# Impacts of COVID-19 on Residential Building Energy Use and Performance

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## Abstract

Following the declaration of the COVID-19 pandemic and the rise in cases across the United States, the typical daily routines of millions were disrupted as the country attempted to control the spread of the virus. As a result, homes became makeshift offices, classrooms, restaurants, entertainment centers, and more. With these changes in how residential buildings are used, surveys and grid-level studies have been conducted to understand how energy use has shifted due to the pandemic, but there are limited efforts that review the impact of energy use at the household-level. In this study, high-resolution, disaggregated data is analyzed to measure the shifts in electricity use related to HVAC loads, non-HVAC loads, and whole-home loads in a comparison of 225 housing units over the years 2018-2020. Key findings from the analyses indicated increased electricity use during periods that occupants would usually be away from home, as found in the non-HVAC analysis with most percent increases occurring between 10 AM-5 PM and HVAC loads increasing in total daily loads compared to the same average daily temperatures of previous years. Additionally, the income group analysis had the largest increases in electricity use for the lowest income group and upper income groups, while the middle income groups experience smaller shifts.

## Keywords

COVID-19 pandemic, residential buildings, energy use, load profiles

## 1. Introduction

Beginning in mid-March of 2020, the COVID-19 pandemic caused significant disruption across the United States. With 45 states announcing state, county, or city-wide stay-at-home orders, at least 316 million people were asked to remain at home in an effort to control the spread of the virus [1]. Across all 50 states, public and private primary, secondary, and post-secondary school closures affected nearly 100 million children and students, displacing them from childcare centers, classrooms, and lecture halls [2]. In-person classroom environments were replaced with remote learning, where most students completed their schooling at home on a computer or tablet. In addition, business operations were also temporarily restricted, generally resulting in non-essential employees either working from home, being furloughed, or laid off. The U.S. Bureau of Labor Statistics (BLS) reported over 35% of the workforce worked from home in May 2020, totaling at 48.7 million workers [3]. At the same time, 49.6 million people were reportedly unemployed, resulting in a 13.3% unemployment rate, a slight improvement from 14.7% recorded in April 2020 [3-5]. These numbers are significantly higher than the 3.5% and 4.4% unemployment rates recorded in February and March 2020, respectively [6, 7]. These statistics show some of the initial impacts of the pandemic; moving forward throughout 2020 and into 2021, COVID-19 has continued to influence the daily lives of millions.

The U.S. Bureau of Transportation Statistics illustrated the sustained impact of COVID-19 through its *Mobility Over Time: National, State, and County level*, in which the population of people staying home per day is provided in 2019, pre-pandemic, and in 2020, during the pandemic [8]. Within the period of March-December 2020, the monthly average population in millions ranged from 75.2 to 94.9 and averaged 85.0, while the pre-pandemic population ranged from 60.1 to 66.5 and averaged 63.6. Overall, these populations are both higher and more variable during the pandemic. The U.S. BLS also illustrated this continued impact in a review of unemployment over the course of the pandemic, including a 54.4% decrease in the unemployment rate since April 2020 with a 6.7% unemployment rate reported in December 2020. This unemployment rate, however, is still nearly double the rate prior to the pandemic [9]. In analyzing the employment recovery, compared to past recessions, 2020 had the sharpest decrease in the unemployment rate, but appeared to slow in its recovery by September, resulting in 10.7 million people unemployed in December 2020. [9, 10]. In summary, the majority of unemployed workers returned to work, though remaining unemployed persons will likely endure the slow process of being matched to new jobs.

In addition to this reduction in travel and employment, Pew Research Center conducted a survey in October on those who teleworked indicating that 20% of employed adults worked from home prior to the pandemic, 71% are currently working from home, and 54% would want to work from home all or most of the time after the pandemic [11]. PwC also conducted a survey related to remote working capturing responses from both employees and employers [12], finding that four in five executives are looking to extend remote work options compared to pre-pandemic periods, the majority of employees would prefer to be remote for at least three days per week while majority of executives preferred employees be in person at least three days per week, and 87% of executives are expecting to transition their offices with mixed plans of reducing central office spaces and/or opening more locations. With these current and projected disruptions in daily human activity, much of the U.S. population is shifting away, at least in part, from the office and other commercial buildings and spending more time in their homes.

As a result of these substantial changes in lifestyle, the COVID-19 pandemic has significantly impacted when and how electricity is consumed. For example, during the first several months of the pandemic, in ERCOT, encompassing much of Texas, peak electricity demands were found to be 2% to 4% lower, and loads from 6:00-10:00 am were consistently reduced by 6% to 10% [13]. For PJM, servicing the northeast region of the U.S., peak electricity demands were estimated to be 6.5% to 15.2% lower, and total electricity demand averaged 7.9% reduction [14]. For MISO, servicing much of the Midwest region, the total load was estimated to be 5% lower, with morning electricity use peaks shifting to later in the day [15]. Such changes in load patterns have continued to evolve throughout 2020 as people have adjusted to a different lifestyle during the pandemic and reflect the substantial and unprecedented changes in people's daily routines.

Further evidence for such lifestyle adjustments and corresponding change in energy consumption behavior is supported by reports on broadband data usage, as there was a 47% increase in average data usage from 273.5 GB to 402.5 GB during the first quarters of 2019 and 2020, respectively [16]. Much of this data usage was attributed to streaming services, though there were also increases in social media use, remote work applications, and gaming. In Zoom's reflection of 2020, the company reported a 30x growth in daily meeting participants in just three months, resulting in 300 million participants that has continued to grow even one year following the start of the pandemic [17]. Based on a survey conducted in January-February 2021, Pew Research Center reported that most social media platforms such as Facebook and Instagram showed no statistically significant change from 2019 to 2021, while YouTube and Reddit experienced statistically significant changes from 2019 to 2021 with an increase from 73% to 81% and 11% to 18%, respectively [18]. Such data support increased use of electronics (i.e. plug loads) and internet services in residential buildings. Beyond personal electronic usage, the use of household appliances is also likely to have increased. Following restaurant restrictions and stay-at-home orders, search data containing the words food, restaurant, recipe, or delivery was analyzed in both English and Spanish revealing searches for restaurant decreased by three times, recipe and delivery increased by three-four times, and food remained relatively constant, all in comparison to their respective trends at the beginning of 2020 [19]. With respect to post-pandemic behavior, survey data indicates that more than half of participants would cook at home more, 1 in 3 stated they would eat out less, and 40% indicated that they will participate in more takeout and delivery compared to pre-pandemic periods [20]. With these existing and anticipated changes, for both electronics and appliance loads there is little quantification in the existing literature of the level of impact of the pandemic on the electricity use from these and other end uses in residential buildings in the U.S.

Beyond increased appliance and electronics electricity use, heating, cooling, and lighting loads in residential buildings are also likely to be impacted. For lighting, unlike some appliances such as refrigerators which operate regardless of the presence or non-presence of people in their homes, lighting is only typically used when a space is occupied. Various recent studies have suggested that occupancy and lighting energy use are linked [21]. For heating and cooling (HVAC) energy use, for the estimated 58% to 64% of households that have programable thermostats [22, 23] that can be used to automatically set back setpoints during unoccupied periods, such level energy savings is not possible if the home is occupied more often. As such, those households using the setback features would be limited in their ability to substantially benefit from reduced heating and/or cooling energy use during unoccupied periods in their homes. In addition, given the substantial increase in time that people have spent in their homes during the pandemic, this may also have led to differences in temperature tolerances which would influence HVAC use. Similar to electronics and appliance loads, there has been very little quantitative data reported demonstrating the impacts of COVID-19 on energy use of lighting and HVAC loads in individual buildings.

