Exploring the effects of California's COVID-19 shelter-in-place order on household energy practices 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 U.S. have imposed restrictions on daily life, resulting in dramatic changes to how and where people interact, travel, socialize, and work. Using a social practice perspective, we explore how California's Shelter-in-Place (SIP) order impacted household energy activities. To do so, we conducted an online survey of California residents (n = 804) during active SIP restrictions (May 5–18, 2020). We asked respondents about changes to home occupancy patterns and household energy activities (e.g., cooking, electronics usage) 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 education and the presence of minors in the home. Examining change in the frequency of household activities during SIP, presence of minors and increased midday occupancy proved important. Finally, we considered relationships to intention to purchase smart home technologies, with the presence of minors and increased activity frequency relating to greater intention to purchase. These findings demonstrate how household activities and occupancy changed under COVID 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, potentially providing insight into future impacts on household practices and electricity demand.

1. Introduction

The 2019 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 exacted a devastating human toll, with over 230,000 deaths attributable to the disease as of November 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 human movement and interaction. Such restrictions have led to lost jobs and closed businesses, disruptions to daily routines, and reduced social contact. Substantial variation exists in when states and communities imposed such COVID-related orders, the content of these orders, the duration of the orders, and what they are called (e.g., Shelter-in-Place, Stay at Home, Healthy at Home) [2]. Yet, one common result of the pandemic is the increased confinement of people within their respective localities. These restrictions—even as they are loosened or tightened—as well as voluntary actions people have

taken to protect 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; financial loss; mental health impacts), one little explored area is how COVID-19 is changing everyday routines and practices within the home environment [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, potentially in ways that may persist even after the health crisis subsides.

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1.1. A social practice perspective on household energy use

Social scientists have long recognized that energy is used to fulfill specific household needs, e.g., for cleanliness, comfort, nourishment, entertainment, etc. [4,5]. The pandemic and associated restrictions are changing when, where, and how these needs are fulfilled – upending routines and concentrating many activities in the home. Social practice theory—which considers practices as the primary unit of analysis [6]— has become more and more commonplace in studies of household energy use [7–9]. A practice is defined as "a routinized type of behavior" (p. 249) [6] and consists of four main elements: "*common understandings* about what the practice means and how it is valued, *rules* about what procedures and protocols must be followed and adhered to, *practical knowledge* about how to carry out and perform a practice, and *material infrastructure*—or the 'stuff' that makes the practice possible, sensible and desirable" (p. 228) [10].

Typically, studies of how energy practices evolve and change over time have focused on longer time horizons (e.g., the widespread adoption of air conditioning) [4,10,11]. A noted exception has been studies of the effect of blackouts, fuel crises and more predictable disruptions like variable electricity pricing on everyday practices and routines. We explore how practices may have changed in a relatively short period of time in relation to a non-energy-related crisis: the COVID-19 pandemic and associated government restrictions. Past studies of energy-related disruptions on household energy practices have revealed, "the temporal fragility of habits and the elasticity of everyday life" (p. 68) [12], as people demonstrate their ingenuity and skill in restructuring and innovating daily routines [10]. What changes in routines and practices are households making in response to COVID-19 and associated government restrictions? Are particular types of households more or less affected? A social practice perspective allows us to focus on how the conventions and routines that comprise total energy consumption may be shifting rapidly in these unprecedented times.

New research suggests that COVID-19 and associated government restrictions are impacting energy production and consumption at a global scale [13–17], leading to a temporary decrease in global carbon emissions that is attributable to the pandemic [18]. 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" (p. 1), become particularly salient in this regard because these technologies are anticipated to play an important role in realizing this transition [19]. From a social practice perspective, smart home technologies affect the material infrastructure of practices. They can quantify and provide feedback, as well as automate and possibly enhance practices. At the same time, they can also be sources of frustration when too complicated or unreliable (and can be disruptive in their own right) [20]. Critically for our study, the use of these technologies is reliant on household adoption [21,22]. As a result of COVID-19, many households are undergoing abrupt and potentially lasting changes to their in-home lifestyles. Such experiences could shape perspectives toward smart technologies in the home.

