Socioeconomic Factors Influencing Residential Occupancy Trends During and Post-COVID Pandemic

The residential building sector accounts for 22% of end-use energy consumption in the United States. Despite the strong influence of occupants' behavior on energy consumption patterns in residential buildings, the impact of households' socioeconomic background on occupancy is not well understood in the wake of the COVID-19 pandemic and its aftermath. This study aims to analyze the changes in occupancy patterns of residential buildings in the United States during and after the pandemic (2020-2022) using 14 socioeconomic variables. The American Time Use Survey (ATUS) data is used to define occupancy patterns, then correlation and regression analysis are applied to determine the most significant variables impacting the hours and when members are at home. Results suggest employment status and household income level are the most significant variables predicting hours at home. Those under 25, low-income households, unemployed, and those identifying as Hispanic have most quickly returned to pre-pandemic (2018-19) occupancy patterns. The results indicate that post-pandemic (2022), occupancy patterns continue to change for those under 55, employed, and middle- and high-income groups, thus must be monitored moving forward as they continue to evolve. These results are critical to help support ongoing electrification of homes and decarbonization of the electric grid.

Introduction

Due to the outbreak of Coronavirus 2019 (COVID-19), the World Health Organization (WHO) declared a global pandemic in March 2020, marking a global shift in lifestyle due to this long-term public health emergency (Cucinotta et al. 2020). Travel restrictions and health safety measures implemented in 2020 were still in effect in many places in early 2023 (CDC 2023). However, in May 2023, WHO declared COVID-19 was no longer a global health emergency but still a health threat (WHO 2023). This 2020-2023 period marks a significant change compared to pre-pandemic life. Due to the strict measures and lockdowns in 2020 in particular, residential electricity demand and resulting emissions increased, while overall annual electricity demand on the electric grid decreased in countries like China and the U.S. (IEA 2020). People spent more time at home, while other grid-impacting sectors, particularly commercial buildings, were being used less (Balemi et al. 2021). This has continued to be the case since 2020. January 2024 reports note that office building vacancies throughout the U.S. were at their highest since 1979 (Putzier 2024). Other research suggests that residential building use has continued to increase, including 8% higher electricity operational costs after adjusting for inflation (U.S. EIA 2022). These findings suggest that it is also important to note that despite reductions in residential energy consumption per capita due to increased energy efficiency, factors such as the occurrence of a pandemic can dominate such improvements in terms of the relative impact on the overall electric grid, emissions, and total energy use (Anand 2023; Jiang et al. 2021; Motuzienė et al. 2022).

Conventional methods to improve energy efficiency can also ignore the complexities of households' roles (O'neill and Chen 2002), in which the savings can be offset by demographic changes, such as income and age (Brounen et al. 2012). As such, other factors in addition to efficiency, including occupancy and activity schedules, are critical components that can help to describe homes' energy use patterns and behaviors. Future projections of shifts in lifestyle patterns, such as hybrid and work-from-home options, continue to be made in the wake of the pandemic (Gagné et al. 2022). However, a consensus on which changes to people's lifestyles will be permanent versus return to pre-pandemic "normalcy" is still somewhat unclear.

Occupant behavior in buildings can be defined as the presence and actions of occupants that can impact the building's environmental conditions and energy consumption (Yan and Hong 2018). Occupants' presence creates both latent and sensible heat in space; their behavior, such as opening/closing windows, turning on/off lights, and using appliances, also impacts total internal loads (Yang et al. 2016) and the need for heating and air conditioning. However, while many studies focus on building envelopes and energy systems, increasingly more attention is being placed on human-related factors such as building operation and maintenance, indoor environmental quality, and occupants' behavior (Hong et al. 2017; Yoshino et al. 2017). During the start of shelter-in-place orders in March 2020 in California, Zanocco et al. (2021) found a significant spike in occupancy was observed for homes with minors, higher income occupants, and/or individuals with a bachelor's degree or higher. By contrast, fewer changes were observed in occupancy among smaller households, single-family units, and young individuals. Recent research (e.g., Mitra et al. 2022) suggests that the time spent at home in the U.S. increased by 1.9 hours on weekdays and 1.2 hours on weekends per household in 2020 in office and kitchen spaces for households with 2 or more members. However, no research has looked at multi-year trends of occupancy in the U.S. in the wake of the pandemic, nor has such research included consideration of how socioeconomic factors may influence such trends and changes.

Other research on the impact of socioeconomic and demographic factors on residential energy consumption also points to the need for further information on post-pandemic occupancy, particularly as they relate to energy equity and energy justice. Household (demographics, socioeconomic factors) and housing (size, age, type, ownership, duration of residence) characteristics have been found to have significant effects on per-capita residential energy use in the U.S. (Brounen et al. 2012; Estiri 2015; Palani et al. 2023; Ramírez-Mendiola 2017). Analysis of Census data has shown that low-income, Black, and Hispanic households were highly correlated with high energy use intensity (EUI), especially heating (Bednar et al. 2017). In addition, energy accessibility has been a long-term issue and unevenly distributed in the U.S., primarily affecting low-income, racial/ethnic minority households (Lewis et al. 2020). The pandemic has also worsened the housing energy insecurity challenges in low-income, Black, and Hispanic households, as well as households requiring medical devices or having young children (Memmott et al. 2021). Specifically, this research suggested that these socioeconomic groups had greater challenges with unemployment, limiting available money for food, medical care, and paying their utility bills. One case study found that working from home could increase annual single-family household utilities in Phoenix, Arizona, by $1,100 per household compared to those working in the office on weekdays (Anand 2023). It also found that shifting to working from home compared with the pre-pandemic level increased utility bill costs by up to 60%. However, various demographic and socioeconomic characteristics restrict the flexibility of working from home. For instance, only 28.6% of lower-wage workers can telecommute compared with 67.9% of higher-wage workers; this gap is even larger when comparing education levels (Yasenov 2020). These studies further emphasize the importance of not generalizing findings using averages across the entire U.S. population. Instead, they suggest the importance of understanding if there are significant social factors influencing residential building use and the implications of this moving forward.

This study aims to understand how occupancy patterns and time spent at home have changed in the U.S. during (2020) and in the post-pandemic (2021 and 2022) periods. The number of people primarily working from home tripled from 5.7% in 2019 to 17.9% in 2021 (U.S. Census Bureau 2022), but this has dropped to 59% of workers saying their jobs can be done from home as compared with 71% in 2020 (Parker et al. 2022). This is accomplished using American Time Use Survey (ATUS) data from 2018 to 2022, including socioeconomic factors and time use data translated into residential occupancy data. Specifically, it seeks to understand changes in the amount of time spent at home and when this occurs based on the most influential socioeconomic factors. It also aims to understand trends in occupancy patterns in which populations have arrived at a post-pandemic "normal," while others are still several years out from stabilizing household occupancy patterns due to the minimal variations seen across the years of pre-pandemic.

The remainder of this research is organized as follows. The methodology details the use of ATUS data and how the socioeconomic variables are selected, along with results generated for the profiles at home. The results section presents the relationship of selected socioeconomic variables with hours at home, average hours, daily profiles across different socioeconomics, and the use of specific areas within homes. The conclusion summarizes the significant findings, limitations, and future work to further extend this research.

Methodology

In this research, first, American Time Use Survey (ATUS) data from 2018 to 2022 was converted into home occupancy data. At the time of this research, 2022 was the most recently available ATUS data available for use, as the ATUS data is made publicly available approximately six months after the end of the prior year. Next, socioeconomic variables were selected using the correlation method. Next, selected variables were tested using regression analysis to determine the significance level in predicting time spent at home. The following summarizes the datasets used, the socioeconomic factors selected, and the analysis method of such data.

American Time Use Survey Data

The use of time-use survey (TUS) data collected using various methods across many countries has been used for generating information on people's behavioral patterns in buildings (Collins et al. 2021; Dong et al. 2024; Motuzienė 2022; Mo and Zhao 2022; Song and Gao 2020). The American Time Use Survey (ATUS) data has been collected annually since 2003 by the U.S.