Such an understanding of time-dependent energy consumption behavior is important for several reasons, the first of which is for supporting the reliable operations of the electric grid. Under pre-COVID scenarios, residential buildings were responsible for approximately 38% of electricity use [24], and in some locations 50% or more of peak demands [26]. During the pandemic, high-level analysis, such as in California, suggest an 8.9 to 12.4% increase in residential electricity use during this period [26, 27]. However, there has generally been limited information quantifying consumption variations by sector, and at the individual household level. As such, as a substantial consumer of electricity, this points to a need for measured data and analysis to quantify such changes. The second reason energy consumption patterns are important to assess is that the increased use of electricity in the residential sector also shifts additional energy costs to households. For low-income households that operate under budget-constrained conditions, such an increase could be a substantial financial burden, relative to middle- and higher-income households that would be less financially impacted by higher energy bills. Therefore, while additional studies offer details such as regional energy demand or energy use survey data to assess COVID-19's impact on energy consumption [28], it is beneficial to study measured data from individual households to understand the direct impact on energy use behavior [29].

In this study, several years of measured, high-frequency, disaggregated residential electricity consumption data from households located primarily in Austin, Texas, in ASHRAE Climate Zone 2A [30], was used to study the comparative energy consumption behavior of households, including pre-pandemic and during the COVID-19 pandemic, in 2020. First the data was quality controlled, eliminating substantial missing or erroneous data. The electricity use data was then separated into thermostatic loads, specifically from the HVAC system, and activity-driven loads (ADLs), also called non-HVAC loads, for the analysis. ADLs include loads that are present due to occupants' behavior. Such a division in the data is made since HVAC loads are dependent on weather conditions, while non-HVAC loads generally are considered to not be substantially influenced by weather. By isolating the weather-dependent loads, these loads were weather normalized, supporting a better comparison of HVAC energy use. Using data analysis techniques, energy consumption patterns were compared across the measured data for the overall assessment of energy use impacts, as well as subdivided by household income to compare variations across income groups.

The results of this research have significant implications and applications. Of substantial importance is its implications for building energy modeling applications. Current building energy modeling methods for residential buildings rely on historical data and assumptions regarding internal loads and occupant behavior for HVAC and non-HVAC loads. COVID-19 has introduced unprecedented changes in how residential buildings are used, and as a result, how HVAC and non-HVAC loads are consumed. With both loads impacted by occupant presence, people may be adjusting their setpoints and/or schedules for their HVAC systems or using their ADLs throughout the day. In addition to these changes in usage, there are the added loads of using their homes as substitutes for the office, classrooms, restaurants, entertainment, and more. These changes in daily usage demonstrate a likely difference in how energy is being consumed.

This research is organized into four sections. In Section 2 and 3, the analyzed data is explained with respect to how the data was collected from the housing units, how the data was organized for the paper, and the methodology used to evaluate the data. In Section 4, comparisons across pre-pandemic and post-pandemic electricity use are made, with discussion of the results as it relates to the magnitude and time. Following this in Section 5, conclusions are drawn to highlight the primary changes in the energy use behavior as a result of the pandemic, and its implications for the re-evaluation of previous assumptions about residential energy use and consideration of future assumptions for use moving forward.

## 2. Data

The data analyzed in this study was gathered from individual circuit-level energy use data in 225 housing units in locations primarily in Texas, but also located in several other states across the U.S. [31]. The data was selected based on quality and availability, as discussed in the Data Quality Control section below, for housing units providing a full year (January 1-December 31) of data during the years of 2018, 2019, and 2020. The data was divided into three datasets to accommodate different data comparisons and are referenced throughout the paper as *2020 Only*, *2018 vs. 2020*, and *2018-2020.* The *2020 Only* dataset contains 225 housing units with locations in Texas (n=156); New York (n=60); California (n=5); and Colorado (n=4). The *2018 vs. 2020* dataset contains 76 housing units located in Texas (n=71); Colorado (n=3); and California (n=2). The *2018-2020* dataset contains 26 housing units located in Texas (n=22); Colorado (n=2); and California (n=2).

To collect the energy use data, a home energy monitoring system [32] was used to regularly measure and record electricity use for each home. CT (current transformer) coils were placed on each circuit, enabling data collection for the whole home as well as from individual circuits. This submetering of building energy usage provides disaggregated data on the duration, magnitude, and frequency of household usage of appliances and other energy consuming systems. Within the analysis, the circuit-level data was separated into three groups to review the electricity consumption: the whole home electricity usage, the total electricity usage of all heating, ventilation, and air conditioning (HVAC) system components, and the total electricity usage of all non-HVAC related electricity-consuming devices, such as lights, appliances, and plug loads. The whole home electricity usage represents all electricity consumed by the home, excluding only electric vehicle charging consumption. If the home had solar generation, this was also not considered in this value. In aggregating the energy use data for the HVAC systems, all heating unit components and all air conditioner components, including the interior air handler/fan, and furnace and exterior air compressor/condenser, were accounted for to represent the HVAC loads. It is noted that since electricity consumption was the focus of this effort, if the heating system used gas for heating, only the fan electricity consumption was included in the analysis. The use of electricity or gas for heating provides two distinct energy consumption signatures for HVAC loads, as discussed further below. In characterizing the non-HVAC loads, the whole home electricity use minus the HVAC energy use was used to calculate these loads. This method was followed instead of summing the non-HVAC circuits, since for some homes, particularly larger homes with more circuits, not all circuits were monitored due to limitations of the number of inputs to the home energy monitoring system.

Supplemental data containing information specific to the studied housing units was used characterize the occupants, their homes, and the outdoor environmental conditions. This data was obtained from metadata, energy audit data and household survey data collected in 2017 and 2019, and weather data from weather stations closest to the locations of monitored homes. The metadata provided the residential building type, city, state, building construction year, and total area. The energy audit and household survey data provided the number of occupants in each household and total annual household income. In the case that the metadata did not provide the building construction year and total area, the survey data was used instead. The weather data was provided for Austin, Texas, where the majority of the housing units are located. Within the weather data, the temperature data was used to analyze HVAC use of the 71 housing units located in Austin for the *2018 vs. 2020* dataset.

Table 1 includes the housing characteristics with respect to housing units in the U.S. and in Texas. As shown, the analyzed data has a higher percentage of single-family homes, newer and larger buildings, and smaller household sizes. The corresponding response percentages of housing units providing the supplemental data for the building type, building age, building area, and household size were 100%, 96-97%, 98-100%, and 40-42%, respectively.