1.2. The California context

California provides a unique setting for our study. While there is substantial state-level variation in renewable energy production and policies intended to increase adoption of smart home technology and 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 [23]. Additionally, California was the first state to impose COVID-19 home confinement restrictions. 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. In this research, we focus on the early stages of California's pandemic response, spanning from March to May 2020.

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 [24]. Early restrictions in the first two weeks of March included bans on gatherings of a certain size and some school closures [25,26]. 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 [27]. 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 [28]. 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 [29]. Throughout this research, we refer to this collection of COVID-19 restrictions in California during the March–May 2020 period of the pandemic response as Shelter-in-Place (SIP) orders.[1]

The first stage of the SIP orders mandated abrupt and substantial changes in where and how people interacted – changes that may persist after the pandemic has ended. At aggregate scales, these mandated restrictions, as well as voluntary behavioral changes to limit the spread of COVID-19, have already been observed through changes in human mobility patterns (e.g., travel to and from common destinations, such as home, work, retail shopping, etc.) and electricity consumption. California mobility trends related to retail, recreation and public transit decreased by 40% or more during SIP orders, while movement within residential environments (i.e., people staying home) increased by 12% [31]. 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 [32]. 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.

1.3. Research questions

By design, compliance with SIP orders should result in longer periods of time spent indoors at home. 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 particularly important in this regard as it not only reflects the changes that households are experiencing but also is consistently linked to residential energy consumption [33]. We therefore posit the following research question:

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[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 [30]. 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.

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. 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 [9,34]. For example, eating meals at home is likely more frequent during SIP, which could lead to increased food preparation and cooking activities within the household or more use of food delivery services and takeout. We also know that many activities within the home can be related to energy consumption, for example, cooking hot meals has been found to be associated with higher electricity usage [33]. 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. 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]. 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 due to SIP orders, people likely had new experiences that influenced their perceptions about how to meet new and changing needs through technology. Research has shown many reasons why households may be more or less likely to adopt certain smart home technologies [3, 21], [35–37.] 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 [19]. Much of this research considers the psychological and technical reasons for adoption. Yet, 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. 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 a moderate perceived level of risk for COVID-19 infection [3]. We thus offer the following research question:

RQ3. *How did SIP orders influence intention to adopt smart home technologies?*

Some households may have experienced more change under SIP orders than others. For example, families with children are now required to provide a variety of child-related services during weekdays at home due to the closure of many schools, daycares, camps, etc. 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 [38]. Prior research has also 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 [39–43]. Given that these are important considerations for both the public and policy makers alike, we offer the following question:

RQ4. *How did household characteristics shape 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 intention, we created a survey instrument administered to a panel of online participants from California. Participants were recruited by the survey research firm Qualtrics, and the survey was fielded from May 5 – May 18, 2020. 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) [44]. In total, we received 804 completed surveys. Respondents matched the ACS estimates 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, respondent households were 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 was below ACS estimates. For single-family housing (*survey* 64.7% vs. *ACS* 57.9%) and owner-occupied housing (*survey* 56.1% vs. *ACS* 50.3%), our sample was above ACS estimates. For these household characteristics, differences between our survey respondents and California ACS population statistics did not exceed 7%.[2]

2.2. Measures

2.2.1. 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 –

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[a]	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

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

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

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 household 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 Appendix A.1 Figure A.1 for the distributional characteristics of this measure.

2.2.2. 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?". Response items included: "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: (1) change in the frequency of all household activities (mean = 2.876; sd = 3.395) and (2) change in the frequency of all household *energy* activities (mean = 2.678; sd = 3.018).

2.2.3. 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?". Response items included: "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", excluding items that had already been adopted. We then formed a smart technology adoption measure by summing each of the recoded items and dividing by the total number of non-adopted items.[3] This smart adoption measure ranged from 0 to 1 (mean = 0.34; sd = 0.29). See Appendix A.2-A.3 Figure A.2, Table A.3 for summary statistics and distribution.

2.3. Analysis

To explore the relationships between respondent and household characteristics, smart device/appliance adoption, 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 data[4] 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 (except 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), and household income. Using these baseline model specifications, we test whether household dynamics, such as changes to midday occupancy and activity frequency due to SIP orders, may be related to intentions to adopt smart technologies.

3. Results

3.1. Change in occupancy related to COVID-19 SIP orders

Comparing midday occupancy before SIP and during SIP on weekdays, we find an increase in occupancy of approximately 0.67 days (Fig. 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 (Appendix A.1, Figure A.1).