Bureau of Labor Statistics (BLS) and includes data for the U.S. population (U.S. BLS 2023). Starting in 2006, the same data collection and methods that are still in use today have been used. The sampling method used is meant to produce a statistically representative sample of the U.S. using weighting factors. ATUS data is collected via in-person, phone calls, and mail interviews to include information on how people in the U.S. spend their time over a typical day (24-hour period); it contains data collection for all days of the week and months of the year. Demographic and socioeconomic information, such as age, household income, and the participants' activities, are then compiled. This data is subdivided into six files made publicly available annually. The ATUS data is also linked to the Current Population Survey (CPS) data, as some CPS participants also participate in the ATUS data collection (U.S. BLS 2023; U.S. Census Bureau 2023). This data provides the labor force statistics for the U.S. population.

When downloading ATUS data, a folder of data files is provided for each year. Within these data files, the following files have been used in this research: “Respondent”, “Roster”, “Activity”, “ATUS-CPS” and “Who”, each of which contains different information on the participants. All data files are linked via the household identification number (TUCASEID), which is present in all files for each year of data. The “Respondent” file has only one record of each ATUS respondent; the “Roster” file includes age, gender, and relationship to the survey respondent for all other household members. The “ATUS-CPS” provides additional socioeconomic information for all people involved in ATUS, as provided by the linked CPS dataset (U.S. BLS 2023; U.S. Census Bureau 2023). The “Activity” file includes a set of activity codes for each participant, associated with a set of timestamped periods, location during each activity, and duration of the activity. The “Who” file contains information on if the respondent and/or others in the household are present during the activity. The sizes of the ATUS dataset for the past five years, from 2018 to 2022, are shown in Table 1. The values shown in the table do not include the weighted values and thus do not reflect the U.S. population as a whole without including the weighted factors.

Table 1. Characteristics of ATUS data for recent years.

Year	Households	Recorded Activities
2018	9,594	184,103
2019	9,436	182,980
2020	8,782	155,109
2021	9,087	164,581
2022	8,136	146,393

ATUS and CPS socioeconomic factors considered

In total, across the available variables within the ATUS data, 14 socioeconomic variables and 1 time variable (time of the week) (Table 2) were considered for use in this study. These socioeconomic variables include age, gender, employment status, employment status of spouse, high school/college enrollment status, enrollment level, highest education level, marital status, income (annual), household sizes, number of children, race, ethnicity, and house tenure (own or rent). These variables are considered in related studies (Brounen et al. 2012; Bednar et al. 2017; Estiri 2015; Lewis et al. 2020; Memmott et al. 2021; Palani et al. 2023; Ramírez-Mendiola et al. 2017). The excluded variables were those not socioeconomic-related, variables that provided more specific information on variables already included in this study, and time-related variables. Overall, as these studies discussed, such variables have strong potential for connections with energy use and behaviors. The statistical weight of data (TUFINLWGT) was also used, following the guidance from the U.S. BLS reference documents, to ensure each participant's data reflects the appropriate portion of the U.S. population. Therefore, the results discussed in later sections can effectively represent the U.S. population.

Table 2. Selected variables and meanings from the American Time Use Survey (ATUS).

Variables	Meaning
TUCASEID	Respondent individual (identification code)
TUFINLWGT	Weight of the data
TEAGE	Age
TESEX	Gender
TELFS	Employment status
TESPEMPNOT	Employment status of spouse or unmarried partner
TESCHENR	High school/college enrollment status
TESCHLVL	High school/college or university enrolled level
PEEDUCA	Highest level of education degree received
PEMARITL	Marital status
HEFAMINC	Household income (annual)
TRNUMHOU	Family size
TRCHILDNUM	Number of children younger than 18
PTDTRACE	Race
PEHSPNON	Hispanic/non-Hispanic
HETENURE	House tenure (own or rent)
WEEKEND	Weekday or weekend
TEWHERE	Location
TRCODE	Activity

Calculating Occupancy based on ATUS and CPS

To determine the amount of time spent at home, this was calculated based on first converting the activity reported as located in a residential building based on the TEWHERE variable. For all entries in which the location was in a home, a “1” was used, while a “0” was used when reporting being elsewhere. If no location was reported, the location of the previous timestep was used. The total hours at home were then calculated by summing the time spent during all activities at home, i.e., where a “1” was used to define that activity’s location as being in a home. Average total hours at home on weekdays or weekends were weighted average values to represent the hours spent at home for the U.S. The occupancy fraction was then calculated as the percentage of the total time spent at home and plotted over a 24-hour period.

Socioeconomic groups and data segmentation for analysis

Among the socioeconomic variables considered, several adjustments were made to the representation of the variables, including age, income level, and household size, for ease of analysis. For age, the analysis of the ATUS age code (TEAGE) was used to divide the participants into five groups: <25, 25-35, 35-45, 45-55, 55-65, 65-75, and 75+, to be consistent with methods used in related research (Mitra et al. 2021; Unnikrishnan and Figliozzi 2020). Second, income level (HEFAMINC) was defined in three groups: low, middle, and high. This is determined based on household size (HRNUMHOU), as shown in Table 3, by considering the average thresholds of federal poverty guidelines for different household sizes from the past five years, from 2018-2022 (U.S. HHS 2023). Finally, for household size, since 85% of households were either 1-, 2-, 3- or 4-member households, the 5+ member households were not included since the total number of household members varied across all households in this category (U.S. Census Bureau 2023). Other variables were assigned integer numbers and were able to be grouped without modifications, including gender, employment status, employment status of spouse or unmarried couples, high school/college enrollment, enrollment level, highest education level received, marital status, number of children, race, Hispanic/non-Hispanic, and house tenure.

Table 3. Household sizes and corresponding income levels define categorization as low-, middle-, or high-income ranges.

Household member #	Annual income range (low; middle; high)
1	<$15,000; $15,000-$60,000 >$75,000
2	<$20,000; $20,000-$100,000; >$100,000
3	<$25,000; $25,000-$150,000; >$150,000
4	<$30,000; $30,000-$150,000; >$150,000

Variable Correlation & Regression Analysis

Statistical analysis methods were then used to identify the variables that were the most significant predictors of occupancy. First, across the 14 socioeconomic variables considered, the

Pearson correlation method was used to assess how closely related each variable was to one another. Pearson correlation values range from -1 to 1, where the absolute value of 0 to 0.3 was considered uncorrelated, the low correlation from 0.3 to 0.5, the moderate correlation from 0.5 to 0.8, and the high correlation from 0.8 to 1. When a correlation coefficient was 0.8 or higher, one of the two variables was eliminated (Guo et al. 2023), thus leaving a set of variables without high levels of correlation for the next steps in the analysis.

Regression analysis methods (Hothorn et al. 2022) in R (Version 0.9-34) (R Core Team 2023) were then used to determine the significance level of each considered variable on time spent at home. This method tested the null hypothesis, which signifies relations between the fitted regression model's predictor and response variable. The p-value was considered significant and set as below 0.05, but it was also evaluated at other levels of significance. The selected recorded socioeconomic variables were chosen using the backward selection or elimination regression method, which iteratively selected the most contributory variables to the results (Barret and Gray 1994; Al-Subaihi 2002). The final variables were significant variables impacting time spent at home.

The resulting coefficients for the variables in the model are either negative or positive. A positive coefficient indicates an increase in the time spent at home with the dependent variable; similarly, a negative coefficient indicates a decrease in the time spent at home with an increase in the dependent variable. The coefficient also helps to measure the strength of the impact of a change in the variable, in which a larger absolute value means a larger impact and a smaller value suggests a lesser effect.

Results and discussion

Changes in time spent by location

Using the ATUS data classification, people can be considered indoors, outdoors, in transit via some form of transportation, and unknown (including non-reported locations). Prior to analyzing the time spent at home, it is helpful to understand the over-location trends. As shown in Figure 1, prior to the pandemic, people spent approximately 94% of their time in indoor locations, 0.7-0.9% outdoors, and 5.0-5.2% in some form of transportation. During the pandemic (2020), time spent in indoor spaces increased by 1.3%, to 95.3%, while time in transportation decreased to 3.7%. Thus, time spent indoors went up by approximately the amount of time participants previously spent in transportation. This trend makes sense since many people worked from home during the pandemic and did not commute, thus not spending time in various modes of transportation as frequently. Furthermore, there was also a surge in the adoption of virtual processes, including e-commerce, food delivery, and streaming services, particularly for remote meetings and entertainment, supporting working and schooling remotely (Auxier and Anderson 2021; Pandey and Pal 2020; Wang et al. 2021).

