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Using electricity customer profiles to combat GHG emissions: New evidence from ComEd AMI data

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ABSTRACT

This first-of-its kind study categorizes the residential customer base of Illinois' largest electric utility, Commonwealth Edison, into slices of customer-usage profiles to determine their marginal Greenhouse Gas emissions for the period 2016−2018. The analysis utilizes anonymous energy-usage data from Advanced Metering Infrastructure, PJM marginal emissions data, and demographic data from the U.S. Census Bureau's American Community Survey of 2017. Using a machine-learning algorithm called k-means clustering, the analysis identifies distinct usage patterns of residential customers and once again proves the value of access to anonymous AMI data. Even more importantly, the results provide new evidence to inform regulators, consumer advocates, policymakers and utilities on how best to customize energy efficiency, weatherization, customer education, and demand response programs for maximum benefit.

1. Introduction

Many U.S. states and cities have recently announced efforts to decarbonize the electric grid and pursue a path toward 100 % clean, renewable energy.[1] Achieving these clean energy goals requires a thorough understanding of how electricity is currently used. Although the electric grid in the United States is gradually becoming cleaner overall, Greenhouse Gas (GHG) emissions caused by electricity consumption vary depending upon the time of day and season. Reducing climate pollution, then, depends not only on continuing to decarbonize the generation mix, but also on encouraging electricity usage when cleaner resources are on the margin and discouraging usage when the reverse is true.

In 'Six unique load shapes: a segmentation analysis of Illinois residential electricity consumers, we used a k-means clustering algorithm to identify distinct summer electricity consumption patterns among residential customers.[2] These summer load profiles ranged from usage that was nearly flat to usage that was significantly peaky, with flatter load shapes substantially more likely to be prevalent in urban areas and low-income communities. This paper builds upon our previous analysis to examine the marginal emissions of different clusters.

We begin by using Advanced Metering Infrastructure (AMI) usage data to repeat our k-means cluster analysis on ComEd residential electric customers, but we include full-year consumption data (not just summer months). We calculate each customer's kilowatt-hour (kWh) usage above or below the residential average for each hour of the period 2016−2018. We then use PJM Interconnection historical emissions data to estimate the carbon emissions for each customer compared to the overall average.[3]

We find substantial differences in marginal GHG emissions produced by the six distinct load shape clusters. Average annual household emissions between clusters ranges from -1.7 to 0.69 metric tons equivalent carbon dioxide ($MTCO_2e$). Total annual cluster emissions range from -97,885 to 133,569 $MTCO_2e$, a difference of 231,454 $MTCO_2e$,

Abbreviations: AEF, average emissions factors; AMI, advanced metering infrastructure; ComEd, Commonwealth Edison; CUB, Citizens Utility Board; GHG, greenhouse gas; kWh, kilowatt-hour; MEF, marginal emissions factors; $MTCO_2e$, metric tons equivalent carbon dioxide.

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1 States that have made a 100% clean energy commitment include: California, Hawaii, Washington, New Mexico, Virginia, New York, New Jersey, Massachusetts, New Mexico, and Maine. Cities include: Atlanta, Chicago, Denver, Kansas City, Los Angeles, Louisville, Milwaukee, Minneapolis, Orlando, Philadelphia, Portland, San Francisco, San Diego, and St. Louis.

2 Zethmayr and Makhija, "Six unique load shapes: A segmentation analysis of Illinois residential electricity consumers."

3 Marginal emissions rates come from WattTime, 2021

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equivalent to 8.7 % of the estimated annual emissions for all customers in the study.[4]

2. Data

This study uses two datasets: residential AMI data from ComEd and PJM marginal emissions data. Using the AMI data, we run a k-means clustering analysis to identify distinct usage patterns of residential customers for the years 2016–2018. Once customers are assigned to a cluster, we then combine hourly usage with the marginal emissions data to calculate the marginal emissions impact of each cluster.

ComEd's residential AMI data became available in 2017 after the Illinois Commerce Commission—the state regulatory body for utilities—approved a plan for Illinois utilities to make customers' usage history available to third parties in an anonymous format. The dataset includes daily observations of half-hour kWh usage for individual households identified by subclass and location at the 9-digit ZIP code level.[5] Because ComEd did not achieve full AMI deployment until 2019, the number of customers included in each monthly dataset increases over time. The average monthly number of households included in this study increases from 472,348 in 2016 to 696,538 in 2018 (Figs. 1–5, 7–9, 11, 13, 14).

The emissions data contain the hourly emission rate, in $MTCO_2e$ per kWh, of the marginal generator in the PJM power stack for each hour of the years 2016–2018.[6]

3. Theory and method

When determining the efficacy of policies such as electrification on reducing climate pollution, it is essential to examine the impact on marginal rather than just average emissions, as it is the marginal generation unit that determines emission levels at any point in time.[7] Without a proper understanding of marginal emissions factors (MEF), policy interventions could lead to suboptimal outcomes. Kaatz and Anders (2016) conclude that allocating emissions based solely on average emissions factors (AEF) ignored the role of "unspecified power," and that more accurate models were needed.[8] The importance of analyzing marginal emissions has been confirmed by multiple studies. Siler-Evans et al. (2012), for example, compare marginal emission factors to AEFs in the United States, and find that AEFs likely misconstrue the impact of policy interventions.[9] Marnay et al. (2002) find that "differentiating between marginal and average emissions is essential" for gauging the impact of energy efficiency and demand response policies in California and that focusing on AEF "could drastically misestimate an entity's emissions due to the large differences in generating resources among the service areas."[10] Similar conclusions are reached by Hawkes, Gordan and Fung, Farhat and Ugursal, and Finenko and Cheah (2016) for energy systems around the world, including Canada, the United Kingdom, Singapore, and Japan.[11],[12],[13],[14]

Achieving a better understanding of marginal emissions, then, is crucial for designing least-cost and maximally effective policy solutions aimed at reducing greenhouse gas and other criteria air pollution emissions in the electricity sector. In this paper, we use newly-available AMI usage data to estimate marginal emissions contributions from residential electricity consumption in the ComEd service territory.

