

Exploring the effects of California's COVID-19 Shelter-in-Place order on household energy lifestyles and intention to adopt smart home technologies

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Abstract

To contain the spread of the novel coronavirus (COVID-19), local and state governments in the United States have imposed restrictions on daily life, resulting in dramatic changes in how and where people interact, travel, socialize, and work. In this research, we explore how California's Shelter-in-Place (SIP) order impacted household energy lifestyles. To do so, we conducted an online survey of California residents (n=804) during a time period of active SIP restrictions (May 5–18, 2020). We asked respondents about changes to home occupancy patterns and energy-related activities due to SIP restrictions, as well as perspectives toward smart energy technologies. Households reported increased midday (10am–3pm) occupancy during SIP, and this increase is related to respondent and household characteristics such as age, education, and presence of minors in the home. When examining change in the frequency of energy and non-energy related activities during SIP, presence of minors and increased midday occupancy is associated with changes in household activity frequency, such as increased cooking and use of electronics. Finally, we considered how changes in midday occupancy and activity frequency are related to intention to purchase smart home technologies. The presence of minors and an increased frequency of household activities are related to greater intention to purchase smart technologies. These findings demonstrate how activities and occupancy in households are changing under COVID-related restrictions, how these changes may be related to energy use in the home, and how such COVID-related changes could be shaping perspectives toward smart home technology. This research highlights the dramatic impacts that pandemic-related restrictions have already had on households and the potentially differential effects associated with household characteristics. It also provides insight into how COVID-related restrictions may impact household lifestyles and electricity demand across longer time horizons.

Keywords: COVID-19, coronavirus, Shelter in Place, Stay at Home, residential energy use, energy lifestyles, household activities, smart home technology

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1. Introduction

The 2019–2020 coronavirus disease outbreak (SARS-CoV-2), commonly referred to as coronavirus, COVID or COVID-19, has impacted global society at a scale and scope that is unparalleled in the post-World War II era. In the United States, the virus has already exacted a devastating human toll and is attributed to over 130,000 deaths as of July 2020 [1]. To protect populations from the spread of this highly virulent disease, many states, counties, and municipalities across the U.S. have responded with policies that restrict the movement and interaction of people that, in effect, are shared sacrifices that have led to lost jobs and closed businesses, disruptions to daily routines, and reduced social contact. While there has been substantial variation in when states and communities have imposed such COVID-related orders, the content of these orders, and what they are called (e.g., Shelter-in-Place, Stay at Home, Healthy at Home) [2], one common result for many areas across the U.S. is the increased confinement of people within homes and their respective localities. Compliance with these restrictions, as well as voluntary actions for protecting family members and the community, have resulted in substantial disruptions to the rhythms of daily life, altering everything from where people work, shop, eat, and travel, to how they educate children, care for the elderly, and socialize with family and friends. While there are many consequences to these disruptions (e.g., increased remote work and learning; reduced social interaction; economic losses; mental health impacts), one little explored area is how COVID-19 is changing interactions within home environments [3]. Everything from when, how, and who performs activities in the home (e.g., food preparation, office work, leisure/recreation) and the intensity, duration, or timing of activities are likely undergoing rapid changes. These changes to activity patterns, especially for activities that use devices or appliances, could be substantially altering energy usage patterns in the home.

At the same time, while the impacts are acute at the individual-level in many areas throughout the U.S., in the aggregate new research suggests that these restrictions are impacting energy production and consumption at world-scale [4]–[8], leading to a temporary decrease in global carbon emissions that is attributable to the pandemic [9]. Such findings suggest that opportunities may exist within this crisis for

helping ease the transition towards a cleaner, lower emissions energy future. Smart home technologies, or “devices that provide some degree of digitally connected, automated, or enhanced services to building occupants” (pg. 1), become particularly salient in this regard because these technologies are anticipated to play an important role in realizing this transition [10]. Yet, the use of these technologies is also reliant on household adoption [11], [12] and households are undergoing abrupt and potentially lasting changes to their in-home lifestyles. Such experiences could shape perspectives toward smart technologies in the home.

While there is substantial state-level variation in renewable energy production and policies intended to increase adoption of smart home technology and/or distributed energy resources (DER), California has been on the forefront of both. It leads the country in renewable energy generation and policies that promote building energy efficiency standards, many of which include integration of smart home technologies [13]. Additionally, California was the first state to impose COVID-19 home confinement restrictions through an executive order on March 19th, 2020. With this in mind, we use the California context to explore the potentially dramatic changes that COVID-related restrictions have had on household occupancy and energy activities, as well as perceptions toward smart home energy technologies.

California and COVID-19

Along with a handful of U.S. states taking similar action in early March 2020 to confront the threat of COVID-19, California’s governor, Gavin Newsom, declared a State of Emergency on March 4, 2020, following a rise in cases and California’s first official coronavirus death [14]. Early restrictions in the first two weeks of March included bans on gatherings of a certain size and some school closures [15], [16]. However, it was not until a rapid increase in COVID-19 cases in Santa Clara County that, on March 17, six San Francisco Bay Area counties (Alameda, Contra Costa, Marin, San Francisco, San Mateo, Santa Clara) and the City of Berkeley declared a Shelter-in-Place public health order, the first of its kind in the U.S. This order affected nearly 6.7 million California residents and required people to stay at home and only engage in essential activities and travel [17]. Additional counties followed suit, with the

Governor ultimately declaring a California-wide stay at home directive by Executive Order on March 19, effectively limiting all nonessential travel and activities with exemptions for operations and activities deemed critical [18]. The first stage of the order, active from March 19 – May 7, imposed the strictest restrictions on travel and activities. On May 8, some of these restrictions were eased for low-risk businesses that were able to follow social distancing guidelines [19]. Throughout this research, we refer to this collection of COVID-19 restrictions in California as Shelter-in-Place (SIP) orders¹.