We next explore which households experienced the most change in midday (Table 2). We find that increased midday occupancy is associated with respondents who hold a bachelor's degree or higher ($\beta = 0.454; p < 0.01$) and households with higher income ($\beta = 0.558; p < 0.001$). In contrast, lower change in midday occupancy is associated with younger respondents ($\beta = -0.342; p < 0.01$), living in a single family home ($\beta = -0.287; p < 0.05$), and smaller households sizes ($\beta = -0.28; p < 0.05$) (Table 2: Model A1). Next we consider how the presence of minors (persons under 18 years old) in the home, many of whom may have typically been at school or childcare during weekdays before SIP, influences changes in midday occupancy (Table 2: Model A2). We find that minors are associated with an average increase in midday occupancy of approximately half a day ($\beta = 0.445; p < 0.01$). The inclusion of this variable does not substantially alter the sign or magnitude of other respondent or household characteristics (compared to Model A1).

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

For all household activities (Fig. 2), respondents reported a change in activity frequency 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 oven", 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 (Fig. 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"), reported changes in activity frequencies for households with minors are significantly higher than those without ($p < 0.05$).

We now consider how respondent and household characteristics

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[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.

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[4] The main source of missing data was respondents who do not wish to share their household income.
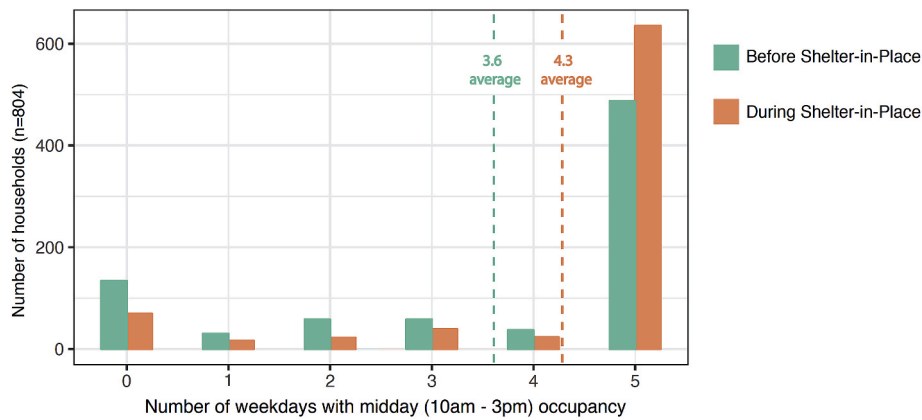
Fig. 1. Reported number of weekdays that the household was occupied from 10am to 3pm, before and during SIP orders.

Table 2
Odinary least squares regression models predicting change in midday weekday occupancy.

	Change in midday weekday occupancy	
	Model A1	Model A2
	Std. beta (p-value)	Std. beta (p-value)
Respondent characteristics		
Female (vs. male)	0.103 (0.376)	0.105 (0.364)
Age (categories)	−0.342** (0.007)	−0.341** (0.007)
Bachelor's or higher (vs. less than bachelor's degree)	0.454** (0.001)	0.457** (0.001)
Household characteristics		
Household income	0.558*** (<0.001)	0.524*** (<0.001)
Single family home	−0.287* (0.020)	−0.294* (0.017)
Owner occupied home	−0.114 (0.392)	−0.088 (0.505)
Household size	−0.28* (0.029)	−0.516** (0.001)
Minors present (younger than 18 years old)		0.445** (0.004)
Intercept (unstandardized)	0.982** (0.001)	1.092*** (<0.001)
R-squared	0.085	0.095
N	747	747