To compare the marginal emissions results of different load shapes, first we sort residential customers into clusters based on their usage patterns. A household's usage in each hour is then compared to the mean usage for all customers in that hour, to calculate that household's amount of consumption above or below average – their marginal usage for that hour. We then apply the hour's emissions rate, as determined from PJM dispatch data, to the customer's marginal usage to determine their marginal emissions. These results are then aggregated for each usage cluster.

Our analysis relies on a machine-learning algorithm called k-means clustering, which is an unsupervised learning algorithm that assigns observations into subsets by minimizing the variance between those individual observations. The algorithm generates sets of cluster assignments for all observations with randomized centroids, and repeats this process until it produces an optimal set with minimal intra-cluster variance. Rather than defining groups beforehand, clustering allows us to identify organically formed groups and potentially determine hidden relationships in the dataset. In recent years, researchers have applied new data mining and statistical techniques to characterize consumer profiles according to their consumption patterns.[15],[16] From our review of the literature on customer segmentation, we selected the k-means clustering method for this analysis.[17] Once a customer has been assigned to a cluster, the next step in this analysis is to determine how much of a household's usage is marginal in each hour. As the marginal emissions rate applies to an additional kWh of usage, it would be incorrect to apply that rate to a customer's total consumption in a given hour; the bulk of usage would be produced by infra-marginal generators. For the purposes of this study, we define individual marginal consumption as the kWh a household consumes above or below the residential average.

After calculating individual hourly marginal consumption for each hour of the three-year timespan, we multiply those values by each hour's emissions rate, to calculate individual hourly marginal emissions. To calculate the average individual marginal emissions, we sum up the monthly marginal emissions for each cluster and divide them by the cluster population for that month. We then estimate total cluster

[4] This is equivalent to the annual emissions of 49,990 automobiles.

[5] ComEd divides residential customers into four separate subclasses: single family homes without electric space heat (SFNH), single family homes with electric space heat (SFH), multi-family units (where a building contains more than four units) without electric space heat (MFNH), and multi-family units with electric space heat (MFH).

[6] Marginal emissions data was acquired from WattTime, "WattTime V2 API".

[7] For a useful primer see, Mandel (2016), "Combating Climate Change by Measuring Carbon Emissions Correctly." On the importance of marginal emissions also see, Greenhouse Gas Protocol (2020), "Greenhouse Gas Protocol".

[8] Kaatz and Anders (2016), "The role of unspecified power in developing locally relevant greenhouse gas emission factors in California's electric sector." Also see, Levin (2019), "Rate design for a decarbonizing grid".

[9] Siler-Evans et al. (2012), "Marginal Emissions Factors for the U.S. Electricity System".

[10] Marnay et al. (2002), "Estimating Carbon Dioxide Emissions Factors for the California Electric Power Sector." Also Kaatz and Anders (2016), "The role of unspecified power in developing locally relevant greenhouse gas emission factors in California's electric sector." and Levin (2019), "Rate design for a decarbonizing grid".

[11] Hawkes (2010), "Estimating marginal CO2 emissions rates for national electricity systems".

[12] Gordon and Fung (2009), "Hourly Emission Factors from the Electricity generation sector-A tool for analyzing the Impact of renewable technologies in Ontario".

[13] Farhat and Ugursal (2010), "Greenhouse gas emission intensity factors for marginal electricity generation in Canada".

[14] Finenko and Cheah (2016), "Temporal CO2 emissions associated with electricity generation: Case study of Singapore".

[15] For more information, see McLoughlin et al. (2015), "A clustering approach to domestic electricity load profile characterization using smart metering data".

[16] Figueiredo et al. (2005), "An electric energy consumer characterization framework based on data mining techniques".

[17] Al-Wakeel and Wu (2016), "K-means Based Cluster Analysis of Residential Smart Meter Measurements".

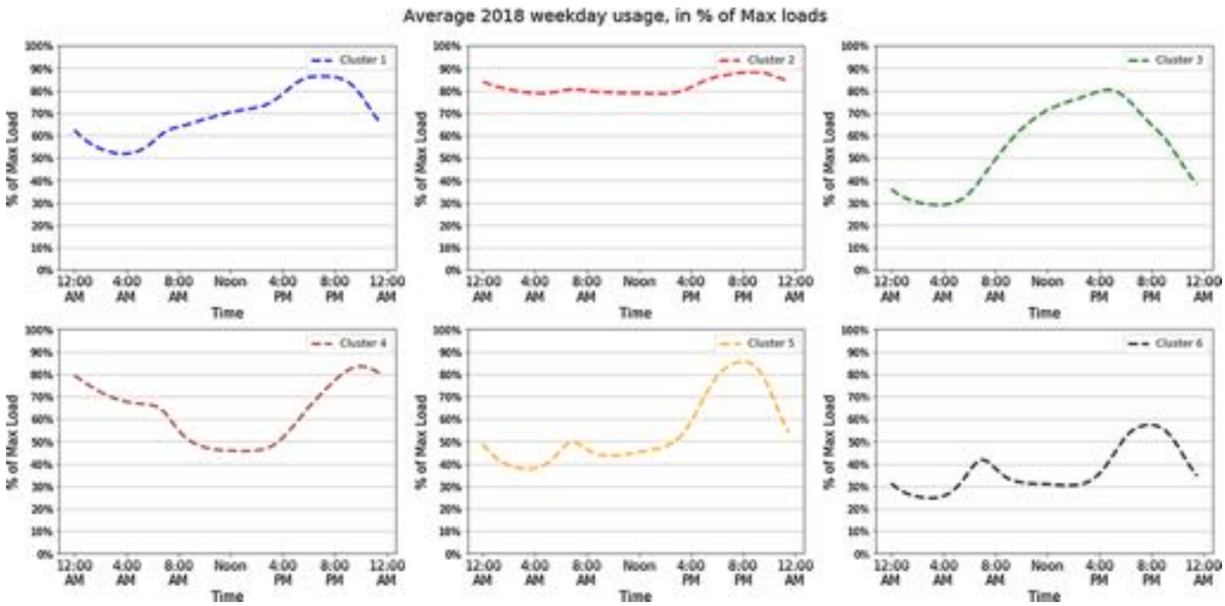

Fig. 1. Cluster Load Shapes, in Percentage of Maximum Load.