*Table 1*. *Characteristics of housing units in the study relative to summary statistics at the state and country level.*

| Category | U.S. homes[a,b] (in thousands) | Texas[a,b] (in thousands) | 2020 Only | | 2018 vs. 2020 | | 2018-2020 |
|---|---|---|---|---|---|---|---|
| | | | *All* | *Income* | *All* | *Income* | *All* |
| *Housing Units* | 139,684 | 11,283 | 225 | 108 | 76 | 40 | 26 |
| *Single-Family Homes* | 63% | 66% | 94.2% | 95.4% | 90.8% | 95.0% | 88.5% |
| *Median Building Age* | 44 | 35 | 23 | 22 | 14 | 13 | 13 |
| *Avg. Area, $m^2$* | 160 | 167 | 209 | 187 | 200 | 189 | 202 |
| *Avg. Household Size* | 2.62 | 2.85 | 2.18 | 2.19 | 1.84 | 1.80 | 2.09 |

[a] American Housing Survey (AHS), 2019 [33]
[b] United States Census Bureau, 2014-2019 [34]

### 2.1 Income Level Data

The total annual household incomes for the studied units were taken from energy audit and household survey data collected in 2017 and 2019. Within this process of combining the audit and survey data, the 2019 data was prioritized over the 2017 data, so the 2017 data was used only if no income data was provided from 2019. As a result, the *2020 Only* dataset and *2018 vs. 2020* dataset contained 108 housing units and 40 housing units, respectively, with household income data. The selected income ranges were chosen based on the granularity of the available energy audit and household survey data, resulting in six ranges: Less than \$50,000, \$50-74,999, \$75-99,999, \$100-149,999, \$150-299,999, and \$300-1,000,000. In the same order, the *2020 Only* dataset contains a housing unit distribution of 11, 11, 12, 33, 32, and 9. For the *2018 vs. 2020* dataset, the housing unit distribution across the income ranges is 4, 4, 7, 9, 10, and 6.

### 2.2 Data Quality Control

To account for potential outliers within the data, the top and bottom 0.5% of data was removed for all circuit data in all homes. These outliers can be caused by events, such as system updates or reconnections between the usage measurements and data collection. The data was also inspected for completeness by grouping the data by month, year, and unit. If a housing unit contained 90% or more of available data points per month and year, for all months and years in the analysis, the housing unit was included in the study. These data quality control methods are consistent with other related research [35, 36].

## 3. Methodology

To conduct the analysis, the data was grouped into three categories of energy consumption: HVAC loads, non-HVAC loads, and the total overall loads. These categories were chosen to provide an overview of the total energy usage of the housing units, while also providing separate analyses for the weather dependent loads and non-weather dependent loads. For the HVAC loads, these loads are largely dependent on outdoor weather conditions, given the efficiency of both the HVAC system and the building's need for heating or cooling are both impacted by the variation in outdoor temperature conditions. With weather being variable across years, weather-normalization for this data enables a fairer comparison across years. In normalizing the data, the total daily HVAC loads were plotted against the average daily temperature. This is a common approach used in similar analyses to normalize data influenced by outdoor temperatures [37]. In addition, linear regression models were fit to each year as an added metric to compare the HVAC use behavior. This method of comparison is frequently used in related studies to represent HVAC consumption during heating or cooling periods [38-40].

In analyzing the non-HVAC loads, previous studies suggest these loads are not generally impacted by weather conditions [36, 41]. For this reason, these loads were separated from the HVAC loads and were not weather normalized. For this analysis, the median hourly loads were determined from across all housing units in each dataset, for each month and year. The data was then represented through load profiles, in which the median hourly loads were plotted against the time of day on an hourly basis. Such load profiles are often used to characterize building energy use.

For the total overall loads, similar methods to the non-HVAC loads analysis were used. Although this data includes weather-dependent loads, these loads were not weather normalized to allow for a complete picture of the load behavior across a day-long period. The study further evaluates the energy consumption with respect to various income levels. In conducting this analysis, the non-HVAC loads were used for the analysis also in the form of load profiles as explained previously.

## 4. Results and Discussion

This section is organized in the following order: non-HVAC loads based on *2018-2020* dataset; non-HVAC loads based on *2018 vs. 2020* dataset, along with hourly percent changes, variances, and rate of change; whole-home loads based on *2018 vs. 2020* dataset; HVAC loads based on *2018 vs. 2020* dataset; and non-HVAC loads by income group based on *2018 vs. 2020* dataset.

The non-HVAC load profiles comparing each year between 2018-2020 by month and time of day is shown in Figure 1. The plot uses the *2018-2020* dataset to compare the three years, along with the *2020 Only* dataset to reference the trends within a larger sample size of homes. The vertical axis represents the median hourly non-HVAC load (kWh) across all days of each month, per hour of the day and year. The horizontal axis represents the time of day for the 24-hour period, in which data is provided at an hourly frequency. For complete months of data during the COVID-19 pandemic (April-December), the average total daily non-HVAC load for 2020 was 11.8 kWh, increasing from an average of 10.9 kWh and 11.0 kWh from 2018 and 2019, respectively. The average percent change in total daily non-HVAC load was +21.2% for 2018 to 2020 and +20.1% for 2019 to 2020, with median percent changes of +20.5% and +19.6% for 2018 and 2019, respectively. These increases in the total daily non-HVAC loads provide evidence that occupants increased their use of their appliances and other plug-loads, likely caused by an increase in the time people are spending at home.

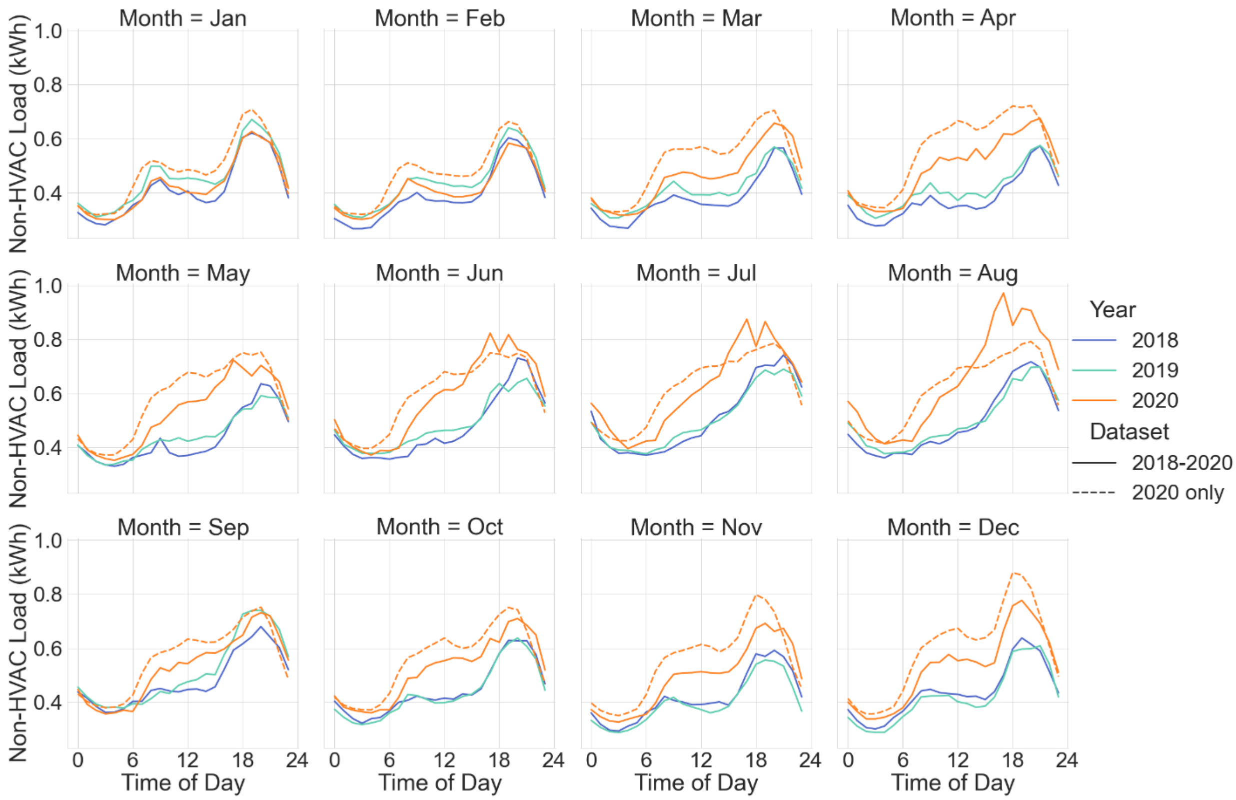


*Figure 1. Median hourly non-HVAC loads for each month during the years 2018, 2019, and 2020. Datasets 2018-2020 and 2020 Only are both represented.*

