency of movement restrictions: (a) 1st Partial Lockdown (March 11th - March 28th); (b) Full Lockdown (March 29th - April 10th); (c) Partial Lockdowns and Looser Restrictions (April 11th - August 14th), (d) Second Wave and Beyond (August 15th - December 31st).[23] Overall, stronger demand reductions are observed during early morning and mid-afternoon hours. The effects are especially striking for the full lockdown period (panel b), where demand at 8 am reduced by about 26%, on average. Nevertheless, during partial lockdown periods the effects were also significant at that hour, reaching almost 11%. Results suggest that intraday demand patterns were already returning to normal after August 15 , but at slightly lower levels compared to the counterfactual.

[23]These cutoffs were based on authors' compilation of official government announcements and news reports. See (Bover et al., 2020) for a more detailed description of these measures.

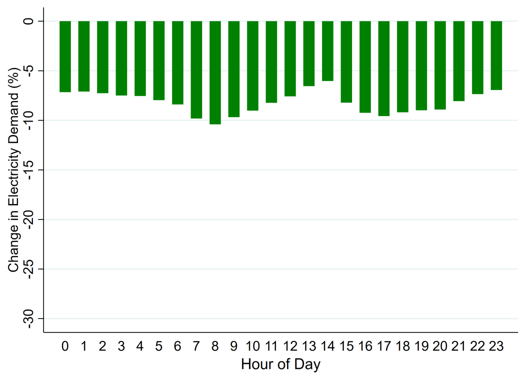
Figure 2: Reduced Demand By Hour of the Day



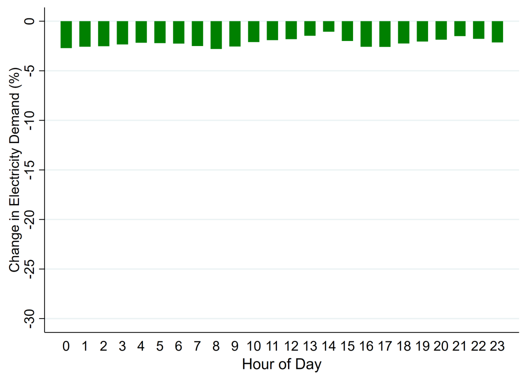
a: 1st Partial Lockdown
(March 11 - March 28)



b: Full Lockdown
(March 29 - April 10)



c: Partial Lockdowns; Looser Restrict.
(April 11 - August 14)



d: Second Wave and Beyond
(August 15 - December 31)

Notes: This figure presents intraday differences between realized and counterfactual electricity demand in Spain, across four distinct time periods of 2020. Lockdown stringencies vary across the four panels presented. We estimate percent average changes by hour of the day.

3.4 Electricity Market Simulations

We now use our hourly estimates of counterfactual electricity demand in order to simulate electricity market outcomes in the absence of the pandemic. By also performing simulations with realized electricity demand, we can assess the impact of the pandemic on carbon abatement.

The model. Our simulations rely on the model developed by De Frutos and Fabra (2012), which reflects key technological and institutional features of electricity markets. In particular, the model allows for strategic behaviour by firms under the assumption that they compete by submitting step-wise supply functions, i.e., a finite set of price-quantity pairs for each of their production units.[24] The auctioneer collects all bids, determines the market clearing price at the intersection between demand and supply, and calls the winning plants to produce (i.e., all plants that offered prices at or below the market clearing price).

De Frutos and Fabra (2012) show that all the Nash equilibria satisfy the following properties. In equilibrium, one firm acts as the price-setter, and all the others behave as non-price setters. The non-price setters produce the same *as if* they were bidding at marginal costs, while the price-setter sets the price that maximizes its profits over the residual demand. Therefore, unless the only equilibrium involves competitive bidding, the price-setter produces less than if it were bidding at marginal costs. The only potential deviation that one needs to check is whether the non-price setters find it profitable to charge a price above the candidate equilibrium price. Equilibrium existence is always guaranteed, as the non-price setters never want to deviate from the highest-price candidate equilibrium.

These properties guide the algorithm that we have used in our simulations, allowing it to be very efficient in the equilibrium search process.[25] Along with the Nash equilibrium, the algorithm also characterizes the competitive equilibrium, at which all firms bid

[24] For simplicity, hydro units are not allowed to bid strategically. Rather, we assume that their production is allocated to shave the peaks of demand net of renewables on a monthly basis. Hence, our equilibrium provides a lower bound on the degree of market power that can be exercised.

[25] This algorithm is called ENERGEIA, and it is available from the authors upon request. See nfabra.uc3m.es/energeia/ for a description.

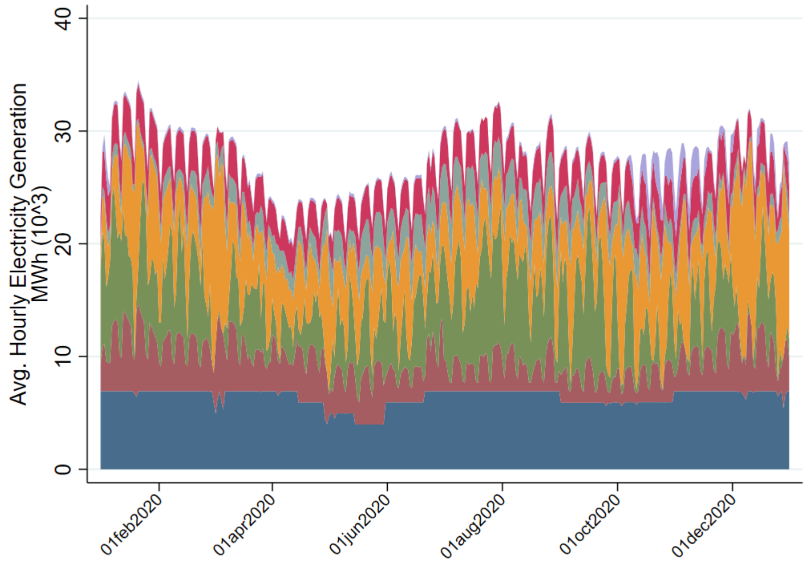
at marginal costs.

We have run simulations of the Spanish electricity market under two scenarios, one with realized demand and another one with counterfactual demand. The difference between the two scenarios gives the effect of the pandemic on the power sector. Since the simulations are conducted at an hourly basis, we have performed 8,760 simulations under each scenario for the whole year of 2020. Appendix A contains details on the data sources we have used for the simulations.

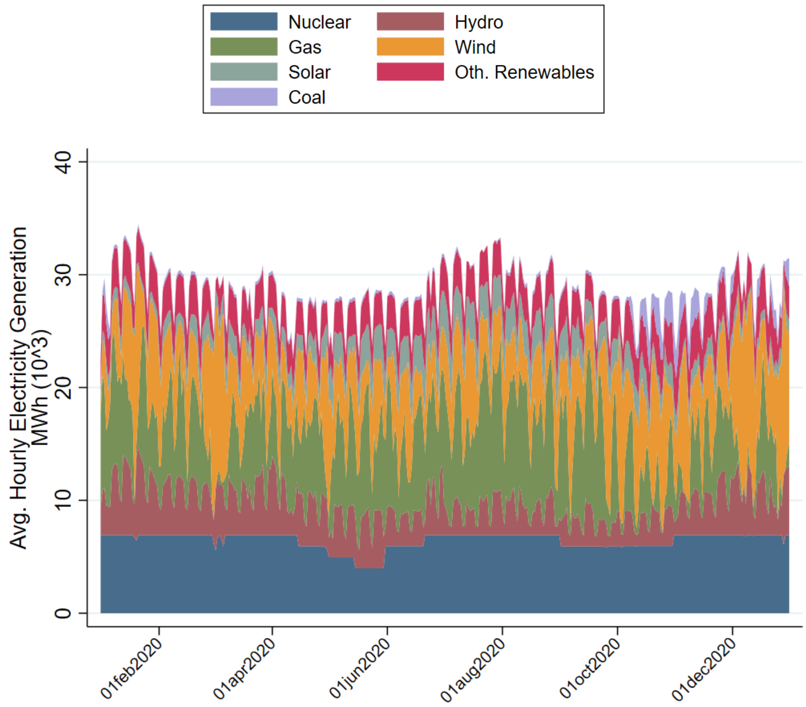
Results of the simulations. Figure 3 plots the evolution of the simulated generation mix under the two scenarios, using realized and counterfactual demand.[26] The pattern of carbon-free generation (nuclear, hydro and renewables) remains unchanged across the two scenarios given their lower marginal costs. Instead, coal and gas plants provide the buffer that absorbs the demand reductions. Indeed, their 2020 production goes down under the scenario with realized demand relative to the counterfactual by 4.8% and 20.5%, respectively. Interestingly, these reductions differ from the ones obtained by comparing the realized generation by coal and gas plants in 2019 and 2020. In particular, actual coal generation in 2020 fell by 55% relative to 2019, while gas generation fell by 25% (REE, 2020b). The main reason for this disparity is that a bulk of the coal plants have gone offline during 2020, leading to a sharp drop in their production from 2019 to 2020, and only a mild drop when comparing 2020 with the counterfactual of no COVID-driven demand reductions. Note also that 2020 has been a particularly humid and sunny year as compared to 2019 (indeed, hydro and solar PV production have increased by 24% and 68%, respectively). This highlights the importance of using a counterfactual scenario rather than changes from one year to the other. Indeed, in the context of the Spanish power market, using the year-on-year changes would overestimate the emission reductions caused by the pandemic.

[26]The figures assume that firms behave competitively. Assuming strategic behaviour has almost no impact on the energy mix by technology.

Figure 3: Simulated Generation Mix



a: Using realized demand



b: Using counterfactual demand

Notes: This figure represents the evolution of the simulated generation mix in the Spanish electricity market during 2020. Simulations in panel (a) have been computed with realized electricity demand; those in panel (b) with the estimated counterfactual demand. The simulations assume that firms behave competitively; strategic behaviour only has a minor impact on the generation mix by technology. “Solar” includes both solar PV and solar thermal. “Oth. Renewables” includes cogeneration, waste and other renewables. We present averages for each day, to smooth out intra-day variation.

As shown in Table 1, changes in the generation mix across scenarios have a direct translation on the amount of carbon emissions avoided. Overall, emissions dropped by 4.13 Million Tons (assuming competitive behaviour) or 3.90 Million Tons (assuming strategic behaviour).[27] This represents a fall in emissions of 11.5% and 10.6%, respectively. In percentage terms, 90-95% of these emissions reductions came from CCGTs, given that these plants absorbed the vast reduction in power demand. Note that the estimated carbon abatement is less than half of the year-on-year power sector emissions reduction (27.9% according to REE (2020b)) since, as already noted, not all of that can be attributed to the pandemic.