SIP orders have mandated abrupt and substantial changes in where and how people interact – changes that may persist after restrictions lift. At aggregate scales, these mandated restrictions, as well as voluntary behavioral changes to limit the spread of COVID-19, can already be observed through changes in human mobility patterns and electricity consumption. California mobility trends related to retail, recreation and public transit have decreased by 40% or more, while residential mobility (i.e., people staying home) has increased by 12% [21]. Electricity usage at the grid level in California also experienced major changes with an estimated 8% decrease in electricity demand during April 2020, the height of active COVID-restrictions in the state [Manuscript in Preparation]. However, the link between these aggregate measures and effects observed at smaller scales, such as the individual- and household-level, is lacking. This is the gap our work is intended to fulfill: linking COVID-19 restrictions to occupancy, activity levels, and preferences for energy-related technologies.

1.1 Research Questions

By design, compliance with SIP orders should result in longer periods of time spent indoors and within households. Before SIP orders, work, school, and other routinized activities, as well as recreation, exercise, and leisure, often led people outside the home throughout the day, and during SIP orders patterns of household occupancy likely changed. Understanding changes in active occupancy is

¹ Throughout this research, we have made the decision to refer to California’s COVID-related restrictions as Shelter-in-Place (SIP) orders, as SIP orders were imposed before the statewide stay home order and are still active in many counties [20]. Furthermore, the term Shelter-in-Place was used by many media outlets during this time to refer to California’s COVID-related restrictions more generally.

particularly important in this regard as it not only reflects the changes that households are experiencing, but also can be used to help understand changes in residential energy consumption [22]. We therefore posit the following research question:

RQ1: How did SIP orders impact residential occupancy patterns?

Relatedly, many activities that may have typically occurred outside the home before COVID-19 (e.g., work, education, leisure, etc.) occurred within the home during SIP, with employees connecting remotely to their workplaces, school programs being taught online, and nightly entertainment in living rooms rather than movie theaters. While no literature exists on how these activities have been specifically impacted by COVID-19 and related restrictions in households, we know from previous studies that understanding the timing and pattern of these activities can be important predictors of health, energy and other sustainability-related outcomes [23], [24]. For example, instead of having many sources of food available that do not require preparation at home, households were likely more responsible for meeting nutritional requirements through food preparation and cooking at home during SIP. Additionally, many activities within the home can be related to energy consumption (e.g., electricity, natural gas, water, etc.), with some activities, such as those related to hot meals, found to be associated with higher electricity usage [22]. This has implications not only for how lifestyles have changed in the home due to changes in the intensity and frequency of activities, but for how households consume energy, depending on shifts in energy and/or non-energy using activities. We therefore offer the following research question:

RQ2: How did SIP orders alter residential energy and non-energy related activities?

Given some of the abrupt changes to daily lifestyles within home environments, people likely had new experiences that influenced perceptions around meeting needs using a variety of technologies within the home. Research has shown many reasons why households may be more likely, or less likely, to adopt certain smart home technologies [3], [11], [25]–[27]. They could be attuned to its benefits – e.g., energy savings, convenience and controllability, cost savings, and system benefits for the energy grid – but also concerned about its risk – e.g., privacy, security, technical reliability, and usability [10]. While much of this research considers the psychological and technical reasons for why households may be interested in

adopting smart home technologies, how perceived benefits and barriers to adoption may interact with a disruptive event like the COVID-19 pandemic and resultant restrictions have received little attention. However, one exception is a study that examined intention to adopt home energy management systems (HEMS) in New York, finding higher willingness-to-pay for groups of individuals with moderate perceived level of risk for COVID-19 infection [3]. Due to the importance of smart home technologies in addressing home efficiency and automation, especially in California where adoption of smart home technologies is already relatively high, as well as potentially changing perspectives about household lifestyles given new reliance on home environments to provide a variety of services and functions, we offer the following research question:

RQ3: How has SIP orders influenced intention to adopt smart home technologies?

Some households may have experienced more change under SIP orders compared to other household compositions. For example, exploration into how families with children have been uniquely impacted during this time is an on-going area of interest, especially considering that households with children are now required to provide a variety of child-related services during weekdays with the closure of many schools, daycares, camps, etc. Indeed, prior research has found that everything from residential building type, to characteristics of individuals within the household, to occupancy patterns can be related to electricity use in the home [28]–[32]. Additionally, recent work exploring consumer spending patterns in the early stages of the pandemic found that households with children tended to spend more, also suggesting potential heterogeneity in impacts of the pandemic [33]. Other work has found changes in self-reported energy use patterns during COVID-19, with higher than average electricity usage overall and a flattening of morning and evening peaks during weekdays [3]. Given that these are important considerations for the both public and policy makers alike, we offer the following question:

RQ4: How have household characteristics shaped occupancy, activities, and energy-technology preferences during SIP orders?

To address these research questions, we fielded an online survey to residents of California under active COVID-19 SIP orders. This approach is described in detail below.