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

Table 3
Ordinary least squares 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 (p-value)	Std. beta (p-value)	Std. beta (p-value)	Std. beta (p-value)
Respondent characteristics				
Female (vs. male)	0.581** (0.006)	0.553** (0.008)	0.638** (0.006)	0.607** (0.009)
Age (categories)	−1.420*** (<0.001)	−1.327*** (<0.001)	−1.694*** (<0.001)	−1.592*** (<0.001)
Bachelor's or higher (vs. less than bachelor's degree)	0.568* (0.018)	0.444 (0.064)	0.751** (0.005)	0.614* (0.021)
Household characteristics				
Household income	0.891*** (<0.001)	0.75** (0.002)	1.078*** (<0.001)	0.921** (0.001)
Single family home	0.082 (0.715)	0.161 (0.469)	0.33 (0.184)	0.418 (0.091)
Owner occupied household	−0.099 (0.681)	−0.075 (0.753)	−0.138 (0.607)	−0.112 (0.674)
Household size	0.206 (0.455)	0.346 (0.209)	0.231 (0.451)	0.385 (0.208)
Minors present (younger than 18 years old)	0.737* (0.010)	0.617* (0.029)	0.888** (0.005)	0.754* (0.016)
Midday occupancy change (weekdays)		0.875*** (<0.001)		0.968*** (<0.001)
Intercept (unstandardized)	3.357*** (<0.001)	3.062*** (<0.001)	3.597*** (<0.001)	3.271*** (<0.001)
R-squared	0.138	0.157	0.156	0.175
N	747	747	747	747

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

shape change in the frequency of these activities during SIP orders (Table 3). In the first set of models (Table 3: Models B1 and B2), we only include activities related to household energy use, excluding "Being physically active outdoors" and "Eating together." In the next set of models (Table 3: Models B3 and B4), we consider all activities. In Model B1, we find that respondents who are female (vs. male) ($\beta = 0.581$; $p < 0.01$), younger ($\beta = -1.42$; $p < 0.001$), in higher income households ($\beta = 0.891$; $p < 0.001$) and households with minors ($\beta = 0.737$; $p < 0.05$) report 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 (Table 3: Models B1–B4). We next consider the role that change in midday occupancy plays in reported activities. We find that households who report increased midday occupancy on weekdays also reported increases in the frequency of both energy-related activities ($\beta = 0.875$; $p < 0.001$) and all activities ($\beta = 0.968$; $p < 0.001$) (Table 3: Models B2 and B4).

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

Lastly, we investigate the impact that changes in occupancy and

activity measures during SIP, as well as respondent and household characteristics, have on intention to adopt smart technologies (Table 4).[5] In our baseline model specification, we find that respondents who are younger ($\beta = -0.109$; $p < 0.001$), male (vs. female) ($\beta = -0.049$; $p < 0.05$), in higher income households ($\beta = 0.062$; $p < 0.05$), and in households with minors ($\beta = 0.089$; $p < 0.01$) have more intention to