Table 1: Power sector carbon emissions under Realized and Counterfactual scenarios

	Counterfactual Demand		Realized Demand		Difference	
MtCO2	Competitive	Strategic	Competitive	Strategic	Competitive	Strategic
Coal	3.23	3.68	3.08	3.52	0.15	0.16
Gas	21.69	21.52	18.00	17.85	3.69	3.67
Cogen + Others	11.16	11.56	10.87	11.49	0.29	0.07
Total	36.07	36.76	31.94	32.86	4.13	3.90

Notes: This table reports total emissions in 2020 under all four scenarios considered in our simulations (using realized or counterfactual demand, and assuming either competitive or strategic firm behaviour). It also breaks total emissions in sources. The last two columns provide the difference across scenarios.

We also run simulations using counterfactual predictions from a fixed effects regression, rather than machine learning. We find that abatement estimates are substantially higher with these simulations: assuming competitive behavior, abatement was 5.82 Million Tons (almost 50% higher than those from ML).[28] This is in line with the results from section 3.2, where we find that FE models overestimate counterfactual demand. The implication is that natural gas plants would have been dispatched more often, thus leading to higher counterfactual emissions.

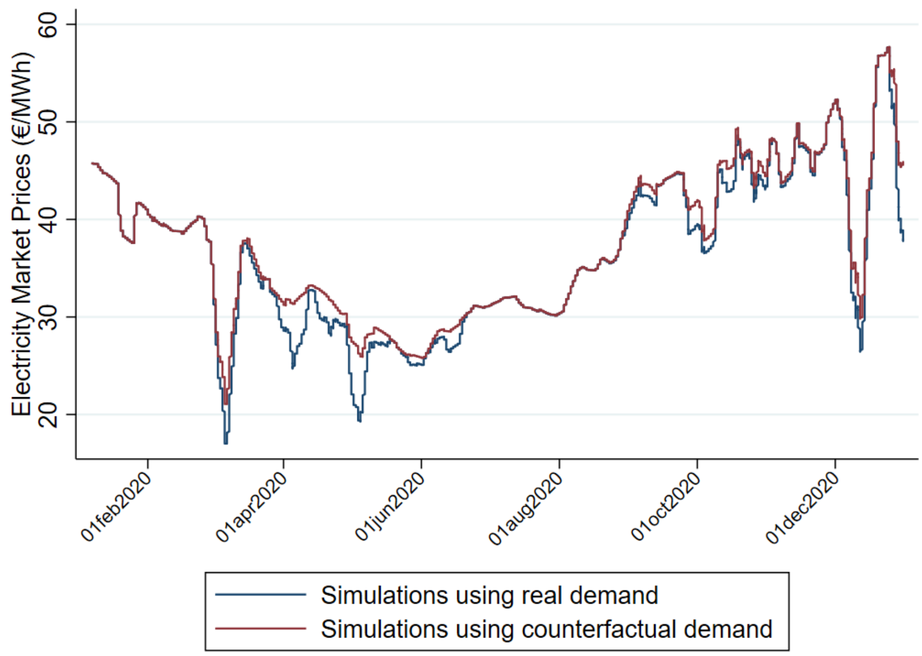
Returning to the simulations with the best-performing ML algorithm, we are also able to assess the effects of the pandemic on other variables of interest, even if not directly related to the main question addressed in this paper. For example, results suggest that the reduction in electricity demand in 2020 caused average electricity market prices to

[27]Using a value of 40 Euro/Ton of CO2, this represents a saving of 156-165 Million Euro.

[28]Results can be found in the Appendix, Table B.2.

fall from 37.5€/MWh to 36.5€/MWh (if firms are assumed to behave competitively) or from 40.3€/MWh to 40.0€/MWh (if they are assumed to behave strategically). The magnitude of the price effect is limited because CCGTs still set the market price during most hours, with the exception of those hours when demand fell so much that market prices were set by renewables instead. Figure 4 depicts the curve of simulated prices under realized and counterfactual demand. Lower prices can be noted especially during the most stringent lockdown periods.

Figure 4: Market Prices Under Realized and Counterfactual Scenarios



Notes: This figure compares daily averages of market prices obtained from the simulation with realized demand (in blue) versus those from simulations with predicted demand (in red). We present 7-day rolling averages, to smooth out intra-week variation in prices. Results assuming competitive behavior.

Our simulations also suggest that the pandemic drove down firms' market revenues because both production and prices fell. In particular, market revenues fell by 6.6% (if competitive behaviour is assumed) or by 4.6% (if strategic behaviour is assumed). However, since generation costs went down by a larger extent (by 11.3% or 11.0%, respectively), firms' profits also fell but less (4.1% or 1.5% respectively) compared to the fall in market revenues. Note that the effects are always milder when strategic behaviour is assumed. The reason is markup adjustment.

Before closing this section, two caveats are in order. First, COVID-19 has also likely affected the prices of fossil fuels to the extent that it has affected their demand. Accordingly, the counterfactual simulations would have to be computed with counterfactual fossil fuel prices rather than with the realized prices. However, computing such counterfactual prices is complex as fossil fuel prices are determined by other factors that have also been affected by the pandemic itself. One option would be to use the future prices of fossil fuels that were published before the pandemic hit the international markets. The drawback of using these is that they lack variability that critically shapes electricity price patterns. In any event, we have run the simulations with the futures prices quoted on December 31st, 2019, and the results regarding emissions remain unchanged. Second, the pandemic might have also affected the availability of nuclear power stations. Indeed, three of them were shut down during the most critical times of the pandemic, making it reasonable to suspect that their availability would have been higher in the absence of the pandemic. To check whether this would have had any implications on our estimates, we have run the simulations under the assumption that nuclear plants were fully available across the year. The results barely change.[29] Last, note that this potential concern does not apply to renewables or hydro given that their availability is exogenously determined.

4 Carbon Emissions from Other Sectors

The focus of this paper is on the power sector, which is a big contributor to overall emissions but certainly not the only one. In order to capture emission reductions in other sectors of the economy, we rely on data provided by the Carbon Monitor (Liu, Ciais, Deng, Lei, et al., 2020). Carbon Monitor produces estimates of daily carbon emissions by downscaling measures that exist at the monthly or annual level. Several factors are taken into account for a dynamic downscaling. For example, the authors collected detailed monthly data on industrial activity indices and emissions factors. Those are then further downscaled to daily levels by weighting according to the share of electricity gen-

[29]More in detail, we find that nuclear production would have been 0.6% higher, leading to a slightly lower emissions reduction of 0.03 Million Tons as compared the emissions reduction reported below.

eration in a given day. In terms of estimates for ground transport, a key data source is hourly congestion data across several cities in Spain. For domestic aviation, the authors collected data on daily kilometers flown and emissions factors for airplanes arriving at and departing from Spain. Finally, for residential emissions, the main factors are fuel consumption for heating/cooling, as well as their relationship with heating degree days.[30]

Figure 5 summarizes their results across different sectors. The figure plots daily emissions from 2019 and 2020. For time periods after lockdowns were implemented, clear patterns of emission reductions can be observed for domestic aviation, ground transport, and industry. Conversely, emissions from the residential sector appear to have remained stable. Table 2 compares 2019 and 2020 in terms of total emissions. Domestic aviation was the sector with the highest reduction in percentage terms (46.7%), but it represents a relatively small reduction in absolute terms (2.6 Million Tons). Ground transport and industry reduced their emissions by 9.4 and 6.6 Million Tons, respectively. Those values are substantially larger than our estimated reductions for the power sector (3.9 to 4.1 Million Tons, as reported in Table 1), consistently with findings from prior literature on global CO2 reductions due to the pandemic (Le Quéré et al., 2020). It should be noted that the reductions presented in Table 2 are likely less accurate than our power sector estimates given that, as already argued, 2019 emissions may not be the ideal counterfactual for 2020 emissions in the absence of the pandemic. Nevertheless, these results serve to illustrate and compare the relative magnitudes across sectors.

We argue that the relatively smaller carbon reductions from the power sector may be partly attributed to the low price and income elasticities of energy demand, especially in the short-run.[31] The power sector, being crucial to all other sectors of the economy, seems to have experienced relatively smaller reductions in activity and thus carbon emissions than other sectors of the economy (Le Quéré et al., 2020). That may have been further aggravated because increases in residential electricity demand partly offset the

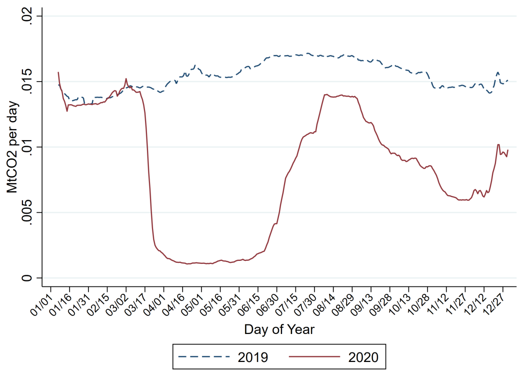
[30] Liu, Ciais, Deng, Davis, et al. (2020) provide further details on the estimation of daily carbon emissions.

[31] For estimates of the short-run elasticity of electricity demand by Spanish households, see Fabra et al. (2021). For results on short-run versus long-run price elasticity see, for example, Labandeira, Labeaga, and López-Otero (2017) for a meta-analysis, and Deryugina, MacKay, and Reif (2020) for quasi-experimental estimates. For evidence on income elasticity see, for example, Krishnamurthy and Kriström (2015).

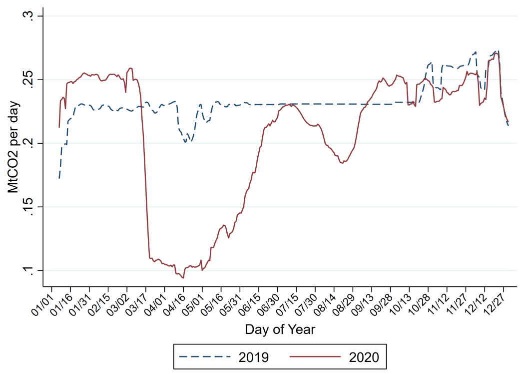
decreases in electricity demand from other sectors during the crisis (Bover et al., 2020). Finally, we note that the emissions factors for electricity generation in Spain have been steadily decreasing over the last five years, thanks to investments in renewables and less dependence on coal (REE, 2020a), and are in any case lower than the emissions rates in other sectors of the economy (notably, transport or aviation). The implication is that a reduction in electricity demand results in a relatively smaller reduction in emissions relative to other sectors.

By adding estimates of reductions across all sectors of the economy, we find that the crisis was associated with approximately 23.14 Million Tons of carbon abatement in 2020.