2. Methods

2.1 Data Collection

To better understand the impacts of SIP orders on household occupancy, energy activities and smart home adoption, we created a survey instrument administered to a panel of online participants from California, recruited by the survey research firm Qualtrics, and fielded in the first half of May 2020 (May 5 – May 18). While not a probability-based sample, all invited survey participants were located within California and recruited to match California-wide demographic estimates of gender, age, and educational attainment in the American Community Survey (ACS, 5-year estimates, 2013-2018) [34]. In total, we received 804 completed surveys with respondents matching the ACS within one percentage point for the target categories of gender, age, and education (see Table 1). While we did not purposively match on respondents' household characteristics, we find that respondent households are similar to California ACS estimates. With respect to household income (*survey* median \$60,000 - \$69,999 vs. *ACS* median \$71,228), size of household (*survey* average 2.8 vs. *ACS* average 3.0), and households with minors (*survey* 28.6% vs. *ACS* 34.8%) our sample is below ACS estimates, while for single family housing (*survey* 64.7% vs. *ACS* 57.9%) and owner occupied housing (*survey* 56.1% vs. *ACS* 50.3%) our sample is above ACS estimates. For these household characteristics, differences between our survey respondents and California ACS population statistics do not exceed 7%².

² This does not include household income where we only have a category range for comparison.

Table 1: Comparison of survey respondent and household characteristics to American Community Survey estimates for California (5-year estimates, 2013-2018)

Measure	Survey Respondents	California ACS 2018 (5-year Estimates)
Gender	Male: 50.0% Female: 49.9% Other: 0.1%	Male: 49.7% Female: 50.3%
Age ¹	18-34: 31.8% 35-64: 50.4% 65 and over: 17.8%	18-34: 32.5% 35-64: 49.9% 65 and over: 17.7%
Education	High school or less: 37.8% Some college: 29.1% Bachelor's or higher: 33.1%	High school or less: 37.7% Some college: 29.1% Bachelor's or higher: 33.3%
Income	Median household income category: \$60,000 - \$69,999	Median household income: \$71,228
Average household size	2.85	3.0
Households with minors	Households with one or more people under 18 years old: 28.6%	Households with one or more people under 18 years old: 34.8%
Housing type	Single family home: 64.7%	Single unit detached: 57.9%
Owner occupied household	56.1% owner-occupied	50.3% owner-occupied

¹ California ACS 2018 estimates for age were adjusted for comparison to the survey sample which did not include participants under 18 years old.

2.2 Measures

Change in midday occupancy on weekdays due to COVID-related restrictions

To measure change in midday weekday occupancy during SIP orders, we first asked respondents “Before your household made any changes due to shelter-in-place orders related to COVID-19 (coronavirus) and excluding pets, how often is someone at home during the day (10am – 3pm) on weekdays (Monday – Friday)?” on a scale from 1=“Never” to 6=“5 days a week”, and then asked this same question with a modification to elicit midday occupancy during SIP (“Since your households made changes due to shelter-in-place...”). We then calculated the difference in midday occupancy before SIP (mean=3.611 days; sd=1.955) and during SIP (mean=4.284 days; sd=1.556) to generate a change in midday weekday occupancy metric (During SIP – Before SIP; mean=0.6729 days; sd=1.591). See Supplement Materials S1 for the distributional characteristics of this measure.

Change in household activities due to SIP orders

We next measured change in household activity frequency during SIP orders using the following question: “Since the shelter-in-place orders related to COVID-19 (coronavirus), are you and members of your household doing the following things more often, less often or about the same?” with response items “Eating together”, “Cooking with a stove top/range or oven”, “Running the dishwasher”, “Doing laundry using a washing machine or dryer”, “Using a computer, game console, tablet, or TV”, “Using electric heating when it’s cold or a fan/AC when it’s hot”, “Being physically active outdoors”, “Being physically active indoors on devices that use electricity”, “Communicating by phone or video”, and “Turning on lights”. Each of these items was situated on the following three-point scale: -1=“Less often”; 0=“About the same amount”; and 1=“More often”. We then use these items to create two additive measures of activity, one that includes change in the frequency of all household activities (mean=2.876; sd=3.395) and the other that includes the change in the frequency of all household *energy* activities (mean=2.678; sd=3.018).

Intention to purchase smart appliances and devices

The final measure that we considered was a respondent’s intention to purchase a smart appliance or device. We asked, “Which statement best describes your household’s intentions to purchase the following items?” with items “Solar panels that generate electricity”, “Smart thermostat (Nest, Ecobee, etc.)”, “Smart appliances (Samsung Family Hub refrigerator, Bosch Home Connect dishwasher, etc.)”, “Home Energy Monitoring System (HEMS) (Sense, CURB, etc.)”, “Home energy storage battery (Tesla Powerwall, etc.)”, “Smart light bulbs (Philips Hue, etc.)” and “Smart plug or power strip”. Response categories for these items were “We have already purchased”, “We intend to purchase in the next 12 months”, “We intend to purchase after 12 months”, “We have no intention to purchase”, and “This cannot be installed at our current home.” We recoded these categories to 0=“No intention to adopt” and 1=“Intention to adopt” and then formed a smart technology adoption measure by summing each of the

items and dividing by the total number of non-adopted items³. This gave us a measure with a value between 0 and 1 (mean=0.34; sd=0.29). See Supplement Materials S2-S3 for summary statistics and distribution of this smart adoption measure. We next applied these characteristics and measures in our analysis.

2.3 Analysis

To explore the relationships between respondent and household characteristics, smart device/appliance adoption, as well as change in midday occupancy and activity frequency during SIP orders, we apply ordinary least squares regression models. Our analytical sample for regression modeling is 746, with missing data⁴ deleted listwise. In our model specifications, we include household characteristics alongside respondent demographics. The reason for this is two-fold. First, we include the respondent characteristics of gender, age, and education because we used these categories for sample selection. Second, while these respondent characteristics do not necessarily describe complete household characteristics (only in the case of single occupant households or 19.4% of our sample), they do provide important insight into the characteristics of the household, such as educational achievement of a household member. In addition to survey respondent characteristics, we also include an indicator for whether minors are present in the home, the average household size during SIP, whether the home is owner occupied, the type of housing (single family vs. other), as well as household income. Using these baseline model specifications, we test whether household dynamics such as midday occupancy and activity frequency change due to SIP orders, as well as how these changes may be related to intentions to adopt smart technologies.