Comparing the same months across pre-pandemic (2018, 2019) and pandemic (2020) years, the maximum and minimum percent change occurred during August and September, respectively, including an increase of 31.2% and 29.5% in August, and an increase of 9.9% and 3.1% in September. For daily loads, August 2020 had a median daily non-HVAC load of 15.6 kWh, compared to 11.9 kWh and 12.0 kWh in 2018 and 2019, respectively. This increase in non-HVAC energy use could be a result of the surge in COVID-19 cases reported during mid-to-late July and early August [42, 43], and the peak in COVID-19 deaths during this time, influencing people to reside in their home more to reduce chances of contracting the virus. For September, the 2020 non-HVAC median daily load was 12.7 kWh compared to 11.5 kWh and 12.3 kWh in 2018 and 2019, respectively. As this is generally when schools are back in session, it would be expected that energy use would increase if remote learning were in use and minimal change would occur if schools continued in-person learning. In reviewing the implemented policy during this time in Austin where majority of the housing units are located, public schools offered both in-person and remote options in Fall

2020 [43-45]. This may partially explain the slightly lower increase in consumption compared to pre-pandemic periods. In analyzing the percent changes with respect to the time of day, the largest percent changes occurred between 11 AM and 4 PM compared to 2018, and 11 AM to 5 PM compared to 2019, further suggesting that people are spending more time in their homes when they would typically be at work or school.

While the *2018-2020* dataset offers additional comparison for energy use behavior across past years, the remaining analyses use the *2018 vs. 2020* dataset to compromise between a larger sample size and comparison of past usage behavior. This is also accompanied by *2020 Only* data for reference, as this dataset is even larger. Similar to Figure 1, the median hourly non-HVAC load profiles comparing *2018 to 2020* is shown in Figure 2.

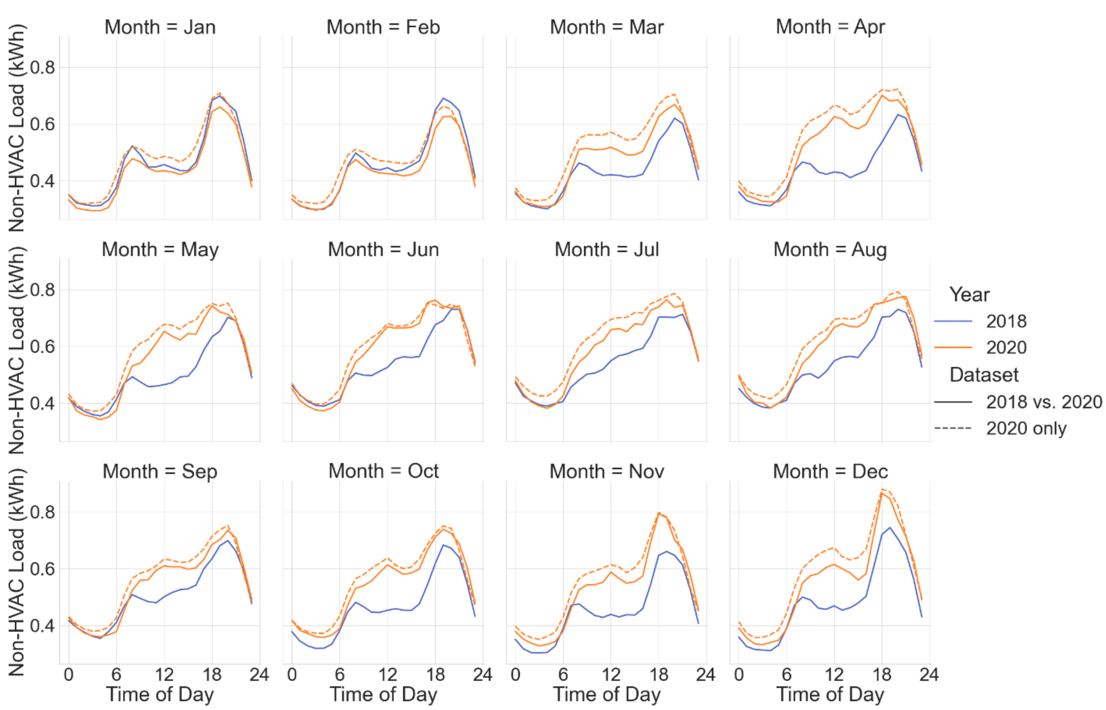


*Figure 2. Median hourly non-HVAC loads per month during years 2018 and 2020, represented through datasets 2018 vs. 2020 and 2020 Only.*

In examining the pandemic-impacted months (April-December), the average and median percent increases in total daily non-HVAC loads were +12.5% and +11.3%, respectively, with an average load change from

11.8 kWh in 2018 to 13.3 kWh in 2020. This is a smaller percent change compared to the 2018-2020 data, possibly explained by the 2018 vs 2020 dataset being less sensitive to large fluctuations in the data, such as in the evening hours in Figure 1, as the dataset contains are larger sample size. The largest total daily percent change occurred in April with a +18.6% increase, while the smallest percent change occurred in September with a +7.0% increase. With April being the first full month in the pandemic, this was likely the result of the stay-at-home orders imposed during this time. This contrasts with the prior analysis, likely due to the higher sensitivity to variation in the data, i.e. during the evening hours of August, as the *2018-2020* dataset has a smaller sample of housing units. For September, this was possibly influenced by school being back in session as previously discussed.

In reviewing the percent changes with respect to time of day, Figure 3 provides the hourly percent changes from 2018 to 2020 with the vertical axis representing the percent change in non-HVAC loads per hour and the horizontal axis representing the time of day. This analysis shows that the largest percent changes occurred between 10 AM and 4 PM. Within this timeframe, the peak percent changes occurred at either 11 AM or 12 PM. The maximum hourly percent change across all months occurred in April at 12 PM with a +45.2% increase from 0.431 kWh to 0.626 kWh. These results are similar to the *2018-2020* data, as it indicates people are spending more time at home when they would usually be away at places, such as at work or school. With the peak percent changes occurring around 11 AM and 12 PM, this shift could be associated with people using their kitchen appliances during this time to make lunch, increasing their energy consumption during a time when they would typically have lunch at work, school, restaurants, etc.