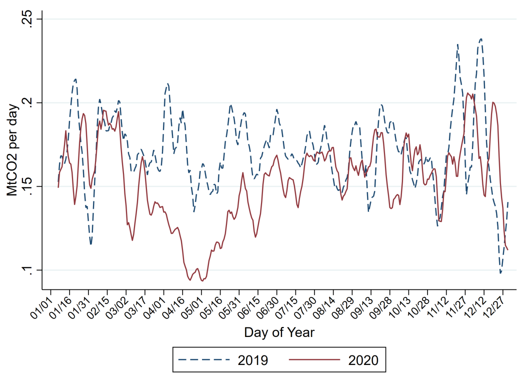
Figure 5: Daily CO2 Emissions from Other Sectors



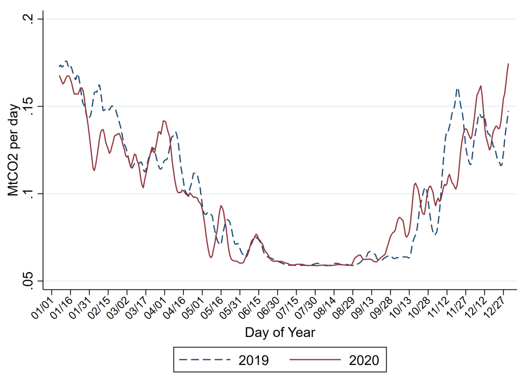
a: Domestic Aviation



b: Ground Transport



c: Industry



d: Residential

Notes: Data from Carbon Monitor (Liu, Ciais, Deng, Lei, et al., 2020). This figure compares CO2 emissions in Spain from 2019 and 2020, across different sectors, excluding the power sector. The lines represent 7-day rolling averages of daily carbon emissions.

Table 2: CO2 Emissions by Sector

	Counterfactual Emissions		Realized Emissions		Emissions Reductions	
	MtCO2	Sector Share	MtCO2	Sector Share	MtCO2	Pct.
Domestic Aviation	5.64	2.5%	3.00	1.5%	2.63	46.68%
Ground Transport	84.83	37.5%	75.40	37.1%	9.43	11.12%
Industry	62.25	27.5%	55.63	27.4%	6.62	10.64%
Residential	36.70	16.2%	36.14	17.8%	0.56	1.53%
Power	36.76	16.3%	32.86	16.2%	3.90	10.61%

Notes: Data on Domestic Aviation, Ground Transport, Industry, and Residential are from Carbon Monitor (Liu, Ciais, Deng, Lei, et al., 2020). For those sectors, "counterfactual" refers to emissions in 2019, while "realized" refers to emissions in 2020. For the Power sector, we take estimates from Table 1, under the strategic scenario.

5 The Implicit Cost of Carbon Abatement

5.1 GDP Loss Caused by the Pandemic

To assess the short-run GDP loss caused by the pandemic, we use data from the Spanish Statistical Office INE (2020), and from the Bank of Spain. Our approach is to compare counterfactual GDP versus realized GDP during the crisis. To construct counterfactual GDP, we rely on quarter-on-quarter growth rate forecasts by the Bank of Spain.

The Bank of Spain's macroeconomic projections are made and published on a quarterly basis. They are constructed by combining the results of econometric models and expert judgement. In this paper, to construct the counterfactual GDP, we use the macroeconomic projections generated in November 2019, thus before any information about the pandemic was available. As it is usual in the last quarter of the year, those projections were prepared jointly by all the Eurosystem central banks in what is called the Broad Macroeconomic Projection Exercise.[32]

We take the forecasted quarter-on-quarter growth rates of nominal GDP from 2020Q1 onward and apply them to the actual GDP published by INE for the last quarter of

[32] Twice a year, on the second and fourth quarters, projections are prepared for the macroeconomic variables of the euro area and of the individual member states, ensuring they are consistent with each other, and applying a common set of external assumptions.

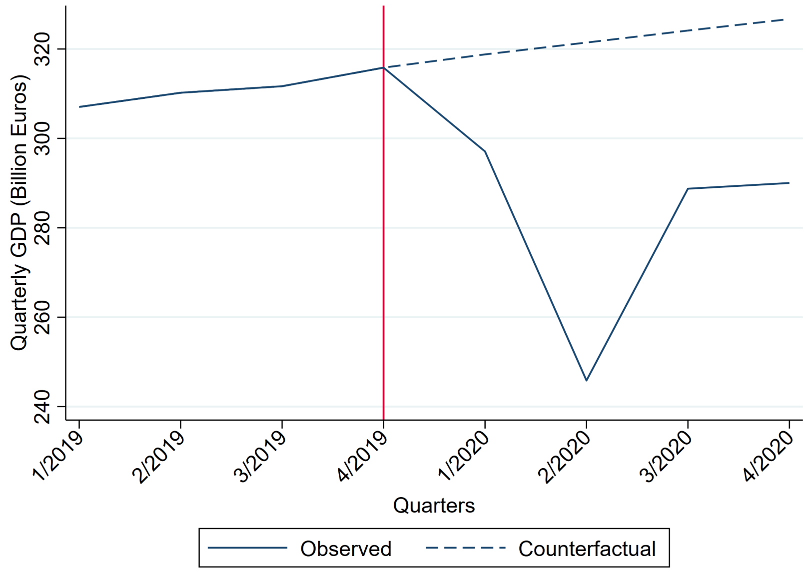
2019.[33] Results are presented in Figure 6, which compares counterfactual and observed GDP across quarters. It can be noted that the biggest differences happened during the second quarter, as expected due to the stricter lockdowns. We note that GDP levels were still far from normal in the last quarter of 2020. The total GDP loss in 2020 was 169.37 Billion Euros.[34]

We compare that GDP loss to the total emissions reductions calculated in the previous sections. We compute the implicit cost of carbon by dividing the short-run GDP loss (169.37 Billion Euros) over the total number of emissions avoided (23.14 Million Tons), resulting in an implicit cost of carbon of 7,319 Euro/Ton. Note that this calculation omits the long-run effects of the crisis, which might affect both future emissions as well as economic growth. It also omits other social costs caused by the growth reduction, such as those associated with increased unemployment, firms' closures, or deterioration of economic expectations, among others. If these costs were taken into account, the implicit cost of carbon would further increase.

[33] Notice that when quarter-on-quarter (qoq) growth rate forecasts were made, there was no information on 2019Q4. In that case, there may have been some forecasting error for 2019Q4, which would have carried over to 2020Q1. We note that these errors were small, nevertheless we decided to apply the growth rate forecasts to the actual figures published later by INE for 2019Q4. The Bank of Spain does not publish the exact qoq growth rates for the forecasting horizon and only publishes annual figures. However, the forecasting department kindly provided those past estimations for nominal GDP qoq growth rates for the four quarters of 2020. Those figures were 0.94%, 0.83%, 0.83% and 0.79%.

[34] According to figures taken from the Bank of Spain (2016), in 90% of the cases, the projection error of 1-quarter-ahead real GDP forecast is lower than 1pp in absolute terms and the projection error of 4-quarter-ahead forecast is lower than 2pp in absolute terms. Something similar would apply to inflation. Taking these errors as granted, a sensitivity analysis could be done using the lower band projection in the 90th percentile: i.e., a lower projected nominal growth of -2pp in the first quarter, -2.6pp in the second, -3.3pp in the third and -4pp in the fourth. This would lead to a lower loss of 37 billions with respect to the 170 billions of the baseline scenario.

Figure 6: Spanish Quarterly GDP



Notes: Data from INE (2020) and Bank of Spain. The graph presents Spanish quarterly GDP. Counterfactual GDP was projected by taking GDP growth rates that were forecasted by the Bank of Spain in November 2019 (i.e. in the absence of information about the pandemic). All values were adjusted to represent Euros in the last quarter of 2019.

5.2 External Validity

As a proof of concept, we estimate the crisis' implicit cost of carbon abatement for two other countries: Italy and France. Both countries implemented early movement restrictions similar to those in Spain. We model counterfactual electricity demand in those countries with the approach described in section 3.1. That allows us to estimate the pandemic's impact on electricity demand. We can then calculate the associated carbon abatement in that sector, assuming that the difference in demand would have been supplied by natural gas plants. For carbon abatement in other sectors we again use data from Carbon Monitor (Liu, Ciais, Deng, Lei, et al., 2020). Finally, we obtain Italy's and France's GDP growth rate data from the OECD (2021). More details on data used for these analyses are presented in Appendix C.

Our estimates suggest that the pandemic led to power sector abatement of 6.77

MtCO2 (3.95%) in France and 2.54 MtCO2 (2.45%) in Italy.[35] Considering all sectors, carbon reductions associated with the pandemic were 30.96 MtCO2 for France and 20.60 MtCO2 for Italy. The short-term GDP losses associated with the pandemic were 179.11 Billion Euros for France and 145.48 Billion Euros for Italy. Finally, the resulting implicit costs of carbon are 5,785 Euro/Ton for France and 7,062 Euro/Ton for Italy. These figures are remarkably similar to the one estimated for Spain, despite the vast differences in economic and power sector structures across these countries. Detailed results for France and Italy are presented in Appendix C.

5.3 Investing in Renewable Energy

Emissions can be decoupled from growth through low carbon investments, including those aimed at improving energy efficiency, increasing interconnection capacity, storage, or renewable energy, among others. For concreteness, and given its relevance, here we focus on the deployment of renewable investments for power generation, whose costs can be more readily estimated. This provides a benchmark with which to assess the implicit cost of carbon abatement during the pandemic. Nevertheless, since an optimal decoupling strategy would involve a combination of all those options, the resulting implicit costs of carbon should only be interpreted as illustrative of the orders of magnitude involved.

In this section, we employ the same simulation model as the one used and described in section 3.4 to shed light on the following questions: how much investment in power sector renewables would have been needed to achieve emission reductions similar to those caused by the pandemic? How would have market outcomes changed in the absence of the pandemic had renewables been scaled up to that level? According to the simulation results reported in Table 1, emissions in the power sector went down by 3.9-4.1 Million Tons. The same outcome could have been achieved through alternative policies, plausibly in combination with one another. We have considered a mix of alternative investments

[35] We assume that abatement comes from reduced dispatch of natural gas plants (CCGTs), which have an emissions factor of 370 gCO2/kWh (IEA, 2011). This could be considered an upper bound for these countries. For instance, in France, nuclear power, which is carbon free, could have been reduced instead. A lower bound would assume an emissions factor at the average carbon intensity for these countries: 49 gCO2/kWh for France and 272 gCO2/kWh for Italy (Climate Transparency, 2020). The resulting lower-bound reductions are 0.9 MtCO2 in France and 1.87 MtCO2 in Italy.

in renewable energy that lead to emission reductions of a similar magnitude: expanding solar PV capacity only, or onshore wind capacity only. According to our simulations, if solar PV capacity had been 7,812 MW bigger by the beginning of 2020 (which represents a 90% increase over existing capacity), carbon emissions would have decreased by 4.2-4.5 Million Tons (using counterfactual demand). These are just slightly higher than the emission reductions caused by the pandemic. Similarly, if onshore wind capacity had been 2,582 MW bigger (or approximately 10% above the actual installed capacity) by the beginning of 2020, carbon emissions would have decreased by 3.8-4.0 Million Tons. This is just about the same figure as the amount of emission reductions caused by the pandemic.

