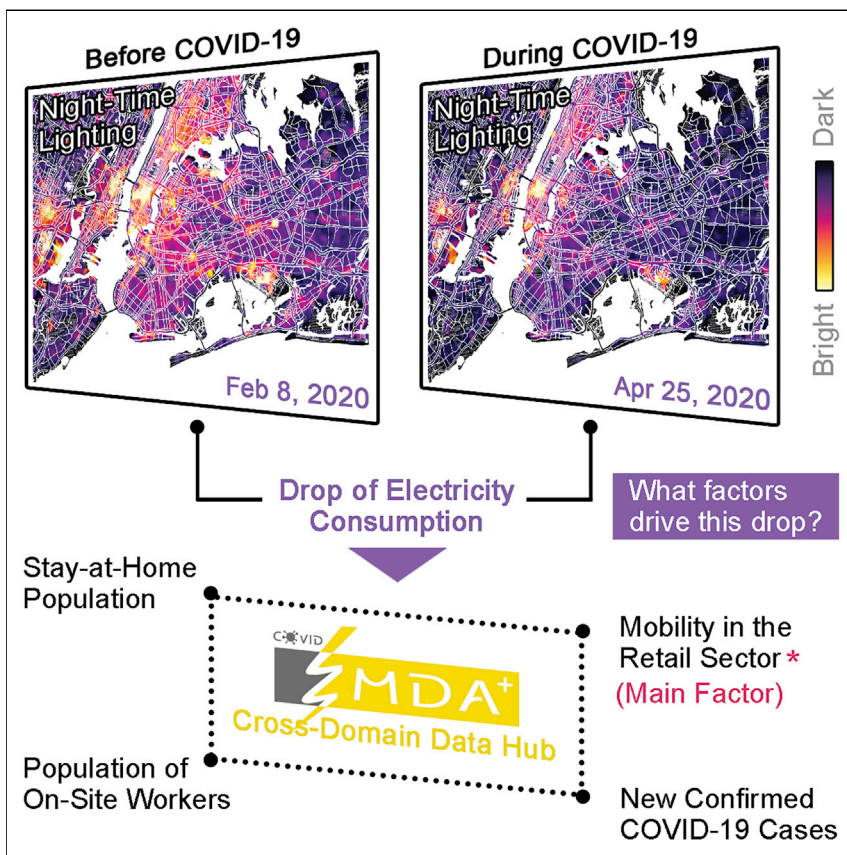


Report

# A Cross-Domain Approach to Analyzing the Short-Run Impact of COVID-19 on the US Electricity Sector



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**HIGHLIGHTS**

Open-access data hub to track the impact of COVID-19 on the electricity sector

Cross-domain analysis of electricity sector using mobility and public health data

Mobility in the retail sector is the key factor influencing electricity consumption

Visualization of the impact of COVID-19 through satellite night-time-light data

We present a cross-domain, data-driven approach to tracking and quantifying the impact of COVID-19 on the US electricity sector, including (1) a first-of-its-kind open-access data hub integrating electricity data with public health, mobility, weather, and satellite data and (2) a cross-domain analysis quantifying the sensitivity of electricity consumption to social distancing and public health policies. Population mobility, particularly in the retail sector, which is indicative of social distancing policy measures, emerges as the key factor driving changes in electricity consumption.



## Report

# A Cross-Domain Approach to Analyzing the Short-Run Impact of COVID-19 on the US Electricity Sector

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## SUMMARY

The novel coronavirus disease (COVID-19) has rapidly spread around the globe in 2020, with the US becoming the epicenter of COVID-19 cases since late March. As the US begins to gradually resume economic activity, it is imperative for policymakers and power system operators to take a scientific approach to understanding and predicting the impact on the electricity sector. Here, we release a first-of-its-kind cross-domain open-access data hub, integrating data from across all existing US wholesale electricity markets with COVID-19 case, weather, mobile device location, and satellite imaging data. Leveraging cross-domain insights from public health and mobility data, we rigorously uncover a significant reduction in electricity consumption that is strongly correlated with the number of COVID-19 cases, degree of social distancing, and level of commercial activity.

## INTRODUCTION

As the US responds to the novel coronavirus disease (COVID-19) and states re-open the economy, there is much uncertainty regarding the duration and severity of the impact on the electricity sector. Given the rapid spread of COVID-19 and the corresponding policy changes, there has been relatively little scholarly work on the impact of COVID-19 on the electricity sector. Several reports from both peer-reviewed<sup>1,2</sup> and non-peer-reviewed venues, such as news media,<sup>3</sup> social media,<sup>4–6</sup> consulting firms,<sup>7,8</sup> non-profit organizations,<sup>9</sup> government agencies,<sup>10,11</sup> and professional communities,<sup>12,13</sup> have shed some light on the adverse impact on the electricity and clean energy sectors, including operational reliability degradation, decrease in wholesale prices, and delayed investment activities. Electricity consumption analyses from regional transmission organizations (RTOs)<sup>14–16</sup> also suggest an overall reduction in energy consumption, especially in zones with large commercial activity.

However, such assessments are still at a nascent stage, with several gaps in existing research. First, the lack of consistent assessment criteria renders results across distinct geographical locations incomparable. Second, several existing statistical analyses do not rigorously calibrate a baseline electricity consumption profile in the absence of the pandemic considering the influence of exogenous factors like the weather. Finally, cross-domain data like public health data (COVID-19 cases and deaths) and social distancing data (mobile device location) that can provide valuable insights have not been considered so far in the analysis of the electricity sector.

Here, we develop a cross-domain open-access data hub, COVID-EMDA<sup>+</sup> (coronavirus disease and electricity market data aggregation+), to track and measure the impact

## Context & scale

As the lifeblood of civil society, the electricity sector is undergoing highly volatile changes due to COVID-19. The dramatic reduction in electricity consumption due to shutdown policies during COVID-19 can in fact be seen from space, as visualized by night-light satellite imagery in our study. In this work, we release a first-of-its-kind open-access data hub and cross-domain analysis integrating traditional electricity data with cross-domain sources such as public health and mobility data to quantify the impact of these social distancing and public health policies on electricity consumption. In the short term, this cross-domain analysis can immediately aid power system operators and policy makers in their response to the ongoing crisis. From a broader perspective, this research departs from the traditional landscape of forecasting, reliability, and risk assessment in the electricity sector by introducing new domains of data that will inform planning, policy, and operation in the future.

of COVID-19 on the US electricity sector.<sup>17</sup> This data hub integrates information from electricity markets with heterogeneous data sources like COVID-19 public health data, weather, mobile device location information, and satellite imagery data that are typically unexplored in the context of the energy system analysis. The integration of these cross-domain datasets allows us to develop a novel statistical model that calibrates the electricity consumption based on mobility and public health data, which have otherwise not been considered in conventional power system load analysis literature thus far. Leveraging this cross-domain data hub, we uncover and quantify a “delayed” impact of the number of COVID-19 cases, social distancing, and mobility in the retail sector on electricity consumption. In particular, the diverse timescales and magnitudes of top-down (federal or state policies and orders) and bottom-up (individual-level behavior change in social distancing) responses to the pandemic collectively influence the electricity consumption in a region. We observe a significant reduction in electricity consumption across all US markets (ranging from 6.36% to 10.24% in April, and 4.44% to 10.71% in May), which is strongly correlated with the rise in the number of COVID-19 cases, the size of the stay-at-home population (social distancing), and mobility in the retail sector (representative of the share of commercial electricity use), which emerges as the most significant and robust influencing factor.

