Electricity Markets Under Lockdown: Insights From New York

BY DAVID BENATIA

Introduction.

Three billion people are under lockdown. Many regions across the globe have taken drastic measures in an effort to contain the outbreak of COVID-19. Restaurants, bars, schools, universities as well as many commercial and industrial operations considered as non-essential have shuttered. Travel bans have been enacted and borders have been closed. In early April 2020, the economic and social consequences of the "Great Lockdown" only start to unravel as millions of workers file jobless claims.

The short- and long-term impacts of containment measures on electricity markets, although sizeable, are not as dramatic as for the rest of the economy. As teleworking becomes the new normal and a large share of economic activities are on pause, many electricity systems experience unusual patterns of consumption and coincidentally low wholesale prices. Lockdown measures are causing unprecedented reductions of electricity demand ranging from up to 15-20% in France (RTE, 2020), down to only 2% in Texas (ERCOT, 2020). Those large sudden variations are unparalleled in history, even during major economic crises.

At the epicenter of the crisis in the U.S., the New York state's electricity market is likely to be the most affected in North America. This article documents the impacts and consequences of the COVID-19 crisis on the New York electricity market using a simple yet powerful machine-learning approach to causal inference (Benatia and de Villemeur, 2019).

Based on this methodology, the New York state is found to have experienced a 7.5% electricity demand reduction since the beginning of lockdown on March 22, 2020. New York City (NYC) is the most affected area with a 12% reduction. Morning peaks have decreased by 17% in NYC and daily consumption patterns have considerably changed. Interestingly, the effects of sheltering measures on daily consumption are qualitatively similar across regions (RTE, 2020).

Additional findings reveal that load forecast errors have surged during the first weeks of containment measures. Over-forecasting results in inefficient daily system operations because of additional operating costs from unnecessary start-ups and provisions of spinning reserves (Ortega-Vazquez and Kirschen, 2006). This article shows that short-term forecasting models have adjusted to new load patterns within a couple of weeks. Around the globe, system operators have mobilized their workforce to attenuate forecast errors. (NYISO, 2020; RTE, 2020).

Finally, wholesale prices have dropped by 50% since the beginning of the lockdown. This reduction is mainly attributed to low fuel prices rather than unexpectedly low demand levels. The main reason is that unexpected load reductions have been offset by the phasing-out of a nuclear power unit. Polluting emissions have hence remained stable.

David Benatia is with Crest Ensae, Institut Polytechnique de Paris. He may be reached at david.benatia@ensae.fr

See footnotes at end of text.

Load forecasting, neural networks and causal inference. The New York electricity system operator (NYISO) uses a combination of advanced neural network and regression type models for load forecasting (NYISO, 2019). This algorithm feeds on weather forecasts and recent load realizations to predict hourly electricity demand in each of the 11 load zones for the following days. The algorithm proves to be reliable with a 3% mean relative absolute error for day-ahead forecasts over the period 2013-2020.

Our modelling approach consists in training a neural network capable of predicting the hourly load for each zone under business-as-usual conditions, but without relying on recent load realizations or other endogenous variables affected by lockdown measures. The objective is to construct a reliable counterfactual electricity demand assuming containment measures had not been enacted for the entire lockdown period. The discrepancies between the model's predictions and the actual realizations have a causal interpretation as the effect of containment measures on electricity consumption. The advantage of this method is to be able to credibly perform causal inference and obtain standard errors for the mean effects of interest.

The model, hereafter denoted N-Net, has a set of 302 predictors, all exogenous to lockdown measures. The set includes hourly weather conditions, such as temperature, humidity, and wind speed measures from 19 weather stations in New York state (source: https://www.wunderground.com), the West Texas Intermediate crude oil prices (source: St-Louis Federal Reserve), spot natural gas prices from Henry Hub, New York, and Chicago (source: Energy Information Agency), two-months lagged load realizations, and time fixed-effects for hour of the day, day of the week, and month of the year. The algorithm has a single-hidden layer with 5 neurons. It is trained in a few minutes using a randomly selected training sample with 70% of the 60,207 hourly observations for the period 2013-2020 prior to school closures in NYC on March 16, 2020. The remaining observations are randomly split into a validation (20%) and testing (10%) datasets.