³ We combine “This cannot be installed at our current home” with “We have no intention to purchase” for two reasons. First, some participants may not make the distinction between “no intention to purchase” and “cannot be installed” because the reason they do not intend to purchase could be because it cannot be installed in their home. Second, we included “single family home” and “owner occupied home” in our modeling, and both of these household characteristics are related to the feasibility of installing some of these smart appliances/devices.

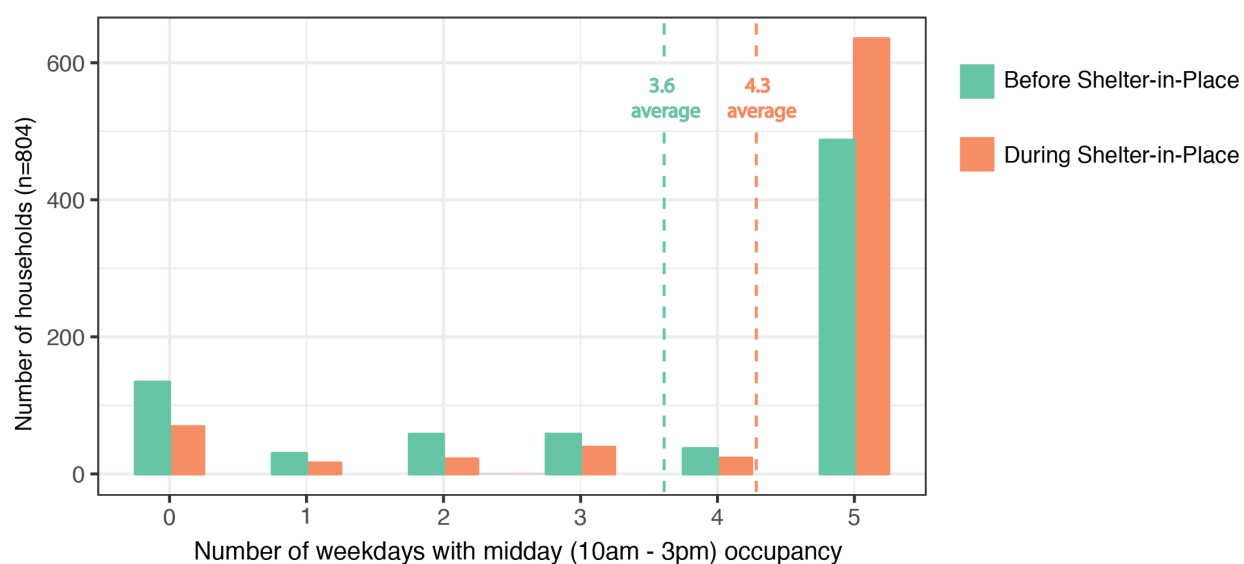
⁴ The main source of missing data was respondents who do not wish to share their household income data.

3. Results

3.1 Change in occupancy related to COVID-19 SIP orders

We first consider the change in the number of weekdays that are occupied during midday (10am – 3pm) during SIP orders. Comparing midday occupancy before SIP and during SIP, there is an increase in occupancy of approximately 0.67 days (Figure 1; $p<0.001$). While a majority of participants did not change midday occupancy (74.2%), the next most frequent category is 5 (7.7%) or a shift from no midday occupancy on weekdays before SIP to midday occupancy on every weekday during SIP (Supplemental Materials S1).

Figure 1: Reported number of weekdays that the household was occupied from 10am – 3pm, before and during SIP orders.



We next explore which households experienced the most change in midday occupancy based on both the characteristics of the survey respondent and characteristics of the household. In our baseline model, we consider how respondent and household characteristics are related to change in midday occupancy (10am – 3pm). We find that increased midday occupancy is associated with respondents who hold a bachelor's degree or higher ($\beta=0.454$; $p<0.001$) and households with higher income ($\beta=0.558$; $p<0.001$), while lower change in midday occupancy is associated with younger respondents ($\beta=-0.342$;

$p<0.001$), living in a single family home ($\beta=-0.287$; $p<0.05$), and smaller households sizes ($\beta=-0.28$; $p<0.05$) (Model A1) . Next we consider how the presence of minors (persons under 18 years old) in the home influences the change in midday occupancy (Model A2) and find that minors are associated with an average increase in midday occupancy of approximately half a day ($\beta=0.445$; $p<0.01$).

Table 2: OLS regression models predicting change in midday weekday occupancy

	Change in midday weekday occupancy	
	Model A1	Model A2
	Std. beta	Std. beta
Respondent characteristics		
Female (vs. male)	0.103	0.105
Age (categories)	-0.342**	-0.341**
Bachelor's or higher (vs. less than Bachelor's degree)	0.454**	0.457**
Household characteristics		
Household income	0.558***	0.524***
Single family home	-0.287*	-0.294*
Owner occupied home	-0.114	-0.088
Household size	-0.28*	-0.516**
Minors present (younger than 18 years old)		0.445**
Intercept (unstandardized)	0.982**	1.092***
R-square	0.085	0.095
N	747	747

Significance level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

3.2 Change in activity frequency due to COVID-19 SIP orders

We next explore the change in frequency of activities during SIP orders (Figure 2). For all activities (Figure 2), respondents reported a change that was statistically different from zero ($p<0.05$), with all activities except for “Being physically active outdoors” occurring more often during SIP. The activities with the highest magnitude of change (over half of respondents reported them occurring more frequently under SIP) are “Using a computer, game console, tablet, or TV”, “Cooking with a stove top/range or over”, and “Communicating by phone or video.” Next, we consider the differential impact

that having minors in the home has in reported changes in activities during SIP orders (Figure 3). We find that for almost all included activities (except “Using electric heating when it’s cold or fan/AC when it’s hot” and “Being physically active outdoors”) there are higher activity reports for households with minors and this difference is statistically significant ($p<0.05$).