### Cross-Domain Data Hub: COVID-EMDA<sup>+</sup>

We first develop a comprehensive cross-domain open-access data hub, COVID-EMDA<sup>+</sup> (The + symbol in COVID-EMDA<sup>+</sup> indicates the integration of cross-domain datasets like public health and mobility data with conventional electricity market data), publicly available on Github<sup>17</sup>, integrating electricity market, weather, mobile device location, and satellite imaging data into a single ready-to-use format. The original sources for each dataset are detailed in the Data and code availability section. We pay special attention to the impact of COVID-19 on electricity markets in the US<sup>18</sup> for two reasons. First, electricity market data are usually timely, accurate, abundant, and publicly available in the US, making the market dataset ideal for impact tracking and measurement. Second, wholesale electricity markets in the US cover the top eight hardest-hit states, and more than 85% of the national number of confirmed COVID-19 cases as of May 2020 (Figure S1C).

There are seven RTOs or electricity markets in the US, namely, California (CAISO),<sup>19</sup> Mid-continent (MISO),<sup>20</sup> New England (ISO-NE),<sup>21</sup> New York (NYISO),<sup>22</sup> Pennsylvania-New Jersey-Maryland Interconnection (PJM),<sup>23</sup> Southwest Power Pool (SPP),<sup>24</sup> and Electricity Reliability Council of Texas (ERCOT).<sup>25</sup> For each regional market, we aggregate data pertaining to the load, generation mix, and day-ahead locational marginal price (LMP). To improve the overall data quality, we also integrate market data from the Energy Information Administration (EIA)<sup>26</sup> and EnergyOnline company.<sup>27</sup> The major challenges in integrating raw electricity market data into a unified framework are summarized in the [Experimental Procedures](#) section. We integrate the electricity market data with weather data<sup>28</sup> (temperature, relative humidity, wind speed, and dew temperature) from the National Oceanic and Atmosphere Administration (NOAA). We will use this data to estimate an accurate baseline electricity consumption profile taking into account weather, calendar, and economic factors (annual GDP growth rate), against which the impact of COVID-19 will be quantified.

To obtain further cross-domain insights, we integrate public health data on COVID-19 cases from multiple sources<sup>29–31</sup> and mobile device location data from SafeGraph<sup>32,33</sup> comprising county-level social distancing data and pattern of visits to points of interests (POIs) like restaurants and grocery stores (see **Note S2** for a detailed description). We aggregate the mobile device location data by county and POI category, and define the

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<https://doi.org/10.1016/j.joule.2020.08.017>

“stay-at-home population” and the “population of on-site workers” (indicative of the social distancing level) as the estimated number of people who stay at home all day, and the number of people who work at a location other than their home for more than 6 h on a typical working day, respectively. The “mobility in the retail sector,” defined as the number of visits to retail establishments per day (see **Note S3** for a list of 25 included merchant types) is also of interest, since it is indicative of the level of commercial activity. Finally, we integrate satellite imagery from the NASA VNP46A1 “Black Marble”<sup>34</sup> dataset into the COVID-EMDA<sup>+</sup> hub as a tool for visualizing the impact of COVID-19 on electricity consumption (see **Note S1** for a detailed description of this dataset). The complete architecture of the data hub is shown in **Figure S1A**. The detailed description of all the original data sources and a summary of the utility of each cross-domain data source are provided in **Note S4**.

Using night-time light (NTL) data from satellite imagery, **Figure 1** visualizes the impact of COVID-19 on electricity consumption for New York City (see **Note S1** for a detailed description of how the NTL data are processed to obtain these plots). The reduction in NTL brightness provides a strong visual representation of the effect of COVID-19 on electricity consumption level in such major urban areas (see **Figure S2** for NTL visualization of other metropolises), where a significant component of the electricity consumption comprises large commercial loads. This result serves as a preview of the insights that emerge from the statistical analysis in the following sections, namely, that the level of commercial activity (quantified by mobility in the retail sector in our later analysis) is a key contributing factor for the change in electricity consumption during COVID-19. In the following analysis, we will leverage the cross-domain COVID-EMDA<sup>+</sup> data hub to quantify this reduction of electricity consumption and demonstrate its correlation with the number of COVID-19 cases, degree of social distancing, and level of commercial activity.

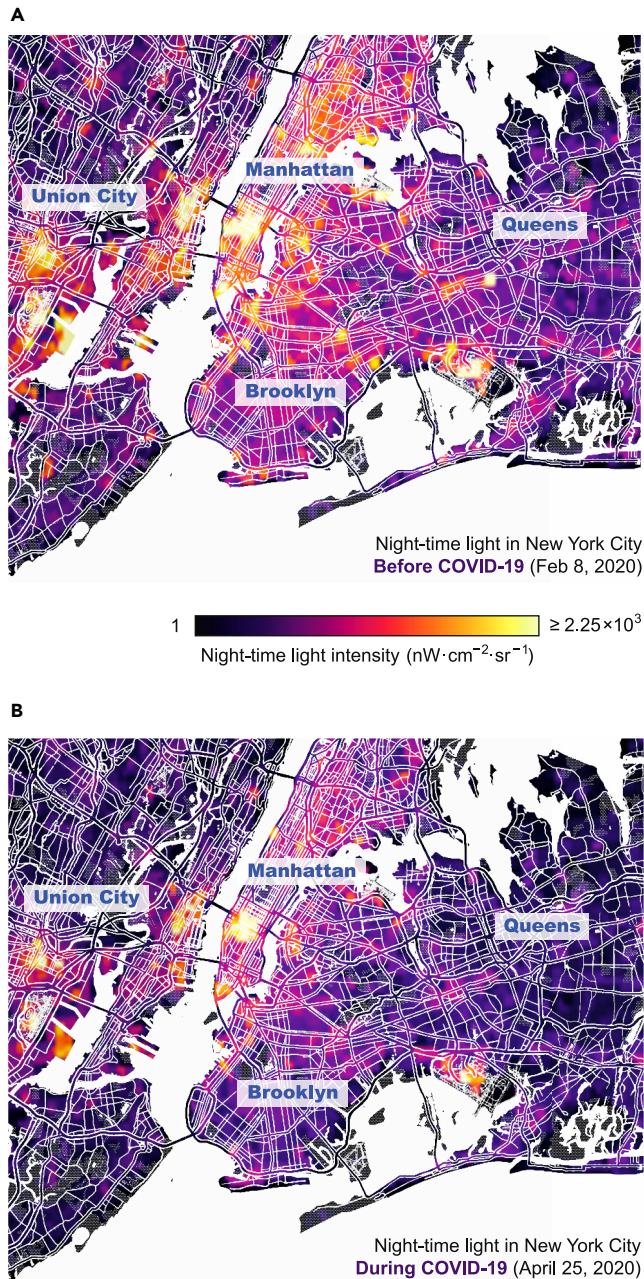
### Quantifying Changes in Electricity Consumption across RTOs and Cities in the US