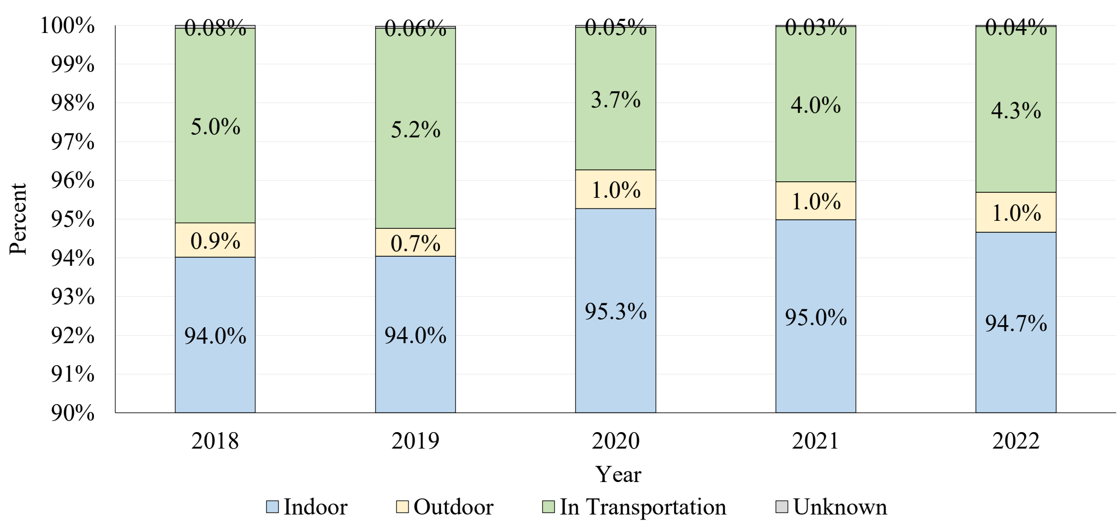


Figure 1. Annual time spent (%) based on location, using ATUS data from 2018-2022.

Interestingly, there was also a slight increase in the amount of time spent outdoors in 2020. While no specific trends were found in terms of when this time was spent outdoors, other recent research suggests that part of the reason for this may be that people were tired of being in their homes but unable to go to indoor places with other people due to social distancing restrictions. Thus, instead, they spend time on outdoor activities (Wagner 2022). This approximately 1% of time spent outdoors has continued to be the same in 2021 and 2022, suggesting that this slightly higher level of time spent outdoors may remain at this level in future years. Given that well-being has been linked to time spent outdoors (e.g., Loebach et al. 2022; Sadick and Kamardeen 2020) and that there has been an increased focus on workplace well-being in the post-pandemic periods (Business Group on Health 2022), such a trend appears to make sense.

Another trend observed is that in 2021 and 2022, compared to 2020, the 1.3% uptick that occurred in time spent indoors decreased by 0.3% per year, slowing being replaced again by time spent in transportation. Based on a survey, Bick et al. (2023) found that people working from home sharply increased to 39.6% in May on workdays compared to 14.4% in February during the pandemic and remained at 28.5% in June of 2021. Based on these trends, it appears that changes in time spent indoors versus in transportation have not yet found a leveling point and continue to change. Analysis of 2023 data would help to understand if this change has continued or is beginning to level off.

Changes in time spent at home

Next, the average amount of time per day that people spent at home each year from 2006 to 2022 is investigated to evaluate how this trend has changed over time, including on both weekdays and weekends (Figure 2). From 2006 to 2019, the average time remained nearly constant, at 17.1 ± 0.14 hours on weekdays and 19.4 ± 0.24 hours on weekends. However, in 2020, this average increased by 1.8 hours on weekdays (18.9 hours total) and 1.4 hours more on weekends (20.8

hours total) at home, respectively, compared to the pre-COVID-19 period. In 2021, the time spent at home decreased by 12 minutes on weekdays and 24 minutes on weekends. By 2022, the decrease in time spent at home dropped by 42 minutes on weekdays and 36 minutes on weekends, compared to 2020. However, this average time at home did not return to pre-pandemic levels in 2021 and 2022. Time at home has continued to decrease, but in 2022, it still remains 1.1 hours more per day on weekdays and 48 minutes more per day on weekends than the averages before the pandemic. In this study, "post-pandemic" is used to refer to the years after 2020. During this time, lockdowns and restrictions were gradually loosened as the first vaccines were produced and began to be administered (U.S. FDA 2020). Even though COVID-19 cases continued to occur, conditions were not as extreme as in 2020.

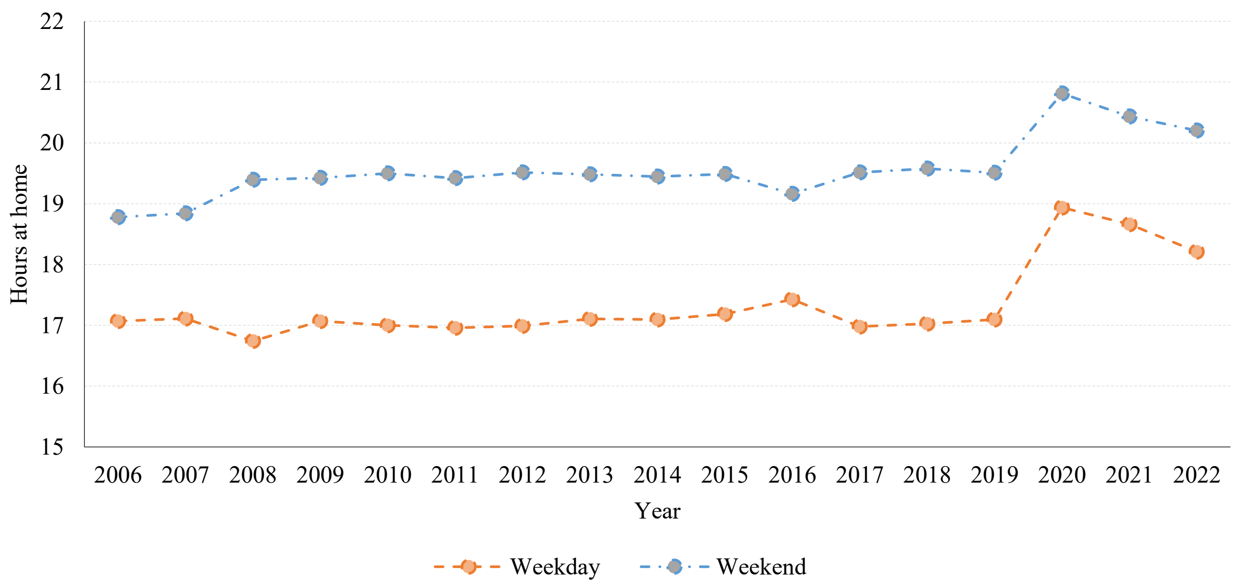


Figure 2. Average hours spent at home per day from 2006 to 2022 for U.S. households.

Analysis of future years of data (2023 and beyond) will help to understand if these trends continue or will level off. Recent discussions have focused on whether return-to-office (RTO) efforts effectively support employee productivity and well-being. Such debates originate from many companies asking formerly completely remote employees during the pandemic to return to the office one or more days per week in 2023 and 2024 (Pandita et al. 2024; Stelson et al. 2023). And how this debate ultimately settles will likely impact the future amount of time-at-home trends look like.

Variables most influencing time spent at home

Next, Pearson's correlation coefficients were determined for the selected socioeconomic variables for the years of ATUS and CPS data that were evaluated (2018 to 2022) to assess the strength and relationship between the considered variables (Table 2). In this analysis, only 2018 to 2022 are used since the 2006-2019 data is highly similar in overall trends. Among the 14 variables considered, most have no or poor correlation with one another, with absolute values less than 0.5. A correlation matrix among these variables for the year 2020 is shown in Figure 3. For the other years, although the correlation coefficients are slightly different, the level of correlation remains the same, i.e., those that are strongly correlated continued to be strongly correlated; those that are poorly correlated continued to be poorly correlated.