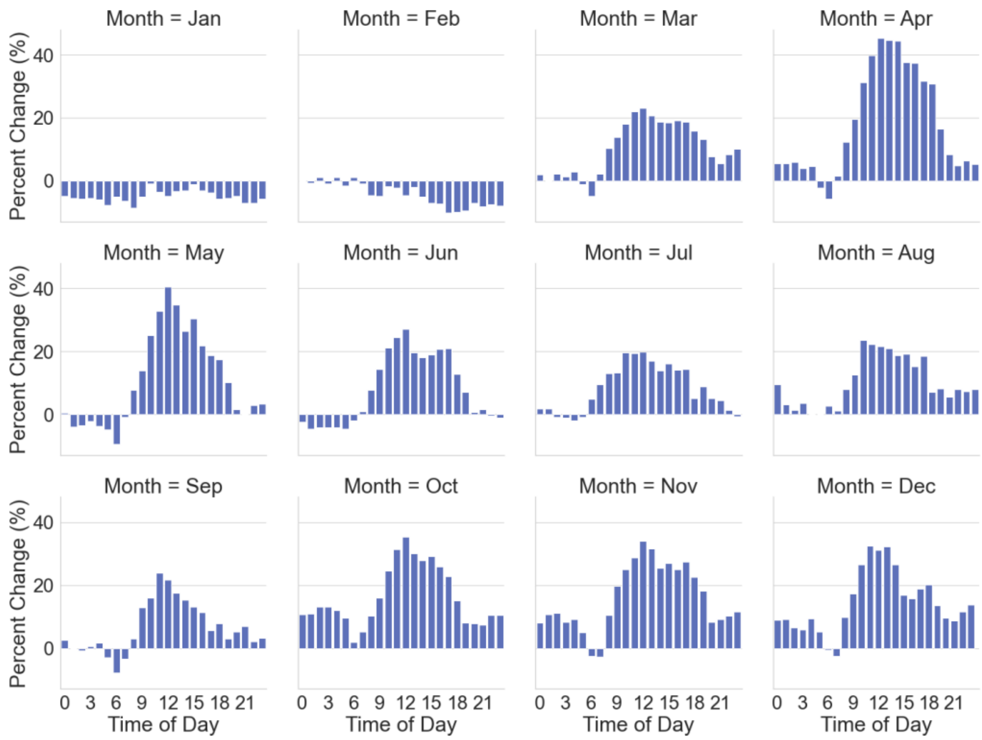


*Figure 3. Percent change in median hourly non-HVAC loads per hour of the day and month from year 2018 to 2020.*

The analysis of the *2018 vs. 2020* non-HVAC load profiles was evaluated further with respect to variance and rate of change. In Figure 4, the variance between the median hourly non-HVAC loads is given, with the vertical axis representing the variance in $kWh^2$ and the horizontal axis representing the time of day with an hourly frequency. The results show the largest variance during the pandemic-effected months occurred between 11 AM and 5 PM, with the majority of peak variance occurring at either 11 AM or 12 PM. The overall maximum variance occurred at 12 PM in April with a value of 0.019 $kWh^2$. These trends are consistent with the previously discussed trends for people occupying their homes during these times.

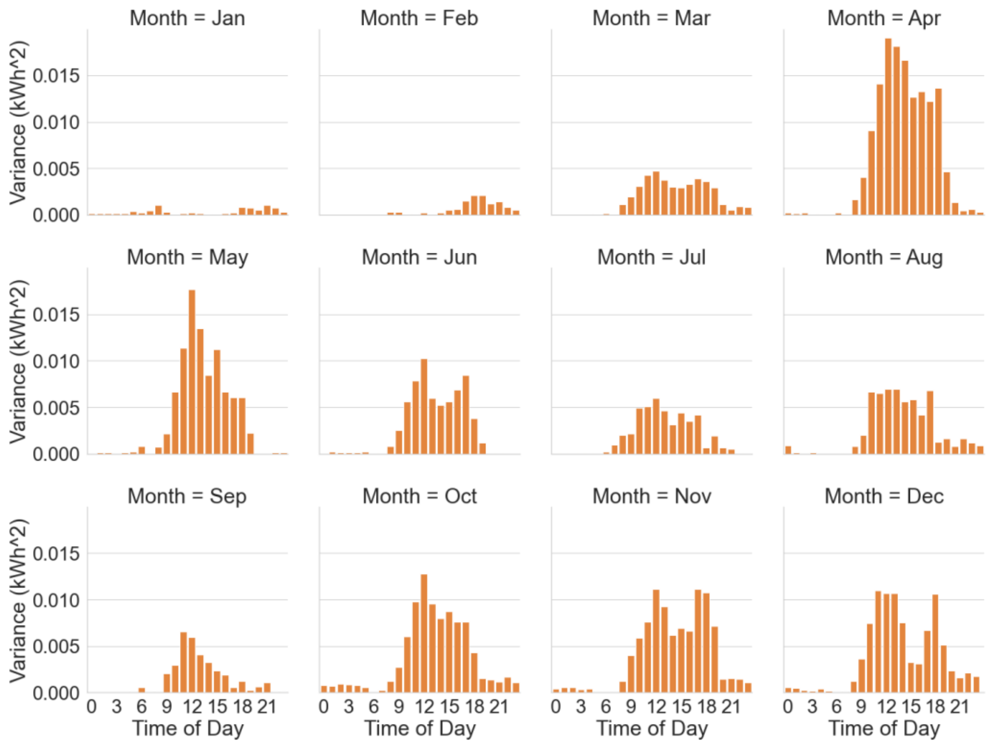


*Figure 4. Variance of median hourly non-HVAC loads from the 2018 vs. 2020 dataset, per hour and month.*

In Figure 5, the rate of change across each hour of the day per month and year is given for the median hourly non-HVAC loads from 2018 vs. 2020. The vertical axis represents the change in non-HVAC load across each hour in kWh/h. The horizontal axis represents the time of day with an hourly frequency. In reviewing the rate of change during pandemic-effected months, the majority of the largest increases occurred between 8-11 AM while the majority of largest decreases occurred between 7-8 PM. The ramping up in energy use occurs after people would typically leave their homes, so during this period people may be logging onto their computers/tablets to begin work or school. This result may also indicate that people are waking up later in the day as they do not need to consider added time to commute to their usual daytime location.