Table 1 reports the performance of N-Net and the day-ahead forecasts used by NYISO to predict hourly electricity consumption. Performance is measured using the Root-Mean-Squared Prediction Errors (RMSPE). Its values on the test set, e.g., 428.6 for total NYISO demand, provides a good measure

Table 1. Forecasting performance (RMSPE): N-Net vs NYISO Day-ahead

	Test set		School closures 03/16 - 03/22		Lockdown 1 03/23 - 03/29		Lockdown 2 03/30 - 04/05		Lockdown 3 04/06 - 04/12	
Zone	N-Net	NYISO	N-Net	NYISO	N-Net	NYISO	N-Net	NYISO	N-Net	NYISO
Capital	55.5	74.5	81.8	35.4	77.8	75.0	68.6	59.3	74.8	49.2
Central	63.4	116.7	121.3	43.5	179.6	73.7	128.5	63.1	144.7	82.2
Dunwoodie	30.8	31.5	36.5	17.9	36.5	28.5	32.8	28.1	55.4	24.8
Genessee	42.2	56.8	40.9	27.2	56.6	45.0	54.0	45.6	59.8	38.9
Hudson Vall.	44.5	64.8	67.7	29.3	75.2	74.4	65.6	43.8	73.5	38.5
Long Island	79.6	87.7	79.2	74.8	135.4	145.0	106.0	94.7	113.4	97.4
Mohawk Vall.	50.7	147.3	149.0	101.4	154.6	109.2	90.8	106.3	49.9	145.5
Millwood	27.9	27.5	26.9	24.5	33.8	22.8	49.5	16.9	47.5	21.6
NYC	**142.3**	**154.8**	**366.2**	**272.4**	**597.2**	**349.3**	**702.2**	**397.1**	**751.7**	**315.0**
North	26.0	24.5	37.9	28.1	28.1	30.3	26.4	30.9	33.6	23.6
West	69.2	76.9	79.0	42.4	128.9	49.4	128.8	57.6	126.2	60.2
NYISO	**428.6**	**665.9**	**951.6**	**325.5**	**1397.4**	**695.3**	**1309.0**	**587.5**	**1311.5**	**578.9**

Note: This table reports performance in terms of Root-Mean-Squared Prediction Errors (RMSPE) of the model (N-Net) versus the day-ahead forecasts used by NYISO. The test set contains 3500 randomly selected observations that were not used to train or validate the model. The last row reports the total load in NY.

of the extent to which the model generalizes to new data. N-Net is found to outperform NYISO forecasts with an average relative absolute error below 2%. Part of this is due to the fact that N-Net is based on actual weather conditions rather than weather forecasts. Nevertheless, it shows that the model performs

Table 2. Weekly electricity consumption reductions (GWh)

	Week before	Schools closure	Lockdown 1	Lockdown 2	Lockdown 3
Zone	**03/09 - 03/15**	**03/16 - 03/22**	**03/23 - 03/29**	**03/30 - 04/05**	**04/06 - 04/12**
Capital	-3.9	-10.4	-7.6	-8.1	-6.9 (2.7)
Central	-8.1	-17.0	-28.3	-18.9	-22.0 (3.2)
Dunwoodie	-1.3	-3.2	-2.6	-3.1	-7.8 (1.6)
Genessee	8.2	1.6	-6.3	-4.4	-3.8 (2.0)
Hudson Val.	-1.2	-4.4	-4.6	-7.0	-7.8 (1.9)
Long Island	-1.7	-4.2	-8.3	-9.8	-11.6 (3.6)
Mohawk Val.	-14.1	-23.3	-24.7	-11.9	-5.5 (2.7)
Millwood	-7.1	-3.8	-4.0	-7.8	-6.8 (1.4)
NYC	**-11.9**	**-56.2**	**-90.7**	**-105.5**	**-113.8 (7.2)**
North	-3.1	-4.6	-3.9	-3.6	-5.2 (1.3)
West	2.3	-9.0	-18.0	-18.0	-17.9 (3.6)
NYISO	**-53.9**	**-141.1**	**-211.0**	**-194.5**	**-193.2 (19.4)**

Note: This table weekly consumption changes per zone in GWh. Standard errors are reported in parentheses in the right-most column. NYISO denotes the total load in New York state.