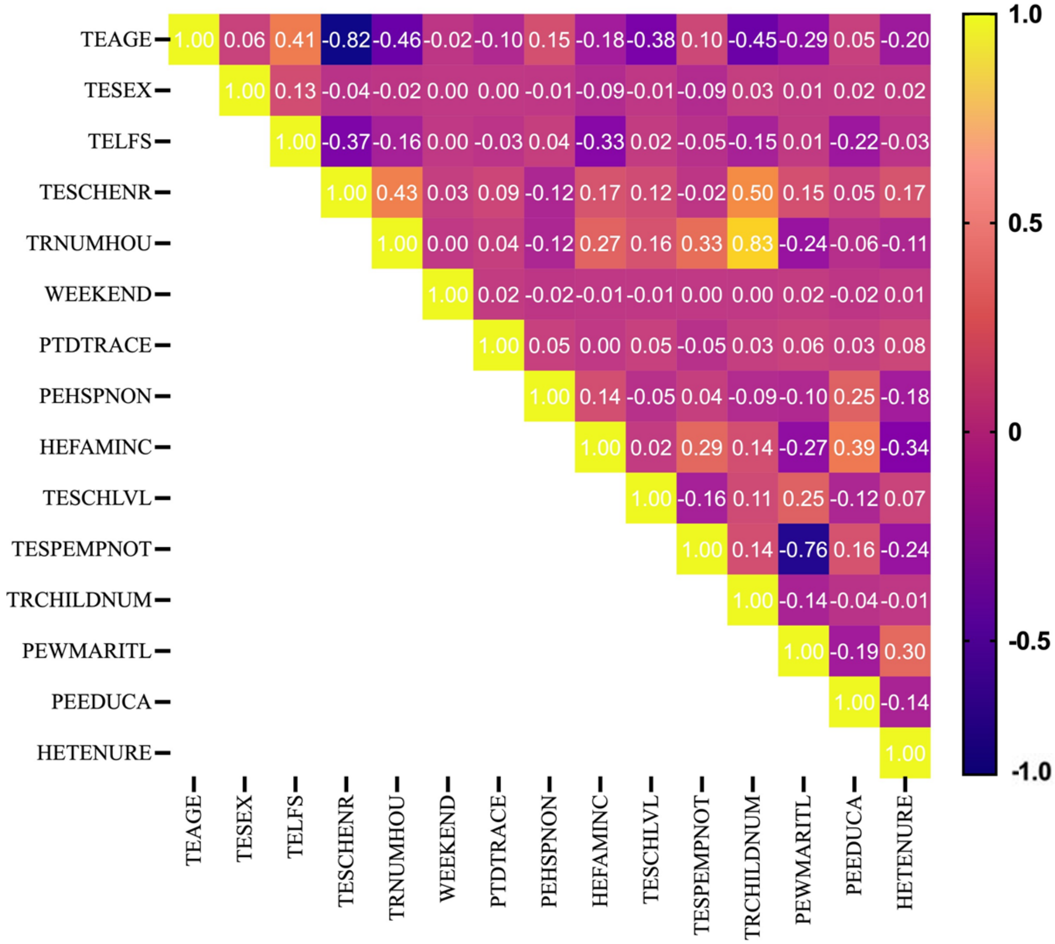


Figure 3. Correlation matrix for selected variables using 2020 ATUS data.

Several pairs of variables are highly correlated, including age (TEAGE), school/college enrollment status (TESCHENR), family size (TRNUMHOU), and number of children (TRCHILDNUM). Age is negatively correlated with school/college enrollment status since older people are less likely to attend school; household size is positively correlated with the number of children, suggesting a larger household is likely to have one or more children. School/college enrollment status (TESCHENR) and children number (TRCHILDNUM) could also be implied by school/college or university enrollment level (TESHLVL) and family size (TRNUMHOU), respectively. Based on this, school/college enrollment status (TESCHENR) and number of children (TRCHILDNUM) were removed, leaving the remaining variables for consideration, all of which have absolute correlation coefficients lower than 0.8 across all years of data. Most are well below this threshold and kept without losing important information for further analysis.

Regression analysis was then used to evaluate the significance level and relative impact of the remaining 12 socioeconomic variables on time spent at home across all years of data (2018-2022). The results of backward stepwise regression suggested using 10 socioeconomic variables, as shown in Table 4. This includes the coefficient resulting from the regression analysis, where a positive value indicates a positive relationship with the amount of time spent at home. The significant level is also provided; coefficients are provided in the table only if the variable was significant (p-value < 0.05) for a particular year; variables with p-values greater than 0.05 are not shown.

Table 4. Regression analysis coefficients and the level of significance of socioeconomic variables predicting the amount of time spent at home.

	2018	2019	2020	2021	2022
Age (TEAGE)	0.0161**	0.0136**	-	-	0.009
Gender (TESEX)	-	-	-	0.312**	0.208
Employment (TELFS)	0.792**	0.809**	0.832**	0.737**	0.699**
Income (HEFAMINC)	-0.115**	-0.079**	-0.043	-0.033	-0.051*
Household size (TRNUMHOU)	-	-	-	-0.092	-
Education (PEEDUCA)	-	-0.068*	0.093**	0.066*	-
House Tenure (HETENURE)	-	-	0.216	-	-
School/ college enrolled level (TESHLVL)	-0.231	-0.265*	-	-	-0.297*
Race (PTDTRACE)	-	-	0.108	0.115	0.133
Hispanic (PEHSPNON)	0.337	0.408	-	0.458*	0.478*
Weekend (WEEKEND)	2.44**	2.34**	1.69**	1.66**	1.81**
R-squared	*0.232*	*0.221*	*0.171*	*0.163*	*0.168*

*Note: Values shown are significant, P<0.05. * Significant for P<0.001; **Significant for P<0.0001.*

Results suggest that employment status (TELFS; 0 for employed, 1 for unemployed), household income level (HEFAMINC), and time of the week (WEEKEND; 0 for weekdays, 1 for weekends) were statistically significant across all years (p-value < 0.05) in predicting time spent at home. The overall regression analysis results suggest that it was significantly more likely for a person to have spent time at home if they are unemployed, and lower income, and/or if it is a weekend compared to a weekday, regardless of whether the year was impacted by the pandemic. Other variables did not show the same consistency across the years, either becoming insignificant or significant during the pandemic. Age (TEAGE) and school/college or university enrolled level (TESCHLVL) were statistically significant in the pre-pandemic (2018-2019), became insignificant during the pandemic in 2020 and 2021, and became significant again in 2022. School/college or university enrollment level (TESHLVL) is negatively correlated with hours spent at home, suggesting that students enrolled in a college or university spent less time at home than high school students.

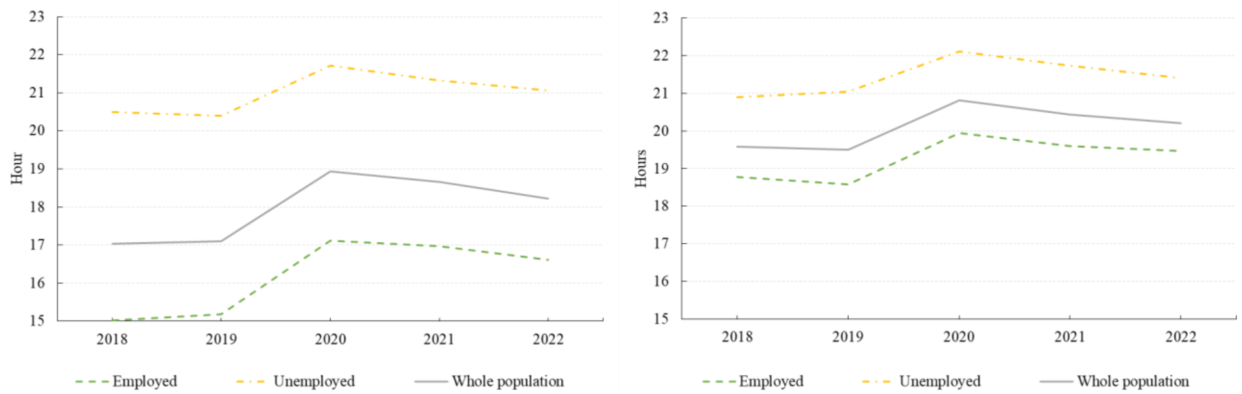
Age positively correlates with time at home, suggesting older people spent more time at home pre-pandemic. Age being a less important variable during (2020) and post-pandemic (2021 and 2022) is likely due to the significantly larger population still of working age and their children spending a more similar amount of time at home to those older. This is not surprising; however, the uptick in age significance in 2022 suggests that those working and/or going to school outside of the home are returning more to pre-pandemic levels of leaving home, at least compared to the older population.