Using the most recent cost estimates provided by IRENA (2020),[36] we have computed the total costs of the investments plus the operation and maintenance costs (O& M).[37] Assuming that the new plants have a lifetime of 25 years,[38] these would result in investment plus O&M costs for the year 2020 of 276 Million Euro and 245 Million Euro for the two options, respectively. Table 3 below summarizes the results.

Table 3: Investment Costs and Emission Reductions in the Power Sector

	Emission Reductions (MtCO2)		Investment Costs (M EUR)		Implicit Cost of Carbon (EUR/Ton)	
	Competitive	Strategic	Total	Annualized Investment+O&M	Competitive	Strategic
Pandemic	4.13	3.90	-	-	-	-
Solar Investments	4.53	4.21	6,890.11	275.60	60.80	65.44
Wind Investments	4.06	3.78	6,122.97	244.92	60.34	64.81

Notes: This table provides the emission reductions triggered by the pandemic (first row), or triggered by investments in renewables: solar PV (second row), or onshore wind (third row). Investment and O&M data come from IRENA (2020). The exchange rate for EUR/USD is assumed to be 0.89, which was the average for 2019. The lifetime of the renewable plants is assumed to be 25 years. The implicit cost of carbon is obtained by dividing the fourth column (Annualized Investment) by either the first or second columns. Values from that division may not necessarily match what is reported in the table due to rounding error.

Similarly to what we did in the previous section, we have computed the implicit cost of carbon for the two investment options: 60.8-65.4 Euro/Ton for the solar PV

[36] These cost estimates are based on the analysis of around 17,000 renewable installations from around the world, together with data from 10,700 auctions and power purchase agreements for renewables.

[37] In particular, in 2019, the total investment costs of solar PV and onshore wind in Spain were 766 USD/kW and 1,552 USD/kW, respectively. These data are obtained, respectively, from Figure 3.4 and Figure 2.5 from IRENA (2020). IRENA estimates O&M costs of 9 USD/kW per year for solar PV in Europe. For onshore wind, the estimates range from 33-56 USD/kW per year, of which we take the average, 44.5 USD/kW.

[38] These are industry standards, although lifetimes could be even longer according to experts (NREL, 2020; Wiser and Bolinger, 2019).

investments and 60.3-64.8 Euro/Ton for the onshore wind investments.[39]

In addition to the environmental benefits, these investments would contribute to keeping electricity prices and generation costs down. The demand-weighted average prices in the counterfactual scenario (no pandemic and no renewable investments) are 37.8€/MWh (competitive) and 40.4€/MWh (strategic), and they fall down to 35.7€/MWh (competitive) and 39.6€/MWh (strategic) under the scenario with solar investments, and to 31.5€/MWh (competitive) and 34.8€/MWh (strategic) under the scenario with wind investments. It is clear that the price depressing effect of wind investments, at least in this context, is stronger both under the assumptions of competitive and strategic behaviour. Also, renewable investments would reduce generation costs: expressed in savings per Euro invested, these amount to 1.3 €/MWh in the case of solar, and to 2.2 €/MWh in the case of wind.

While simulations are useful to quantify the market impacts of renewable investments and the implicit cost of carbon abatement, there are nevertheless some caveats. Notably, we have assumed that the availability factors of the new renewable investments are the same as the ones of the existing projects. This might lead to overestimating renewable production, and hence, carbon abatement, to the extent that the new sites are likely to be less productive than the ones that were exploited first. If so, our implicit cost of carbon would be slightly under-estimated. Nevertheless, it is important to note that our model allows for renewable curtailment if their supply exceeds total demand. Hence, the increased incidence of curtailment as renewable investment ramps up does not lead to an overestimation of carbon abatement. Last, our model only analyzes the generation impacts and the costs associated with them, without summing up the costs of other infrastructures that would also be needed to support the renewables deployment. Notably, this would require reinforcing the transmission and distribution grids and scaling

[39] We note that our estimates of implicit cost of carbon are slightly higher than those reported by Gillingham and Stock (2018). However, they are in line with those reported by Callaway, Fowlie, and McCormick (2018) for the case of California, which is more comparable to Spain. There are a couple of reasons for these disparities. First, as discussed by Callaway, Fowlie, and McCormick (2018), these implicit costs depend on the technologies being displaced. Given that Spain is advanced in the energy transition, renewable investments displace mostly gas plants, which are already less carbon intensive than coal. Second, investment and operation and maintenance costs also depend on the region being studied. Moreover, investment costs have been falling, and our cost data are more recent.

up storage.

We want to conclude this section by stressing again that these figures omit long-run effects. Notably, the renewable investments create other positive externalities beyond the environmental benefits (including learning by doing economies, as pointed out by several authors; see Borenstein, 2012; Gillingham and Stock, 2018). Furthermore, as reported in previous studies, low carbon investments contribute to wealth and employment creation through their multiplier effects. For instance, the UK's Office for National Statistics (2019) reports that the turnover and employment multipliers for solar PV investments in 2017 were 1.87 and 1.96, respectively.

6 Conclusions

In this paper we have computed the implicit cost of carbon abatement caused by the COVID-19 pandemic. We benchmark this figure against the costs of reducing emissions through power sector renewable investments under a counterfactual scenario of no decrease in electricity demand. The comparison of both figures suggests that structural reductions in emissions should be anchored on sustained and ambitious policies to foster the deployment of clean energy solutions, allowing economic growth to be decoupled from carbon emissions.

We believe that the Spanish experience provides valuable insights for other countries, notably those at a similar stage of development. However, it is important to note that the effects of the carbon abatement strategies need not be linear. First, as noted by Jorgenson (2014), the relationship between growth and emissions is heterogeneous across countries and over time. And second, as noted by Callaway, Fowlie, and McCormick (2018), there is substantial variation in the costs per Ton of CO2 avoided, as these depend on the quantity of emissions displaced by the low carbon technologies and therefore on the state of the energy transition in each country. Nevertheless, there is a substantial difference between the implicit costs of carbon abatement during the pandemic versus those from renewable investments, which contributes to the robustness of our overall conclusion. Namely, transforming our current energy system, to decouple it from economic growth, seems to be a feasible and desirable strategy to tackle climate change.

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Appendix – For Online Publication

A Data Appendix

A.1 Data used in the prediction models for the power sector

Daily weather data were obtained from AEMET (2020) for all the weather stations in Spain. Then, simple averages of weather observations were taken at the province level, resulting in 52 variables for min. temperature, max. temperature, median temperature, precipitation, wind direction, wind speed, and solar radiation. However, there were still some data missing for some days in 2020. We thus dropped variables for provinces that had too many missing observations, otherwise we would have to drop important dates from our sample of interest. We also create variables for average weather across the whole country, which are simply the averages of the 52 province-level variables. We take daily lags (up to three) for the averages and the province-level variables. Finally, we transform the weather variables into their quadratic and cubic forms.

The machine learning prediction models also include: month of the year; day of the month; day of the year; week of the year; daily time trends; monthly time trends; hour of the day; and holidays. Those are included as binary, and as continuous variables. Holidays are taken from the Spanish Boletín Oficial del Estado (BOE), including both national and regional holidays. The variable takes the value of 1 for national holidays, and a value between 0 and 1 for regional holidays depending on the weight of the regional electricity consumption (provided by the Spanish System Operator, REE).

The machine learning algorithm that we implement recursively builds a complex model, where each iteration randomly selects a different set of variables. Ultimately, the variables with best predictive power are given more weights by the algorithm.

Table A.1 below presents descriptive statistics for the main weather variables used in the prediction models for the power sector. The first column presents averages and standard deviations for the pre-pandemic period (2015-2019), while the second column present information for 2020. The third column presents the average differences between those periods and the associated standard errors. The last column presents the P-values of the differences. The standard deviations suggest significant overlap in terms of observations across the samples. However, the fourth column shows that we cannot reject that weather patterns in 2020 were different from those observed during the pre-pandemic period. This provides evidence that simply using pre-pandemic demand data, without adjusting for weather, would lead to biased estimates of the counterfactuals in 2020.

Table A.1: Descriptive Statistics for Main Variables in the Study

	Averages			
	2015-2019	2020	Difference	P-value of Diff.
Electricity Demand (MWh)	28655.590	27078.422	-1577.168	0.000
	(4566.608)	(4673.601)	(53.596)	
Min Temperature (C)	9.725	10.221	0.496	0.000
	(5.372)	(5.009)	(0.062)	
Max Temperature (C)	20.864	21.174	0.310	0.000
	(6.969)	(6.744)	(0.081)	
Median Temperature (C)	15.295	15.698	0.403	0.000
	(6.076)	(5.784)	(0.070)	
Precipitation (mm)	1.647	1.714	0.068	0.018
	(2.483)	(2.263)	(0.029)	
Wind Direction (degrees)	197.181	195.820	-1.361	0.003
	(39.042)	(39.734)	(0.458)	
Wind Speed (m/s)	2.822	2.805	-0.017	0.053
	(0.762)	(0.736)	(0.009)	
Solar Radiation (hours/day)	7.347	7.220	-0.127	0.000
	(2.869)	(2.915)	(0.034)	
Hourly Observations	43,824	8,784		
Daily Observations	1,826	366		

Notes: This table presents averages for the main variables used in the predictive models. Standard deviations, or standard errors for the case of the third column, are presented in parentheses. The first column presents averages and standard deviations for the pre-pandemic period (2015-2019), while the second column present information for 2020. The third column presents the average differences between those periods and the associated standard errors. The last column presents the P-values of the differences. Weather data presented in this table are based on average readings across all of the provinces of Spain. However, the models incorporate weather data disaggregated by province. Additionally, models consider date/time fixed effects. Electricity demand data were available hourly, while weather data were available daily.

A.2 Data used in the power market simulations

We have used several data sources to feed the power market simulations algorithm. These simulations were performed using the software ENERGEIA (see: De Frutos and Fabra (2012); nfabra.uc3m.es/energeia/). ENERGEIA requires the user to specify the marginal costs of production of each generation plant in the Spanish electricity market. The marginal costs of the thermal plants depend on their heat rates (i.e., how much gas or coal they need to burn in order to produce a MWh), as well as on their carbon emission rates. These parameters were obtained from the Spanish system operator (REE). In turn, their costs also depend on the prices of the inputs (coal, gas and CO2 allowances), which are negotiated in international exchanges. We have obtained the API2 price for coal (converted from USD to Euro) and the EUA carbon price from Bloomberg, and the price of gas from the website of the Spanish's exchange, MIBGAS; all on a daily basis.[40] The marginal costs of the remaining units (hydro and renewables) are set at an estimate of their variable operation and maintenance costs.

