Evidence of Flexibility and its Economic Implications on the Day-ahead Electricity Market

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I use the first wave of COVID-19 as a natural experiment to document evidence of flexibility on the German day-ahead electricity market. I parameterize a model that represents uncertainty on the demand side as intermittency of renewables. I then compare pre- to post-COVID-19 data to investigate lower-bound economic implications. Post-COVID-19 and with 44% of renewable shares, electricity prices were most sensitive to fuel costs, and almost completely passed through, while they remained rigid to CO_2 costs. A decrease in demand consumption had a detrimental welfare effect on both, consumers and producers. An increase in demand consumption was slightly beneficial in the afternoon peak, mainly for consumers. Although the distributional gap was reduced, both actors, were worst off post-COVID-19. This kind of flexibility response was likely the result of a reduction in the minimum generation. CO_2 emissions were lower by 22% on average, of which emissions from lignite showed only a small reduction of 8% of total emissions from fossil fuels. If the observed consumption pattern persists to some extent, in a market with higher renewable shares and more extreme weather conditions, more appropriate market rules would be necessary to achieve allocative efficiency.

1 Introduction

If it looks like a duck, swims like a duck, and quacks like a duck, then it probably is a duck. Anonymous.

In 2008, the National Renewable Energy Laboratory introduced a rapid diagnosis to illustrate the change in ramping requirements arising from the expansion of renewables; this diagnosis was later referred to as the "duck chart" (or the duck curve from here on) by the California Independent System Operator in 2013 (1; 2). We can construct the duck curve for a set of days, or average time frames, using the net load, where the net load is the total

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load requirement minus renewables from wind and solar, either actual or forecasted. By mirroring the effects of renewables on conventional generation, the duck curve helps to illustrate the problem of curtailment, that is, the effects of reducing or shutting down renewable production due to overgeneration, and its consequent increase in costs and incurred losses in reducing greenhouse gas emissions. To avoid curtailment, potential solutions from the supply side include operating at a minimum generation level (reducing conventional generation or "fattening the duck"), shifting supply via storage (also referred to as "flatenning the duck"), offering more flexible generation, and engaging in regional interchange. From the demand side, mainly via "flatenning the duck", common solutions include shifting load (either in response to higher prices or to market-based incentives), designing flexible tariffs, and organizing optimized purchases (e.g., via virtual power plants). Other demand-side solutions that fatten the duck include providing services to reduce conventional generation at part load (2). To date, these solutions can be implemented, although with many restrictions, in the balancing, reserves, day-ahead, and real-time electricity markets. In sum, the problem of curtailment in systems under renewables expansion entails not only analyzing the technical impacts of curtailment on the reliability of the grid but also analyzing the economic impacts of energy and climate policies, such as the renewable portfolio standard (RPS), the emissions trading scheme (ETS), carbon price controls, and direct taxes on carbon in electricity systems.

Literature review.- Various studies have examined least-cost solutions to avoid curtailment under policies addressing climate change. For example, (3) found that lower-emission and flexible plants with a given specified ramp rate are likely to dominate the Australian electricity market. Further, (4) conceptualized and modeled a probabilistic duck curve to plan flexible resource adequacy for Qinghai, China. Under high photovoltaic shares, they found that a combination of retrofitted coal units with storage would be the least-cost option. In addition, for the wost overgeneration scenario cases, the most efficient solutions were suggested to be demand response solutions, as they have near-zero capital investment. Focusing on demand side solutions in Germany, (5) combined the eLOAD model with a survey on industrial consumers and found that only 3.5% of industrial consumers conducted demand response. An additional minimum deployment of 0.13 TWh was available in the short term to reduce renewable surplus electricity at peak hours (negative demand response), which translated in about €3 million in revenues. From a program in the PJM electricity market under locational marginal prices, (6) found that negative demand response resulted in higher wealth transfers from generators to non-price-responsive loads compared to the system as a whole. In addition, the value of saved costs exceeded consumer subsidies, and the subsidies provided a mechanism to correct two market failures: treating demand as inelastic and the prevalence of free-riding behavior during load curtailment. They concluded that systems will obtain higher benefits from programs that achieve higher values of price elasticity of demand. Focusing on positive demand response, namely an increase in demand due to lower electricity prices during off-peak hours (using discount

rates from a survey on a Time of Use tariff or ToU), (7) designed a multi-hour net benefit test to show that system benefits are higher under a positive demand response compared to a negative one. Further, (8) proposed the use of the net load concept for the future design of price-responsive electricity tariffs, such as ToU or critical peak pricing. They found that in Germany, the net load at peak hours coincided with price inelastic responses, while at off-peak hours it coincided with price elastic responses. In addition, tariffs should differ during the day by more than the current two options (day and night) and according to net load levels. Tariffs should also differ during the week (weekdays differ from weekends and holidays), and in between seasons (summer tariffs would differ from winter tariffs). In California, (2) recommended shorter scheduling intervals for system operations. Moreover, they found that variations in the duck shape would be best addressed by using a combination of grid flexibility options with price-responsive tariffs and fixed price intervals.
Regarding studies on electricity systems investigating energy and climate policy impacts on economic outcomes, (9) examined the merit order effect under the implementation of RPS in Germany. They found that there were wealth transfers from households and small business to energy-intensive industries. In another study, (10) examined the distributive effects between producers and consumers under RPS and ETS. They found an opposite distributive effect due to the interaction of both policies and suggested that a mix of policies would be better for the system in terms of achieving allocative efficiency. Using theory and solving a numerical exercise with the model EMMA reimplemented in PyPSA, (11) argued that the downward trend in market values is a result of the policies in place, in particular feed-in-tariffs and RPS, and not of the variability of renewable production. Moreover, carbon prices enable producers to recover their costs. Thus, total system cost would be a better measure of market integration. They suggested that market values would remain stable even in systems under 100% renewables as long as flexibility for transmission and storage are available in the grid.

From these findings, it follows that quantifying the economic impact of solutions that can provide flexibility for electricity systems under renewable expansion is of timely importance; this issue is thus the focus of the current work. Furthermore, I explore the following research gap: Do flexibility solutions alter the allocative efficiency in electricity systems under a mix of energy and climate policies, such as the RPS and ETS?

To solve this question, I use the methodology developed in (12). To explore the allocative efficiency of flexibility solutions interacting with energy and climate policies, I use the first wave of COVID-19 in the German day-ahead electricity market as a exogenous shock on the demand side. Using this event as point of inflection, I make parallels between pre-COVID-19 and post-COVID-19 data. This allows me to observe a "fattening the duck" type solution post-COVID-19, likely the result of a reduction in minimum generation requirements on the supply side (or a reduction of the base load). I thus compare the low-boundary economic implications in these two states, namely, the effect on pass-through of input costs and on the distribution of wealth between consumers and producers.

The remainder of the article follows this structure. Section 2 explains the global and local context of COVID-19 and, for Germany, weather conditions and fluctuations of key electricity market determinants. I also describe the data used in this study. Section 3 summarizes the methodology used for measuring the pass-through of input costs and welfare distribution. Section 4 compares the results, pre- and post-COVID-19. Section 5 discusses the implications and limitations of this study and Section 6 concludes.