A similar trend is seen for household income (HEFAMINC). Income is more strongly negatively correlated with hours spent at home pre-pandemic. In 2020 and 2021, it was not significant, and then in 2022, it was statistically significant again but to a lesser extent than pre-pandemic. Previous research found that high-income groups were more likely to spend more time away from home on weekdays pre-pandemic (Mitra et al. 2021). The change in the significance of household income suggests that the middle- and high-income groups' occupancy patterns became closer to low-income groups' occupancy patterns during the height of the pandemic and have returned to be somewhat different, but still not to pre-pandemic levels. This is likely due to the significant increase in work-from-home jobs available, particularly to middle- and high-income groups or those working in higher-tech industries (Baker et al. 2020). Remote working also enables employees to travel and be absent from home while still working for their employer. Further information about the format of respondents' employment, such as in-person, remote, hybrid, and others, could be included in the future version of ATUS data due to the increasing demand and availability among the companies. Such variables could help further characterize the amount of time spent at home in the future.

The highest education received (PEEDUCA) variable became significant during the pandemic, with a positive correlation to the time spent at home. This means that the higher the degree a person completed, the more time they spent at home, with more time being dedicated to working at home. Gender (TESEX; 0 for male, 1 for female) was positive and significant in 2021. This suggests that females were spending more time at home. However, it is unclear why it is only significant in 2021. This may be partly due to the increased number of females that either left the workforce in the wake of the pandemic or continued to work at home (Azcona et al. 2020; Fisseha et al. 2021). Additionally, many women also took childcare responsibilities or were at home instead of at school and/or work due to pandemic restrictions. Family responsibility, as well as combining gender and number of children, could be added into future studies for further analysis of the impact on time at home. Household size (TRHUMHOU) and race/ethnicity (PTDTRACE/PEHSPNON) also influenced time spent at home but were less significant than the previously mentioned variables. In particular, those who identified as Hispanic (PEHSPNON) were statistically more likely to spend more time at home during and post-pandemic, as compared to pre-pandemic. In addition, those who identified as minorities also spent more time at home. This may be in part related to trends that suggested that minority groups were more likely to lose their jobs during the pandemic (Fan and Moen 2023).

Trends in time at home for most significant variable predictors

After the initial regression analysis, time spent at home trends were evaluated by subdividing the sample population by the most significant variables. The hours spent at home by employment status and income level are shown in Figure 4 for weekdays and weekends. Age and race/ethnicity are also shown. These were chosen as recent research suggests that those who are elderly and minorities were more likely to lose jobs and thus be at home more (Bednar et al. 2017; Lewis et al. 2020; Memmott et al. 2021; Mitra et al. 2022).



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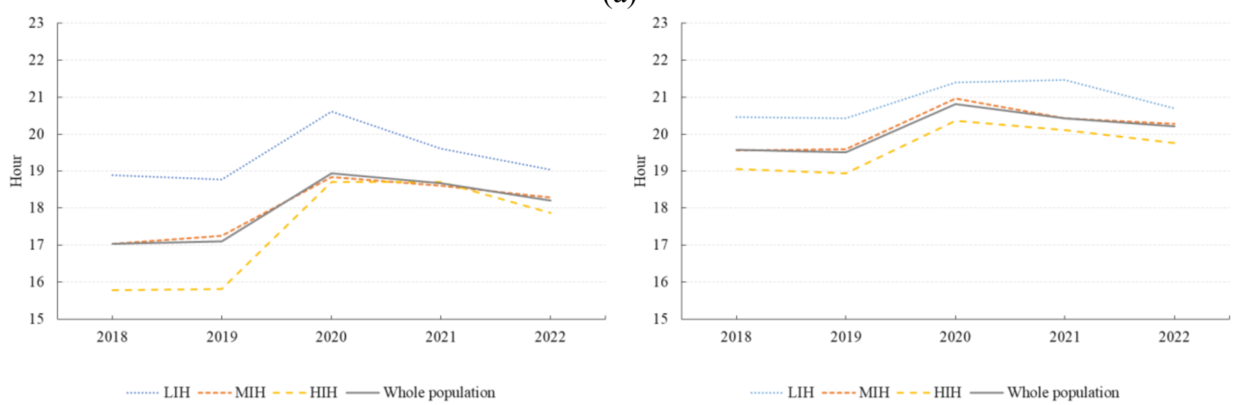

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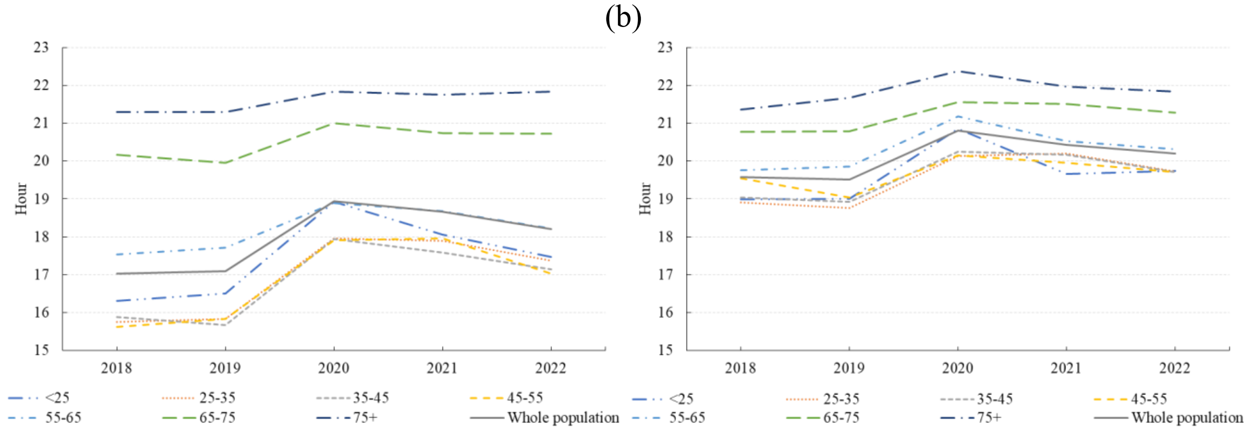
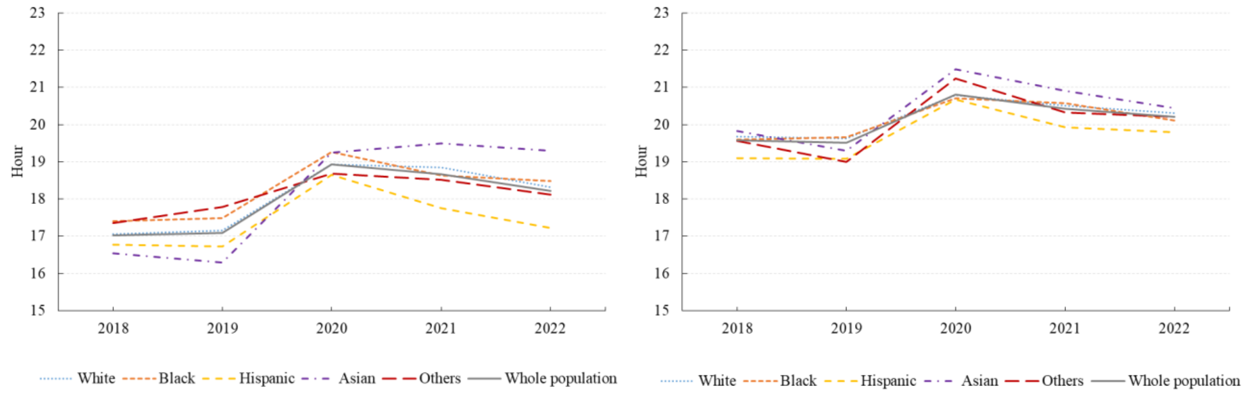


(c)



(d)

Figure 4. Hours spent at home for weekdays (left) and weekends (right) based on (a) employment, (b) income, (c) age, and (d) race/ethnicity between 2018 and 2022. (*Note: LIH = low-income household, MIH = middle-income household, HIH = high-income household*)

The biggest differences in time spent at home across the studied years are seen associated with employment (Figure 4a), with unemployed households spending close to five hours more at home per day on weekdays and two more hours per day at home on weekends. While the pandemic clearly impacted the amount of time spent at home, interestingly, the jump in time spent at home followed similar trends for both those employed and unemployed.