Following the idea of predictive inference,<sup>36</sup> we leverage the cross-domain COVID-EMDA<sup>+</sup> data hub to derive statistically robust results on the changes in electricity consumption correlated with the COVID-19 pandemic. We achieve this by carefully designing an ensemble backcast model to accurately estimate electricity consumption in the absence of COVID-19, which is then used as a benchmark against which the impact of COVID-19 is quantified.

We begin by analyzing the reduction in electricity consumption in the New York area, which is the epicenter of the pandemic in the US. **Figure 2** shows the comparison between actual electricity consumption profile, ensemble backcast results (with 10%–90% and 25%–75% quantiles), and the electricity consumption profile in previous year (aligned by day of the week using NYISO data; for example, February 4, 2019 and February 3, 2020 are compared because they are both Mondays of the fifth week in the respective year). The strong match between the curve shapes indicates that the ensemble backcast estimations reliably verify the insignificant change in electricity consumption before the COVID-19 outbreak (February 3 and March 2) and much larger change afterward (April 6 and 27). Note that the electricity consumption profile in 2019, although being a common and simple choice in many analyses, is typically an inaccurate baseline for impact assessment in 2020.

A cross-market comparison, with both the point- and interval-estimation results, is conducted in **Table 1** to show the impact of COVID-19 on different marketplaces. The interval estimation is calculated using the 10% and 90% quantiles, which can be regarded as reliable estimation boundaries. The ensemble backcast models



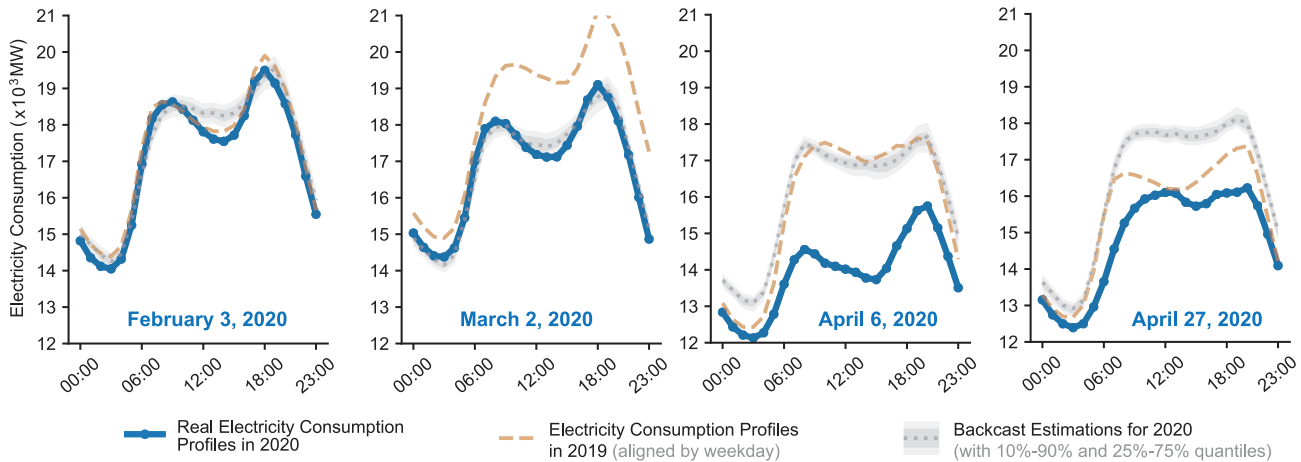


**Figure 1. Visualization of the Impact of COVID-19 on Electricity Consumption Using NTL Data for New York City**

(A) NTL imagery before the outbreak of COVID-19 (February 8, 2020).

(B) NTL imagery during the outbreak (April 25, 2020). The sampling time of both representative snapshots is 1 a.m. on Saturday, when the sky is clear of cloud. The raw data are pre-processed to filter out ambient noise and focus on only the urban area of the city. A color map is used to clearly illustrate the light intensity, in which bright color indicates strong light and dark color indicates dim light. The background city map is retrieved from OpenStreetMap.<sup>35</sup> See also Figure S2.

successfully capture the dynamics of changes in electricity consumption and provide a reliable statistical comparison among different regions. It is clearly seen that all the markets experienced a reduction in electricity consumption in both April and May; however, the magnitudes of the reductions were diverse, varying from 6.36% to



**Figure 2. Electricity Consumption Profile Comparison in NYISO between the Ensemble Backcast Estimations, Past Profile, and Real Profile**  
 Four typical Mondays are chosen for comparison during February to April. The ensemble backcast estimations include both a point- and interval-estimation, and the 10%–90% and 25%–75% quantiles are also given. The past electricity consumption profiles in 2019 are aligned with the real profiles by the day of the week.

10.24% in April, and 4.44% to 10.71% in May. Additionally, our estimation results for April match well with official reports.<sup>14–16</sup> According to Table 1, NYISO and MISO experienced the most severe reduction in electricity consumption in both April and May, while ERCOT and SPP suffered the least. All electricity markets showed a rebound in electricity consumption in June that may be correlated with partial reopening of the economy; however, the magnitudes of the rebound were once again diverse across markets as seen in Table 1. Finally, in dense urban areas, the impact of COVID-19 was more pronounced, with New York City and Boston experiencing a 14.10% and 11.32% reduction in electricity consumption respectively in April, likely due to the high population density and large share of commercial energy use in these areas. (The same factors explain why Houston, which is more geographically dispersed, was not significantly impacted.) We will examine such potentially relevant factors more closely in the following section.

**Impact of Public Health, Social Distancing, and Commercial Activity on Electricity Consumption During COVID-19**

In order to interpret the changes in electricity consumption during COVID-19, we begin by investigating three potential influencing factors, namely, public health (indicated by the number of COVID-19 cases), the social distancing (indicated by the size of the stay-at-home population and the population of on-site workers), and the level of commercial activity (indicated by a reduction in visits to retail establishments). These influencing factors possess two important features that must be taken into account while interpreting their influence on electricity consumption.