Second, we had to specify the plants' availability. For gas and coal units, we set availability at their historical average; for the hydro plants, we have assumed that their availability on a monthly basis equals their monthly production. Data on the daily availability of the nuclear plants has been obtained from Revista Nuclear (2020). And data on the hourly availability of the renewable units has been computed by dividing their actual production during 2020 over their installed capacities on a monthly basis.

Last, we had to specify the hourly demand levels. We have obtained the realized hourly demand values from the Spanish system operator. The counterfactual demand values have been estimated as explained in section 3.1.

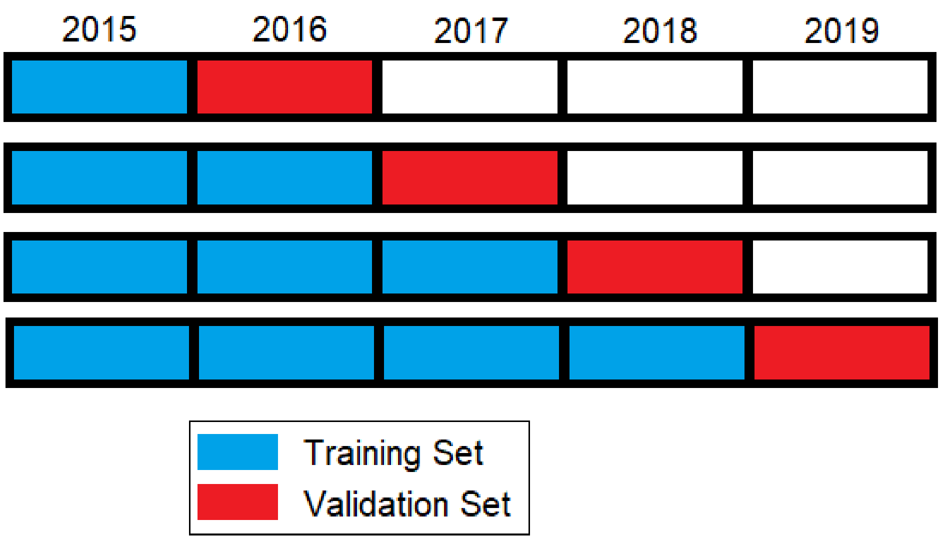
[40] The price for uranium has been set constant. This is inconsequential as nuclear plants have the lowest marginal costs, only after renewables, thus implying that they always produce at their available capacities.

B Further Details on Counterfactual Predictions

B.1 Choice of the cross-validation approach

We aim to assess *out-of-sample* prediction errors of our predictive models. We thus implement cross-validation. However, in the context of this paper, we argue that validation folds should not be defined at random, given the time-series nature of the data. With random splits, there is the possibility, for example, of using future data to predict the past, which is inconsistent with our main predictive objective. Established literature on forecasting recommends forward chaining as an alternative (Hyndman and Athanasopoulos, 2018). Therefore, we implement year-forward chaining, as illustrated in Figure B.1. Note that the size of the training set increases with each iteration, and that each iteration uses a different year as the validation set. Errors in 2019 are the most relevant for the analyses in this paper, since that year is temporally closer to the year of the crisis.

Figure B.1: Forward Chaining Cross-Validation



We assess out-of-sample errors for the year of 2019 to select and tune the *hyperparameters* of the algorithms considered. Note that hyperparameters, as opposed to standard parameters, are not estimated by the models. Rather, hyperparameters are chosen by the researcher prior to running the models. One example of a hyperparameter is the maximum number of regression trees that will constitute an ensemble model. Standard practice is to consider several options and combinations of hyperparameters, selecting the best-performing combination according to some pre-established criteria. In our case, we choose the algorithm and hyperparameter setup with lowest root-mean squared errors in the validation year of 2019. Then, we use that setup re-estimate the model with the full pre-pandemic sample spanning from 2015 to 2019. More details on the tuning process for this paper can be found in section B.2.

We emphasize that forward chaining is particularly useful for obtaining unbiased estimates of model *errors*. In principle, the model selected by other cross-validation approaches may coincide with that from forward chaining, even though their validation set errors may differ substantially. To illustrate this point, Figure B.2 below compares residuals according to forward chaining versus residuals from 10-fold (random splits) cross-validation. For both cases we use the same ML algorithm, with the same hyperparameters (model ML1 described in section B.2), with the objective of predicting electricity consumption in Spain. We present the validation errors for the year of 2019. Figure B.2 shows that residuals from 10-fold CV are, on average, substantially smaller than those from forward chaining. The errors from 10-fold CV are also better centered around zero. We argue, however, that these errors may not accurately reflect the errors that would be observed in 2020. That is because standard k-fold cross-validation does not guarantee that the training set consists only of observations from time periods prior to validation set.

Conversely, in Figure B.3 we show that forward chaining produces errors that are similar to those from a "test" set that was completely held out from the tuning process. Validation errors from January 1st to March 10th 2019 are compared to test set errors from January 1st to March 10th 2020. We note substantial overlap in the distribution of errors, which are also close in terms of their average (279 versus 236 MWh).

Figure B.2: Forward Chaining versus Random Splits

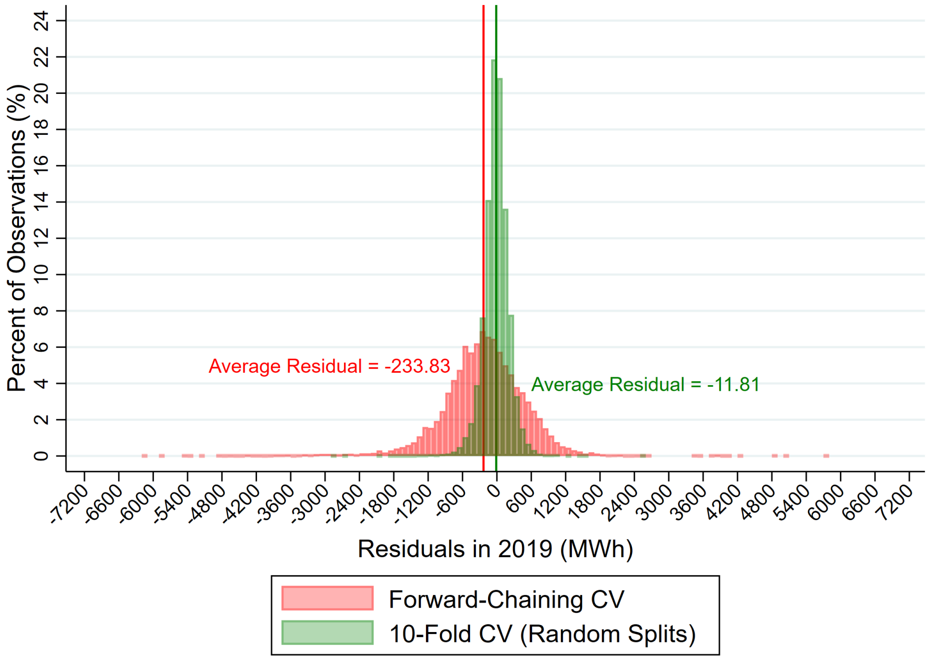
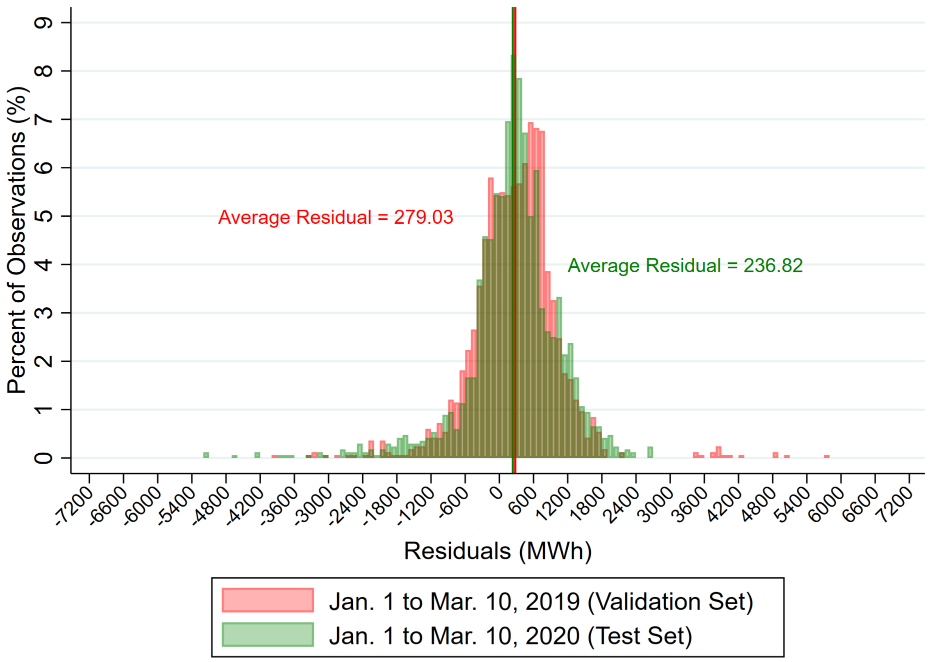


Figure B.3: Forward Chaining versus Test Set Errors



B.2 Model selection and tuning

In terms of machine learning algorithms, we consider four hyperparameter configurations for XGBoost (Chen and Guestrin, 2016), which is a flexible tree-based approach. We keep the number of regression trees 'ntrees', and the minimum number of observations per node 'minobspernode' fixed at 2000 and 20, respectively. We allow the maximum depth 'max_depth' of the trees to be either 10 or 30, and the 'shrinkage' parameter to be either 0.05 or 0.5.

In terms of fixed effects regressions, we consider four specifications with increasing complexity: month-of-year FE; week-of-year FE; day-of-year FE; day-of-year FE plus hour-of-day FE interacted weather variables. All the FE specifications also include: Min, max, and mean temperature; precipitation; wind speed; squared weather variables; lagged (up to 3) weather variables; wind direction indicators; day of week, hour of day, and day of month fixed effects; wind direction indicators; daily time trend.

With forward-chaining cross-validation, it was possible to obtain out-of-sample prediction errors for 2016-2019 for the models described above. Table B.1 Panel A presents results in terms of root-mean squared errors (RMSE). Panel B again describes the specifications, for ease of comparison. The Table provides a few key insights. First, it is clear that the size of the training set is important in this context, since the errors for the ML algorithms are consistently lower in 2019. Interestingly, the FE specifications do not exhibit that pattern, revealing how they can be unstable for out-of-sample predictions. Second, it is clear that the ML algorithms dominate the FE specifications in terms of performance. Model ID ML 1 exhibits the best overall predictive performance, with a RMSE of 809 MWh. The best-performing fixed effects model was FE 4, with RMSE of 1,095 MWh. A comparison between the errors from models FE3 and FE4 suggests that the added interactions between weather and fixed effects help explain variation in electricity consumption. Again we highlight that those interactions are naturally considered in the ML approach, since we use a tree-based algorithm. Finally, we note that results favor ML algorithms with slightly less complexity (smaller 'max_depth' or degree of interactions between variables), and with a slower learning rate (smaller 'shrinkage';

i.e. smaller importance for each new tree added to the full model).