Compared with the pre-COVID period, those employed during the pandemic spent an additional 2 hours at home on weekdays and 1 hour on weekends in 2020; this is similar for those unemployed, who spent approximately 1.1 more hours on weekdays and weekends at home. It is important to note in considering these trends that in March and April 2020, 26 million workers in the U.S. filed for unemployment benefits (Czeisler et al. 2020; U.S. DOL 2020), suggesting that some households likely bounced between the "employed" and "unemployed" groups. Thus, it is important to keep in mind that a single household may not have followed only one of these trends but a combination of both. In 2021 and 2022, hours at home decreased on weekdays and weekends for employed and unemployed households. Those employed saw a slightly higher rate of decrease in time spent at home on weekdays, suggesting that return-to-office trends may influence this. Those employed also saw a lower rate of decrease in time spent at home on weekends.

For income, low-income households spent the most time at home across all years, followed by the middle- and high-income households, on both weekdays and weekends. The middle-income households closely followed the overall population trend across all years studied. In terms of the impact of the pandemic, in 2020, low-income households spent an additional 1.8 hours at home on weekdays (20.6 hours total), middle-income increased by about the same (18.8 hours total), and high-income households increased the most by about 2.9 hours (18.7 hours total). The pandemic also brought the amount of time that mid- and high-income households spent at home together, with both groups spending a similar amount of time (about 18.7 hours) at home on weekdays in 2020 and 2021. Since this time, the amount of time at home has decreased for all income levels; however, in 2022, high-income households' time at home on weekdays decreased more than middle-income households for the first time, suggesting high-income earners may be subject to more return-to-office trends or leisure activities than middle-income earners (Morasae et al. 2022). In 2022, middle- and high-income households' time at home is still lower than low-income households (0.8-1.1 hours less in 2022), but compared to pre-pandemic (1.8-3 hours less in 2018/2019), the gap between income groups in time spent at home is substantially smaller (1-1.9 hours less in 2022 than the pre-COVID). Also important to note is that low-income households' time at home on weekdays returned to pre-pandemic levels in 2022, while middle- and high-income households were still 1.1-2.1 hours more than the pre-COVID period. This is likely due partly to the reduced likelihood that lower-income households have jobs that allow for working from home (Yasenov et al. 2020). For weekends, the differences in amount of time at home across income groups is smaller, and trends have generally been similar across 2018-2022.

For age groups, those 55-65 most closely followed the overall population trend on both weekdays and weekends. People younger than 55 were most affected by COVID-19, with all groups under 55 spending an additional approximately two hours at home in 2020 on weekdays. Following the pandemic, for those under 55, the rate of decrease in time spent at home between 2020 and 2022 was also greatest on weekdays, while particularly for those 65 and older, time spent at home did not change more than 0.3 hours in 2021 and 2022.

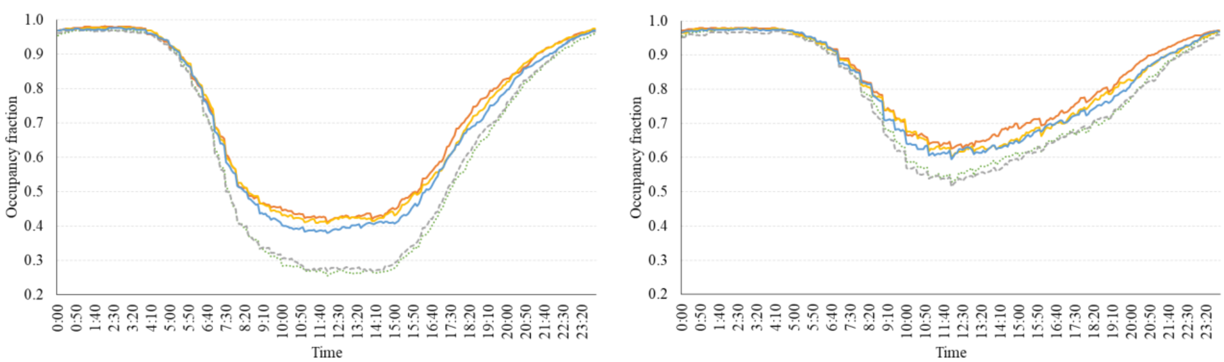
Considering trends across different races/ethnicities, this is particularly important since minorities were more affected by the pandemic due to their household characteristics (Lewis et al. 2020; Memmott et al. 2021); this could explain some of the differing trends seen in this analysis. Those who identify as Asian saw the biggest jump in time spent at home in 2020, jumping from 16.4 to 19.3 hours per day on weekdays; this same group continued to spend the most time on weekdays and weekends in 2021 and 2022, differentiating themselves from other racial/ethnic groups. Those identifying primarily as White follow similar trends to those identifying as Black and Hispanic. Each saw an increase in time spent at home in 2020 and a similar level of decrease each year through 2022.

The main difference between these groups is that those identifying primarily as Black generally spent slightly more time on average at home on weekdays, and those identifying as Hispanic generally spent slightly less time at home. Other races/ethnicities, including non-Hispanics (e.g., American Indian, Native Hawaiian, Native Alaskan), followed slightly different trends, with a slightly smaller increase in time spent at home in 2020 on weekdays but a slightly higher increase on weekends. On weekdays, those identifying as Hispanic have been the quickest to return to pre-COVID levels. In contrast, all other races/ethnicities had not yet returned to similar levels by 2022, particularly those identifying as Asians. For weekends, those identifying as Asian, Hispanic, and Other decreased their time at home in 2021 compared to 2020, while those identifying as Black and White maintained a similar amount of time at home. Hours spent at home decreased for all races/ethnicities on weekends in 2022, with Asians having the highest amount of time at home (20.4 hours) by a small amount.

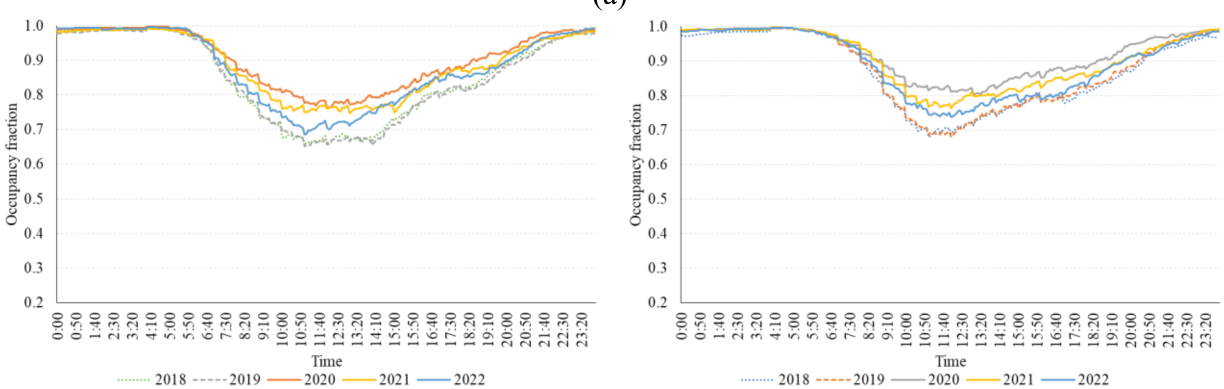
Occupancy profile variations across the most significant variable predictors

Related to total time at home, occupancy profiles are also influenced by various socioeconomic variables. Occupancy profiles are essential in the context of energy and sustainability of buildings as they have been shown to affect overall energy consumption and carbon footprint of households (Brounen et al. 2012; Dubois et al. 2019; Estiri 2015; Memmott et al. 2021). Occupancy profiles also impact the potential for demand response, particularly for large appliances such as HVAC systems and other occupant-driven large appliance loads (e.g., washers, dryers, dishwashers, water heaters, etc.). A higher occupancy fraction indicates a higher likelihood of being at home (1 = home; 0 = absence). In this case, the middle of the day is generally the period of time when the least number of people are present for most households. The likelihood of being away from home in the middle of the night is very low compared to during the day (i.e., the greatest variations in occupancy patterns are seen during the day).