2 Background and Data

2.1 Global and local context

A pneumonia case of unknown causes was reported to the World Health Organization (WHO) office in China on December 31, 2019. After a couple of months of worldwide alert, on March 11, 2020, the WHO elevated COVID-19 to the level of a global pandemic (13). Around the world, a wide array of national strategies was implemented to contain COVID-19, resulting as well in higher (or lower) infections per capita. Figure 1 shows the 7-day rolling average of new COVID-19 cases of various countries, including Germany, from all continents (with the exception of the Antarctica), up to December 2020. In Germany, the Robert Koch Institute published a national pandemic plan on March 5, 2020 (14). In the following days, on March 18, 2020, Angela Merkel declared COVID-19 to be "the greatest challenge since World War II" (15), which officially started the beginning of the first wave of COVID-19 in Germany. For the purposes of this study, I split the data using March 11, 2020 as the crucial date reflecting the point of inflection that separates the pre-COVID-19 from the post-COVID-19 analysis of the first wave.

Before and during the first wave of COVID-19, Germany also registered temperature anomalies between 1°C to 2°C higher compared to the previous year in the months of January, February, April, and May (see Figure 2). March was the exception, with lower temperatures anomalies, between 1.5°C and 2.5°C, compared to the previous year (16). Post-COVID-19, day-ahead electricity prices and fuel input prices were lower than pre-COVID-19, which coincided with lower demand levels and higher renewable shares from wind and solar, see Figures 3 and 4.

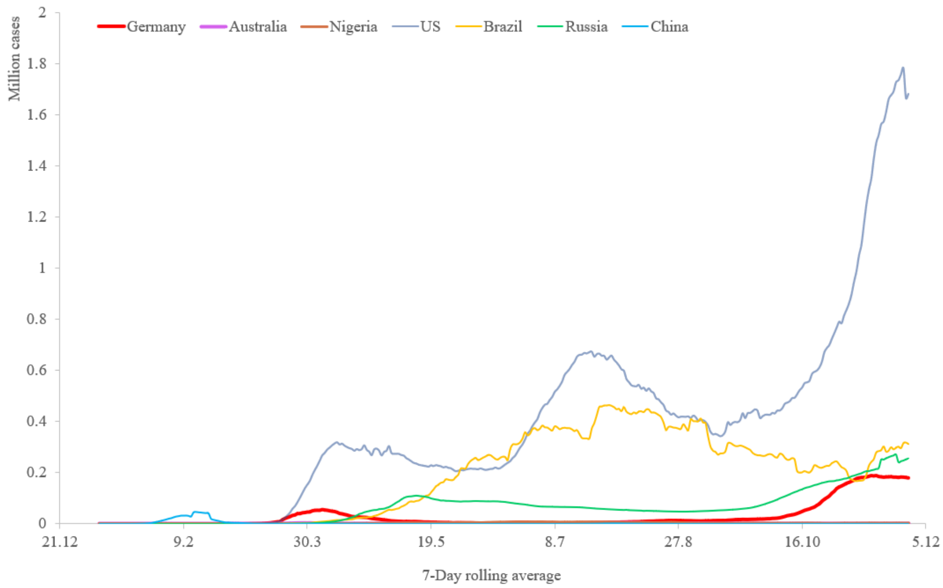

Figure 1: 7-Day rolling average of COVID-19 new cases, from December 2019 to December 2020