Figure 2: Reported change in activities during SIP orders. Points represent means, lines 95% confidence intervals for a one sample t-test. All activity changes are statistically different from zero.

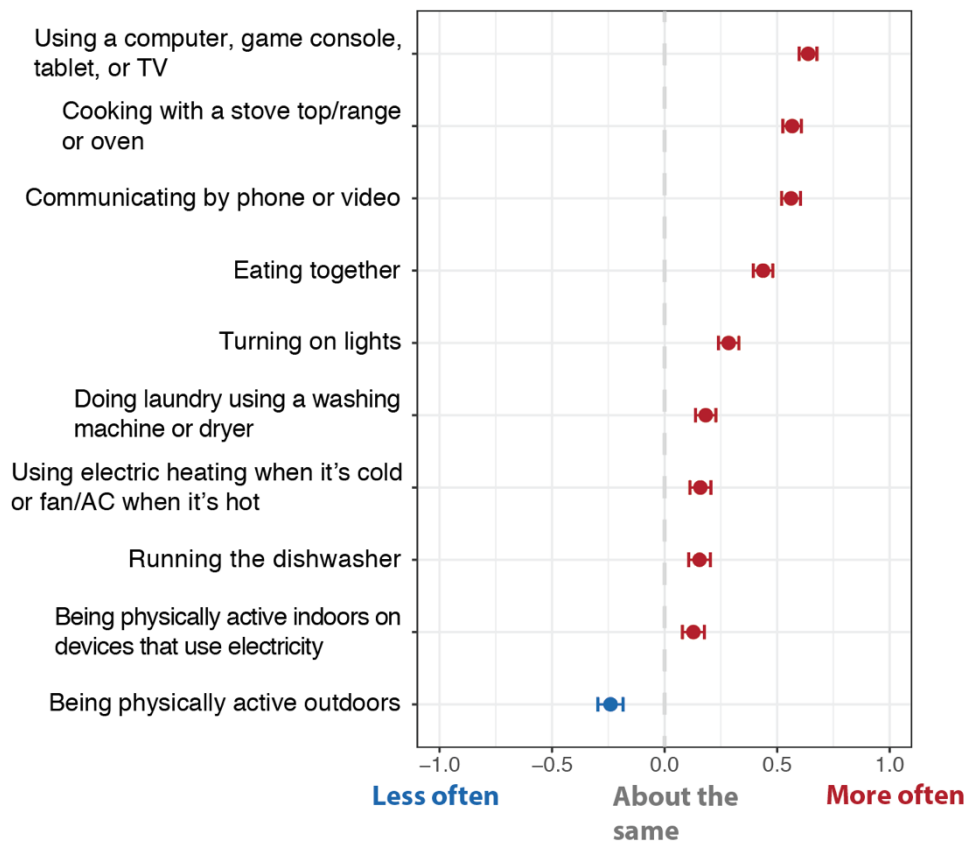
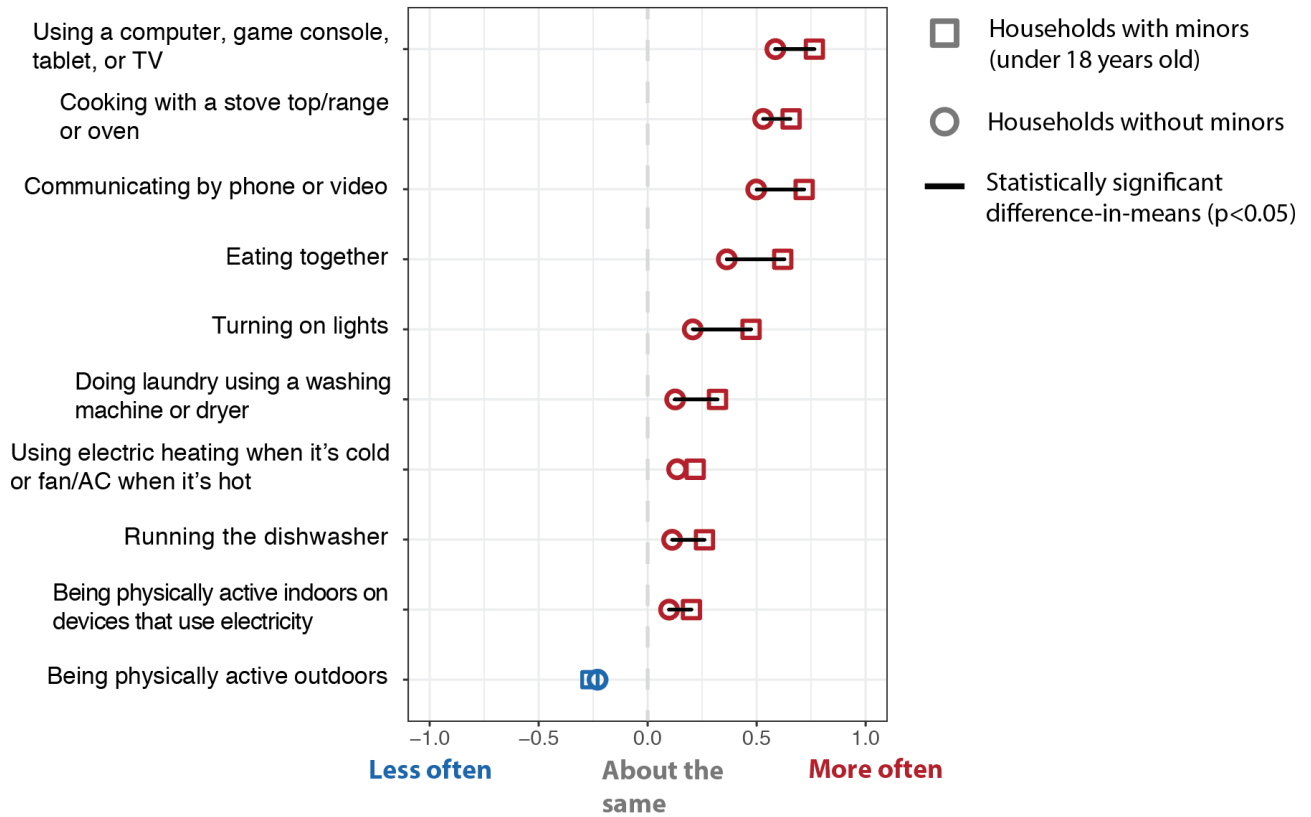