This analysis used employment status to compare occupancy fractions for employed versus unemployed during the study period. This was chosen because it was one of the most significant factors influencing occupancy in the previous section. For the pre-COVID period, the occupancy fraction for those employed remained at approximately 0.28 at noon on weekdays and 0.55 at midday on weekends (Figure 5). Higher occupancy fractions were observed at midday for those who were unemployed, including 0.66 and 0.70 on weekdays and weekends, respectively. During the pandemic, occupancy fractions increased by 0.15 for employed and 0.1 for unemployed on weekdays; 0.1 for both on weekends. One possible reason, as suggested in other literature, is that unemployed household members may be at home more during this period due to the need to spend available income on essentials, such as food and medical care, rather than on leisure activities that may occur outside the home (Memmott et al. 2021). Thus, they may have spent more time at home on weekends than in other places. In 2021, this trend was similar to 2020 on weekdays, but in 2022, the occupancy fraction decreased, particularly for unemployed people. Those who were employed continued to do some work from home in 2022, but to a lesser extent, those who were unemployed followed an occupancy pattern that was more similar to pre-COVID levels.



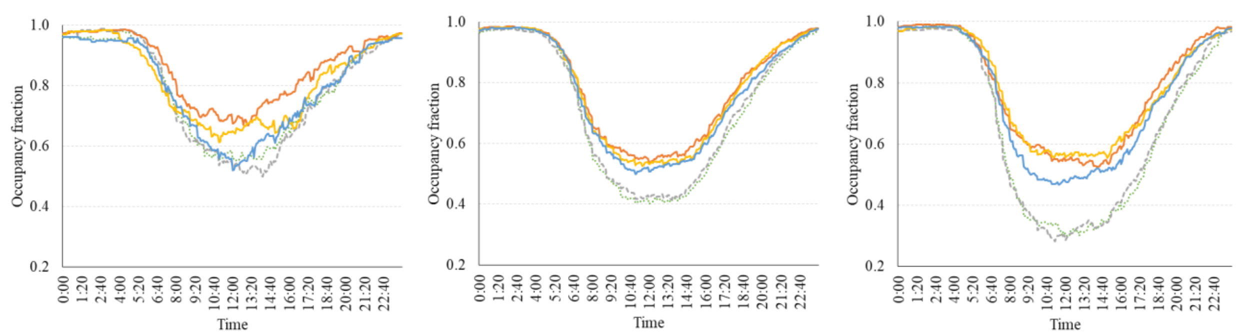
(a)



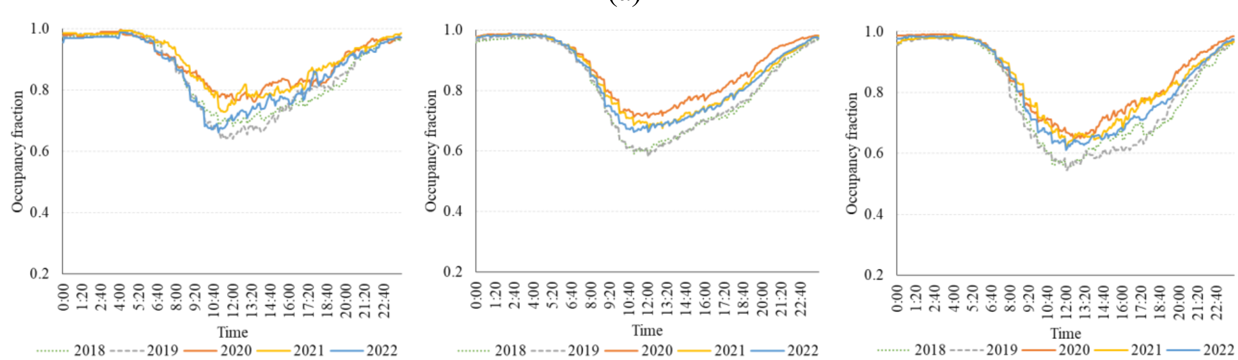
(b)

Figure 5. Occupancy fraction at home for (a) employed and (b) unemployed on weekdays (left) and weekends (right).

As household income level was also found to impact occupancy significantly, this variable is also used to compare occupancy fractions (Figure 6). In pre-COVID periods, low-income households (LIH) had the highest occupancy fractions during the day, followed by middle-income households (MIH) and then high-income households (HIH) on both weekdays and weekends. On weekdays, low-income households spent more time at home, with an occupancy fraction of 0.50 midday. This is aligned with literature suggesting low-income households are more likely to be unemployed and/or have childcare responsibilities and thus need to be at home (Carlin et al. 2019). Middle-income households had an occupancy fraction of 0.40 pre-COVID but spent more time away from home; high-income household members spent the most time away from home, with an occupancy fraction of 0.3 midday.



(a)



(b)

Figure 6. Occupancy fraction at home for low- (left), middle- (center), and high-income (right) households on (a) weekdays and (b) weekends.

During and post-COVID, similar trends emerged with some distinct differences, particularly for middle- and high-income earners. Weekdays in 2021 and 2020 were nearly identical for middle- and high-income households, with an occupancy fraction of 0.53 and 0.55 midday, respectively. This changed from the pre-COVID period when these occupancy schedules were significantly different. In 2022, middle- and high-income household members were less likely to stay home during the day but were still much more similar in occupancy fraction compared to pre-COVID. High-income households saw a slightly larger drop in occupancy fraction (0.03) at midday. On weekends, all income groups have increasingly been away from home, particularly in 2022 compared to 2021 and 2020.

Low-income households have been the quickest to return to the pre-COVID period patterns for weekdays and weekends in 2022. However, middle- and high-income households have not yet returned to the pre-pandemic level for weekdays and weekends, especially on weekdays. This may be partly due to the higher likelihood that middle- and higher-income households have jobs that enable them to work at least partly from home. Also, important to note in terms of implications of such trends is the varied impact that participation in programs such as demand response using adjustments in setpoints could have on different income households (Wilson et al. 2019). While closer in occupancy schedule across income groups than pre-pandemic, lower-income households are still more likely to be at home than middle- and high-income groups, and thus may be potentially more impacted in terms of comfort from participation in demand response programs.

Variation in location within home

By using the recorded activities (used as TRCODE in ATUS) and the duration time, the daily home locations were assigned to the bedroom, bathroom, dining area (including kitchen), living room, office/study, garage, and "other" (all other locations). For example, sleeping was assigned to the bedroom, and work-related activities are associated with office/study. Please see (Mitra et al. 2021) for more details on this methodology. This was completed for all years of study and then compared to assess trends in time spent in different areas of the home across 2019-2022 (Figure 7). Note, in Figure 7, a positive number indicates an increase in hours spent in that particular home area compared to 2019; a negative indicates a decrease in hours spent in an area.