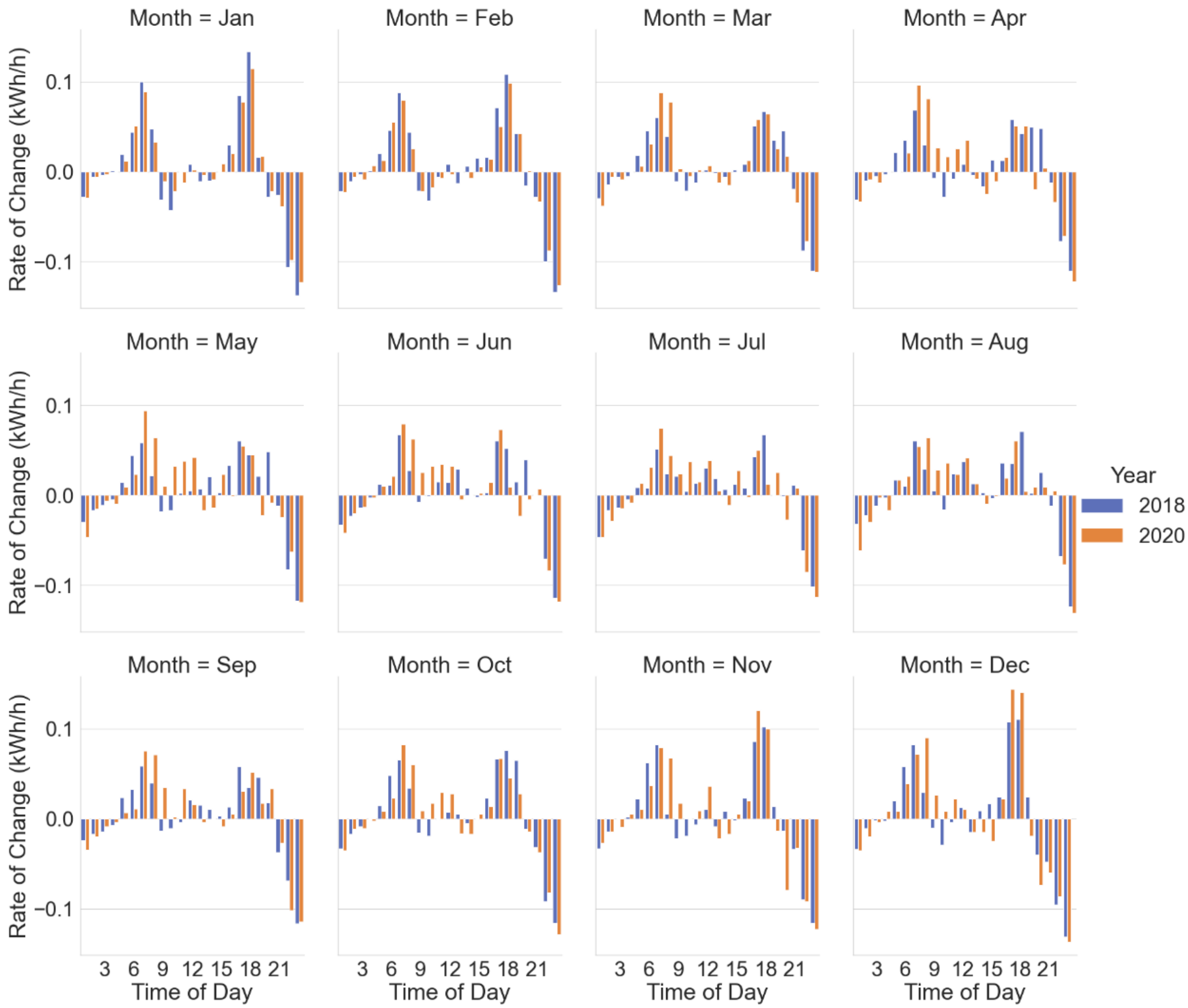


*Figure 5. Rate of change for median hourly non-HVAC loads across each hour of the day, per month and year.*

To study the 2018 vs. 2020 data further, the total, whole-home loads (non-HVAC and HVAC loads) and HVAC loads were analyzed. The whole-home load profiles are shown in Figure 6 with a similar format as Figure 1 and Figure 2, with the vertical axis representing the total combined loads in kWh, the horizontal axis representing the time of the day with an hourly frequency, and the 2020 Only dataset plotted for reference. The results show an average and median percent increase of 8.7% and 8.1% in the total daily load, respectively. The average load was 22.9 kWh in 2018 and 24.3 kWh in 2020. The months of April and October had the largest percent increase in total daily load with a 26.4% increase to 15.1 kWh and 25.3% increase to 18.9 kWh, respectively. In May, June, and September, there was a lower total daily combined load with percent decreases of 3.8%, 5.3%, and 4.5% to 22.5 kWh, 31.3 kWh, and 22.6 kWh respectively. In reviewing the data on an hourly basis, majority of the largest increases occurred between 10 AM and 1 PM.

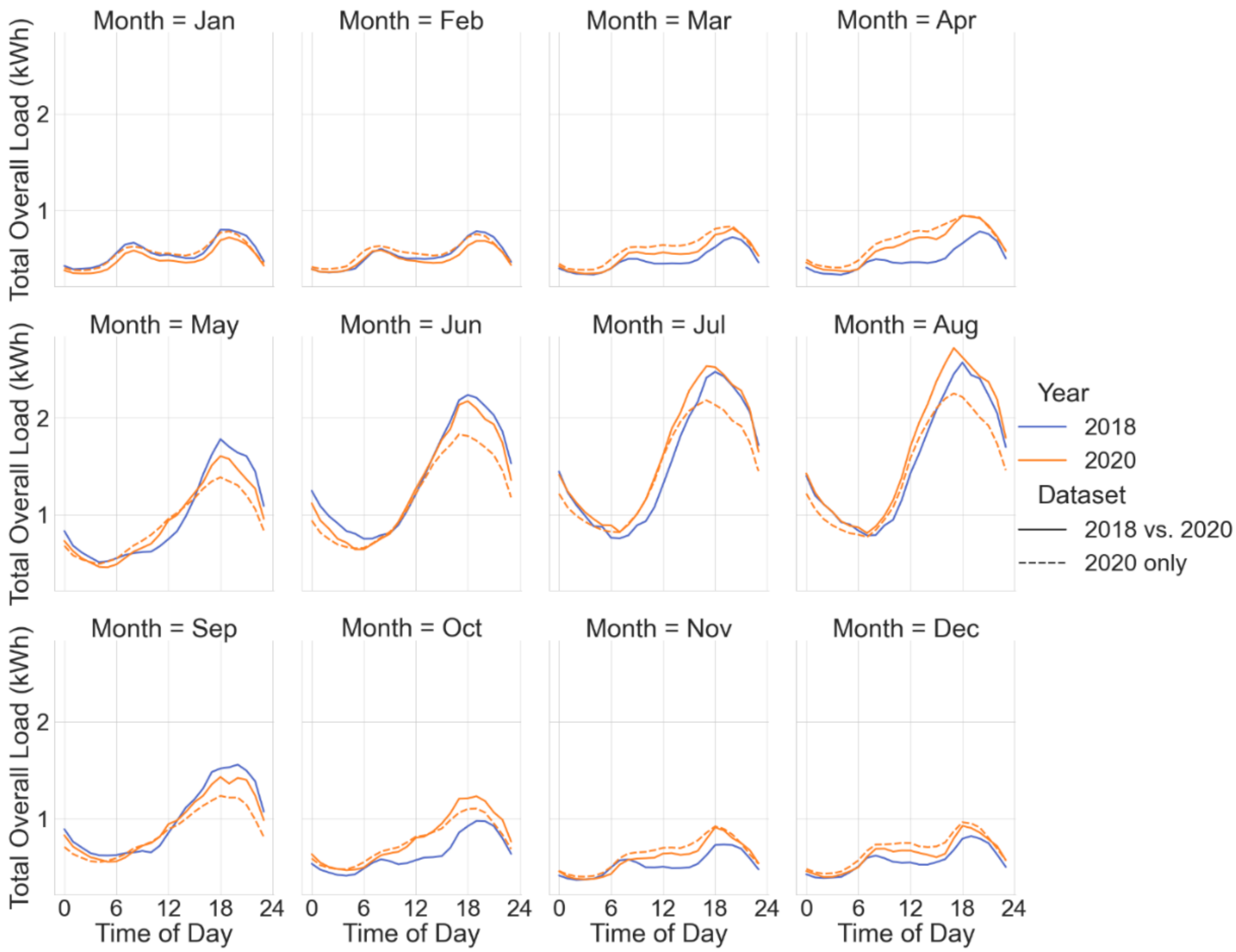


*Figure 6. Median hourly whole home load (combined HVAC and non-HVAC loads), across each month for years 2018 and 2020, represented by datasets 2018 vs. 2020 and 2020 Only.*

In understanding these results, it appears the months that felt the largest impact were during months that typically experience relatively mild temperatures, while the other months may experience warmer temperature and could, therefore, be influenced by the use of the HVAC systems of these housing units. Given that HVAC loads dominate summer electricity use patterns, variations in the weather conditions across 2018, 2019 and 2020, likely impacted these results. For this reason, the following analysis normalizes for the temperature differences across these months and years.