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[5] For analysis that considers intention to purchase each smart home technology as a dependent variable in separate models, see Appendix A.4 - A.5. When we compare statistically significant respondent and household characteristics across these separate smart technology models, we find that estimates are consistent with findings from Table 4.
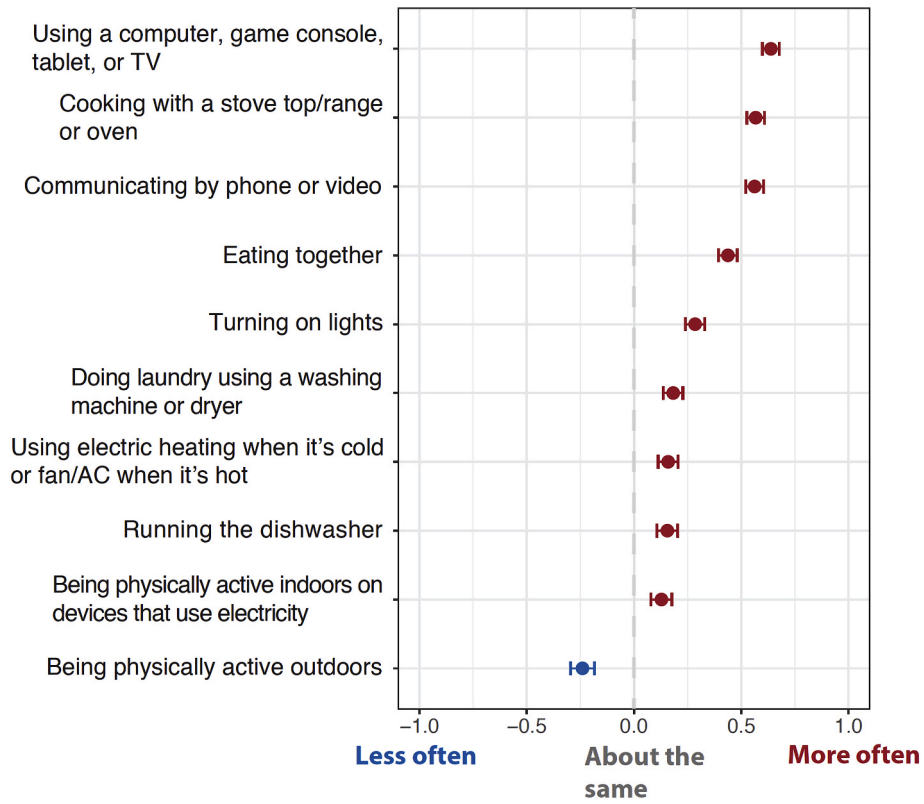
Fig. 2. Reported change in activities during SIP orders. Points represent means, lines 95% confidence intervals for a one sample *t*-test. All activity changes are statistically different from zero.
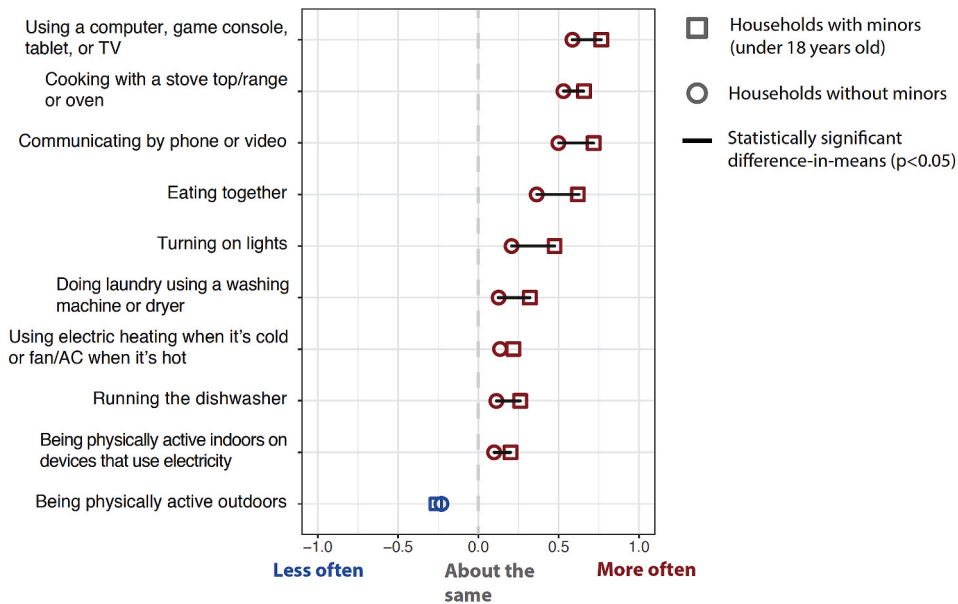

Fig. 3. Reported change in activities during SIP orders for households with minors and households without minors. Shapes represent means, and a dark line indicates that the difference-in-means between the two household groups is statistically significant ($p < 0.05$).

Table 4
Ordinary least squares 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 (p-value)	Std. beta (p-value)	Std. beta (p-value)	Std. beta (p-value)
Respondent characteristics				
Female (vs. male)	−0.049* (0.019)	−0.050* (0.018)	−0.058** (0.006)	−0.058** (0.005)
Age (categories)	−0.109*** (<0.001)	−0.107*** (<0.001)	−0.088*** (<0.001)	−0.084*** (<0.001)
Bachelor's or higher (vs. less than bachelor's degree)	0.009 (0.719)	0.006 (0.806)	−0.000 (0.995)	−0.002 (0.917)
Household characteristics				
Household income	0.062* (0.010)	0.059* (0.015)	0.048* (0.047)	0.046 (0.060)
Single family home	−0.002 (0.941)	0.000 (0.998)	−0.002 (0.923)	−0.006 (0.794)
Owner occupied household	0.004 (0.854)	0.005 (0.837)	0.006 (0.798)	0.007 (0.780)
Household size	−0.017 (0.533)	−0.014 (0.610)	−0.019 (0.491)	−0.019 (0.477)
Minors present (younger than 18 years old)	0.089** (0.002)	0.086** (0.003)	0.077** (0.006)	0.075** (0.008)
Midday occupancy change (weekdays) during SIP		0.019 (0.381)	0.006 (0.766)	0.005 (0.816)
Change in frequency of energy-related activities during SIP			0.085*** (<0.001)	
Change in frequency of all activities SIP				0.096*** (<0.001)
Intercept (unstandardized)	0.479*** (<0.001)	0.473*** (<0.001)	0.429*** (<0.001)	0.426*** (<0.001)
R-squared	0.080	0.081	0.100	0.104
N	746	746	746	746