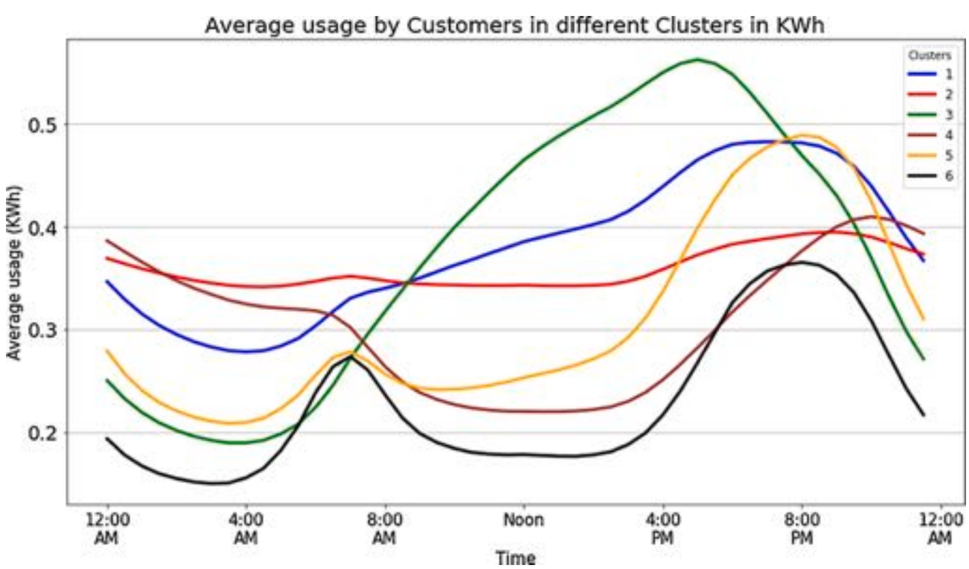

Fig. 2. Average Cluster Weekday Load Shapes.

emissions for 2016 and 2017 by multiplying cluster average emissions by each month's 2018 cluster populations.

4. Results

4.1. Cluster analysis

The results of our cluster analysis using annual data are similar to our previous analysis using only summer data.[18] The largest group, Cluster 1, has the highest average volume, with a consistent evening peak. Cluster 2 has consistently flat usage, with average volume. Cluster 3 has a higher and earlier peak, with volume close to the residential average. Cluster 4, 5, and 6 have below average volume, with Cluster 4 exhibiting low daytime usage with a late evening peak, and Clusters 5 and 6 showing morning and evening peaks, with Cluster 5's evening peak reaching a significantly higher level.

4.2. Demographic analysis

Our demographic analysis reveals a number of marked differences between the different usage clusters. Figs. 6 through 9 show which clusters are most prevalent in each location, and Fig. 10 shows the raw demographic composition of each cluster.

4.2.1. Cluster 1: "Jo Suburban"

As with our previous residential cluster analysis, Cluster 1 was used as the basis of comparison for the purpose of logistic demographic regression. This is primarily because this cluster has the largest population, and exhibits an average load shape closest to the overall load shape of ComEd residential customers. These customers exist throughout the study's geographic footprint, though are particularly prevalent in the Chicago suburbs; compared to Cluster 1, every other

[18] Zethmayr and Makhija (2019), "Six unique load shapes: A segmentation analysis of Illinois residential electricity consumers".

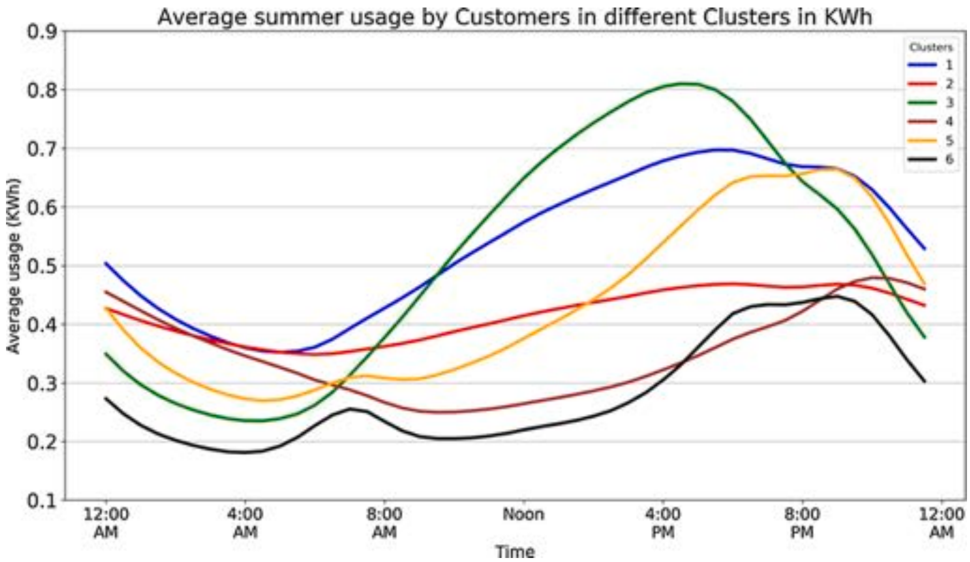

Fig. 3. Average Summer Weekday Load Shapes.