Table B.1: Validation Set Predictive Performance (RMSE)

Panel A: Validation Year RMSE				
Model ID	2016	2017	2018	2019
ML 1	1155.88	934.42	856.18	809.13
ML 2	1160.67	984.78	871.45	815.45
ML 3	1517.53	1219.22	1165.42	1063.05
ML 4	1532.10	1266.84	1152.23	1083.03
FE 1	1778.87	1732.69	1717.40	1805.22
FE 2	1798.48	1662.92	1616.46	1710.66
FE 3	3687.60	1685.73	1615.97	1698.22
FE 4	2104.35	1009.69	904.53	1095.10

Panel B: Details on Model Specifications				
Model ID	ML Hyperparameters			
	ntrees	max_depth	shrinkage	minobspernode
ML 1	2000	10	0.05	20
ML 2	2000	30	0.05	20
ML 3	2000	10	0.5	20
ML 4	2000	30	0.5	20
Model ID	Fixed Effects Included			
FE 1	Month of year			
FE 2	Week of year			
FE 3	Day of year			
FE 4	Day of year; hour of day interacted with weather			

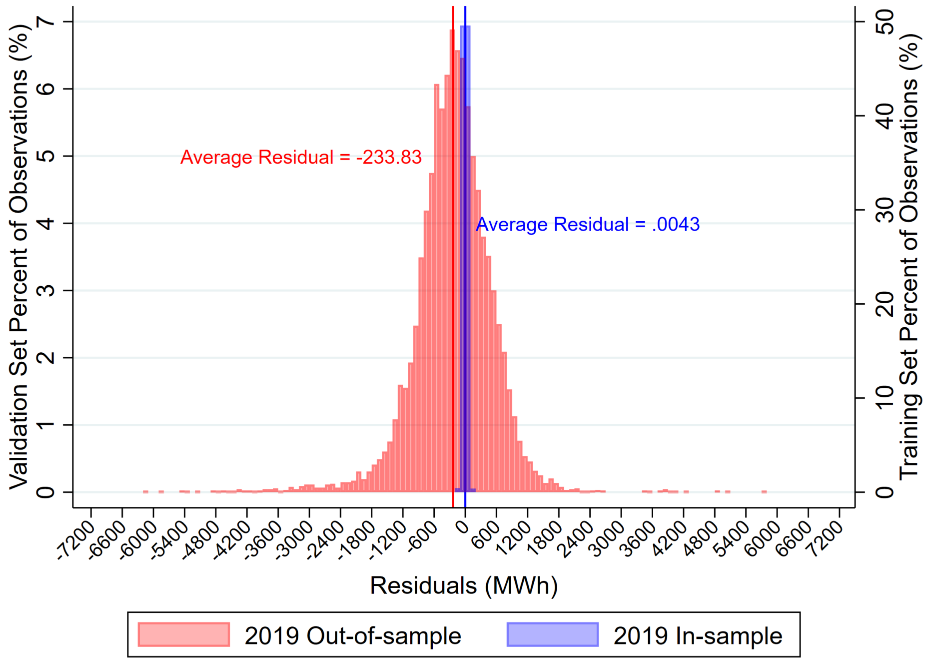
Notes: This table presents results from hyperparameter tuning via forward chaining cross-validation. All ML models considered are XGBoost. FE specifications are estimated with OLS. The top panel presents out-of-sample root mean squared errors (RMSE) for all specifications and for all years used as the validation set. RMSE can be compared to the average hourly consumption in 2019 = 28,528 MWh, or the standard deviation = 4,525 MWh. Moving from left to right, the number of years in the training set increases, as shown in Figure B.1. The bottom panel presents the hyperparameter configurations, and the fixed effects included for each specification. In addition to the fixed effects presented in the table, all FE specifications include: Min, max, and mean temperature; precipitation; wind speed; squared weather variables; lagged (up to 3) weather variables; wind direction indicators; day of week, hour of day, and day of month fixed effects; wind direction indicators; daily time trend. Specification FE 4 includes a total of 1,029 variables.

B.3 In-sample versus out-of-sample errors

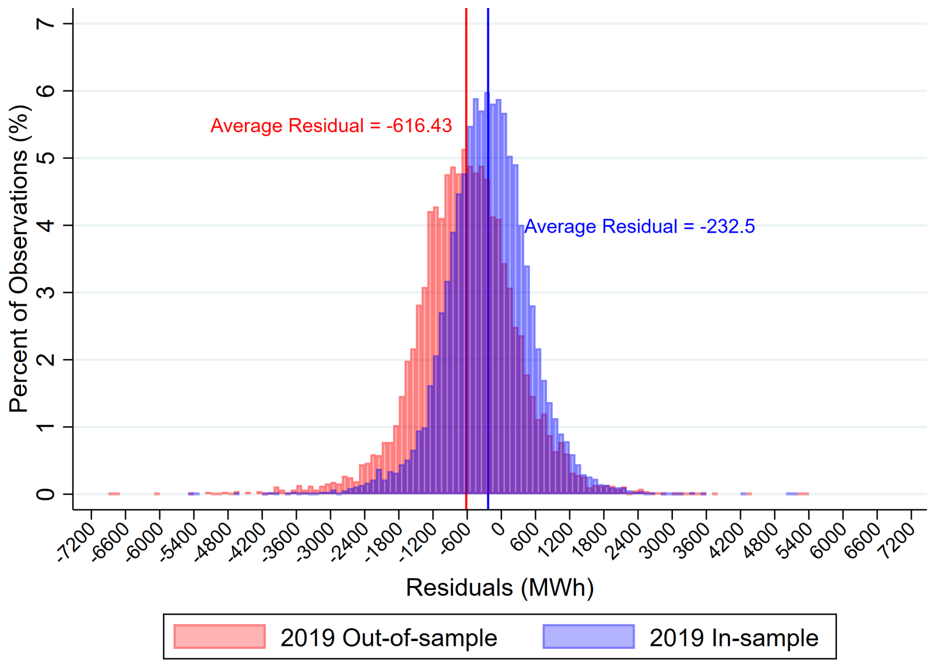
Here we highlight the importance of assessing out-of-sample, rather than in-sample errors. Figure B.4 plots the distributions of residuals in 2019 for models that are trained using 2015-2019 data (in which case 2019 is 'in-sample') versus models that exclude 2019 data (in which case 2019 is 'out-of-sample'). Panel (a) presents results for the best-performing ML algorithm. As expected, in-sample errors (in blue) are significantly smaller compared to their out-of-sample (in red) counterparts. Nevertheless, the out-of-sample errors exhibit a shape that resembles a normal distribution, suggesting that systematic errors are unlikely. Further, he average residuals for the ML algorithm are close to -234 MWh, which is less than 1% of the average hourly consumption in 2019 = 28,528 MWh.

Panel (b) of Figure B.4 presents the distribution of residuals in 2019 for the most complex fixed effects mode that we consider (which includes day of year FE plus hour of day FE interacted weather variables). Distributions for both in-sample and out-of-sample residuals seem to be shifted to the left, suggesting systematic overestimation of electricity usage. Comparing panels (b) and (a) we also note that the average out-of-sample residuals from the FE specification are also substantially higher than those from the ML algorithm (-616 MWh versus -234 MWh; or -2.16% versus -0.82%). Given that these residuals are representative of potential errors in the counterfactual model for 2020, it is clear that the FE approach can lead to biased estimates of the effect of the pandemic. On the other hand, potential bias from the ML approach seem to be substantially smaller. In the next section, we further dissect the potential errors from the ML approach.

Figure B.4: Distribution of Prediction Errors



a: Machine learning algorithm ML1



b: Fixed effects specification FE4

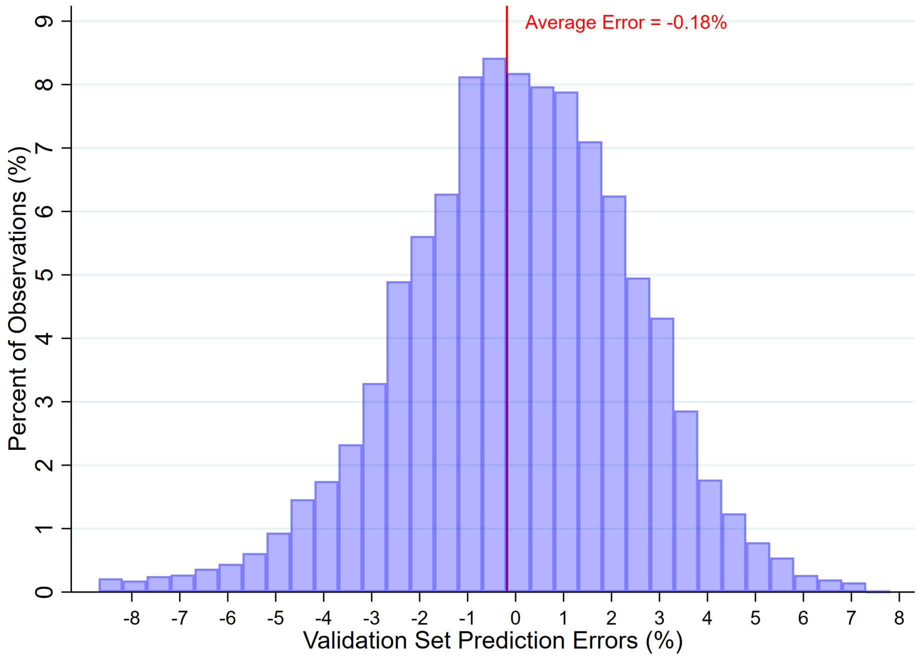
B.4 Decomposition of ML prediction errors

This section provides further details on the validation set prediction errors from the ML approach. Here we analyze the out-of-sample errors from both 2018 and 2019. Figure B.5 presents the distribution of percent prediction errors for that validation set and for the year 2020. It can be note that validation errors are well centered around zero, with the average error being -0.06%. Conversely, the errors in 2020 are skewed to the right, representing energy reductions of 5.1%, on average. It is unlikely that those reductions are driven by systematic biases in the ML model, given evidence that the validation set errors appear to be normally distributed.