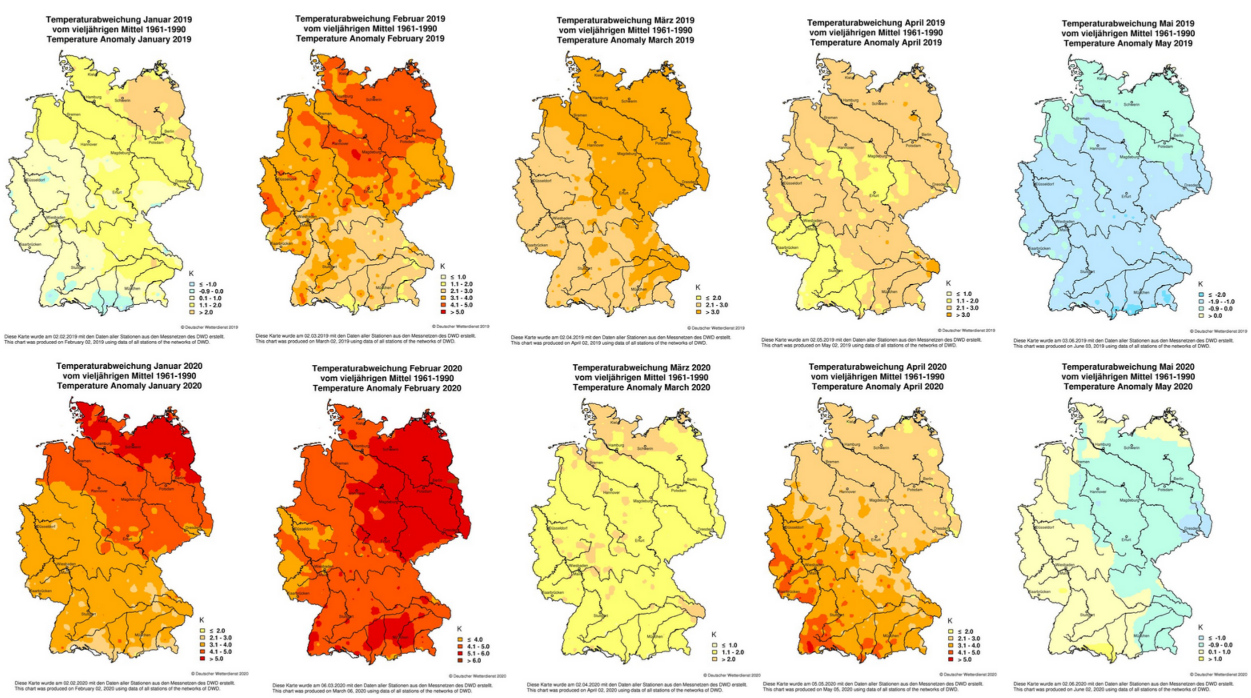

Figure 2: Temperature anomalies between January and May in 2019 and 2020

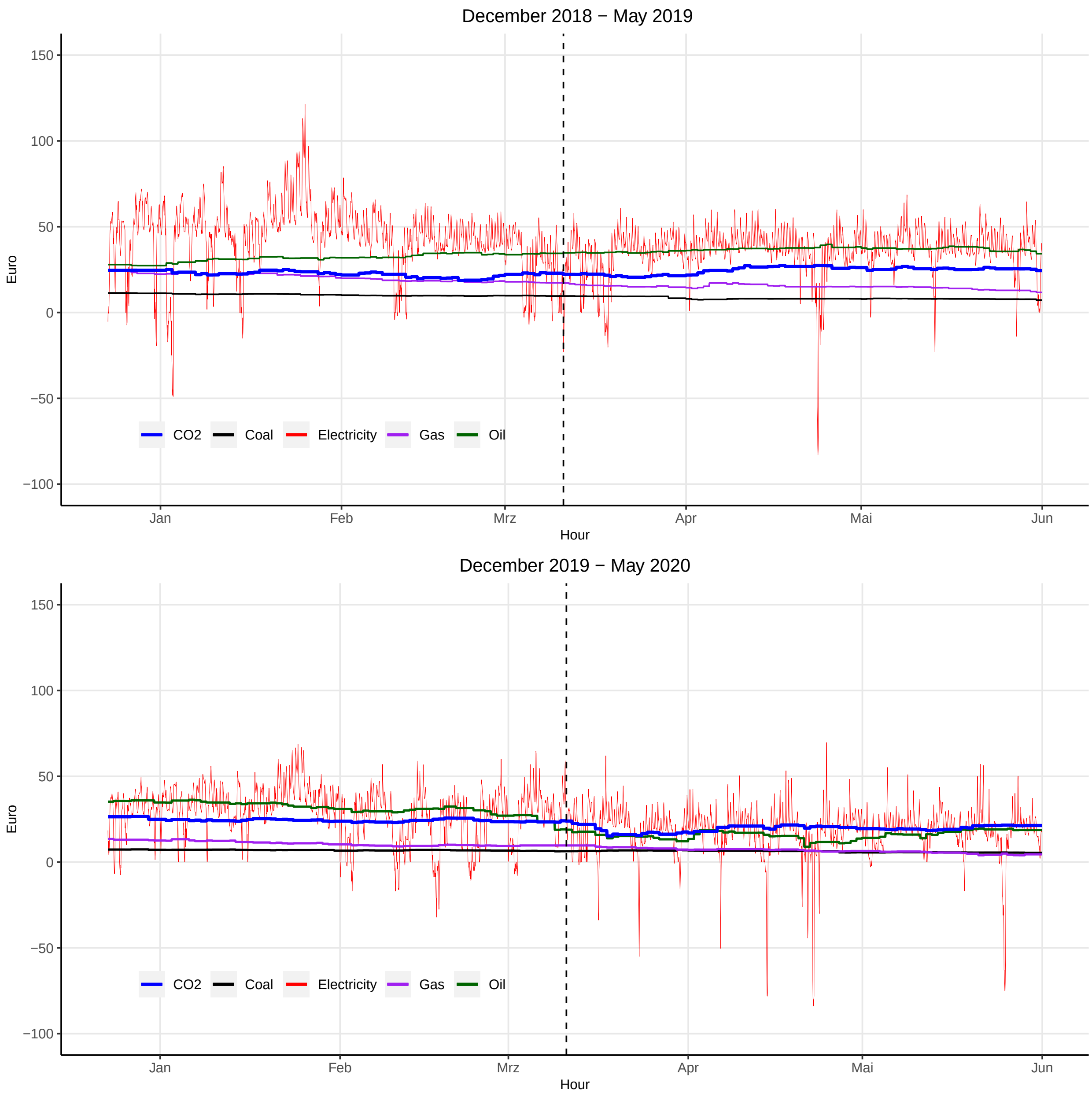

Figure 3: Electricity prices and fuel input costs for December 23 to May 31 between 2018 and 2019, and December 23 to May 31 between 2019 and 2020

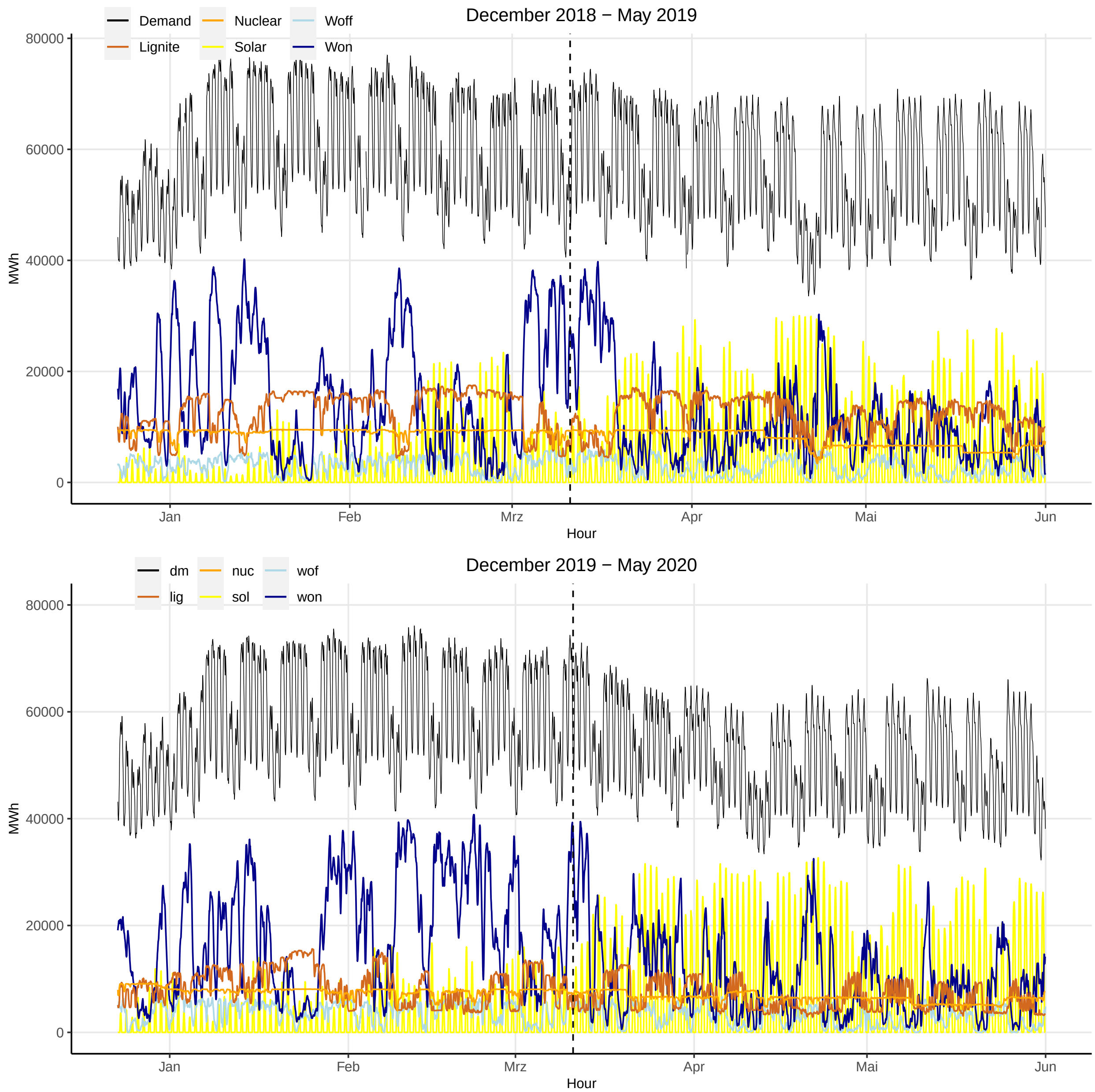

Figure 4: Demand consumption, renewable energy, lignite, and nuclear production for December 23 to May 31 between 2018 and 2019, and December 23 to May 31 between 2019 and 2020