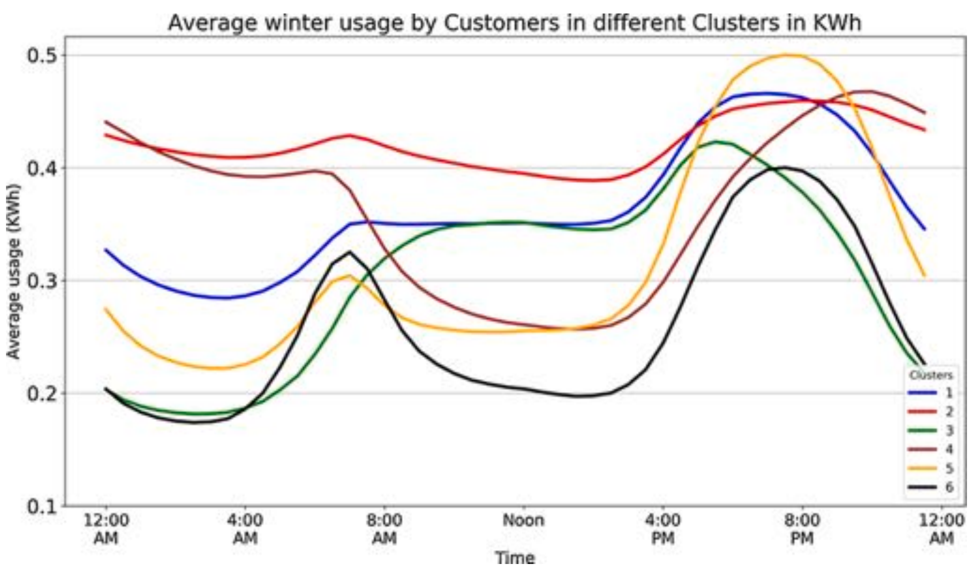

Fig. 4. Average Winter Weekday Load Shapes.

	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
2016	138,727	88,646	63,003	55,832	89,830	36,312
2017	170,629	110,599	86,318	74,454	124,573	59,824
2018	194,501	125,531	93,680	83,871	141,879	57,076

Fig. 5. Cluster Populations by Year.

cluster is less likely to live in those suburbs. They are also the most likely cluster to live in housing units worth greater than $105,000, and in low-density areas.

4.2.2. Cluster 2: "Flat City"

Cluster 2 customers are significantly more likely than average to live within the Chicago city limits and to earn less than $50,000 per year.[19] Interestingly, they are also the most likely cluster to earn more than $150,000 per year. This cluster includes the customers most likely to hold less than a high school degree, while also including those highly likely to hold a graduate or professional school degree. These results suggest this load shape is driven by location and housing type; i.e., these customers' comparative demographic profile largely reflects the difference between Chicago residents and the rest of Northern Illinois. These customers are more likely than average to be less than 33 years of age, and less likely than average to be greater than 56 years of age (1.2 times [x] and 0.7x, respectively). This cluster also contains the highest concentration of electric space heat customers, as identified by subclass, with 6.7 % of these customers belonging to that subclass.

4.2.3. Cluster 3: "Exurban Empty Nesters"

Cluster 3 customers are significantly more likely than average to live in exurban and rural locales (1.5x and 1.3x, respectively), and slightly more likely to be over 56 years in age, at 1.4x versus the average customer. They are also relatively likely to consist of two-person, familial households, and unlikely to be families of five or more (1.2x and 0.8x, respectively).

[19] Customers in Cluster 2 are 2.2 times (x) more likely to live in Chicago, 2.6x more likely to earn less than $50,000 per year.

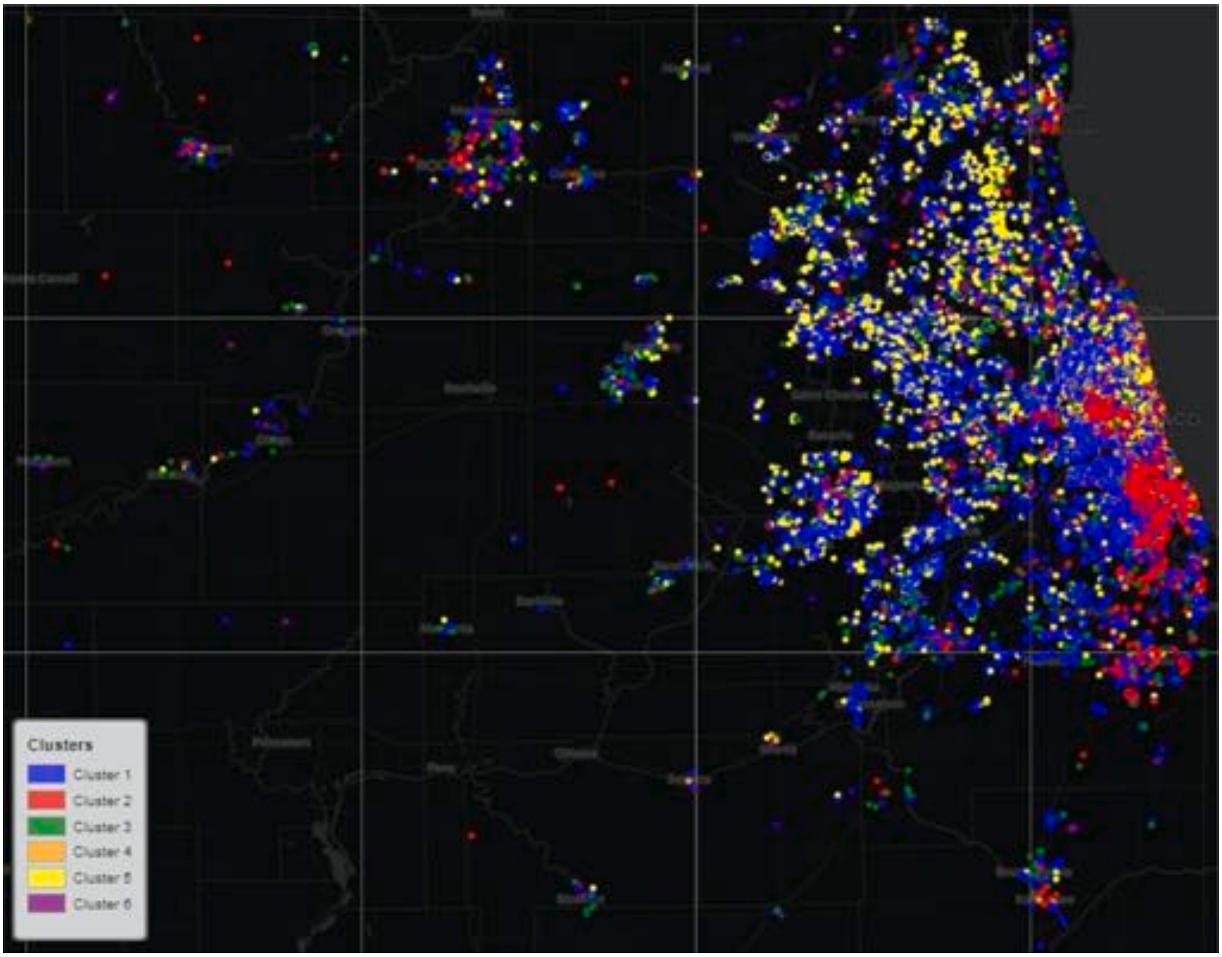

Fig. 6. Full Study Area Map.