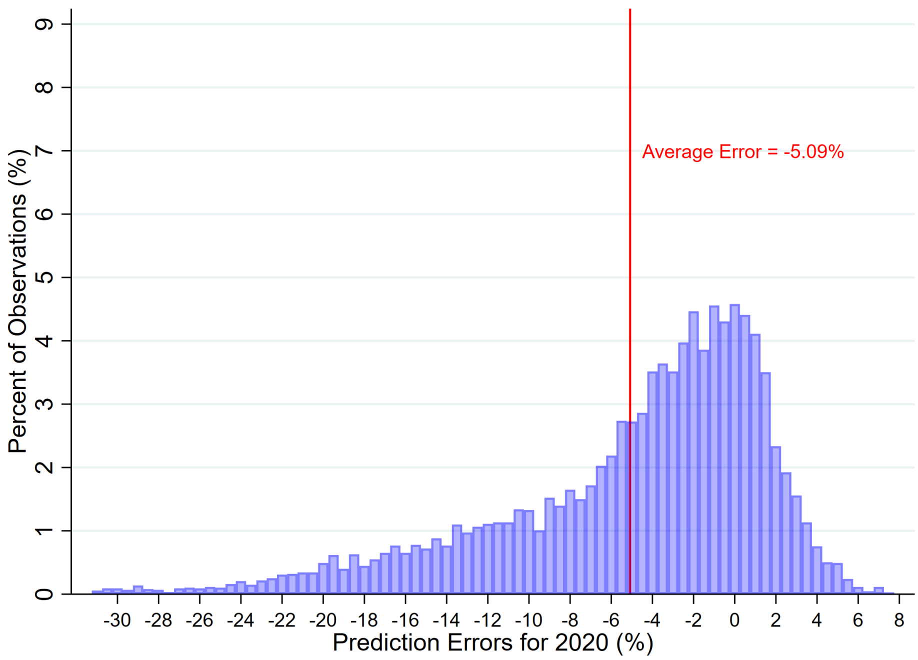
We also analyze the ML errors in more detail by plotting them across different subsamples. Results are summarized in Figure B.6. Panel (a) reports errors by bins of observed demand. We observe a pattern that is typical for models for predicting energy demand: underestimation for high-usage hours, but overestimation for low-usage hours. That is expected, since the model should not perfectly predict outliers at both ends of the demand distribution, otherwise that could be evidence of overfitting. The figure shows that potential biases occur only at the tails, at regions with relatively few observations. Errors by other covariates (panels b through f) are generally smaller than half percent. Even though some patterns emerge for some cases (e.g errors by hour of the day), the magnitude of the errors are small, thus unlikely to significantly affect the main results of the paper.

Finally, in Figure B.7 we assess validation set errors over time, from January 2018 to December 2019. Similar to Figure 1 from the main text, we find that our counterfactual predictions closely follow realized demand during that time period. Although some dates exhibit larger prediction errors, we cannot identify clear patterns in terms of months of the year that are prone to errors. For example, for 2018 the errors are mostly observed in the months of February through April, while for 2019 we observe more errors in the months of April through July. Therefore, we cannot clearly identify which months, if any, would suffer prediction biases in 2020.

Figure B.5: Distribution of Prediction Errors

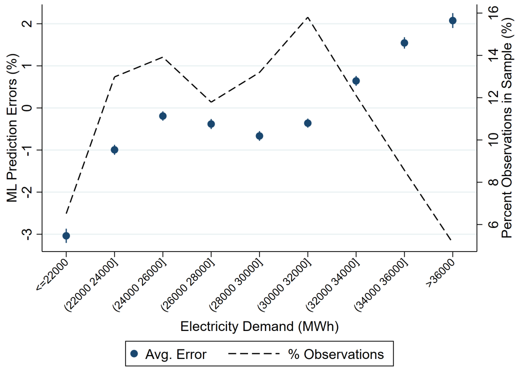


a: Validation Set Errors (Years 2018 and 2019)

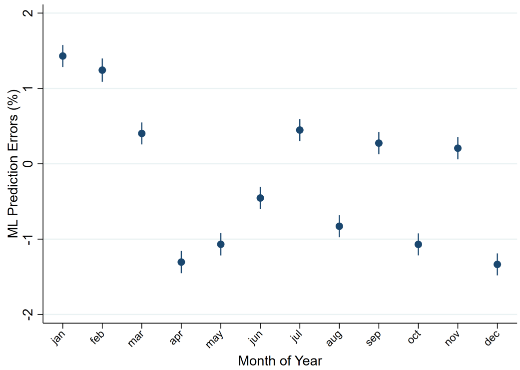


b: Errors in 2020

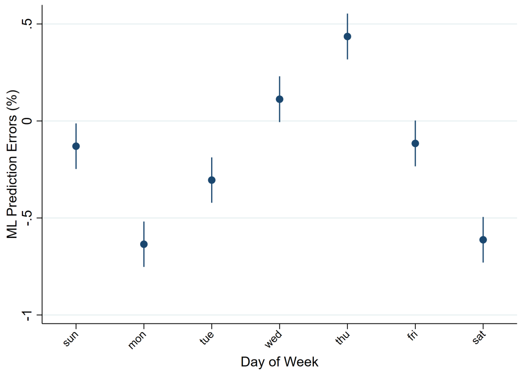
Figure B.6: ML Errors Across Subsamples



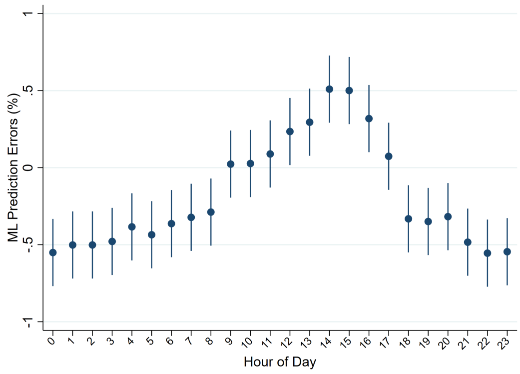
a: Errors by observed usage



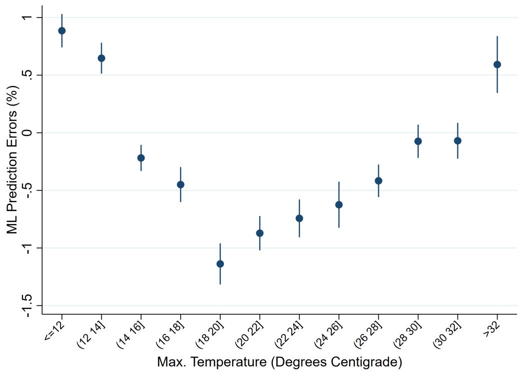
b: Errors by month of year



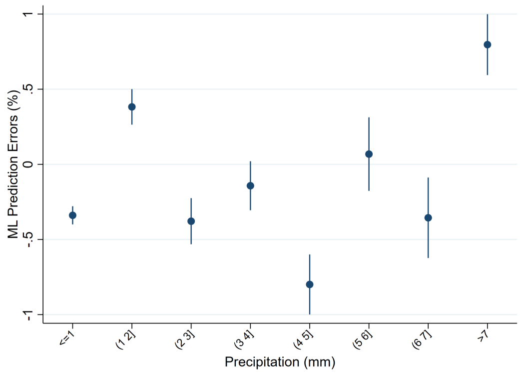
c: Errors by day of week



d: Errors by hour of day

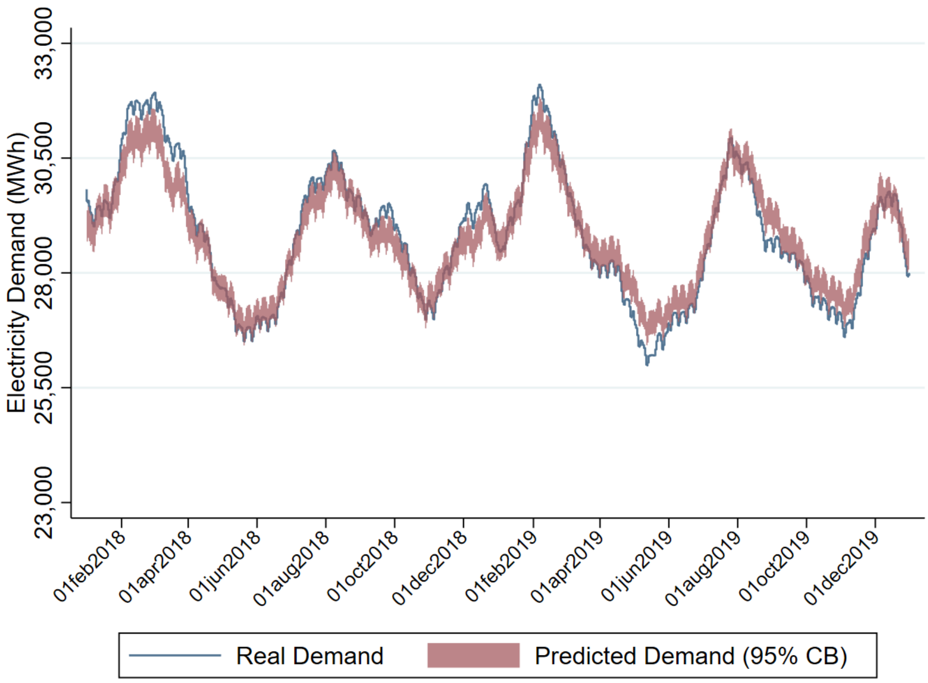


e: Errors by max. temperature



f: Errors by precipitation

Figure B.7: Validation Errors in 2018 and 2019



B.5 Inference Following our Two-Step Approach

Here we use notation as in section 3.1 from the main text. Let b_t be the effect of the pandemic at time t. Define $E_t(1)$ as realized electricity demand, and $E_t(0)$ as counterfactual demand. Then we have:

$$\hat{b}_t = E_t(1) - \hat{E}_t(0)$$
$$\hat{b}_t = E_t(0) + b_t - \hat{E}_t(0)$$
$$b_t = \hat{b}_t + \hat{E}_t(0) - E_t(0)$$
$$b_t = \hat{b}_t - \hat{r}_t \quad ,$$

where $\hat{r}_t$ are residuals from the prediction of $E_t(0)$. Now assuming that $\hat{b}_t$ and $\hat{r}_t$ are independent allows:

$$Var(b_t) = Var(\hat{b}_t) + Var(\hat{r}_t) \quad .$$

Thus we need to adjust the variance of our estimates to take into account the residuals from the predictive step. Recall that the true counterfactual residuals $\hat{r}_t$ cannot be observed, so we proxy them with the (out-of-sample) residuals from 2019, resulting in the expression presented in the main text. This highlights the importance of the cross-validation step of our approach. Cross-validation serves to produce unbiased estimates of $\hat{r}_t$. This is similar to the concept of "honest inference," as defined by Wager and Athey (2018). For example, in the context of regression trees, honesty is achieved as follows: (i) divide the training sample into two or more subsamples; (ii) use one of the subsamples to define the tree splits, holding the other subsamples out; (iii) use the held-out subsamples for within-leaf estimation. Our approach is similar in that we use data from 2015-2018 for training the models, while 2019 is held out for estimation of errors.