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

purchase smart technology (Table 4: Model C1). When change in midday occupancy during SIP is added to this model specification (Table 4: Model C2), we do not observe statistically significant effects. However, when we add change in the frequency of energy activities during SIP (Table 4: Model C3), those who report higher changes ($\beta = 0.085$; $p < 0.001$) also express greater intention to adopt smart technologies, at a magnitude 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 ($\beta = 0.096$; $p < 0.001$; Table 4: Model C4).

5. Discussion and conclusions

We find broad evidence that Californians in our sample spent more time at home during the middle of the day (10am – 3pm) on weekdays under SIP orders (RQ1), with average midday occupancy increasing by approximately half a day per five-day week (Monday-Friday). Reported midday occupancy was already high in our sample before SIP (on average, 3.6 days per week), so there was not much room for additional increases in occupancy during SIP orders. Larger households were less likely to report changes in midday occupancy during SIP. However, households with minors were, 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 and practices 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 activities that use devices with a screen/display or are food-related. Moreover, there was an increase in all activities that were energy-related. These finding suggests that many practices are shifting to the home environment. 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 experienced SIP orders differently and perhaps more intensively. 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. Other respondent characteristics—age, gender, income and education—are also associated with changes in activity frequencies. Our 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 childcare responsibilities during COVID-related restrictions (many of which involve energy use) [45]. 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 report higher activity frequency.

We now explore how SIP orders may reach beyond activities and occupancy to shape preferences toward and perceptions of 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 [46]—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 midday occupancy during SIP 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 undoubtably have an impact on the intention to adopt smart technology, as shown in previous research [46], 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 automate and enhance their lives through some of the features that smart devices provide. Additionally, nearly all of the devices we asked about are associated with energy savings or efficiency, and some households could be looking toward these technologies to save money. Yet another reason is that, because people are at home and interacting with devices more frequently, they could be more motivated to improve their home environment by integrating smart technologies, perhaps even amplified through increased exposure to social media or advertisements while at home. While we did not consider smart home technologies unrelated to energy savings or efficiency, if the above is true, our expectation is that there could also be higher intentions to adopt devices that can enhance home environments in other ways (e.g., smart air purification systems). Future research is needed to better elucidate these links and the adoption of other types of smart technologies.

We also explored how differences in household characteristics may relate 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 as educators

and childcare providers [47]. 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 are 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. Some of these barriers may be reflected in our findings that higher income households are associated with greater intention to adopt smart technologies. We also see some changes in family lifestyles during SIP orders that are associated with healthier lifestyles, such as respondents reporting prepping meals at home and eating meals together more often [48]. This finding indicates that practices associated with cooking may be been particularly affected in this crisis. At the same time, other reported activity frequency changes are less healthy – e.g., reduced outdoor exercise and increased screen time – as indicated by previous scholarship [49,50].

These findings support the preponderance of media reporting that society—and the practices and routines that underpin daily life—are 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 whether our results would have been different if we had surveyed respondents earlier, perhaps a week after the first statewide order. When we 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. At the same time, polling directly after SIP in late March could have better captured immediate changes in household practices and lifestyles due to SIP orders. The immediacy of the disruption 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 individual survey respondents. Given the similarity in composition of our sample 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 was one of the best options among the limited options available to us at the time of the survey.

From a theoretical perspective, our results suggest many adjustments to everyday practices as a result of the disruptions caused by the pandemic and associated government restrictions. Such findings add a dimension to social practice theory not yet well documented in the literature, the element of change in practices. To date, practices are considered as stable, enduring, and relatively resistant to rapid, short term change. Adjustments in practices in this case appears more

pronounced for households with minors. Whether practice-related adaptations to SIP remain in place after the pandemic is not yet known but offers intriguing avenues for future research. Our results also highlight the role of non-energy-related crises in shaping energy-related practices, suggesting another avenue of research for social practice scholars.