4.2.4. Cluster 4: City Duck Curve

Cluster 4 customers are the most likely to be less than 33 years of age, and least likely to be greater than 56 years of age (1.4x and 0.4x, respectively). They are mostly likely to hold a graduate or professional degree, and it is highly unlikely they will live in exurban or rural locales (0.7x as likely as average for both categories).

4.2.5. Cluster 5: Exurban Commuters

These customers are the least likely to be low income—0.8x as likely as the average customer to earn less than $50,000 per year. They are also less likely to live in Chicago, and more likely to live in exurban locations (0.7x and 1.3x, respectively). They are also the most likely cluster to hold a bachelor's degree, and highly likely to hold a graduate or professional degree (1.4x versus average for both measures).

4.2.6. Cluster 6: Small City Apartment Dwellers

Cluster 6 includes the smallest population of customers and there are only a few significant demographic differences from the average. Customers in this cluster are most likely to have fewer than four rooms in their home and the least likely to have greater than five rooms (1.6x and 0.3x as likely as the average customer, respectively). They are also highly unlikely to live in Chicago, and more likely than average to live in exurban locales. This cluster contains the second highest concentration of homes with electric space heat, with 12.8 % of customers belonging to the two space heat subclasses.

4.3. GHG analysis

The variations in cluster load shape lead to markedly different levels of marginal emissions and reveal seasonal differences in usage patterns. During every month of the year, Cluster 1 ("Jo Suburban") has above average marginal emissions, peaking at 0.11 $MTCO_2e$ in July. Clusters 2 ("Flat City") and 4 ("City Duck Curve") have above average emissions in the winter, and then dip below average in the summer. Cluster 3 ("Exurban Empty Nesters") customers have below average winter emissions, but spike in the summer, nearly matching Cluster 1 customers' July peak at 0.1 $MTCO_2e$. Cluster 5 ("Exurban Commuters") customers show little variation compared to the mean, consistently causing slightly lower emissions than average, with slight spring and fall peaks. Cluster 6 ("Small City Apartment Dwellers") customers have consistently low marginal emissions, reaching a low of 0.26 $MTCO_2e$ below average in July.

Over the course of a year, these monthly differences add up. Fig. 12 shows the cumulative marginal emissions of an individual cluster member through the months of the calendar year. By May, a typical Cluster 2 customer will have 0.29 $MTCO_2e$ higher marginal emissions than average; however, this value reduces close to zero by September, then rises throughout the fall, until they show emissions of 0.17 $MTCO_2e$ above average for the year. Cluster 3 shows the opposite trend: by May, the average Cluster 3 member has caused 0.31 $MTCO_2e$ less emissions than average, which rises to near zero over the course of the summer, and goes back down during the fall. Cluster 4 members caused average emissions that were slightly above average through the early spring, but by the end of the year show 0.63 $MTCO_2e$ less emissions than average.