First, there is a complex multi-dimensional relationship between the number of COVID-19 cases, social distancing, shut down rate of commercial activity, and electricity consumption, as shown in Figure 3A. For example, stricter social distancing and shutdown of commercial activity slow down the spread of COVID-19. Conversely, a rise in the number of COVID-19 cases results in an increase in social distancing (size of the stay-at-home population), as well as shut down of businesses (commercial loads). This trend is clearly discernible in mobile device location data as an increase in the stay-at-home population (Figure S3) and a reduction in visits to retail establishments (Figure S4). Figure 3C shows the trace of the evolution of daily

**Table 1. Comparison of Changes in Electricity Consumption across Electricity Markets and Cities in the US**

Electricity Consumption Reduction (%)	CAISO	MISO	ISO-NE	NYISO	PJM	SPP	ERCOT
Average in February	-1.31 [-4.10, 1.24]	-0.14 [-2.09, 1.77]	2.15 [-0.47, 4.58]	0.84 [-1.47, 3.14]	0.54 [-1.65, 2.57]	-0.90 [-3.18, 1.27]	-1.52 [-4.06, 0.86]
Average in March	2.68 [0.52, 4.78]	1.77 [0-0.41, 3.88]	5.24 [2.33, 7.88]	4.51 [2.01, -7.00]	2.68 [0.19, 5.02]	2.47 [-0.36, 5.14]	-1.30 [-1.00, 3.43]
Average in April	9.24 [6.64, 11.72]	10.24 [7.88, 12.66]	9.47 [6.26, 12.32]	10.20 [7.26, 12.91]	9.44 [6.74, 12.07]	7.72 [4.49, 10.71]	6.36 [3.77, 8.80]
Average in May	6.46 [3.24, 9.35]	10.71 [8.28, 13.16]	10.44 [6.70, 13.90]	10.47 [7.17, 13.54]	7.35 [4.45, 10.20]	9.24 [6.22, 12.07]	4.44 [2.10, 6.59]
Average in June	0.29 [-2.74, 3.04]	3.49 [1.44, 5.54]	1.79 [-1.78, 5.06]	5.72 [2.37, 8.78]	0.14 [-2.57, 2.52]	2.66 [-0.05, 5.17]	2.41 [0.54, 4.06]

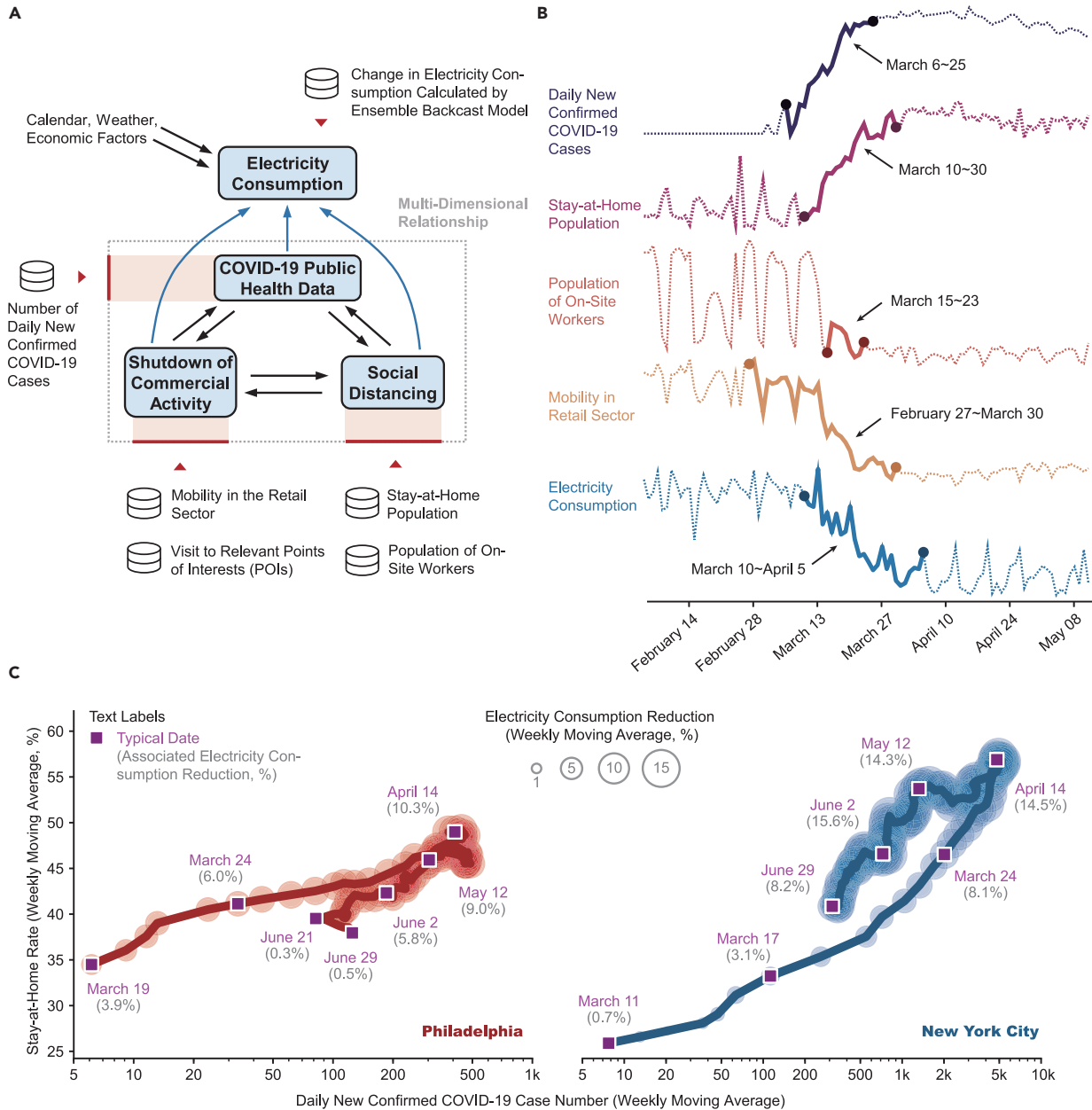
Electricity consumption reduction (%)	Boston	Chicago	Houston	Kansas City	Los Angeles	New York City	Philadelphia
Average in February	0.40 [-1.93, 2.60]	0.09 [-2.41, 2.43]	-0.55 [-3.02, 1.93]	0.10 [-2.76, 2.89]	-1.12 [-4.27, -1.83]	0.43 [-2.12, -2.90]	0.75 [-1.98, -3.40]
Average in March	7.12 [4.63, 9.53]	2.95 [0.26, 5.49]	-0.53 [-3.01, 1.70]	0.24 [-3.44, 3.57]	3.32 [0.61, 5.85]	5.27 [2.60, 7.80]	3.94 [-0.96, 6.86]
Average in April	11.32 [8.55, 13.93]	9.81 [6.70, 12.66]	5.33 [2.63, 7.79]	9.04 [5.00, 12.55]	11.06 [8.11, 13.82]	14.10 [11.26, 16.80]	8.93 [5.42, 12.18]
Average in May	9.36 [6.02, 12.41]	9.51 [6.32, 12.51]	3.63 [0.86, 5.85]	7.01 [3.22, 10.67]	3.91 [0.59, 7.06]	14.77 [11.61, 17.76]	8.24 [4.58, 11.71]
Average in June	0.41 [-3.03, 3.38]	3.24 [0.36, 5.84]	4.41 [2.05, 6.48]	0.21 [-2.56, 2.62]	-1.90 [-5.42, 1.34]	11.07 [7.60, 14.02]	2.07 [-1.20, 5.06]