From a policy perspective, these changes in activity and occupancy during SIP orders suggest that households are likely demanding more energy, particularly electricity, and at different times of day. These increases in electricity demand may impact households differentially, with households with minors facing increased energy bills and possible energy insecurity. Such inequalities may be exacerbated if these 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 [51]. On the other hand, we find evidence that SIP orders may also be influencing intention to purchase smart home technologies in many of the same types of households that have been differentially impacted. In this sense, the pandemic and associated restrictions could serve as a focusing event that places new attention on the relationship between household activities and energy use, helping people realize the importance of smart home technologies—for those that can afford them—in a transition toward a greener and cleaner grid.

It is important to note the exploratory nature of this research, which provides a static snapshot of a highly dynamic and continually evolving pandemic response. We conducted this study during the height of California's initial Shelter-in-Place orders, which represents some of the most stringent COVID-related restrictions in California to date. And while some of these restrictions have been lifted, there are indications that the United States, as of November 2020, is entering a new, and perhaps deadlier, phase of the pandemic [52]. In this respect, our research could be particularly informative for understanding the effects of tighter restrictions on households, while also providing a lens to view future impacts as areas across the world adjust the intensity of their pandemic response.

Credit author statement

Chad Zanocco: Writing - original draft, Conceptualization, Methodology, Formal analysis, Visualization. **June Flora:** Conceptualization, Methodology, Writing - review & editing, Project administration. **Ram Rajagopal:** Conceptualization, Supervision, Funding acquisition. **Hilary S. Boudet:** Conceptualization, Methodology, Writing - review & editing, Supervision, Project administration, Funding acquisition.

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.
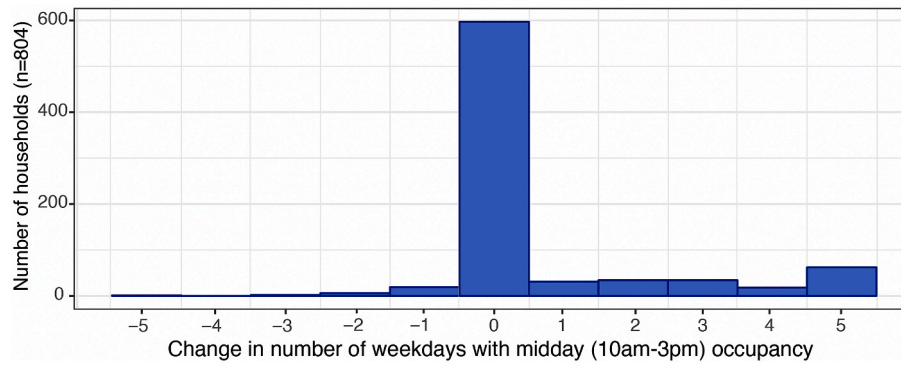
Acknowledgments

Appendix

Fig. A.1. 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.
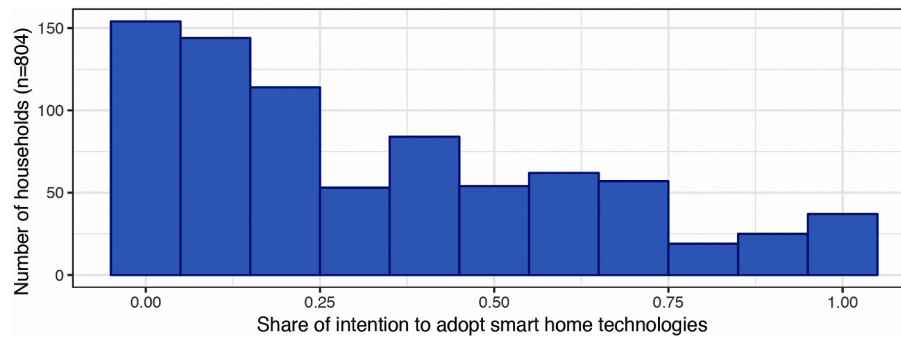

Fig. A.2. Distribution of intention to adopt metric for all respondents (n = 804) where 0 indicates no intention to purchase and 1 indicates an intention to purchase all appliances/devices.