B.6 Electricity market simulations with alternative counterfactual predictions

Table B.2: Power sector carbon emissions under Realized and Counterfactual scenarios

	Counterfactual Demand (FE Model)		Realized Demand		Difference	
MtCO2	Competitive	Strategic	Competitive	Strategic	Competitive	Strategic
Coal	3.29	3.81	3.08	3.52	0.22	0.29
Gas	22.94	22.74	18.00	17.85	4.94	4.90
Cogen + Others	11.53	11.56	10.87	11.49	0.66	0.07
Total	37.76	38.12	31.94	32.86	5.82	5.26

Notes: Simulations that generate these results were performed using counterfactual predictions from the most accurate fixed effects regression. We report total emissions in 2020 under all four scenarios considered in our simulations (using realized or counterfactual demand, and assuming either competitive or strategic firm behaviour). The last two columns provide the difference across scenarios.

C Implicit Cost of Carbon for Other Countries

As mentioned in the main text, we benchmark the results from Spain by performing the analysis also for France and Italy. Specifically, we are able to estimate counterfactual electricity consumption for both countries by implementing the machine learning procedure from section 3.1. We obtain hourly demand data from ENTSOE (2021). Daily weather data from stations across both countries are obtained from the European Climate Assessment & Dataset (ECA&D; Klein Tank et al., 2002). For Italy, the following variables were available: min. temperature; max. temperature; and precipitation. For France, humidity data were additionally available. We also complement those with satellite data on solar radiation (CAMS Radiation Service; Gschwind et al., 2019), windspeed and dew point temperature (ERA; Hersbach et al., 2018) in Paris, Toulouse, Rome, Milan, and Palermo.

The emissions factor for natural gas plants (370 gCO2/kWh) was obtained from IEA (2011). Average power sector emissions factors for France and Italy were obtained from Climate Transparency (2020). Finally, GDP forecasts were obtained from OECD (2021). With all these ingredients, it is possible to approximately replicate (for France and Italy) the analyses that we performed for Spain, excluding those steps that require an electricity market model. The following sections presents machine learning validation metrics, electricity consumption counterfactual prediction estimates, carbon emissions estimates, and finally the GDP loss estimates.

C.1 France

Table C.1: Validation Set Predictive Performance (RMSE) for France

Panel A: Validation Year RMSE				
Model ID	2016	2017	2018	2019
FR 1	2556.72	2544.66	2072.26	1859.71
FR 2	2587.80	2581.79	2076.15	1921.97
FR 3	2537.62	2512.04	2044.68	1870.99
FR 4	2545.44	2544.22	2097.80	1882.54

Panel B: Details on Model Specifications

Model ID	ML Hyperparameters			
	ntrees	max_depth	shrinkage	minobspernode
FR 1	2000	10	0.05	20
FR 2	2000	30	0.05	20
FR 3	2000	10	0.05	60
FR 4	2000	30	0.05	60

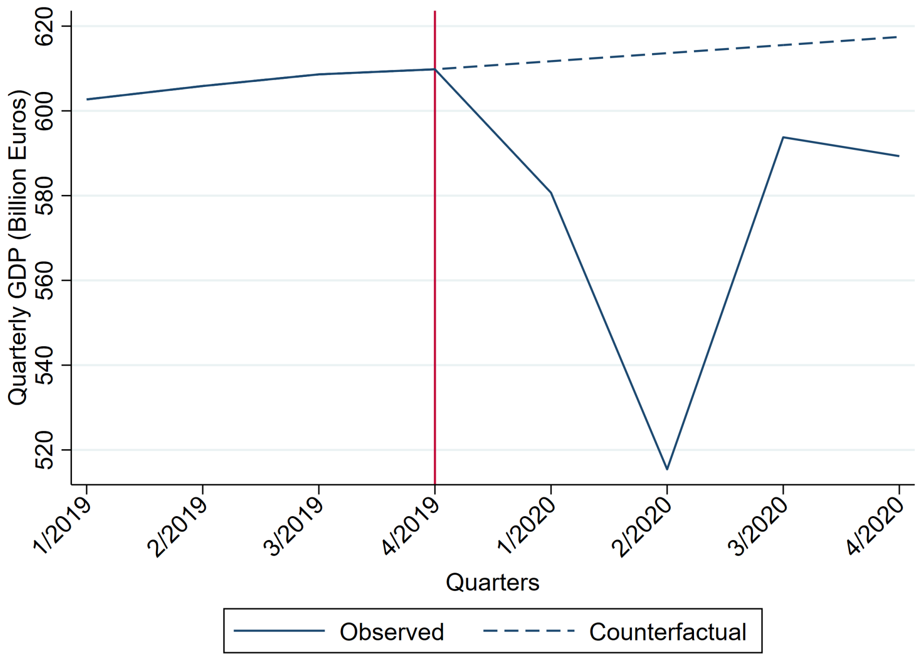
Notes: This table presents results from hyperparameter tuning via forward chaining cross-validation. All ML models considered are XGBoost. The top panel presents out-of-sample root mean squared errors (RMSE) for all specifications and for all years used as the validation set. The bottom panel presents the hyperparameter configurations. RMSE can be compared to the average hourly consumption in 2019 = 53,375 MWh, or the standard deviation = 11,281 MWh. For France, the best-performing model was FR 3.

Table C.2: CO2 Emissions in France

Sector	MtCO2 Emissions			
	2019	2020	Diff.	Pct. Diff.
Domestic Aviation	2.33	1.29	1.04	44.53
Ground Transport	116.62	104.80	11.82	10.14
Industry	61.67	54.47	7.20	11.67
Residential	79.87	75.75	4.12	5.16
	Counterfactual	Realized	Diff.	Pct. Diff.
Power (lower bound)	22.68	21.79	0.90	3.95
Power (upper bound)	171.28	164.50	6.77	3.95
Total (lower bound)	283.17	258.10	25.07	8.85
Total (upper bound)	431.77	400.81	30.96	7.17

Notes: power sector estimates based on counterfactual predictions. Lower-bound estimates assume an emissions factor of 49 gCO2/kWh (Climate Transparency, 2020). Upper-bound estimates assume abatement comes from natural gas plants with an emissions factor of 370 gCO2/kWh (IEA, 2011). Data for other sectors were obtained from Carbon Monitor (Liu, Ciais, Deng, Lei, et al., 2020).

Figure C.1: French Quarterly GDP



Notes: Data from OECD (2021). The graph presents French quarterly GDP. Counterfactual GDP was projected by taking GDP growth rates that were forecasted at the end of 2019 (i.e. in the absence of information about the pandemic). The difference between observed and counterfactual curves from the graph represent a GDP loss of 179.11 Billion Euros in France.

C.2 Italy

Table C.3: Validation Set Predictive Performance (RMSE) for Italy

Panel A: Validation Year RMSE				
Model ID	2016	2017	2018	2019
IT 1	1896.65	1542.93	1360.54	1559.30
IT 2	1909.97	1665.40	1414.21	1621.30
IT 3	1911.48	1552.53	1336.23	1525.88
IT 4	1869.75	1538.29	1400.26	1599.09

Panel B: Details on Model Specifications				
Model ID	ML Hyperparameters			
	ntrees	max_depth	shrinkage	minobspernode
IT 1	3000	10	0.05	20
IT 2	3000	30	0.05	20
IT 3	3000	10	0.05	60
IT 4	3000	30	0.05	60

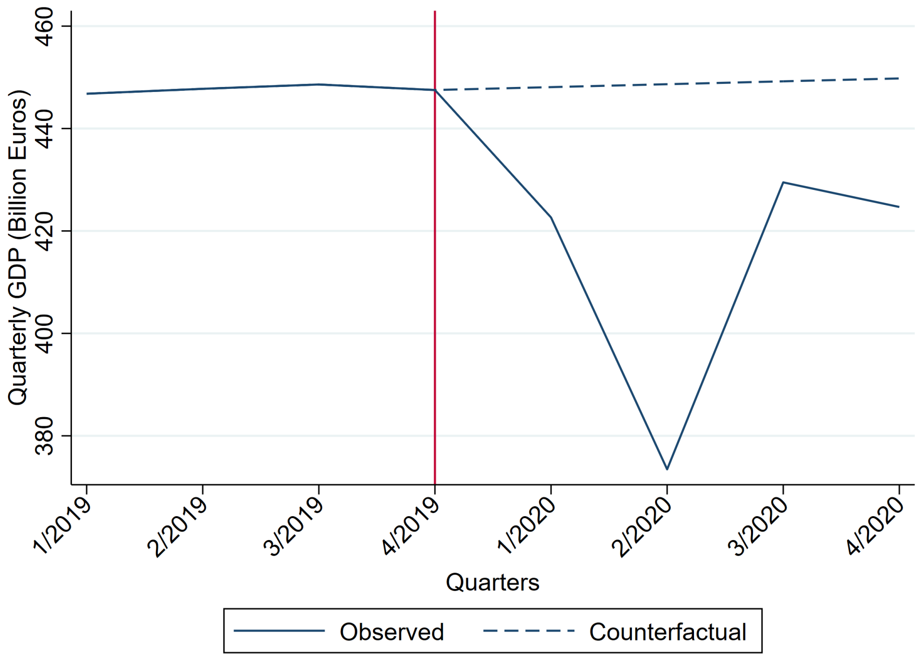
Notes: This table presents results from hyperparameter tuning via forward chaining cross-validation. All ML models considered are XGBoost. The top panel presents out-of-sample root mean squared errors (RMSE) for all specifications and for all years used as the validation set. The bottom panel presents the hyperparameter configurations. RMSE can be compared to the average hourly consumption in 2019 = 33,578 MWh, or the standard deviation = 7,731 MWh. For Italy, the best-performing model was IT 3.

Table C.4: CO2 Emissions in Italy

Sector	MtCO2 Emissions			
	2019	2020	Diff.	Pct. Diff.
Domestic Aviation	1.89	1.00	0.89	47.02
Ground Transport	91.13	81.63	9.50	10.42
Industry	54.39	47.75	6.64	12.21
Residential	74.95	73.92	1.04	1.38
	Counterfactual	Realized	Diff.	Pct. Diff.
Power (lower bound)	76.18	74.31	1.87	2.45
Power (upper bound)	103.62	101.08	2.54	2.45
Total (lower bound)	298.54	278.61	19.93	6.68
Total (upper bound)	325.98	305.38	20.60	6.32

Notes: power sector estimates based on counterfactual predictions. Lower-bound estimates assume an emissions factor of 272 gCO2/kWh (Climate Transparency, 2020). Upper-bound estimates assume abatement comes from natural gas plants with an emissions factor of 370 gCO2/kWh (IEA, 2011). Data for other sectors were obtained from Carbon Monitor (Liu, Ciais, Deng, Lei, et al., 2020).

Figure C.2: Italian Quarterly GDP



Notes: Data from OECD (2021). The graph presents Italian quarterly GDP. Counterfactual GDP was projected by taking GDP growth rates that were forecasted at the end of 2019 (i.e. in the absence of information about the pandemic). The difference between observed and counterfactual curves from the graph represent a GDP loss of 145.48 Billion Euros in Italy.