All markets and cities experienced a reduction in electricity consumption in April but with diverse magnitude. Particularly, dense urban areas suffered the most severe reduction in April.

Note: the RTOs are listed in an order from the Federal Energy Regulatory Commission, and the cities are given in an alphabetical order.

new confirmed cases and social distancing, and the associated rate of reduction in electricity consumption for two representative metropolises—New York City and Philadelphia, indicating a fast-developing period in March 2020 and a more stable period afterward. A slight rebound in the electricity consumption that may be correlated with the partial reopening of the economy, and the relaxation of some social distancing restrictions, is also observed in the trace of the electricity consumption during June 2020. Similar trends are observed in other COVID-19 hotspot cities that are in various stages of evolution of the pandemic (Figure S5). An alternative visualization of the same result is shown in Figure S6 for all metropolises. The trace of evolution of electricity consumption demonstrates the dynamically evolving, multi-dimensional relationship between the number of COVID-19 cases, the size of the stay-at-home population, and the reduction in electricity consumption.

Second, these influencing factors exhibit very different temporal dynamics. For example, in New York City, Figure 3B shows a wide variation in the timescales of the changes in the electricity consumption, public health, stay-at-home, work-on-site, and retail mobility data. The mobility in the retail sector has the earliest response in terms of the rate of change (gradually dropping from late February 2020 and continuing to go down until late April 2020), resulting from bottom-up responses of consumers to the emerging pandemic. On the other hand, the



**Figure 3. Factors Influencing Electricity Consumption during COVID-19**

(A) Multi-dimensional relationship between case load, social distancing, shut down of commercial activity, and electricity consumption. Heterogeneous data sources from COVID-EMDA<sup>+</sup> are applied as indicators of these factors.

(B) Wide variation in the timescales of different factors influencing electricity consumption during the COVID-19 pandemic. The raw number of confirmed COVID-19 cases are offset by 1 and plotted on a logarithmic scale. The segments in bold indicate the transition periods for each variable (see Figure S10 for the details on how these transition periods are defined and identified). It is apparent that the electricity consumption started dropping almost immediately after the national emergency declaration. The number of new confirmed cases started to significantly rise a couple of days earlier. The stay-at-home population and population of on-site workers started changing around the time of the national emergency declaration, while the slight rebound around April 20 coincided with reopening policies in a few states. The mobility in the retail sector started dropping at the very early stages of the COVID-19 outbreak, due to individual consumer responses to the pandemic.

(C) Trace of the evolution of daily new confirmed cases and social distancing, and the associated rate of reduction in electricity consumption for two representative metropolises—New York City and Philadelphia. The bubble sizes indicate the percentage reduction in electrical consumption (with larger bubble sizes indicating more reduction in consumption). The number of COVID-19 cases and the size of the stay-at-home population are smoothed by a weekly moving average to properly extract the trends. Both cities follow a fast-developing period in March 2020 and a more stable period afterward. A slight rebound in the electricity consumption is also observed in the trace during June 2020. See also Figures S5, S6, and S10.



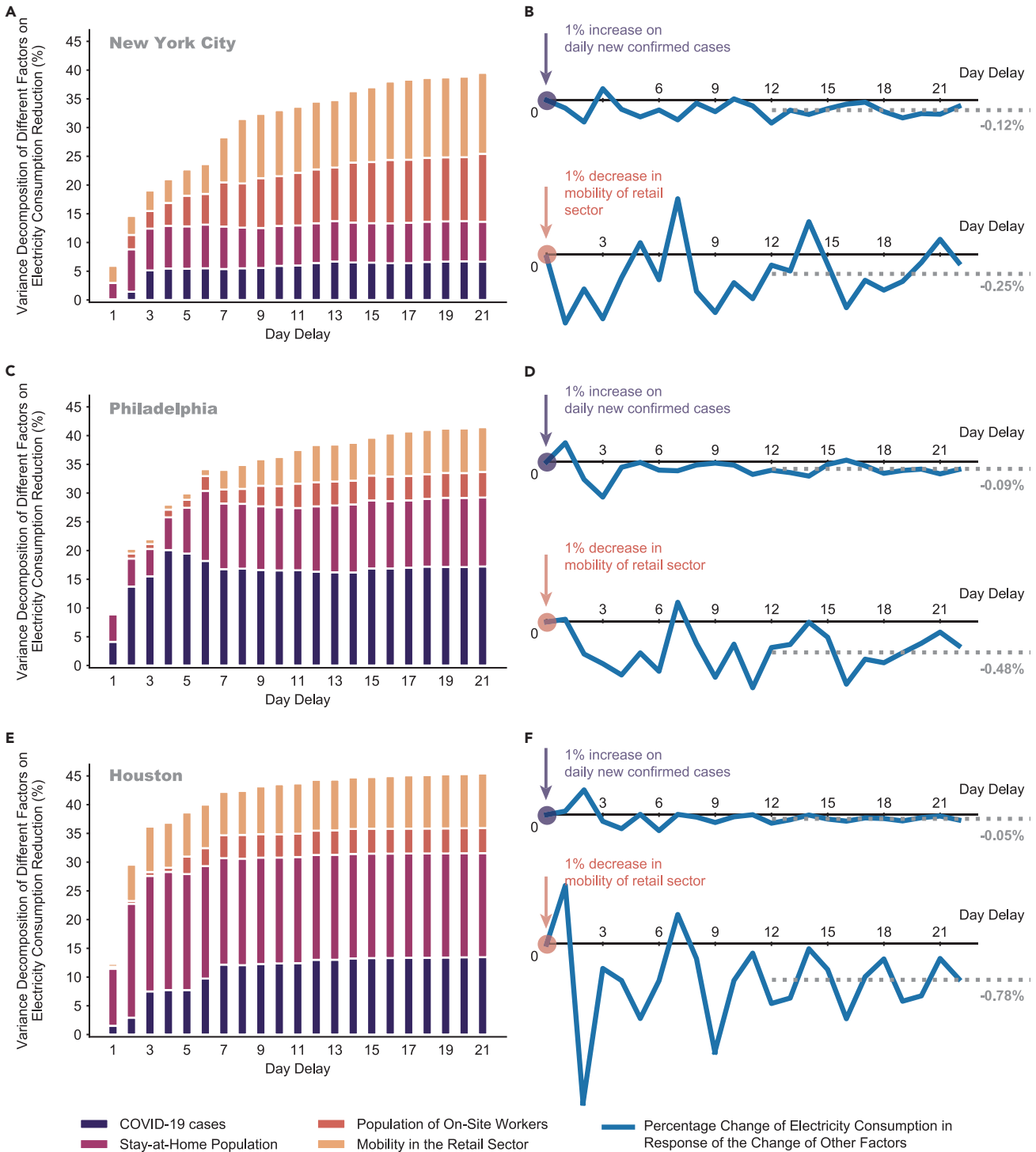
population of on-site workers shows a sharp, abrupt change right around mid-March, as a result of top-down federal and state-level policy decisions, such as stay-at-home orders. This insight, to our best knowledge, is first revealed in [Figure 3B](#) and suggests a very different efficacy of social distancing arising from top-down government policies and from bottom-up individual responses. Finally, the electricity consumption shows a delayed reduction with respect to the number of COVID cases.