The weather-normalized HVAC loads for the *2018 vs. 2020* dataset are represented in Figure 7. The vertical axis represents the total daily HVAC load calculated from the median hourly HVAC loads for each month. The horizontal axis represents the average daily temperature calculated from the weather data for Austin, TX. The months chosen for the analysis are months with a higher number of cooling degree days. It is also noted that housing units analyzed are only those located in Austin, Texas, which was chosen to minimize differences in HVAC system usage and preferences across climate zones and locations [30]. Linear regression models were fit to the data for each month and year, accompanied by their respective equations and coefficients of determination.

There is an overall increase in the HVAC loads under equivalent weather conditions for 2020 compared to 2018 with May, June, July, and October having the greatest separation between years. September appears to have smaller separation between the two years, while August has some overlap for lower temperatures. These trends are consistent with the previous analyses as it shows that people are using their HVAC systems more under the same temperatures during 2018, likely due to longer periods of occupancy and thus limited to no setbacks in HVAC use during these times that were previously unoccupied. Some of this variation may also be due to variation in setpoints adjusted by the homeowners. September also appears consistent with the previous trends in non-HVAC use, as there was minimal change during this month. August does not seem to follow the same trends as the other months, however, which is somewhat unexpected as it is typically one of the warmest months of the year.

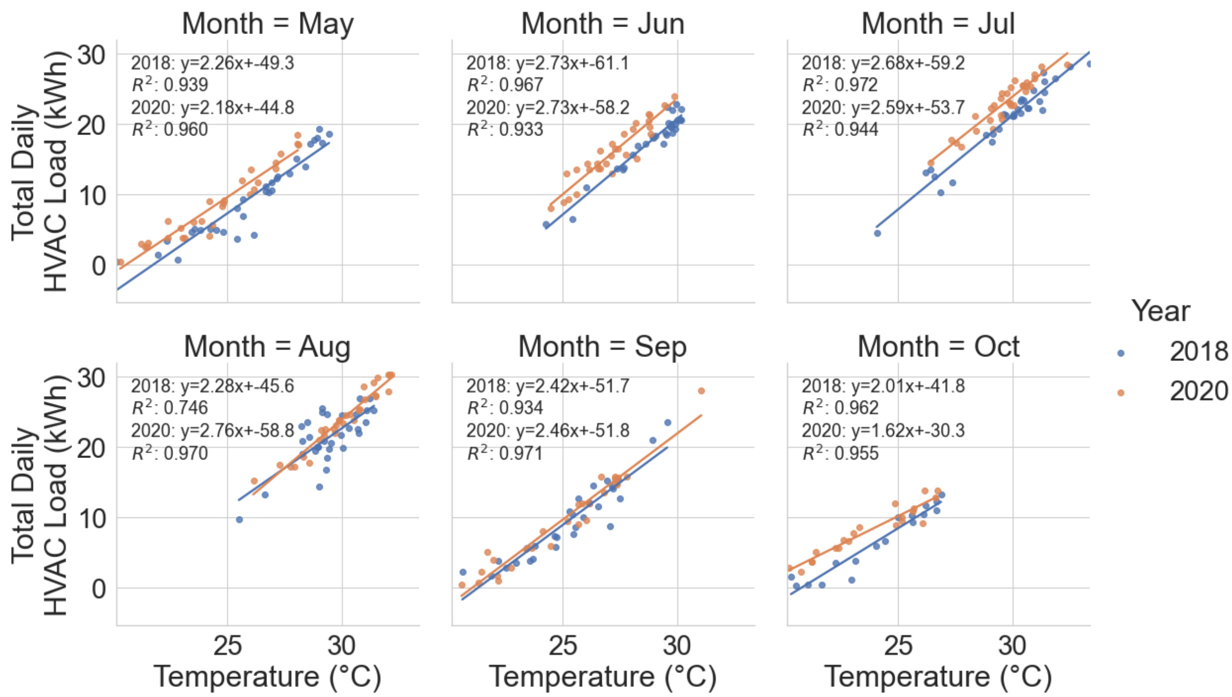


Figure 7. Total daily HVAC loads based on the median hourly HVAC loads as a function of the average daily temperature. The data is represented by month and year and fitted with a linear regression model.

Next the load profiles across income ranges were analyzed, as seen in Figure 8. The vertical axis represents the median hourly non-HVAC loads, and the horizontal axis represents the time of day at an hourly frequency. To compare different income ranges, each row represents a different household annual income groups and is represented by numerical values (Group 1 – Less than $50,000, Group 2 – $50-74,999, Group 3 – $75-99,999, Group 4 – $100-149,999, Group 5 – $150-299,999, and Group 6 – $300-1,000,000), and each column represents each month during the pandemic-affected period. Similar to Figures 1, 2 and 6, both the *2018 vs. 2020* dataset and *2020 Only* dataset are represented with the solid line representing the *2018 vs. 2020* comparison and the dashed line representing the *2020 Only* dataset with the larger sample size of housing units.