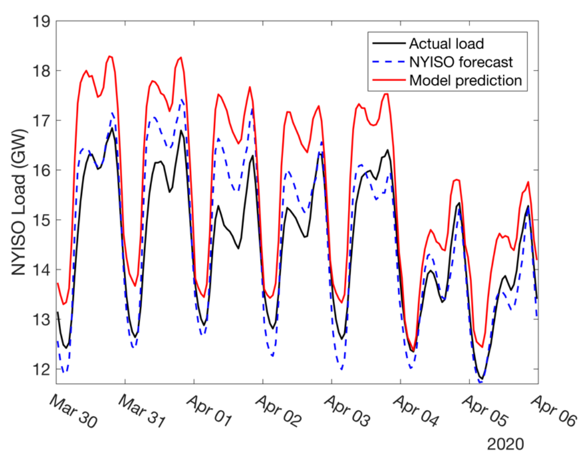

Figure 1. Actual load (black), day-ahead forecast (blue) and counterfactual load (red)

accurately, without relying on recent load realizations. This table also shows that NYISO forecast errors have increased temporarily during the first weeks of containment measures. The forecast algorithm has quickly adapted since then as errors have reduced in the third week of lockdown.

As an illustration, the actual NY total load (black line), the NYISO forecast (dashed blue line) and the N-Net counterfactual load (red line) are shown in Figure 1 for the second week of lockdown (March, 30 to April, 5). The deviations between the actual load and the NYISO forecast does not reveal large consumption reductions. However, the discrepancy with respect to the counterfactual load identifies a sizeable effect of lockdown measures during the entire week.

Weekly electricity consumption reductions. Weekly demand reductions are estimated as the aggregated differences between actual demand and its counterfactual in the absence of containment measures over the course of each week. Table 2 reports the estimated weekly demand reductions (in GWh) separately for each zone during the week before schools closure and the following four weeks. Standard errors are reported in parentheses in the right-most column.[1] The load reduction during the week preceding any official measure is estimated at less than 2% for the entire state (-53 GWh). The purpose of schools closure, enacted on March 16, is to induce parents to stay home. It has resulted in a 6.3% (-56 GWh) decrease in NYC and 5.1% (-141 GWh) statewide. Finally, electricity demand under lockdown is found to be 10-13% smaller than usual in NYC and 7-8% smaller statewide. Interestingly, there are zones such as Long

Table 3 Estimated relative change in daily load (percentage) under lockdown (weekdays)

Table 1. Estimated relative change in daily load (percentage) under lockdown (weekdays)

Zone	Night		Morning		Afternoon		Evening	
Capital	-0.02	(.04)	-0.07	(.03)	-0.04	(.05)	-0.02	(.04)
Central	-0.07	(.03)	-0.10	(.03)	-0.09	(.03)	-0.09	(.03)
Dunwoodie	0.01	(.05)	-0.08	(.04)	-0.06	(.05)	-0.05	(.05)
Genessee	-0.03	(.03)	-0.07	(.03)	-0.04	(.04)	-0.02	(.04)
Hudson Vall.	-0.01	(.04)	-0.08	(.03)	-0.07	(.04)	-0.02	(.04)
Long Island	-0.03	(.03)	-0.07	(.03)	-0.03	(.04)	-0.03	(.03)
Mohawk Vall.	-0.09	(.05)	-0.11	(.05)	-0.12	(.05)	-0.10	(.05)
Millwood	-0.13	(.06)	-0.14	(.06)	-0.09	(.09)	-0.12	(.07)
NYC	**-0.07**	**(.02)**	**-0.17**	**(.02)**	**-0.16**	**(.02)**	**-0.12**	**(.02)**
North	-0.05	(.04)	-0.05	(.04)	-0.04	(.04)	-0.03	(.04)
West	-0.06	(.03)	-0.11	(.03)	-0.07	(.04)	-0.07	(.04)
NYISO	**-0.05**	**(.02)**	**-0.11**	**(.02)**	**-0.09**	**(.02)**	**-0.07**	**(.02)**

Note: This table weekly consumption changes per zone in GWh. Standard errors are reported in parentheses in the right column. NYISO denotes the total load in New York state.