Taking into account these two features, we rigorously quantify the multi-dimensional relationship shown in [Figure 3A](#) by calibrating several city-specific restricted vector autoregression (restricted VAR)<sup>37</sup> models. Restricted VAR models are powerful tools for multivariate time series analysis with complex correlations and have been widely adopted in econometrics<sup>38</sup> and electricity markets.<sup>39</sup>

Compared with ordinary regression analysis, the restricted VAR model allows for dependencies between model variables that are too complex to be fully known.<sup>38</sup> Please refer to the [Experimental Procedures](#) section for the definition, **Methods S1–S3** for details on the calibration and validation of the restricted VAR model, and [Tables S1–S4](#) for the model parameters and results of statistical tests on the model. We now examine the restricted VAR model using the variance decomposition and impulse response analyses as described in **Method S4**. The variance decomposition analysis indicates the influencing factors that contribute to changes in electricity consumption, while the impulse response analysis describes the dynamical evolution of the reduction in electricity consumption that would result from a unit shock (1% increase or decrease) in one influencing factor. We note that the restricted VAR model can be further fine-tuned by selecting the most significant influencing parameters (see **Note S5** and [Figure S9](#) regarding the choice of VAR model parameters, and **Method S5** for the VAR model selection procedure). [Figures 4](#) and [S7](#) present the variance decomposition and impulse response analyses for various COVID-19 hotspot cities, indicating the “delayed” impact of various influencing factors on electricity consumption. By analyzing [Figures 4](#) and [S7](#), we obtain three key findings.

The first key finding is that the mobility in the retail sector is the most significant and robust factor influencing the decrease in electricity consumption across all cities. This factor accounts for a significant proportion of the change in electricity consumption in both the variance decomposition results ([Figures 4A, 4C, and 4E](#)) and the impulse response analyses ([Figures 4B, 4D, and 4F](#)). For example, in Houston, a 1% decrease in the mobility of retail sector results in a 0.78% reduction in electricity consumption in the steady state. Further, from the impulse response analyses ([Figures 4B, 4D, 4F, S7B, S7D, S7F, and S7H](#)), the electricity consumption is typically most sensitive to changes in the mobility in the retail sector.

The second finding is that the number of new confirmed COVID-19 cases, although easy to obtain, may not be a strong direct influence on the change in electricity consumption. This finding is supported by observations of a low sensitivity of the electricity consumption to this factor in impulse response results across all cities [Figures 4B, 4D, and 4F](#). Note that a high proportion of a particular factor in the variance decomposition may not always mean a high sensitivity to that factor in the impulse response analysis; therefore, the variance decomposition analysis alone cannot be used to infer the magnitude of influence of dependent or correlated influencing factors.<sup>40</sup> The low sensitivity of the electricity consumption to the number of COVID-19 cases in the impulse response analysis, taken together with its occurrence as an important influencing factor in the variance decomposition,



**Figure 4. Restricted VAR Model Analyses for New York City, Philadelphia, and Houston**

(A, C, and E) Variance decomposition (excluding the inertia of the electricity consumption itself) indicating the contribution of different influencing factors, namely, the daily new confirmed COVID-19 cases, the stay-at-home population, and the population of on-site workers (indicative of social distancing), and mobility in the retail sector (indicative of commercial electricity loads), to changes in electricity consumption.

(B, D, and F) Dynamical evolution of the reduction in electricity consumption that would result from a unit shock (1% increase or decrease) in one influencing factor. See also [Figure S7](#).

indicates that it exerts an indirect influence on the electricity consumption through other influencing factors (such as social distancing and commercial activity). This result also partly explains the sharp corner in the trace of New York City's electricity consumption in [Figure 3C](#) after mid-April, where no immediate growth in the electricity consumption is observed despite the decrease in number of daily new confirmed cases.

The third finding is that high sensitivities to some influencing factors may be observed in cities with a mild overall reduction in electricity consumption. For example, [Figure 4F](#) indicates that the change in electricity consumption in Houston is very sensitive to variations in the level of commercial activity (mobility in the retail sector), despite the magnitude of the change in electricity consumption not being very significant ([Table 1](#)). Therefore, such cross-domain insights that are not readily available from traditional analyses may need to be considered in evaluating policy decisions pertaining to the electricity sector. In summary, our findings quantify the dynamics of the interplay between the rise in the number of COVID-19 cases, increased social distancing, and reduced commercial activity, in influencing electricity consumption in the US.

## DISCUSSION

We introduced a timely open-access easy-to-use data hub aggregating multiple data sources for tracking and analyzing the impact of COVID-19 on the US electricity sector. The hub will allow researchers to conduct cross-domain analysis on the electricity sector during and after this pandemic. We further provided the first assessment results with this data resource to quantify the intensity and dynamics of the impact of COVID-19 on the US electricity sector. This research departs from conventional power system analysis by introducing new domains of data that would have a significant impact on the behavior of electricity sector in the future. Our results suggest that the US electricity sector, and particularly the Northeastern region, is undergoing highly volatile changes. The change in the overall electricity consumption is also highly correlated with cross-domain factors, such as the number of COVID-19 confirmed cases, the degree of social distancing, and the level of commercial activity observed in each region, suggesting that the traditional landscape of forecasting, reliability, and risk assessment in the electricity sector will now need to be augmented with such cross-domain analyses in the near future. We also find very diverse levels of impact in different marketplaces, indicating that location-specific calibration is critically important.