Figure 3: Reported change in activities during SIP orders for households with minors and households without minors. Shapes represent means, and a dark line indicates that the difference-in-means between the two household groups is statistically significant ($p < 0.05$).



We now consider the relationship between respondent and household characteristics and change in the frequency of these activities during SIP orders. In the first set of models (Model B1 and B2) we apply only the activities that are related to household energy use, excluding “Being physically active outdoors” and “Eating together.” In the next set of models (Model B3 and B4) we consider all of the activities listed in Figures 2 and 3. In Model B1, we find that female respondents (vs. male) ($\beta = 0.581$; $p < 0.01$), younger respondents ($\beta = -1.42$; $p < 0.001$), households with higher income ($\beta = 0.891$; $p < 0.001$), and households with minors ($\beta = 0.737$; $p < 0.05$) are all associated with increases in energy-related activity frequency during SIP orders. We also find that the sign and magnitude of these estimates are consistent for all activity frequency models (Models B1-B4). We next consider the role that change in midday occupancy has in increased reported activities. We find that households who report increased occupancy

during midday on weekends are also associated with increased frequency in activities ($\beta=0.875$; $p<0.001$), which holds for both energy-related activities and all activity dependent variables (Models B2 and B4).

Table 3: OLS regression models predicting change in the frequency of energy-related activities and change in the frequency of all included activities.

	Change in frequency of energy-related activities		Change in frequency of all activities	
	Model B1	Model B2	Model B3	Model B4
	Std. beta	Std. beta	Std. beta	Std. beta
Respondent characteristics				
Female (vs. male)	0.581**	0.553**	0.638**	0.607**
Age (categories)	-1.42***	-1.327***	-1.694***	-1.592***
Bachelor's or higher (vs. less than Bachelor's degree)	0.568*	0.444	0.751**	0.614*
Household characteristics				
Household income	0.891***	0.75**	1.078***	0.921**
Single family home	0.082	0.161	0.33	0.418
Owner occupied household	-0.099	-0.075	-0.138	-0.112
Household size	0.206	0.346	0.231	0.385
Minors present (younger than 18 years old)	0.737*	0.617*	0.888**	0.754*
Midday occupancy change (weekdays)		0.875***		0.968***
Intercept (unstandardized)	3.357***	3.062***	3.597***	3.271***
R-square	0.138	0.157	0.156	0.175
N	747	747	747	747

Significance level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

3.3 Relationship between COVID-19 SIP orders and intention to adopt smart home technologies

Lastly, we investigate the impact of change in occupancy and activity measures during SIP, as well as respondent and household characteristics, have on intention to adopt smart technologies. In our baseline model specification we find that respondents who are younger ($\beta=-0.109$; $p<0.001$) and male (vs. female) ($\beta=-0.049$; $p<0.05$), and are in households with higher income ($\beta=0.062$; $p<0.05$) and have minors present in the home ($\beta=0.089$; $p<0.01$), have more intention to purchase smart technology (Model

C1). When change in midday occupancy during SIP is added to this model specification (Model C2), we do not observe statistically significant effects. However, when we examine the relationship between intention to purchase smart technology and change in frequency of energy activities during SIP (Model C3), those who reported higher changes in activity frequency ($\beta=0.085$; $p<0.001$) are associated with greater intention to adopt smart technologies, and this is at a magnitude that is similar to age (the highest magnitude characteristic in Model C1 and C2). We find even stronger effects when we apply the activity frequency measure that includes all activities ($\beta=0.096$; $p<0.001$; Model C4).

Table 4: OLS regression models predicting intention to purchase smart appliances.

	Share of smart technology intention to purchase			
	Model C1	Model C2	Model C3	Model C4
	Std. beta	Std. beta	Std. beta	Std. beta
Respondent characteristics				
Female (vs. male)	-0.049*	-0.050*	-0.058**	-0.058**
Age (categories)	-0.109***	-0.107***	-0.088***	-0.084***
Bachelor's or higher (vs. less than Bachelor's degree)	0.009	0.006	-0.000	-0.002
Household characteristics				
Household income	0.062*	0.059*	0.048*	0.046
Single family home	-0.002	0.000	-0.002	-0.006
Owner occupied household	0.004	0.005	0.006	0.007
Household size	-0.017	-0.014	-0.019	-0.019
Minors present (younger than 18 years old)	0.089**	0.086**	0.077**	0.075**
Midday occupancy change (weekdays) during SIP		0.019	0.006	0.005
Change in frequency of energy-related activities during SIP			0.085***	
Change in frequency of all activities SIP				0.096***
Intercept (unstandardized)	0.479***	0.473***	0.429***	0.426***
R-square	0.080	0.081	0.100	0.104
N	746	746	746	746