Table A.3
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

Table A.4
Binary logistic regression models predicting intention to purchase individual smart home technology items: solar system; electric vehicle; smart thermostat; and smart light.

	Solar system	Electric vehicle	Smart thermostat	Smart light
	Model D1	Model D2	Model D3	Model D4
	Odds ratio (p-value)	Odds ratio (p-value)	Odds ratio (p-value)	Odds ratio (p-value)
Respondent characteristics				
Female (vs. male)	0.412 (0.070)	0.765 (0.166)	0.790 (0.194)	0.962 (0.838)
Age (categories)	0.737*** (<0.001)	0.741*** (<0.001)	0.875 (0.079)	1.035 (0.669)
Bachelor's or higher (vs. less than bachelor's degree)	0.697*** (<0.001)	1.637* (0.020)	1.002 (0.992)	0.768 (0.230)
Household characteristics				
Household income	1.087* (0.013)	1.074* (0.023)	1.021 (0.487)	1.017 (0.589)
Single family home	1.173 (0.448)	0.754 (0.166)	1.188 (0.367)	0.936 (0.739)
Owner occupied household	1.436 (0.109)	1.020 (0.928)	1.224 (0.315)	0.760 (0.197)
Household size	1.080 (0.356)	0.965 (0.667)	0.926 (0.326)	0.947 (0.490)
Minors present (younger than 18 years old)	1.462 (0.134)	1.541 (0.080)	1.633* (0.035)	2.026** (0.005)
Midday occupancy change (weekdays) during SIP	0.920 (0.185)		1.024 (0.662)	1.076 (0.222)

Table A.4 (*continued*)

	Solar system	Electric vehicle	Smart thermostat	Smart light
	Model D1	Model D2	Model D3	Model D4
	Odds ratio (p-value)	Odds ratio (p-value)	Odds ratio (p-value)	Odds ratio (p-value)
Respondent characteristics				
Change in frequency of energy-related activities during SIP	1.011 (0.754)	0.938 (0.273) 1.030 0.377	1.154*** (<0.001)	1.157*** (<0.001)
Intercept	0.412 (0.070)	0.588 (0.262)	0.470 (0.101)	0.522 (0.174)
Akaike information criterion	669.97	733.12	782.35	699.42
N	662	712	641	522

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

Table A.5
Binary logistic regression models predicting intention to purchase individual smart home technology items: smart appliance; smart plug; home energy monitoring system; and home battery storage

	Smart appliance	Smart plug	Home energy monitoring system	Home battery storage
	Model E1	Model E2	Model E3	Model E4
	Odds ratio (p-value)	Odds ratio (p-value)	Odds ratio (p-value)	Odds ratio (p-value)
Respondent characteristics				
Female (vs. male)	0.528*** (<0.001)	0.993 (0.968)	0.814 (0.195)	0.508** (0.001)
Age (categories)	0.818** (0.008)	1.065 (0.421)	0.779*** (<0.001)	0.770** (0.002)
Bachelor's or higher (vs. less than bachelor's degree)	0.942 (0.775)	0.602* (0.019)	0.858 (0.402)	1.366 (0.162)
Household characteristics				
Household income	1.028 (0.346)	1.040 (0.195)	1.018 (0.491)	1.016 (0.612)
Single family home	1.073 (0.714)	0.749 (0.131)	1.071 (0.686)	1.009 (0.967)
Owner occupied household	1.230 (0.311)	0.714 (0.102)	0.894 (0.542)	1.227 (0.363)
Household size	0.934 (0.374)	0.921 (0.290)	0.933 (0.325)	1.043 (0.606)
Minors present (younger than 18 years old)	2.136** (0.001)	1.283 (0.309)	0.693 (0.092)	1.346 (0.234)
Midday occupancy change (weekdays) during SIP	0.963 (0.493)	1.130* (0.042)	1.049 (0.355)	0.969 (0.597)
Change in frequency of energy-related activities during SIP	1.141*** (<0.001)	1.110** (0.001)	1.020 (0.469)	1.090* (0.015)
Intercept	0.794 (0.611)	0.584 (0.248)	5.512*** (<0.001)	0.455 (0.107)
Akaike information criterion	798.00	749.29	955.02	701.29
N	661	557	707	718

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

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