The cross-domain analysis of the electricity sector presented here can immediately inform both power system operators and policy makers as follows. Power system operators can leverage the analysis for short-term planning and operation of the grid, including load forecasting, and rigorous quantitative assessments of impacts like renewable energy curtailment<sup>41,42</sup> during COVID-19. From a policy-making perspective, the restricted VAR analysis can be exploited to infer both the key influencing factors such as the mobility in the retail sector that may not be apparent from conventional analyses and the varied timescales of top-down (policy-level) and bottom-up responses (individual-level), driving changes in electricity consumption.

This work also opens up several directions for future research by incorporating cross-domain data into the analysis of the electricity sector. For example, vulnerable populations like low-income households are facing an increased energy burden due to COVID-19.<sup>43,44</sup> In this context, we are exploring the integration of socio-economic

data on demographics<sup>45</sup> and the social vulnerability index (SVI)<sup>46</sup> into the COVID-EMDA<sup>+</sup> data hub. The new cross-domain sources and analysis can then be leveraged by policy makers to infer the energy burden on such vulnerable populations. The change in electricity consumption can also be an early indicator of the economic impacts of COVID-19 that are not yet reflected in traditional economic indicators like the GDP growth rate. Historically, there has been a significant correlation between electricity use and economic growth over the last four decades.<sup>47–49</sup> Leveraging the cross-domain COVID-EMDA<sup>+</sup> data hub, the changes in the electricity sector may be used by policy makers to provide short-term forecasts of the economic impact of COVID-19, including the GDP growth rate, and the level of commercial and industrial activity. The cross-domain restricted VAR analysis can also be extended to analyze the impact of various policy decisions on the electricity sector, and consequently, the short-term economic health.

## EXPERIMENTAL PROCEDURES

### Resource Availability

#### *Lead Contact*

Further information and requests for resources and materials should be directed to and will be fulfilled by the Lead Contact, Le Xie ([le.xie@tamu.edu](mailto:le.xie@tamu.edu)).

#### *Materials Availability*

No materials were used in this study.

#### *Data and Code Availability*

The COVID-EMDA<sup>+</sup> data hub and codes for all the analyses in this paper are publicly available on Github<sup>17</sup>. The supporting team will collect, clean, check, and update the data daily and provide necessary technical support for unexpected bugs. In the Github repository, the processed data (CSV format) are shared along with the original data (CSV format) and their corresponding parsers (written in Python). Several simple quick start examples are included to aid beginners. The details of the original sources are shown in **Note S4**.

### Data Aggregation and Processing Methodology

In order to obtain cross-domain insights about the impact of COVID-19 on the electricity sector, we integrate data from all US electricity markets with other heterogeneous data like weather, COVID-19 public health, satellite imagery, and mobile device location data. The original sources for each dataset are provided in the [Data and code availability](#) section. Although all seven US electricity markets have established websites for public information disclosure, their download centers, database structures, and user interfaces differ widely. Further, file formats, definitions, historical data availability, and documentations are also extremely diverse across these markets, making it difficult to integrate these data into a unified framework. The major challenges in integrating data across different electricity marketplaces are as follows.

- (1) Some data are stored in hard-to-find pages without user-friendly navigation links.
- (2) Some data are not packed and collected in an aggregated file for the requested date range. A batch downloader is needed to download these data files one by one and then aggregate them into the desired single file.
- (3) Inconsistent definitions and abbreviations are used among different markets. The same concepts used by different data categories do not follow the same terminology even within the same market.

- (4) Geographical information often lacks documentation.
- (5) The data quality is not satisfactory. Data redundancy, duplicate data, and missing data are common problems across all markets.

As shown in [Figure S1](#), we design a processing flowchart to reorganize and harmonize all heterogeneous data sources, following three principles—data consistency, data compaction, and data quality control, as follows.

#### *Data Consistency*

- (1) For each source of electricity market files, a specific parser is designed to transform the data into a standard long table with date and hour indices. After processing by the parser, raw data from different markets is converted to a unified format.
- (2) Geocoding is adopted to match the geographical scale of electricity market data, COVID-19 case data, and weather data.
- (3) In the final labeling step, all the field names of data files are translated to the corresponding standard name from a pre-selected name list.

#### *Data Compaction*

- (1) Redundant data are dropped by parsers, and the packing step transforms the standard long tables into compact wide tables by pivoting the hour indices as new columns. Usually, the compact wide table can achieve more than 10x file compression rate compared with the unprocessed raw files.
- (2) COVID-19 case data are aggregated to the scale of market areas.
- (3) The minute-level weather observations are re-sampled into an hourly basis to align with the resolution of market data.

#### *Data Quality Control*

- (1) Single missing data (most frequent) are filled by linear interpolation. For consecutive missing data (for example, consecutive missing dates, which are very rare), data from the EIA, or EnergyOnline are carefully supplemented.
- (2) Outlier data samples are automatically detected when they are out of the pre-defined reasonable range. Exceptions such as price spikes and negative prices in LMP data are carefully handled.
- (3) Duplicate data are dropped, only the first occurrence of each data sample is kept.

The detailed flow chart of the data quality control used in the COVID-EMDA<sup>+</sup> data hub is shown in [Figure S8](#).

#### **Ensemble Backcast Model**

The ensemble backcast model is used to estimate the electricity consumption profile in the absence of the COVID-19 pandemic, so that the difference between an ensemble backcast model and the actual metered electricity consumption can be used to quantify the impact of the pandemic. A backcast model is expressed as a function that maps potential factors that may affect electricity consumption level, including weather variables (such as temperature, humidity, and wind speed), date of year, and economic prosperity (yearly GDP growth rate) to the estimated electricity consumption. Given a group of backcast models, ensemble forecasting is widely recognized as the best approach to provide rich interval information. A group of backcast models for the daily average electricity consumption can be described by



$$\hat{L}_{md} = \frac{1}{N} \sum_{i=1}^N \hat{f}_i(C_{md}, T_{mdq}, H_{mdq}, S_{mdq}, E_m), \quad \forall m, d, \quad (\text{Equation 1})$$

where  $C_{md}$  is the calendar information including month, day, weekday, and holiday flag,  $\hat{L}_{md}$  is the estimated daily average electricity consumption for month  $m$  and day  $d$ ,  $\hat{f}_i$  is the  $i$ th backcast model,  $T_{mdq}$ ,  $H_{mdq}$ ,  $S_{mdq}$  are temperature, humidity, and wind speed within the selected quantiles  $q$ , and  $E_m$  is the estimated GDP growth rate. We typically include 25%, 50% (average value), 75%, and 100% (maximum) quantiles, and the final inputs should be decided based on the data after extensive testing. With the backcast estimations, the daily reduction in electricity consumption,  $r_{md}$ , is calculated as follows,

$$r_{md} = \left( 1 - \frac{1}{\hat{L}_{md}} \cdot \frac{1}{T} \sum_{t=1}^T L_{mdt} \right) \times 100\%, \quad \forall m, d, \quad (\text{Equation 2})$$

where  $T=24$  is the total number of hours in one day, and  $L_{mdt}$  is the electricity consumption metered at time  $t$  on month  $m$  and day  $d$ . Equation 2 compares the ensemble backcast and actual electricity consumption results and can be readily extended to interval estimations by adjusting the ensemble backcast result.