2.2 Data

I constructed four samples using hourly data from public and private sources. Panel A includes data between December 23 to March 10 of the years 2018 - 2019 (19a) and 2019 - 2020 (20a). Panel B includes data from March 11 to May 31 of both, 2019 (19b) and 2020 (20b). I use the SMARD database to obtain the aggregate real and forecast demand[1], electricity production, and day-ahead prices. Electricity production of each of the 118 plants come from AURORA and ENTSO-e (see Table 1). Production from these plants with installed capacities above 100 MW sum up to 54% on average of total domestic demand. The analysis includes pump storage, hydro, nuclear, lignite, coal, gas, oil, solar, and wind offshore and onshore technologies. I use commodity prices (coal, gas and CO_2) as supply instruments. These data come from AURORA database; the ARA coal spot price (CIF without transportation fees); the Gaspool price; and the Brent crude oil price for Germany. Since commodities register prices only on weekdays, I consider, similar to other studies, the last weekday available as the value for weekends and holidays. CO_2 spot prices come from the EEX database under EUSP contracts. I also shift the day-ahead electricity price one day after to match it to commodity prices. The demand instruments include data on temperature from the Deutscher Wetterdienst. Data on the CO_2 emissions rate of fossil fuels comes from the Umweltbundesamt. I obtain heat rates and installed capacities per plant from the Open Power Project. Finally, some hours do not register measurements of electricity production or temperature; when these are point estimates, I take the average of the previous and following data. But longer periods of time with missing data and with share values equal to zero result in a loss of about 52% of a total of 916,776 observations. Tables 1, 2, 3, and 4 describe the statistics of the variables I use to construct the supply and demand curves. I gather data on plant operations that use combined heat power (CHP), similar to (12). I then use these data to examine the pass-through and welfare implications corresponding to the observed changes in the consumption pattern, which resulted in a more pronounced duck curve post-COVID-19 (see Figure 5 of Section 4, panels A and B). Similar to (12) I divide the day into three blocks of hours: an off-peak block from 20:00 to 06:00 (night), a peak 1 block from 6:00 to 13:00 (morning), and a peak 2 block from 13:00 to 20:00 (afternoon). Finally, for this study I also use the ramping assumptions considered in (12).

[1] I use the forecast demand to draw net load curves.

Table 1: Plants analyzed in this study with capacities higher than 100 MW

Technology	Plant
CHP must-run	1
Coal	37
Gas steam turbine	4
Gas OCGT	1
Gas CCGT	24
Hydro	4
Nuclear	7
Lignite	9
Oil steam turbine	2
Oil OCGT	1
Other fossil fuel	2
Other renewables	2
Pump storage	13
Wind offshore	10
Wind onshore	1
Total plants	118

I model an artificial must-run CHP plant. OCGT refers to open cycle gas turbine and CCGT refers to combined cycle gas turbine. The category "other fossil fuel" corresponds to a gas-fired plant using as fuels blast furnace gas, coke oven gas, or natural gas. The category "other renewables" corresponds to waste (12).

Table 2: Descriptive statistics for Dec 23, 2018 to March 10, 2019

	Mean	Standard deviation	Min.	Max.
Market share	0.009	0.020	0.000	0.347
Day-ahead price (€/MWh)	46.131	18.927	-48.930	121.460
Load factor	0.565	0.305	0.000	1.000
Temperature	2.957	4.880	-22.400	20.600
Fuel costs (€/MWh)	21.340	20.643	0.000	98.005
CO_2 costs (€/MWh)	9.790	9.130	0.000	30.457
Coal prices (€/MWh)	4.987	5.162	0.000	11.410
Gas prices (€/MWh)	9.914	10.336	0.000	24.870
CO_2 prices (€/MWh)	10.867	11.284	0.000	25.020
Observations	130,693			

Fuel costs equal fuel price multiplied by the heat rate factor. CO_2 costs equal CO_2 prices multiplied by the heat rate factor and corresponding emission factor. I include costs of oil plants in the analysis, but I exclude prices of oil as supply side instrument.

Table 3: Descriptive statistics for March 11 to May 31, 2019

	Mean	Standard deviation	Min.	Max.
Market share	0.009	0.019	0.000	0.378
Day-ahead price (€/MWh)	36.713	13.539	-83.010	68.610
Load factor	0.494	0.303	0.000	1.000
Temperature	8.855	5.516	-17.600	27.300
Fuel costs (€/MWh)	17.226	19.317	0.000	111.464
CO_2 costs (€/MWh)	10.118	10.182	0.000	33.427
Coal prices (€/MWh)	3.565	4.124	0.000	9.630
Gas prices (€/MWh)	6.504	7.517	0.000	17.180
CO_2 prices (€/MWh)	10.541	12.204	0.000	27.460
Observations	113,920			

Fuel costs equal fuel price multiplied by the heat-rate factor. CO_2 costs equal CO_2 prices multiplied by the heat-rate factor and corresponding emission factor. I include costs of oil plants in the analysis, but I exclude prices of oil as supply side instrument.

Table 4: Descriptive statistics for Dec 23, 2019 to March 10, 2020

	Mean	Standard deviation	Min.	Max.
Market share	0.009	0.309	0.000	0.020
Day-ahead price (€/MWh)	30.834	14.528	-32.140	68.64
Load factor	0.530	0.310	0.000	1.000
Temperature	4.221	3.886	-18.700	20.400
Fuel costs (€/MWh)	15.447	16.253	0.000	102.051
CO_2 costs (€/MWh)	10.230	9.828	0.000	32.331
Coal prices (€/MWh)	3.212	3.457	0.000	7.390
Gas prices (€/MWh)	5.013	5.453	0.000	13.430
CO_2 prices (€/MWh)	11.293	12.150	0.000	26.560
Observations	104,260			

Fuel costs equal fuel price multiplied by the heat-rate factor. CO_2 costs equal CO_2 prices multiplied by the heat-rate factor and corresponding emission factor. I include costs of oil plants in the analysis, but I exclude prices of oil as supply side instrument.

Table 5: Descriptive statistics for March 11 to May 31, 2020

	Mean	Standard deviation	Min.	Max.
Market share	0.007	0.016	0.000	0.235
Day-ahead price (€/MWh)	18.936	14.139	-83.940	69.680
Load factor	0.397	0.289	0.000	1.000
Temperature	9.626	5.859	-11.100	27.700
Fuel costs (€/MWh)	11.017	9.769	0.000	53.021
CO_2 costs (€/MWh)	8.346	8.264	0.000	29.081
Coal prices (€/MWh)	2.628	3.092	0.000	7.030
Gas prices (€/MWh)	2.938	3.568	0.000	9.690
CO_2 prices (€/MWh)	8.259	9.743	0.000	23.890
Observations	87,769			

Fuel costs equal fuel price multiplied by the heat-rate factor. CO_2 costs equal CO_2 prices multiplied by the heat-rate factor and corresponding emission factor. I include costs of oil plants in the analysis, but I exclude prices of oil as supply side instrument.

3 Methodology

I use the highly parametrized model developed in (12). This methodology allows one to represent the intermittency of renewables on the demand side using a random logit, and it allows a linear approximation of the supply side. It solves a joint equilibrium under Bertrand competition using the pyblp package (17). I then compare the four samples in the following manner. First, within the time frame in Panel A, I calculate the average percentage change between 2018-2019 and 2019-2020. In a similar manner, I obtain the second difference within the time frame in Panel B, as the percentage change between 2018-2019 and 2019-2020. Finally, I and report the third difference using these average percentage points as post-COVID-19 metrics, from March 11, 2020 to May 31, 2020.