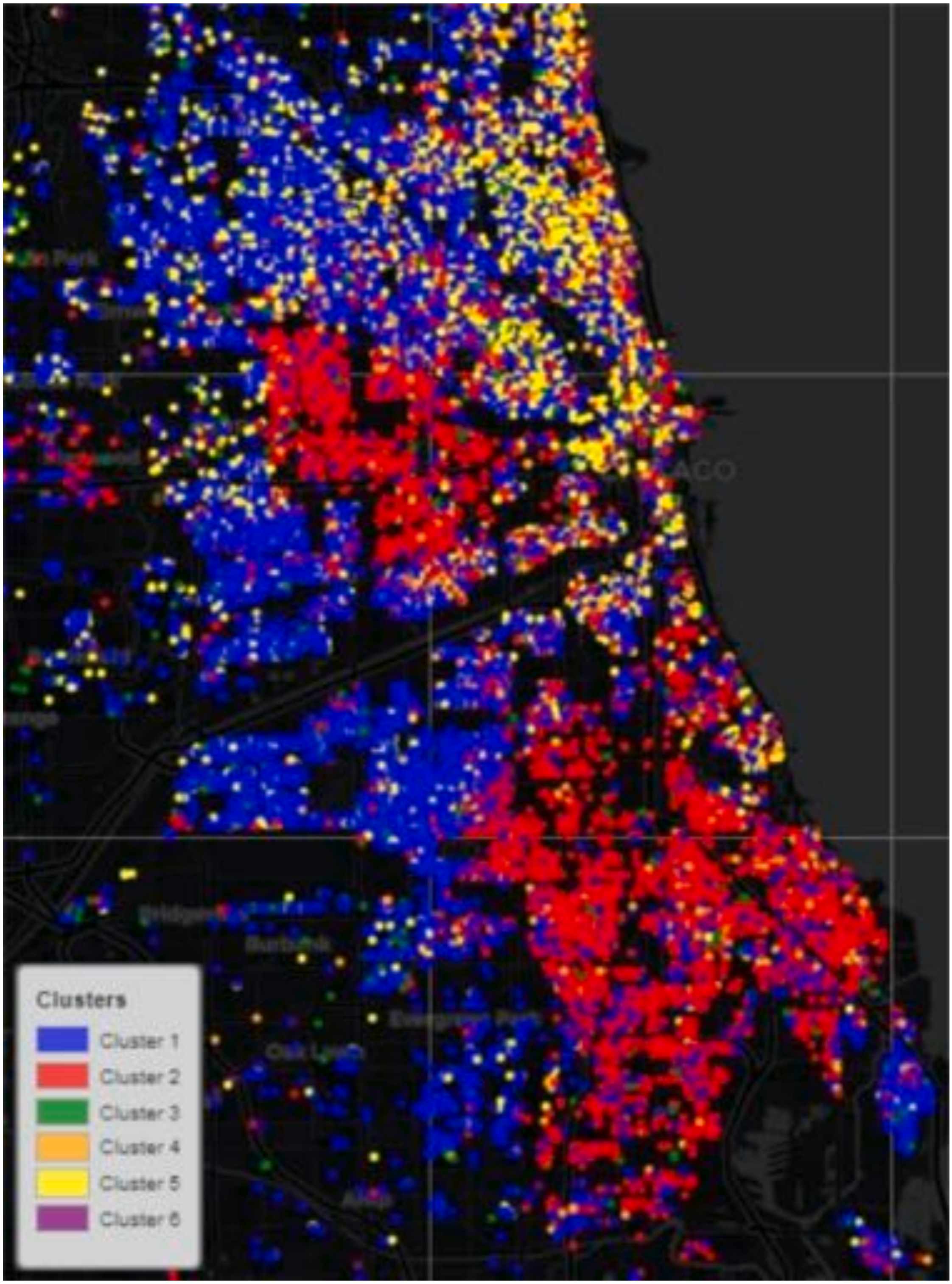

Fig. 7. Chicago Area Cluster Map.

Cluster 1, 5, and 6 members show steady trends in this value over the year, with average Cluster 5 and 6 customers causing 0.41 and 1.75 $MTCO_2e$ below-average emissions by the end of the year, and Cluster 1 members causing 0.67 $MTCO_2e$ above average.

When these individual results are combined to show emissions for the clusters as a whole, we see the cumulative impact of individual load shapes. Cluster 1, with both the highest population and the highest marginal emissions rate, peaks at +22,072 $MTCO_2e$ in monthly marginal emissions in July, with a cumulative annual total of +133,569 $MTCO_2e$, equivalent to 5% of the estimated annual emissions of all customers in the study. Cluster 2 sees its cumulative marginal emissions peak in April at +36,804 $MTCO_2e$, but finishes the year with a cumulative +21,359 $MTCO_2e$. Cluster 3 peaks in monthly emissions, with +9,789 $MTCO_2e$, in July, but finishes the year -13,702 $MTCO_2e$ below average. Clusters 4, 5, and 6 finish the year with -52,994 $MTCO_2e$, -58,006 $MTCO_2e$, and -97,885 $MTCO_2e$ below average marginal emissions, respectively.

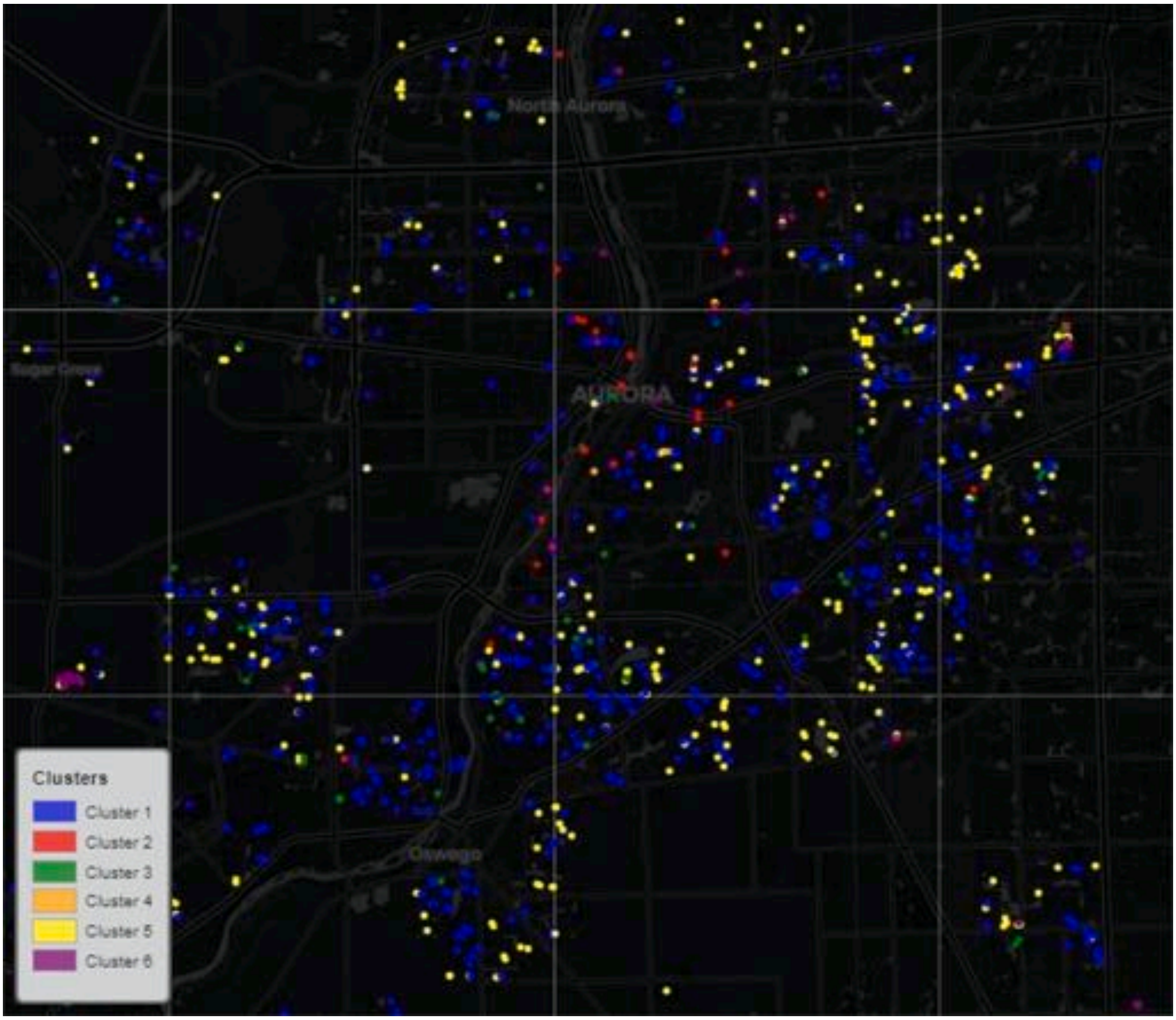

Fig. 8. Aurora Area Cluster Map.