Island or Capital where the effects of those measures have been much more limited (less than 4%). Part of

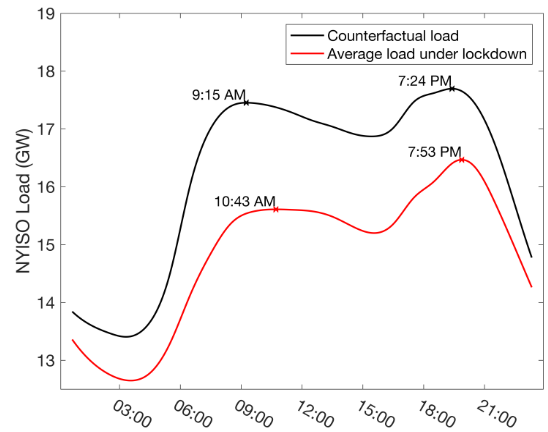

Figure 2. Average load pattern under lockdown (weekdays

this finding is explained by New Yorkers fleeing to less densely inhabited areas.

Changes in daily load patterns. New daily load patterns have been observed in all regions under lockdown. Table 3 reports the average estimates for the three (first) weeks of lockdown in New York. Each value is the estimated average relative changes in electricity demand during night hours (10 pm to 6 am), morning hours (6 am to 12 pm), afternoon hours (12 pm to 6 pm) and evening hours (6pm to 10 pm). Standard

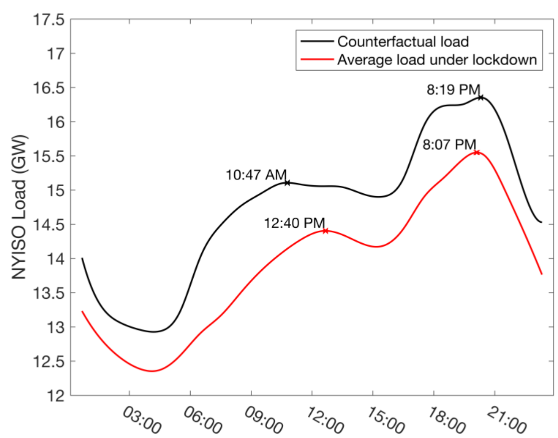

Figure 3. Average load pattern under lockdown (weekends)

errors are reported in parentheses.[2] The main finding is an attenuation of morning demand, down by 17% in NYC and 11% statewide. This effect is found to be statistically significant in nearly all zones. Reductions during other hours are relatively smaller. In many areas, such as Long Island, the afternoon consumption level under lockdown is not found to be significantly different than usual. The effect of schools closure is smaller, with an attenuation of morning demand of about 8% in NYC and 5% statewide.

Sheltering measures have also affected consumption timing. Figure 2 shows the daily load for weekdays averaged over the lockdown period (in red) and the average counterfactual load (in black), had lockdown measures not been enacted. The morning peak turns out to be much flatter and reaches its maximum 1.5 hours later. This pattern bears resemblance with what is usually observed during a widespread snow day (NYISO, 2020). Those changes are driven by increased demand from residential consumers and reduced commercial energy use. This finding may also suggest that lockdown measures affect sleeping patterns.

Figure 3 shows the average daily load and its counterfactual during weekends. The morning peak is deferred by nearly 2 hours due to lockdown measures. This finding is suggestive of the large reduction in economic activities during weekends and possibly modified sleeping patterns. E[4]vening consumption increases more gradually and decreases less sharply after the peak.

Limited short-term consequences. Although unprecedented, those changes in electricity demand do not have far-reaching short-term implications for electricity markets. The discussion in this section is based on findings obtained using a similar methodology.

Forecast errors have been larger for 2 to 3 weeks. Learning algorithms take some time to adjust to new load patterns and manual adjustments are required to prevent systematic deviations. The market data from NYISO do not reveal statistical significant increase prices for ancillary services. The economic consequences of forecast errors have hence been limited.