4 Results

I show the net load patterns pre- and post-COVID-19 in Figure 5. Panel A shows a lower net load in 2020 compared to 2019, both pre-COVID-19, but almost no change in flexibility requirements. The lowest point of the night valley was 23,197 MW at 02:00 in 2020, and the ramping requirement in the morning between 04:00 and 07:00 increased by 1525 MW in 2020, with an average value for the two years of 11,252 MW. During the afternoon peak, the lowest point of the afternoon valley was 34,576 MW at 14:00 in 2020, and the ramping requirement between 16:00 and 19:00 increased by 174 MW from 2019 to 2020, with an average value of 2,348 MW.

In contrast, Panel B shows a "fattening of the duck" phenomenon for both, 2019 and 2020. In this case, we observe a more pronounced valley in the afternoon post-COVID-19. The lowest point of the night valley was 28,014 MW at 02:00 in 2020, and the ramping requirement in the morning between 04:00 and 07:00, decreased by 1,625 MW in 2020, with an average value for the two years of 8,351 MW. During the afternoon peak, the lowest point of the afternoon valley was 21,974 MW at 14:00 in 2020, and the ramping requirement between 16:00 and 19:00 increased by 4,501 MW from 2019 to 2020, with an average value of 12,817 MW, and a maximum value of 15,068 MW post-COVID-19.

Overall post-COVID-19, ramping requirements decreased in the morning by 32 percentage points and increased in the afternoon by 35 percentage points.

4.1 Pass-through of input costs

Panel A of Figure 6 shows a slightly higher pass-through of fuel costs for 2020 compared to 2019, pre-COVID-19, and a small upward trend from off-peak to peak 2, with a daily average of 0.73. In contrast, Panel B shows values close to unity for all blocks of hours post-COVID-19, higher than the same period in 2019. Post-COVID-19, the lowest value

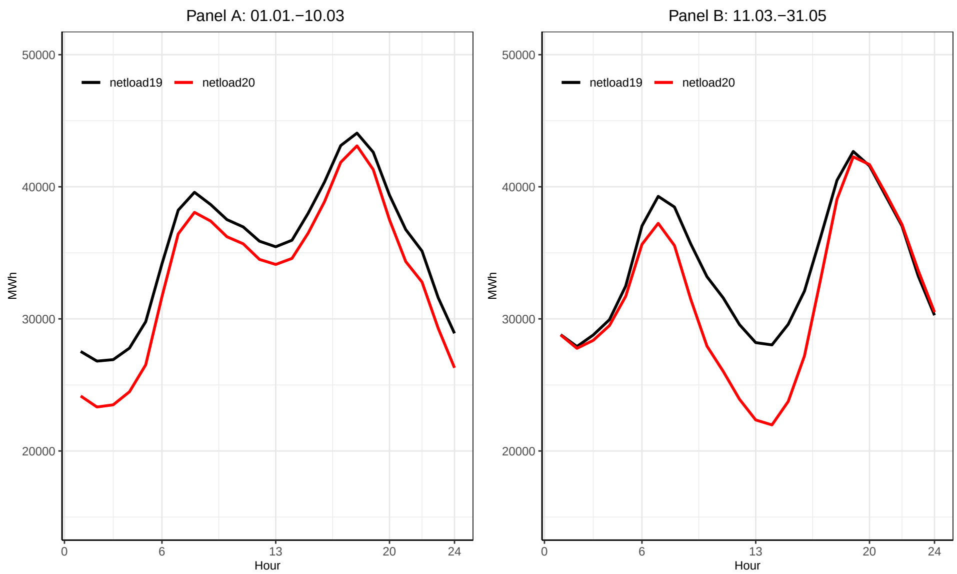

Figure 5: Duck Curve for December 23 to May 31 between 2018 and 2019, and December 23 to May 31 between 2019 and 2020

of the pass-through of fuel costs coincided with the afternoon valley. Comparing Panel A with B, post-COVID-19 the pass-through of fuel costs spiked 63 percentage points on average.

In the opposite direction of the results of pass-through of fuel costs, Panel A of Figure 7 shows that pre-COVID-19, there was a much lower pass-through of CO_2 costs for 2020 compared to 2019, and a small downward trend from off-peak to peak 2, with a daily average of 0.78. Similar to Panel A, Panel B shows a daily average of 0.58 post-COVID-19, lower than the same period in 2019. Post-COVID-19, the highest value of pass-through of CO_2 costs coincided with the afternoon valley. Comparing Panel A with B, the pass-through of CO_2 costs went down 10 percentage points on average post-COVID-19. In both panels and pre-COVID-19, the highest values of pass-through of CO_2 costs also coincided with the afternoon valley.

Electricity prices are less sensitive to fuel costs during the afternoon valley. Electricity prices are more sensitive to CO_2 costs during the morning. The ramping cost coefficients are positive in most cases and not significant in the afternoon and at night post-COVID-19.

To obtain a more general view, I also show results for the total pass-through of input costs, including ramping costs, which show an average daily increase of 32 percentage points post-COVID-19. In total, about three quarters of total input costs were passed through to electricity prices post-COVID-19 (Figure 8).

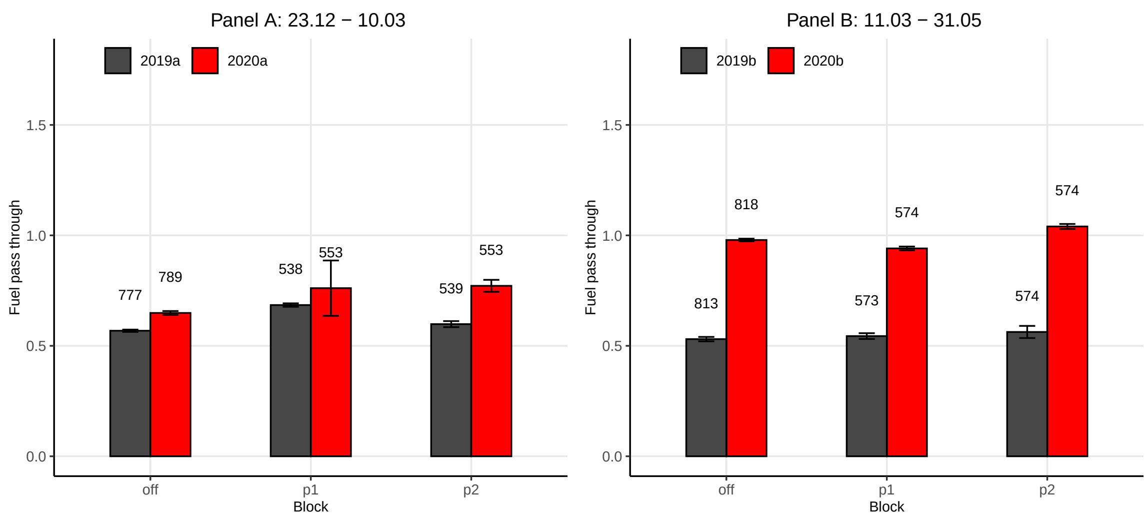

Figure 6: Fuel pass through for the periods of analysis

4.2 Welfare

Panel A of Figure 9 shows that pre-COVID-19, there was a lower total welfare level mainly for consumers. In contrast, Panel B shows a trend with small higher total gains for both actors at off-peak hours in addition to the afternoon peak. Consumers' total welfare was on average 12 percentage points lower post-COVID-19. Post-COVID-19, the highest loss was found at 14:00 with -35 percentage points, followed by small gains in the afternoon peak with 10 percentage points. Producers' total welfare was also negative post-COVID-19, but it shows an increase of an average of 59 percentage points. The lowest post-COVID-19 gain was found at 15:00, with 49 percentage points, followed by gains in the afternoon peak with 76 percentage points.