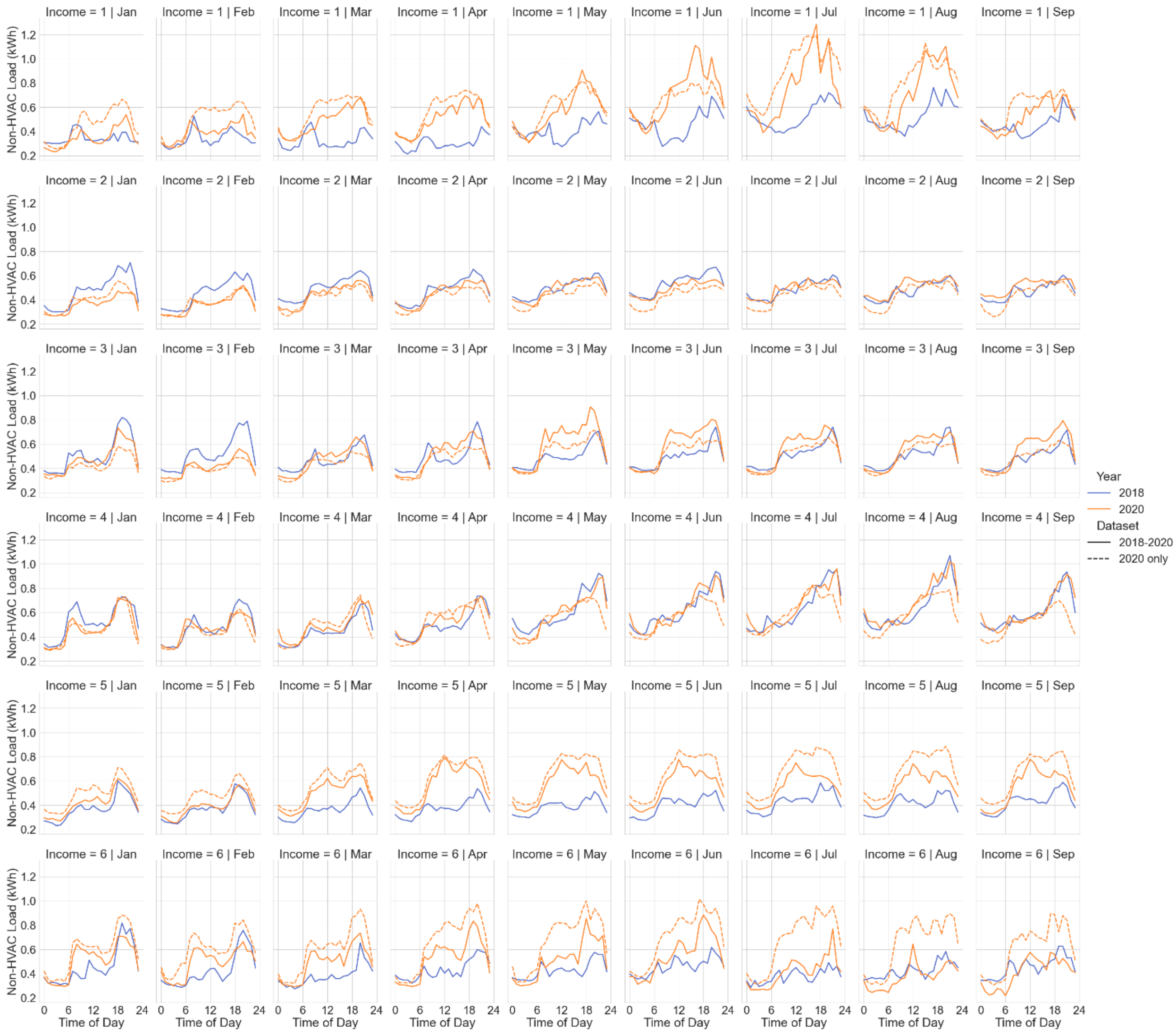


*Figure 8. The median hourly non-HVAC loads for each month across different income ranges. Each row represents the different income range groups and each column represents a different month. The key for the income range groupings is as follows: 1 – Less than \$50,000, 2 – \$50-74,999, 3 – \$75-99,999, 4 – \$100-149,999, 5 – \$150-299,999, and 6 – \$300-1,000,000.*

In understanding the load profiles by income group by first observing the pre-pandemic months, January ranged from -23.3% to 12.5% change in total daily non-HVAC loads across 2018 to 2020, averaging at a -2.9%, and February ranged from -21.1% to 15.4% change, averaging at -1.4%. Both of these variations are to be expected from year-to-year and are fairly small on average. After transitioning to stay-at-home precautions during March, April ranged from -5.8% to 66.9% change in total daily non-HVAC loads, averaging at 23.4%, which are much higher increasing compared to the pre-pandemic months.

In reviewing the individual impacts on the income groups during April, the largest increase of 66.9% was for the less than $50,000 group (1) with an increase from 7.2 kWh to 12.1 kWh. This trend could be a function of the decline in the service industry during the pandemic affecting those with lower incomes. The second largest percent change was in the $150,000-$299,999 household income group (5) with a 50.5% increase from 9.0 kWh to 13.5 kWh. One possible explanation for this change could be that this group contains individuals that could be taking more precaution during the pandemic and, therefore, spending more time inside their homes. These individuals in higher income households may have also held jobs that previously required in-person office work thus they were away from their homes during the day, however during the pandemic their jobs allowed them to work 100% remotely. Though the $300,000-1,000,000 household income group (6) does not experience as large of shifts in its loads for *2018 vs. 2020*, there does appear to be similarities in the load profiles for Group (5) and (6) based on the *2020 Only* dataset. This discrepancy could be a product of the variability in the smaller sample of housing units and should be investigated further. In the following months, similar trends continued to occur with the low-income group (1) and higher income groups (5) and (6).

The income groups that experienced the smallest changes in April were the middle income ranges at $50,000-74,999 (2), $75,000-99,999 (3), and $100,000-149,999 (4), with changes of -5.8%, 2.8%, and 5.2%, respectively. In contrast to the middle-high income group (5), these could be individuals at a lesser risk for serious effects from the virus and, thus, took less precaution for staying at home. Another reason could be they held jobs that require in-person work, i.e. essential workers such as in the healthcare industry. Group (2) and (4) continued to experience occurrences of negative change during the pandemic-affected months, with the highest income group (6) also experiencing negative change during August and September based on its *2018 vs. 2020* representation. While this trend appears with Group (6), it is important to note again its similarity to Group (5) for the *2020 Only* dataset which still held a large increase in the non-HVAC loads. Group (3) appears not to have been affected until May, in which the total daily load increased from 11.8 kWh to 14.6 kWh, possibly indicating that this group required an adjustment period before occupying their home or these people may be essential workers that are subject to the fluctuation in the number of cases/hospitalizations.

## Conclusions

As residential buildings became makeshift offices, classrooms, restaurants, entertainment centers, and more, the impacts of the COVID-19 pandemic on the energy use in buildings can be represented through the analyses of non-HVAC loads, HVAC loads, and whole-home loads.

The key outcomes from the non-HVAC loads analyses provided the time and magnitude of the shifts in energy use, with the largest percent changes occurring between 10 AM-4 PM and the peak changes occurring at 11 AM or 12 PM. This increase during this timeframe provides evidence of these residential buildings being occupied and consuming electricity during periods people would normally be at the office or school. The peak increase during typical lunch hours may indicate an increased use of kitchen appliances, leading to further investigation into the individual appliances that are causing these shifts. Additionally, the hourly rate of change showed the largest increases during 8-11 AM and the largest decreases during 7-8 PM. Without the need to commute to work, it is possible that people are waking up later in the day before logging in for work or school. Similarly, without the commute home, the evening peak may have shifted earlier as occupants can assume their evening routines sooner compared to pre-pandemic periods.

The whole-home loads analysis also showed increases in energy use during times where people would usually be away from home, with majority of percent increases occurring between 10 AM-1 PM. In weather-normalizing the data, the results of the HVAC loads analysis provided evidence that occupants were using more energy for similar average daily temperatures when comparing 2020 to 2018. Across all the analyses, the largest increases commonly occurred during April and October, the smallest during September, and conflicting results during August. While April was expected as the first full month in the pandemic, further investigation may be needed for the August-September period.

In understanding the non-HVAC loads by income group, the lowest income group and highest income groups experienced the largest percent increases in total daily loads, while the middle income groups experienced a smaller impact during the pandemic. These trends may be a product of the job occupations these income groups held during this period either leading to job loss, essential work, or remote work. While this dataset was limited in sample size, there still appears relatively large differences across the income groups that could merit further investigation.

In conclusion, the COVID-19 pandemic has transformed how residential buildings are used, and as survey data suggests greater adoption of remote working and home cooking, among other activities, for post-pandemic behavior compared to pre-pandemic behavior, these shifts in energy use should be considered for future assumptions of residential energy use. In addition to studying individual appliance load profiles, projections for residential energy use could be investigated to gain insight on how assumptions may need to be adjusted based on the projected adoption of the behaviors formed as a result of the pandemic.

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