4.4. *Effects of electric space heat*

Clusters 2, 4, and 6 contain the three highest concentrations of space heat subclass customers, at 6.7 %, 7.4 %, and 12.8 %, respectively, with distinctly different annual emissions profiles. Fig. 15 shows the average winter weekday load shape of electric space heat customers by cluster.

Space heaters in Clusters 2 and 4, the two clusters that exhibit above-average marginal emissions in the winter and lower emissions in the summer, have significantly higher overnight usage than space heaters in other clusters, with cluster 4 customers exhibiting a sharp drop in the middle of the day. Space heaters in Cluster 6, however, have relatively low overnight usage, with high morning and evening peaks.

A look at the demographic profiles of these customers suggests a potential reason for these disparities. Cluster 2 and 4 customers are the two groups both most likely to live in Chicago, and most likely to live in housing units 70 or more years old. They are also the two most likely groups to earn less than $50,000 a year. Cluster 6 customers, in contrast, are the least likely to live in Chicago, highly likely to live in an exurb, and unlikely to earn less than $150,000 a year. This suggests housing stock may be a large driver of the load shape difference. Space heat customers in older dwellings with poorer insulation require significantly more energy to maintain comfortable temperatures overnight, while newer exurban homes retain their heat better. Given the similar demographic profiles of Cluster 2 and 4 customers, and their distinct winter load shapes, the primary difference may be that Cluster 4 homes are unoccupied during the middle of the day (and thus less heated), whereas Cluster 2 homes are occupied throughout the day.

These results highlight the potential emissions reductions that could be achieved through weatherization and customer education measures. If all Cluster 2 space heat customers were to adjust their winter load shape to match that of Cluster 4 space heat customers, this would result in a 12,817 $MTCO_2e$ reduction in annual emissions, equivalent to taking 2,768 cars off the road.[20] While there are likely structural obstacles, such as building type, if all Cluster 2 and 4 space heat customers were to adjust their winter load shape to match Cluster 6 space heat customers, this would lead to a 20,165 $MTCO_2e$ reduction, or 4,355 cars off the road.[21] The first of these interventions would depend on customer education efforts; the latter reduction would require both customer education and weatherization programs.

5. Conclusion

The load shape of a residence is influenced by structural factors such as housing size and type, and household makeup. We have found that

[20] U.S. Environmental Protection Agency (2021a,b), “Greenhouse Gases Equivalencies Calculator - Calculations and References”.

[21] These estimates are based on the cluster populations included in this study; results for the rest of the ComEd service territory would be significantly higher.

Fig. 9. Rockford Area Cluster Map.

Cluster Composition			Delivery Service				Area			
Cluster	Size	%	SFNH	SFH	MFNH	MFH	Chicago	Chicagoland	Ex-urbs	Rural
1	195028	27.85%	127486	227	61093	6222	101024	39873	19860	34272
2	126252	18.03%	69208	306	48628	8110	82129	20252	8487	15384
3	94267	13.46%	58183	185	31356	4543	35676	22009	13370	23212
4	84168	12.02%	41161	280	36739	5989	55525	12969	5849	9825
5	142119	20.30%	84063	168	53376	4512	71564	28049	16067	26440
6	58416	8.34%	17815	304	33124	7172	30222	10623	6520	11051
Total	700250	100.00%	397916	1470	264316	36548	376140	133775	70153	120184

Fig. 10. Cluster Composition.

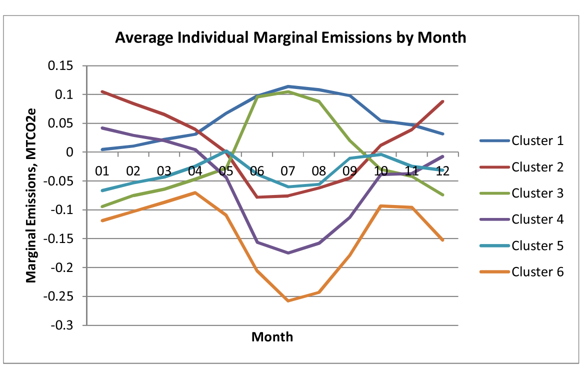

Fig. 11. Average Individual Marginal Emissions by Month.

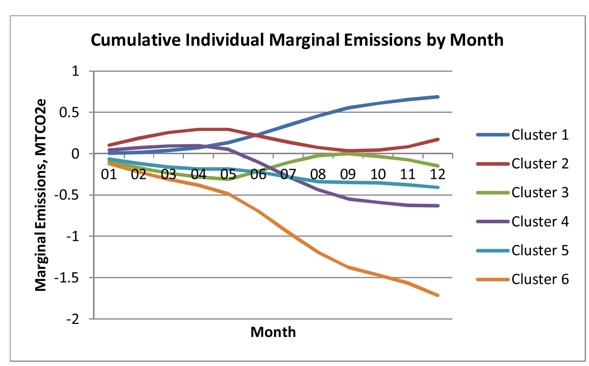

Fig. 12. Cumulative Individual Marginal Emissions by Month.

within these sub-groups, clusters of customers with similar dwelling unit characteristics and in similar age and income brackets have load shapes with significantly different emissions outcomes. Therefore, efforts to shrink residential GHG emissions must focus on reducing consumption at times when a customer's marginal emissions are highest. Customer-facing programs and messaging should be tailored to fit different household load shapes.