The distributional gap between consumers and producers was reduced by 36% on average during the day, but overall, consumers lost significantly more welfare compared to producers post-COVID-19.

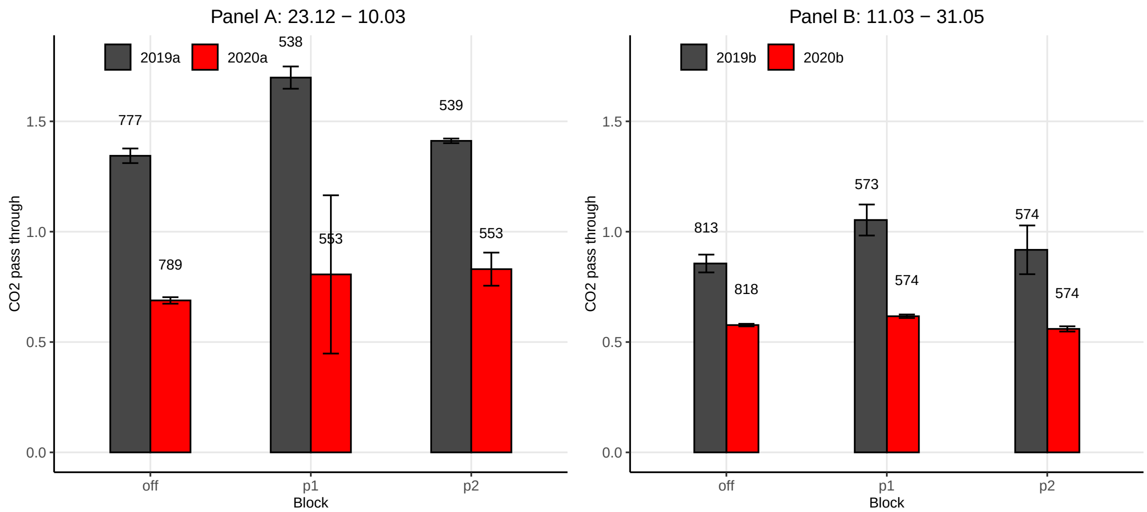

Figure 7: CO_2 pass through for the periods of analysis

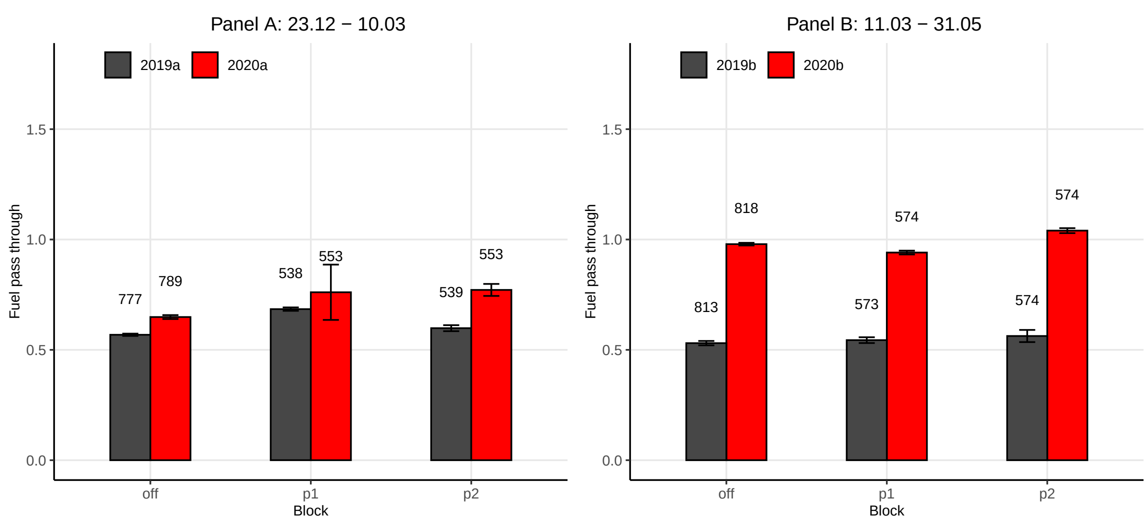

Figure 8: Total pass through the periods of analysis

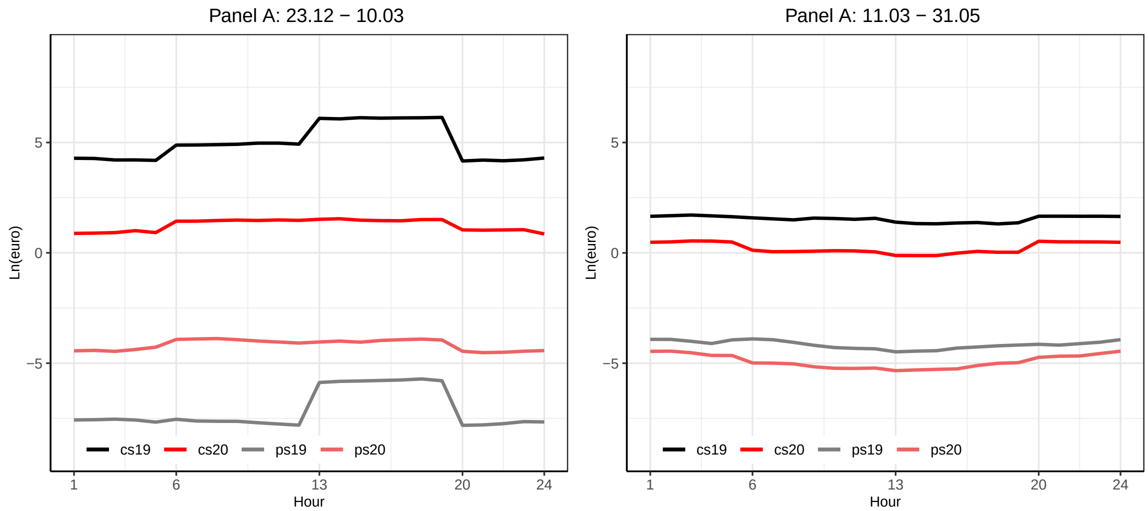

Figure 9: Consumer and Producer surplus for the periods of analysis

5 Discussion

I find that the type of flexibility response studied in this analysis corresponded to a "fattening the duck" strategy under ETS and RPS policies. This produced mainly negative economic outcomes, with respect to the pass-through of fuel costs and total welfare levels. I also find, to a lesser extent, positive economic outcomes related to a reduction in the welfare gap between consumers and producers throughout the day, reduced losses for producers, and the slightly increase in consumption pattern in the afternoon. These results follow the lowest point of the valley of the duck curve. Moreover, they correspond to the observed decreases and increases in consumption patterns. The lowest point of the valley, both pre- and post-COVID-19 is associated with the highest values of price elasticity of demand, lowest values of pass-through of fuel costs, and lowest welfare levels for producers and consumers. Post-COVID-19, a negative consumption pattern in net load is also associated with the lowest value of pass-through of fuel costs and lower or equal welfare levels for producers and consumers. In contrast, a positive consumption pattern in net load is associated with higher welfare levels, more so for consumers than producers, and higher values of pass-through of fuel costs. Overall, the results coincide with lower average values of: electricity prices, fuel costs, and net load in 2020, both pre- and post- COVID-19.
One exception is the pattern observed in estimates of the pass-through of CO_2 costs. These do not show a clear association, and seem to be independent of the type of flexibility response studied in this analysis.