In New York, day-ahead and real-time prices have decreased from around \$30/MWh to \$15/MWh coincidentally with demand reductions caused by the lockdown. \$30/MWh corresponds to the median price whereas \$15/MWh is around the 5th percentile. Nevertheless, no systematic occurrences of negative prices have been observed, unlike in European electricity markets, and prices have been relatively stable. The analysis of market data does not support the claim that price reductions are caused by unexpectedly low demand levels. Two main factors explain this result. First, the average demand reductions of about 1,200 MW due to lockdown measures have been offset by the phasing out of Indian Point's Unit 2, a 1,299 MW nuclear power generating unit, during March. Second, large drops in fuel prices are the main culprits behind wholesale price reductions. In March and early April, average spot prices for natural gas and oil have been, respectively, 22% and 45% smaller with respect to their February levels.

Polluting emissions have remained stable due to the retirement of Indian Point's 2. The energy mix has not changed significantly, unlike in other regions. The only noticeable difference is the substitution of some dual-fuel production with gas-fired generation.

Potential longer-term consequences. The low price environment jeopardizes investment profitability in electricity markets. The 50% price reductions caused by fuel price drops may hinder new capacity additions in the medium to long run as investors update their expectations about future market conditions.

In addition, containment measures may delay the commissioning of current projects (renewable capacity additions, refurbishment of transmission lines, equipment maintenance, etc.) as all non-essential works are now on pause. Those delays could have detrimental consequences on small firms with tighter credit constraints in the renewable energy sector. Temporary load reductions from sheltering measures should nevertheless have virtually no effect in the long-run.

The most pressing issue for utilities in the U.S. is perhaps the suspension of $6.4 billion in pending rate hikes. It has been recently announced in many states, including New York, as a measure to protect the most vulnerable populations. Some utilities in New York have proactively asked to delay rate hikes through mid-September. Although it is a good news for residential consumers in the short-term, rate recovery of fixed-costs for utilities is essential to guarantee reasonable borrowing costs for large capital projects. The combination of delayed rate hikes and the financial struggle of energy consumers caused by containment measures may increase the cost of capital and ultimately affect energy bills in the long term.

Conclusion. Electricity consumption is a good indicator of economic activity. Containment measures have resulted in large demand reductions in the state of New York. The effects of lockdown measures on electricity markets are however quite limited. The unparalleled changes in daily load patterns have had virtually no short-term effects in terms of prices and system reliability so far. In the longer term, new installations may suffer from some delays and utilities may face the risk of increased borrowing costs due to suspended regulated rate hikes.

The COVID-19 crisis has brought two major challenges to electricity systems. First, forecasting models take several weeks to learn from new data and urgent adjustments are required to prevent inefficient system operations caused by large forecast errors. Second, and most importantly, system operators had to come up with a pandemic response plan to ensure the security of supply and safety of its employees. NYISO has perhaps implemented the starkest measures: 37 operators, managers and support staff volunteered for total sequestration from the outside world until further notice. "Just like planes can't fly without pilots and co-pilots, the electric system can't run without electricity operators", said NYISO's VP of Operations.

Footnotes

[1] Standard errors are calculated following an "honest inference" approach (Wager and Athey, 2017). More specifically, the test set is used to compute the covariance matrix of prediction errors across hours of the day. Assuming each day to be an i.i.d. realization of daily load, the sum of errors over the course of a week has the same distribution for all weeks.

[2] Estimated relative changes being ratio of random variables, the delta-method is used to calculate standard errors based on the previously estimated covariance matrix.

[3] http://www.ercot.com/content/wcm/lists/200201/ERCOT_COVID-19_Analysis_FINAL.pdf.

[4] https://www.nyiso.com/documents/20142/2923301/dayahd_schd_mnl.pdf/0024bc71-4dd9-fa80-a816-f9f3e26ea53a.

[5] https://www.nyiso.com/-/covid-19-and-the-electric-grid-load-shifts-as-new-yorkers-respond-to-crisis.

[6] https://www.rte-france.com/sites/default/files/impacts_de_la_crise_sanitaire_covid-19_sur_le_systeme_electrique.pdf.

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