Significance level: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

4. Discussion

Regarding changes to occupancy patterns during SIP orders (RQ1), we find broad evidence that Californians in our sample spent more time at home during the middle of the day (10am – 3pm) under SIP with average midday occupancy increasing by approximately half a day per five-day week (Monday-Friday). It is important to note that reported midday occupancy was already high before SIP (on average, 3.6 days per week), so there was not much room for additional increases in occupancy during SIP orders. The negative relationship between household size and midday occupancy suggests as much, where households that are larger are associated with less change in midday occupancy during SIP. However, we see an opposing effect with households where minors are present, reflecting how patterns of school-aged children have changed from being away at school to being home in the middle of the day. Such a finding suggests that households with minors experienced changes in household lifestyles during SIP in a way that distinguishes them from other household compositions.

When examining changes in the frequency of household activities during SIP (RQ2), we find evidence that there is, on average, an increase in the frequency of reported activities, particularly for those that use devices with a screen/display or are food related. Moreover, all activities that we asked about that were energy activity-related increased. And, while energy activities were the focus of this survey, non-energy related activities such as eating together increased in frequency while being physically active outdoors decreased. When we compare differences between households with minors to those without, we again find results reinforcing that families with minors may experience SIP orders differently. For example, reported activity frequency is higher for households with minors for all activities apart from heating/cooling and exercising outside. In regression modeling we find that the presence of minors is associated with an increase in reported activities, with other respondent characteristics such as those who are younger, have a bachelor's degree or higher, have higher incomes, and female all associated with increased activity frequencies. This last finding related to gender echoes media coverage of the differential impacts of SIP orders on household members – with women and particularly mothers viewed as taking on most of the increase in domestic and child care responsibilities during COVID-related

restrictions (many of which involve energy use) [35]. Additionally, when we include midday occupancy change during SIP in our model specification, it also has an impact on the frequency of activities during SIP. Such a result is consistent with our expectations: households that reported more midday occupancy also reported higher activity frequency.

We now explore how SIP orders may reach beyond activities and occupancy through its role in potentially shaping preferences and perceptions toward smart home technology (RQ3). When we examine factors associated with the intention to adopt smart home technology, we find – consistent with the existing literature on smart home technologies [36] – that men, younger respondents, and higher income households have greater intentions to adopt. We also find that households with minors have higher intentions to purchase smart home technology. Additionally, while change in occupancy is not associated with intention to purchase smart technology, both reports of increased *energy-using activities* and *all energy and non-energy activities* are associated with greater intention to purchase such technologies. This suggests that, while individual and household characteristics undoubtedly have an impact on the intention to adopt smart technology as shown in previous research [36], higher levels of reported activity frequency during SIP are also important. There are a few potential reasons why we would find this effect. First, households that are reporting more frequent household activities due to SIP may be looking for ways to improve their lives through some of the automated features that smart devices provide. Additionally, nearly all of these devices are associated with energy savings or efficiency, and some households could be looking toward these technologies to save money. Yet another reason is that as people are at home and interacting with devices more frequently, there could be more motivation to improve the home environment, and some of these improvements may include integrating smart technologies.

In the final research question, we explored how differences in household characteristics may be related to behavioral and attitudinal responses during SIP orders (RQ4). Here, we found that household composition, as well as demographics, matter. Additionally, there has been much focus in the media around how households with minors have had challenges in adapting to SIP orders, with adults in the household taking on new roles such as educators and childcare providers [37]. We see evidence that

households with minors are experiencing SIP orders differently, even after controlling for other household and individual characteristics. These experiences for households with minors were associated with greater home occupancy during midday and more frequent energy-using activities. Such patterns suggest that, overall, families with children may be facing potentially larger electricity bills and more time constraints, two reasons why respondents from these households may have higher intentions to adopt smart technology. However, acquiring these technologies can be expensive, perhaps prohibitively so for families on tight budgets or facing new income insecurity due to the impacts of COVID-19, and some of these barriers may be reflected in our findings that higher income households are associated with greater intention to adopt smart technologies (and vice versa). We also see some changes in family lifestyles during SIP orders that are associated with healthier lifestyles, particularly so for those who live with minors, such as respondents reporting prepping meals at home and eating meals together more often [38]. At the same time, other reported activity frequency changes are less healthy – e.g., reduced outdoor exercise and increased screen time [39], [40].

These findings support the preponderance of media reporting that society is undergoing substantial changes due to COVID-related restrictions. Our research considers a two-week window in May 2020, during which there were indications that some California SIP restrictions would be lifted in the near future. It is difficult to know if we had polled respondents earlier, perhaps a week after the first statewide order, whether our results would have been different. When we had conducted our poll, SIP orders had been in place for over a month. By this time, we expect some households were following a more regular daily routine and becoming more cognizant of the activities they performed in their home. At the same time, polling directly after SIP in late March could have better captured changes in household lifestyles compared to before SIP orders, and, because of this, the immediacy and disruption of this event may have led our respondents to report even higher levels of perceived change. While it is difficult to unpack these specific dynamics, we believe that the timing of our survey struck an appropriate balance between when the SIP order was first imposed and the length of time the population was under this order.

Another challenge to conducting research about households is that it is individuals within these households that are sampled. To some extent we helped account for this by including the demographic characteristics we used for sampling in all our modeling specifications. However, unless the respondent is from a single occupant household, it will always be challenging to make claims about households using survey respondents. Given the composition of our sample and its similarity to the California population, and the obvious challenges of conducting a probability / address-based mail survey during active SIP orders, we feel that this online survey convenience sample approach, matched to California demographics, was one of the best options among the limited options available to us at the time of the survey.