It is also relevant to note that in 2020 there share of renewables was 40%, whereas in the previous period it was 32%. In addition, CO_2 emissions were reduced on average 22% in 2020 compared to the previous year. For lignite, shares and emissions dropped on average 7% and 8% respectively, from 2019 to 2020 (Figure 10).

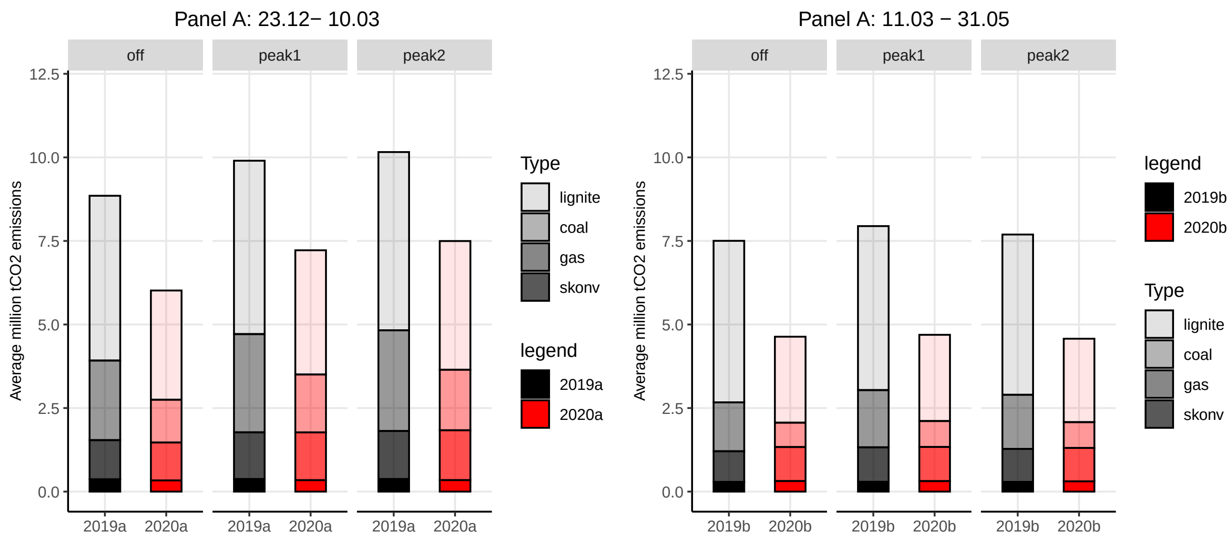

Figure 10: CO_2 emissions for the periods of analysis

A mechanism that potentially explains the type of flexibility observed post-COVID-19 is that the minimum generation available from must-run conventional generation is reduced to avoid curtailing renewables and to mitigate oversupply. In their second report, (18) defined the minimum generation as the share of conventional generation base load that is available to be reduced when day-ahead electricity prices are negative. The minimum generation pertains to the following services: positive redispatch service, positive control reserve, negative control power, and securement of the negative control reserve. It can also be activated for other services, including the instantaneous reserve, voltage maintenance, and short-circuit power. Because these additional services can also cause variation in the minimum generation levels, its real quantity is not available to date. For the years 2016 - 2018, the lower boundary of the share of minimum generation was between 38% and 61%. This high variability is due to the variation in individual plant requirements, whereby less responsive plants were operating for heat production. Moreover, although the lowest points of the valley of the duck curve coincided with higher values of price elasticity of demand during the day, the resulting post-COVID-19 value (-0.16) is still very low. It is thus likely that the benefits of flexibility responses for a minimum generation reduction are of limited range and incomplete for the electricity market. A limitation in this regard, is that it is difficult to precisely quantify renewable production and its associated reduction in greenhouse gases that could have been curtailed but remained available to the system due to the reduction in the minimum generation.

A reason for the observed rigidity in the response of CO_2 costs to electricity prices might be that the observed reduction in CO_2 emissions that coincided with higher shares of renewables in the grid, also activated the reduction of the short-term oversupply of allowances and motivated their cancellation under the functioning market stability reserve (19). In addition, CO_2 prices dropped on average 30% pre- to post-COVID-19 during the first wave in 2020.

Overall, we might wonder whether there are reasons to expect that the observed electricity consumption pattern will hold in the future. Using smart meter data from Texas in the US, (20) found that daily routines changed during the pandemic, and residential consumption increased, while industrial consumption dropped. In addition, (21) argues that 22% of all full work days will be supplied from home in the US post-COVID-19. Furthermore, they found a potential of 2.4% higher productivity of working from home rather than at the office. Thus, they conclude that working from home will stick in the US. Since the results of the current study show that after the first wave there was a change in consumption patterns, with a reduction in the morning and an increase at night, it is plausible that this trend will hold as well in Germany.

Through the lens of a lower-boundary study and expanding the methodological framework in (12) to include flexibility and temperature anomalies as additional drivers (see Figure 11 in Appendix B for a causal diagram), this analysis is thus relevant for discussions about the future of flexibility regulations under current energy and climate policies. Moreover, it sheds light on the economic implications of flexibility under the "fattening the duck" strategy, which was likely the result of a reduction in the minimum generation. This study is limited by the fact that it did not analyze the heterogeneity in consumers and producers and the exact quantification of the minimum generation responsiveness, which were not possible with the data used. In addition, assessing whether the benefits from a 31% reduction of greenhouse gases exceeded the losses in welfare was beyond the scope of this study.

Future studies could analyze whether there could be more integral ways to add higher levels of responsiveness of CO_2 costs into daily system flexibility requirements. Analyzing the effects of differentiated carbon price controls during the day could add more insight to the design of electricity tariffs. Furthermore, studying the allocative efficiency of positive demand responses (7) on the base load versus the reduction of the minimum generation would be another way to analyze the economic impacts of different types of flexibility responses.

This study also contributes to the discussion of efficient pricing structures under current climate policies. As electricity systems with high shares of renewables transition to a low-carbon economy, flexibility requirements will become more important to reflect scarcity conditions in electricity tariffs. They could also reduce the extent of transmission expansion due to congestion. In their study, (22) argues that electricity systems with high renewable shares continue to challenge the paradigm of representing the supply of electricity as a homogeneous good that meets a consistent consumer pattern. In addition, liquid innovative derivative products between suppliers and retails, and cap-style pricing contracts for consumption of a fixed capacity band would be optimal for consumers in Australia. However, the question of whether the marginal cost of an extra unit of energy would be trivial in systems under high renewable expansion, as result of achieving an equalizing goal between off-peak and peak hours (also due to storage), is open to further discussion.