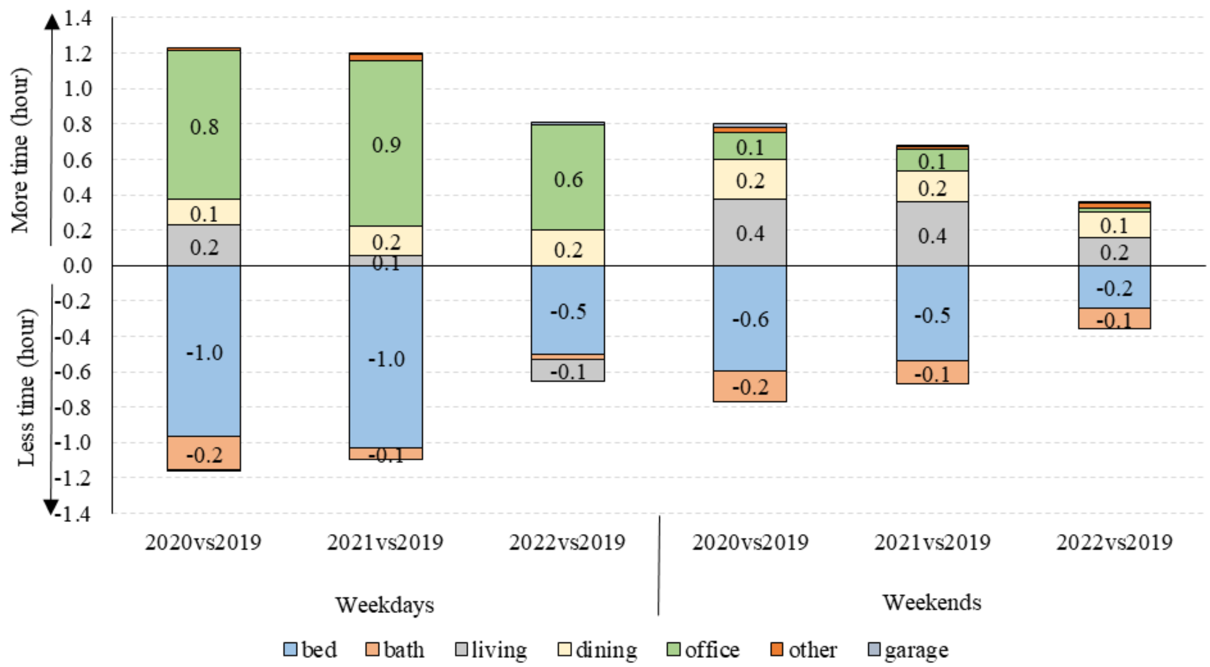


Figure 7. Hours spent at home based on locations for both weekdays and weekends compared to pre-pandemic (year 2019). *Note: a positive number means an increase in hours in a particular location compared to 2019; a negative number indicates a decrease in hours spent in a particular location.*

The greatest increases in locations spent compared to pre-COVID, across all years, is in the office/study (working from home, schoolwork, etc.) and dining area (cooking, eating, etc.) on both weekdays and weekends. The greatest decreases in time spent in various locations include a decrease in time spent in the bedroom (sleeping) and bathroom on both weekdays and weekends. Interestingly, these trends across categories remained similar on weekdays and weekends and across 2020, 2021, and 2022 compared to 2019. However, the amount of difference changes, particularly in 2022 compared to 2020 and 2021.

In particular, on weekdays, 2021 was similar to 2020 in time spent in the office/study and bedroom; however, in 2022, there was a 0.6-hour decrease in office/study time and a 0.5-hour increase in the bedroom (sleeping) time compared to 2021 and 2020. The notable shift that differentiates 2022 and the other years is the shift in living room use, where people spent 30 minutes less in 2022 compared to 2019 but 30 minutes more than in 2020 and 2021. For weekends, people spent 0.6 hours less in the bedroom (sleeping) in 2020 compared to 2019, then have steadily increased back to this time. They also spent 0.4 hours more hours in the living room in 2020 and 2021. By 2022, people stayed 0.4 hours more in the bedroom and 0.2 hours less in the living room compared to the hours in 2021. For the dining/kitchen area, there was an increase of 0.1 hours during 2020 and 0.2 hours for 2021 and 2022 on weekdays, 0.2 hours (2020 and 2021), and 0.1 hours (2022) on weekends.

Regarding implications from a building energy perspective, these trends provide some potential clues as to why residential building energy use changed since pre-pandemic. Due to the increased use of dining/kitchen areas, people will likely spend more time cooking using ranges/stoves and washing dishes using dishwashers. The 0.8-hour increase in the office/study area suggests longer use of laptops, desktops, and other plug-in electronics/appliances. The increased use of the living room could mean more use of electronics such as televisions, video games, cleaning, lighting, and other related activities. More time in the office/study area and the increased use of video and audio would lead to more plug load use and internal heat generation

(Pandey and Pal 2020). An increase in hours spent at home suggests a likely increase in heating and cooling energy needs and other factors that would benefit from further investigation. Findings from previous research also suggest this is likely to be the case (Kawka et al. 2021). Increased time at home could also be associated with less transportation energy use, as previously shown in Figure 1. As a result, it would be beneficial in future studies to analyze how the likely increase in energy use from home use may balance out decreased use from transportation to evaluate net energy use impacts. Conversely, the decrease in bathroom time compared to 2019 suggests less use of water heaters and other bathroom appliances.

Conclusions

This study examines the impact of the global pandemic due to COVID-19 in 2020, considering residential households' socioeconomic characteristics, using the ATUS data. The study evaluates the importance of 14 possible variables, such as age, race/ethnicity, employment status, and income levels, on the time spent at home across five years, from 2018 to 2022. The findings of this study are summarized as follows:

- The time spent in indoor spaces increased by 1.3% during the pandemic (95.3%), mainly shifting from the time spent in transit to another location. From 2021 to 2022, the 1% increase in the indoor portion gradually decreased by 0.3% each year and was added back to the time spent commuting to other locations.
- By 2022, the decrease in time spent at home dropped by approximately 40 minutes for both weekdays and weekends compared to 2020. However, neither had yet returned to pre-COVID levels compared to the average values from 2006 to 2019.
- Employment status (TELFS), income level (HEFMINC), and time of the week (WEEKEND) for weekdays and weekends were the most statistically significant

variables for total time spent at home across the five years studied. In 2020, employment status (TELFS), highest education received (TEEDUCA), and time of the week (WEEKEND) were most significant, while others were not as significant during the pre-COVID period. Age (TEAGE) and school/college or university enrollment level (TESHLVL) became less significant in 2020 and 2021, while race/ethnicity appeared to be becoming more important during and post-pandemic.

- Across different races/ethnicities on weekdays, those identifying as Hispanics were the quickest to return to the pre-COVID levels of home occupancy, while all the others have not yet returned to pre-COVID levels, especially those identifying as Asian (highest 19.3 hours). Those identifying as White most closely follow the overall trend for weekdays; those identifying as Black most closely follow the overall trends on weekends.
- The midday occupancy fraction increased by approximately 0.15 (weekdays) and 0.1 (weekends) in 2020 for those who were employed and 0.1 (on both weekdays and weekends) for those unemployed. In 2021, this trend was similar to 2020, but in 2022, the occupancy fraction decreased, particularly for those who were unemployed. This suggests that those employed continued to do some work from home in 2021 and 2022 but the unemployed individuals returned to pre-COVID occupancy patterns.
- In 2022, low-income households returned to nearly pre-COVID occupancy profiles for both weekdays and weekends. However, middle- and high-income households decreased in occupancy, did not return to pre-COVID levels, and have remained similar in occupancy profiles compared to pre-COVID, when their profiles were quite different.

- Across 2020, 2021, and 2022, people spent more in the office/study, living (2020 and 2021), and dining areas of their homes on weekdays but less time in the bedroom and bathroom. Similar trends were observed on weekends for these three years as compared to 2019.

In terms of future work, it is clear that for many household types and specific demographics, occupancy patterns are still changing in the wake of COVID. Occupancy patterns have not returned to pre-pandemic levels for many, and it is not clear if they will ever do so, or if they will level off and remain the same as the previous year in 2023 and moving forward. Therefore, continuous investigation is necessary to understand the still dynamic situation. Also, of importance to note is that this study focuses on the hours at home, but similar approaches could be applied to the commercial sector based on selected locations. Additionally, the hours spent at home and occupancy fraction are the metrics used in this study. However, other factors could also be considered in future analysis to determine the frequency of certain activities, such as working from home. The time could be more granular and not just for the average profile on weekdays or weekends but could also be considered individually across each day through the week.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

Date availability

Data will be made available on request.

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