The usage characteristics of each cluster suggest differentiated energy management strategies to harvest the "low-hanging fruit" of emissions reductions. For example, Cluster 1 customers, who make up the largest single cluster, exhibit similar typical load shapes as Cluster 3 customers and are prevalent in the same geographic areas. However, Cluster 1 customers average 0.8 $MTCO_2e$ more annual emissions because of higher usage during both winter and summer peak periods. This suggests that an effective Cluster 1 strategy might focus on summer

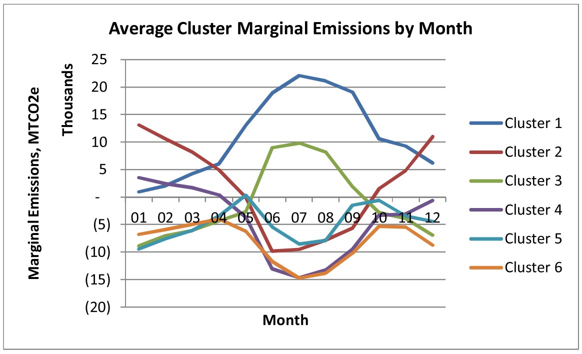

Fig. 13. Average Cluster Marginal Emissions by Month.

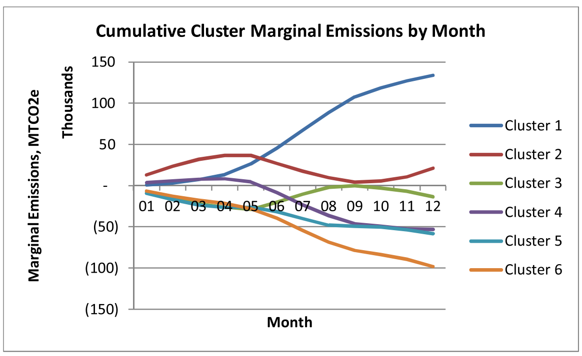

Fig. 14. Cumulative Cluster Marginal Emissions by Month.

peak reduction using pre-cooling and direct load control measures, behavioral incentives such as peak time rebate programs and time-variant pricing, and customer education targeted at lowering overnight usage. Bringing Cluster 1 peaks down to average would reduce ComEd residential electric emissions by 162,017 MTCO$_2$e, or 1.8 %, and would create a more efficient and lower cost system load shape. Extrapolating this result to the entire ComEd residential class, assuming these customers occur with the same frequency, the total savings would be 494,888 MTCO$_2$e – 5.5 % of total residential emissions, and the equivalent of taking 106,887 cars off of the road.

Cluster 2 customers, while largely co-located and of similar age and income brackets as Cluster 4 customers, have load shapes that result in 0.8 MTCO$_2$e higher annual emissions. Because the bulk of these marginal emissions occur during the winter, weatherization programs targeted towards these customers are likely to yield emissions reductions. If all Cluster 2 customers were able to adjust their usage to match the Cluster 4 load shape, this would result in a 100,676 MTCO$_2$e drop in emissions, equivalent to 1.1 % of ComEd residential emissions. Extrapolating these results to the entire ComEd residential class, this would result in a 249,856 MTCO$_2$e reduction – 2.8 % of total residential emissions, and the equivalent of taking 53,965 cars off the road.

The urgency of combating global warming demands effective and immediate action in all economic sectors, including electricity generation, which accounts for 27 % of carbon emissions.[22] Global greenhouse gas emissions must drop by 7.6 % annually over the next decade to avoid the worst effects of climate change, according to the United Nations Emissions 2019 Gap Report.[23] That reduction target may be reached in 2020 due to the negative economic effects of the COVID-19 pandemic, but the longer term emissions vectors continue to point up, not down.[24] While commercial and industrial electricity demand temporarily plummeted during Illinois' mandate COVID-19 stay-at-home period, residential usage increased.[25] If more working at home becomes a long-term trend in the recovering U.S. economy, usage patterns may change, due to factors such as higher daytime residential air-conditioning demand and lower growth in electric vehicle charging. Future studies will monitor the effects of evolving usage patterns and load-shaping efforts on the clusters we have identified and compare them over time to the baseline data established in this study.

Funding

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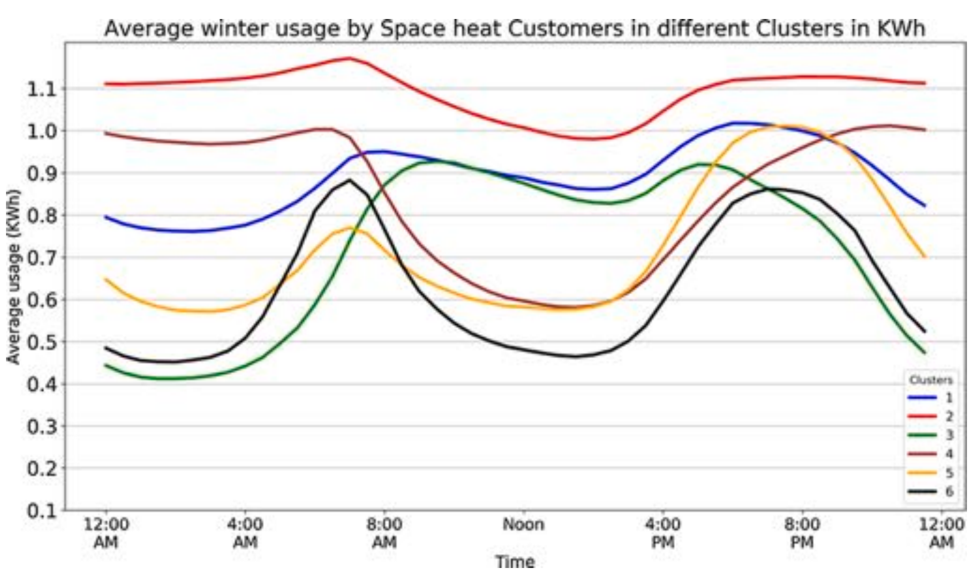

Fig. 15. Average winter usage by space heat customers.

[22] U.S. Environmental Protection Agency (2021a,b), "Global Greenhouse Gas Emissions Data".

[23] United Nations Environment Programme (2019), *Emissions Gap Report 2019*.

[24] International Energy Agency (2020). *Global Energy Review 2020*.

[25] See Hinson (2020), "COVID-19 is Changing Residential Electricity Demand." Also Englund (2020), "See how covid-19 is reshaping the electric rhythms of New York City."

Declaration of Competing Interest

The authors report no declarations of interest.

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