6 Conclusion

Considering RPS and ETS policies, this study analysed the economic impacts of flexibility under a "fattening the duck" strategy from the supply side, likely the result of a reduction in minimum generation. I used COVID-19 as source of exogenous shock on the demand side, and I employed a model that represents the uncertainty from intermittent renewables on the demand side as non-price and price determinants of demand. During the first wave of COVID-19, I found that the low positive economic impacts derived from flexibility responses of this type were overridden by negative economic impacts on the day-ahead electricity market.

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A Appendix

Table 6: Pass-through of input costs

	01.01 - 10.03			11.03 - 31.05		
	2018-2019	2019-2020		2018-2019	2019-2020	
	(1)	(2)	*Markets*	(3)	(4)	*Markets*
Fuel costs (γ_1)						
off-peak	0.568***	0.649***	777/789	0.530***	0.979***	813/818
	(0.006)	(0.009)		(0.010)	(0.006)	
peak1	0.685***	0.761***	538/553	0.544***	0.941***	573/574
	(0.008)	(0.125)		(0.013)	(0.009)	
peak2	0.598***	0.771***	539/553	0.563***	1.040***	574/574
	(0.014)	(0.027)		(0.028)	(0.011)	
CO_2 costs (γ_2)						
off-peak	1.344***	0.688***	777/789	0.856***	0.577***	813/818
	(0.033)	(0.015)		(0.040)	(0.006)	
peak1	1.698***	0.806*	538/553	1.053***	0.617***	573/574
	(0.050)	(0.359)		(0.070)	(0.008)	
peak2	1.412***	0.830***	539/553	0.918***	0.559***	574/574
	(0.011)	(0.075)		(0.110)	(0.012)	
Ramping costs (γ_3)						
off-peak	0.091***	0.091***	777/789	0.109***	0.118***	813/818
	(0.015)	(0.010)		(0.010)	(0.012)	
peak1	−0.089***	0.090	538/553	0.049**	0.152***	573/574
	(0.023)	(0.063)		(0.017)	(0.018)	
peak2	−0.065***	0.000	539/553	0.044**	0.103***	574/574
	(0.024)	(0.021)		(0.015)	(0.020)	
Price (γ_1)						
off-peak	−11.500	−0.252***	777/789	−0.144***	−48.803***	813/818
	(84.890)	(0.047)		(0.024)	(0.426)	
peak1	−6.508	−0.157	538/553	−0.137***	−84.000***	573/574
	(34.868)	(0.211)		(0.0309)	(0.886)	
peak2	−0.114***	−0.150***	539/553	−0.159*	−41.530	574/574
	(0.007)	(0.041)		(0.077)	(1145)	
Load (γ_2)						
off-peak	−2385, 84	0.045	777/789	0.006	−4216***	813/818
	(22000)	(266.756)		(358.037)	(0.005)	
peak1	−2543.030	0.034	538/553	0.001	−5354.760***	573/574
	(13024)	(3730.861)		(3660)	(0.014)	
peak2	0.009	0.029	539/553	0.003	−2391.130	574/574
	(381.318)	(633.866)		(1931)	(65976.82)	
GMM Objective	1.38E+03	2.69E+03		9.26E+02	6.48E+02	

I apply a low cost bound of €24.99/MWh. I report the highest GMM Objective for off-peak, peak 1, and peak 2 subsamples.

Table 7: Total pass-through of input costs

	01.01 - 10.03			11.03 - 31.05		
	2018-2019	2019-2020		2018-2019	2019-2020	
	(1)	(2)	*Markets*	(3)	(4)	*Markets*
Total costs (γ_1)						
off-peak	0.762***	0.660***	777/789	0.626***	0.765***	813/818
	(0.008)	(0.010)		(0.016)	(0.008)	
peak1	0.948***	0.773***	538/553	0.706***	0.763***	573/574
	(0.014)	(0.120)		(0.126)	(0.009)	
peak2	0.956***	0.796***	539/553	0.672***	0.778***	574/574
	(0.019)	(0.055)		(0.036)	(0.006)	
Price (γ_1)						
off-peak	−8.110	−0.252***	777/789	−0.145***	−0.253*	813/818
	(36.204)	(0.050)		(0.021)	(0.131)	
peak1	−7.379	−0.158	538/553	−0.138***	−0.318*	573/574
	(38.089)	(0.131)		(0.023)	(0.149)	
peak2	−1.072	−0.150**	539/553	−0.159**	−0.353***	574/574
	(1.124)	(0.054)		(0.055)	(0.103)	
Load (γ_2)						
off-peak	−1691.920	0.044	777/789	0.004	0.002	813/818
	(7770)	(281)		(315)	(2407)	
peak1	−2895.890	0.030	538/553	0.001	−0.001	573/574
	(14595)	(2274)		(2746)	(1204)	
peak2	1461.955	0.024	539/553	0.002	0.004	574/574
	(1628)	(844)		(1349)	(1098)	
GMM Objective	1.21E+03	5.68E+02		1.75E+03	1.63E+03	

I apply a low cost bound of €24.99/MWh. I report the highest GMM Objective for off-peak, peak 1, and peak 2 subsamples.

B Appendix

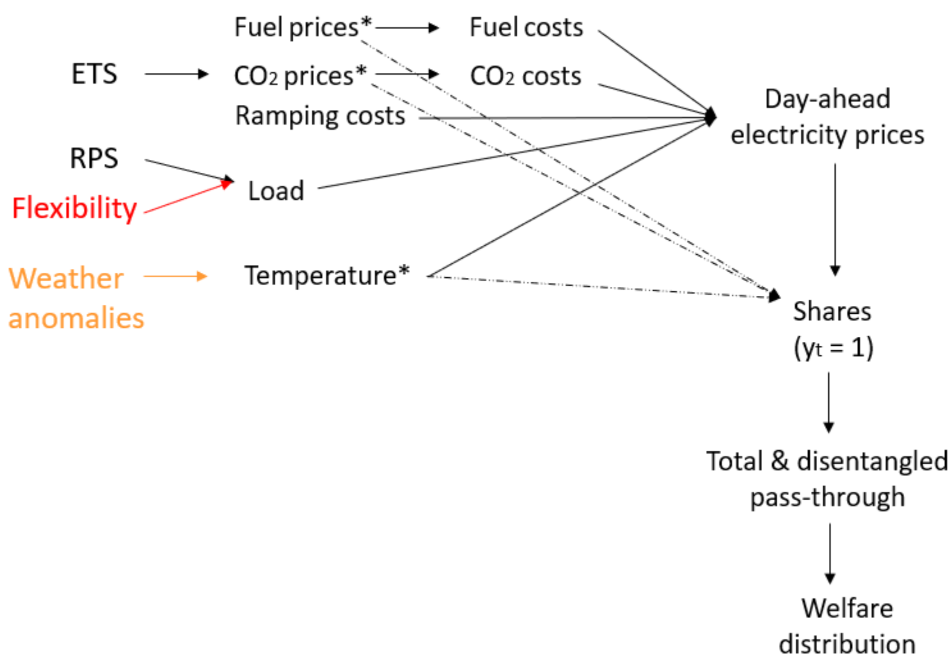

Figure 11: Drivers analyzed in this study. Confounders are denoted with (*)