The detailed procedure adopted here for building the ensemble backcast model is as follows:

- (1) Feature selection: we select calendar information (year-month-day, weekday-weekend, holiday flag, etc.), weather data (daily average temperature, humidity, wind speed, etc.), and economic conditions (monthly state-wide GDP) as the input features.
- (2) Base model selection: we choose a neural network as the base model and determine the number of layers and the number of neurons in each layer that minimize the training error, through a random search over the hyperparameter space. Based on this approach, we find that a four-layer fully connected neural network with ReLU activation function showed the best performance in terms of accuracy and robustness.
- (3) Model training: we then create a large group of model candidates by changing the number of neurons in the base model in a pre-defined range. These model candidates are trained individually by randomly sampling the training data, wherein 85% of the data points in 2018 and 2020 are randomly selected as training data, while the remaining 15% are reserved for verification and evaluation of model performance.
- (4) Model validation: the performance of each model is measured by testing over the verification dataset, which contains 15% of the data points from 2018 and 2020. We calculate the average prediction error of each month and obtain a  $1 \times 12$  vector for each model and use the  $L_2$  norm of that vector as the error metric. This metric prefers those models that have a reasonable prediction accuracy for every month, instead of those that are very accurate in predicting the load for some months and poor in predicting the load for other months. We train 800 different models and the top 25% models with the lowest error metric are selected for the final ensemble backcast model.

In contrast to other algorithms that calibrate weather factors,<sup>50</sup> our approach (1) possesses a high degree of flexibility in incorporating more potential influencing factors, (2) has the ability to capture more complicated correlations, and (3) gives an accurate estimation of not only expected value but also the probability distribution of the forecasted quantity.

### Restricted VAR

VAR<sup>37</sup> is a stochastic process model that can be used to capture the linear correlation between multiple time series. We model the dynamics of reduction in electricity consumption using a restricted VAR model of order  $p$  as follows:

$$X_t = C + A_1 X_{t-1} + \dots + A_p X_{t-p} + E_t, \quad (\text{Equation 3})$$

where

$$A_i = \begin{bmatrix} a_{1,1}^i & a_{1,2}^i & \dots & a_{1,n}^i \\ a_{2,1}^i & a_{2,2}^i & \dots & a_{2,n}^i \\ \vdots & \vdots & \ddots & \vdots \\ a_{n,1}^i & a_{n,2}^i & \dots & a_{n,n}^i \end{bmatrix}, \quad X_t = \begin{bmatrix} x_t^1 \\ x_t^2 \\ \vdots \\ x_t^n \end{bmatrix}, \quad C = \begin{bmatrix} c^1 \\ c^2 \\ \vdots \\ c^n \end{bmatrix}, \quad E_t = \begin{bmatrix} e_t^1 \\ e_t^2 \\ \vdots \\ e_t^n \end{bmatrix}, \quad (\text{Equation 4})$$

in which  $A_i$  is the regression matrix,  $x_t^1$  represents the target output variable at time  $t$ , namely the reduction in electricity consumption we wish to model,  $x_t^2, \dots, x_t^n$  represent the selected  $n - 1$  parameter variables including confirmed case numbers, stay-at-home population, median home dwell time rate, population of on-site workers, mobility in the retail sector, and etc.,  $C$  and  $E_t$  are respectively column vectors of intercept and random errors, and the time notation  $t - p$  represents the  $p$ -th lag of the variables.

The full procedure of building the restricted VAR model mainly contains four steps as follows, including pre-estimation preparation, restricted VAR model estimation, restricted VAR model verification, and post-estimation analysis. These steps, outlined below, are detailed in **Supplemental Methods 1–5**.

#### Pre-Estimation Preparation

- (1) Data preprocessing: several datasets are collected to calculate the inputs of restricted VAR model, including electricity market data, weather data, number of COVID-19 cases, and mobile device location data. We take logarithms of several variables, including electricity consumption reduction, new daily confirmed cases, stay-at-home population, population of full-time on-site workers, population of part-time on-site workers, and mobility in the retail sector, while only keeping the original value of the median home dwell time rate.
- (2) Augmented Dickey-Fuller (ADF) test: test whether a time series variable is non-stationary and possesses a unit root.
- (3) Cointegration test: test the long-term correlation between multiple non-stationary time series.
- (4) Granger causality Wald Test: estimate the causality relationship among two variables represented as time series.

#### Restricted VAR Model Estimation

- (1) Ordinary least square (OLS): we impose constraints on the OLS to eliminate any undesirable causal relationships between variables.

#### Restricted VAR Model Verification

- (1) ADF test: verify if the residual time series are non-stationary and possess a unit root.
- (2) Ljung-Box Test: verify the endogeneity of the residual data that may render the regression result untrustworthy.
- (3) Durbin-Watson test: detect the presence of autocorrelation at lag 1 in the residuals of the restricted VAR model.

- (4) Robustness test: test the robustness of the Restricted VAR model against parameter perturbations.

### Post-Estimation Analysis

- (1) Impulse response analysis: describe the evolution of the Restricted VAR model's variable in response to a shock in one or more variables.
- (2) Forecast error variance decomposition: aid in the interpretation of the Restricted VAR model by determining the proportion of each variable's forecast variance that is contributed by shocks to the other variables.

### SUPPLEMENTAL INFORMATION

Supplemental Information can be found online at <https://doi.org/10.1016/j.joule.2020.08.017>.

### ACKNOWLEDGMENTS

D.W., X.Z., S.S., and L.X. acknowledge partial support from the National Science Foundation grants NSF ECCS-2035688, ECCS-1839616, and CCF-1934904. H.Z. and C.K. acknowledge partial support from the National High-End Think Tank Construction Project of the National Governance and Global Governance Institute of Tsinghua University (2020WTF044).

### AUTHOR CONTRIBUTIONS

Conceptualization, G.R., D.W., X.Z., S.S., and L.X.; Methodology and Investigation, G.R., D.W., and X.Z.; Software, G.R., D.W., and X.Z.; Writing – Original Draft, G.R., D.W., X.Z., and S.S.; Writing – Review & Editing, S.S., L.X., and M.A.D.; Supervision, H.Z., C.K., M.A.D., S.S., and L.X.

### DECLARATION OF INTERESTS

The authors declare no competing interests.

Received: June 6, 2020

Revised: July 11, 2020

Accepted: August 24, 2020

Published: September 21, 2020

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