From a policy perspective, these changes in activity and occupancy during SIP orders suggest that households are likely demanding more energy, and particularly electricity, and at different times of day compared to before SIP orders were enacted. These increases in electricity demand may impact households differentially, with families with minors facing increased energy bills and possible energy insecurity, which may be exacerbated if increases in electricity use correspond to times of day when electricity rates are higher (e.g., time of use pricing) and economic prospects remain uncertain [41]. On the other hand, we find evidence that these SIP orders may also be influencing perspectives toward intention to purchase smart home technologies for many of the same household characteristics that are differentially impacted. In this sense, SIP orders could serve as a focusing event that places new emphasis and attention on the relationship between household activities and energy use and helps people realize the importance of smart home technologies—for those that can afford them—in a transition toward a greener and cleaner grid.

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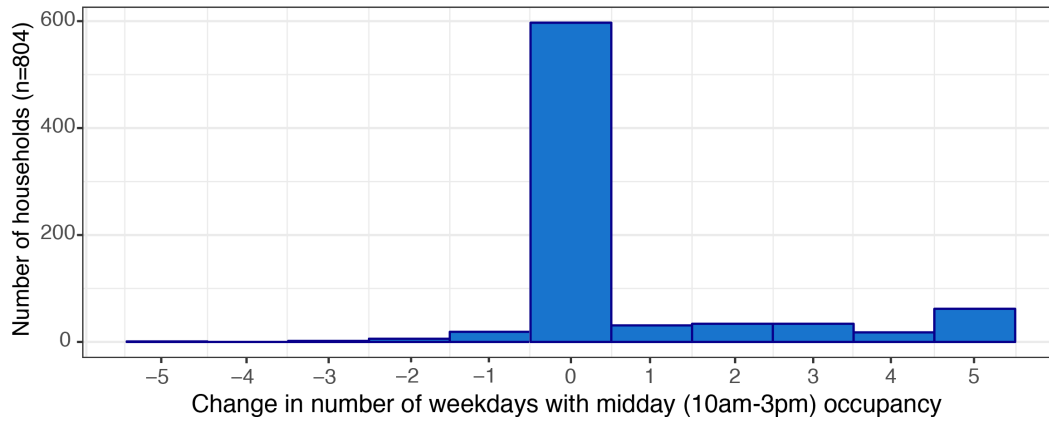
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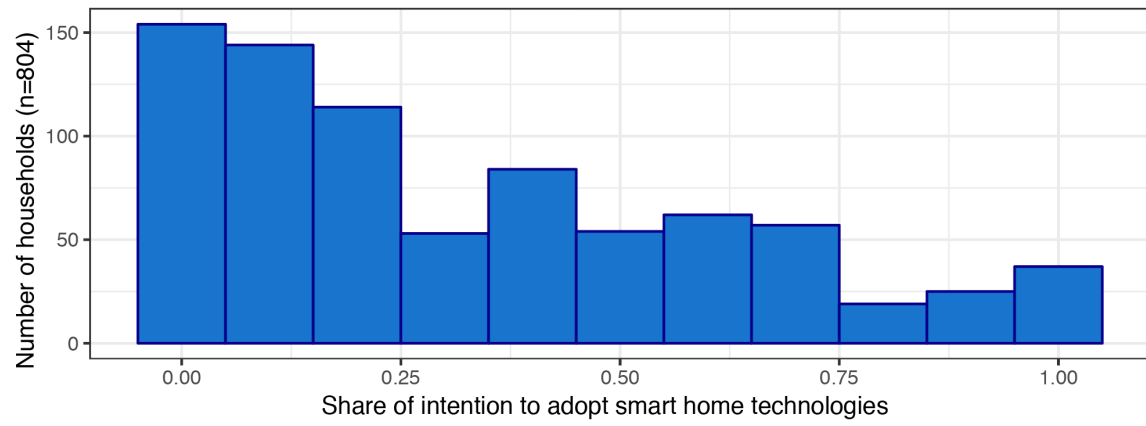
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Supplemental Materials

S1. Figure: Distribution of change in midday (10am-3pm) occupancy on weekdays (during SIP – before SIP). Positive values indicate an increase in midday occupancy days related to SIP orders, negative values indicate a decrease in midday occupancy days related to SIP orders.



S2. Figure: Distribution of intention to adopt metric for all respondents (n=804) where 0 indicates no intention to purchase and 1 indicates an intention to purchase all appliances/devices.



S3. Table: Intention to adopt smart home technologies. Table includes smart home technology items and percentage of respondents' intention to purchase.

Smart home technologies	Intend to purchase (%)	Do not intend to purchase (%)	Already Purchased (%)	Cannot be installed in current home (%)
Solar panels that generate electricity	19.7	36.1	11.6	32.6
Plug-in electric vehicle	20.7	56.8	4.1	18.4
Smart Thermostat (Nest, Ecobee, etc.)	26.6	43.7	13.9	15.8
Smart light bulbs (Philips Hue, etc.)	30.5	33.8	29.1	6.6
Smart Appliances (Samsung Family Hub refrigerator, Bosch Home Connect dishwasher, etc.)	28.5	47.8	10.9	12.8
Smart plug or power strip	30.5	37.8	25	6.7
Home Energy Monitoring Systems (HEMS) (Sense, CURB, etc.)	21.2	59.1	3.9	15.8
Home energy storage battery (Tesla Powerwall, etc.)	18.8	61.3	3.6	16.3