Electricity Consumption of Singaporean Households Reveals Proactive Citizen Response to COVID-19 Progression

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Article

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Electricity Consumption of Singaporean Households Reveals Proactive Citizen Response to COVID-19 Progression

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Abstract

Understanding how populations' daily behaviors change during the COVID-19 pandemic is critical to evaluating and adapting public health interventions. Here, we use residential electricity consumption data to unravel behavioral changes within citizens' homes in this period. Based on smart energy meter data from 10,246 households in Singapore, we find strong correlations between the pandemic progression in the city-state and the residential electricity consumption. In particular, we find that the daily new COVID-19 cases constitute the most dominant influencing factor on the electricity demand in the early stages of the pandemic, before a lockdown. However, this influence wanes once the lockdown is implemented, signifying the arrival of a 'new normal' in the residents' lifestyles. These observations point to a proactive response from Singaporean residents—who increasingly stayed at home during evenings despite not being forced by the government to do so using a lockdown—a finding that surprisingly extends across all demographics. Overall, our study enables policymakers to close the loop by utilizing residential electricity usage as a measure of community response during unprecedented and disruptive events such as a pandemic.

Introduction

Mitigation of the coronavirus disease 2019 (COVID-19) pandemic hinges on effecting massive behavioral changes in individuals across the world, at least until pharmaceutical interventions are developed and made available at scale [1, 2]. In this context, it is imperative to accurately assess populations' responses during the pandemic, which enables policymakers to adjust their interventions—particularly during critical periods such as the initial stages of its progression—adaptively as well as retrospectively [3–5]. For instance, showing that citizens are actively modifying their daily routines, e.g., by increasingly working from home, and avoiding venturing into public spaces, can inform authorities about the extent to which they follow-through

on recommendations from public health experts. The challenge, then, is to identify specific measurable indicators that can constantly and accurately capture such behavioral changes.

By reviewing the pertinent literature, we have identified the following indicators that are currently being used to study social behavioral changes during the COVID-19 pandemic. The first indicator comprises of responses gathered from the population by means of surveys. Thereby, researchers have attempted to obtain an overview of public perceptions (e.g., see [6, 7]). But this approach has several disadvantages: (i) self-reported responses could either be untrue, or experience a skew towards ideal or expected behaviors rather than reflecting the reality (e.g., respondents could report that they are concerned about the pandemic and are self-isolating, while in reality taking no such actions); (ii) surveys only present snapshots of the population's behavior at a particular time. Therefore, it may be difficult to glean any meaningful trends given the fast-changing environment. The second indicator encompasses anonymized data from mobile phones, including passive geolocation data collected by mobile phone operators and actively collected contact-tracing data through dedicated applications [8–14]. By determining the time spent by people at their homes and outside (e.g., in workplaces, shops, etc.) and analyzing how these behaviors change over time, recent studies [4, 5, 15–18] have attempted to discern the social response and design targeted interventions. However, this approach suffers from limitations as well: (i) contact-tracing apps may not be used by many phone users, especially at the early stages of the pandemic; (ii) individuals could own more than one mobile phone, or multiple individuals may share a phone; (iii) demographic differences in phone usage exist, with groups such as children and the elderly potentially under-represented. These factors could distort the outcomes of such studies. Further, it is important to note that the utility of mobile phone data vanishes when people enter their place of residence; no further behavioral or lifestyle changes within the home can be captured. That is, these data can only be used to ascertain if and when people may be at home, but not what they do therein.

Yet, while the above indicators attempt to gain insight into citizens' daily behaviors during the pandemic, surprisingly, studies in this context to date have not considered another potential indicator: the residential electricity consumption. This information is routinely collected through smart energy meters and available to policymakers in real time, and avoids all of the previously mentioned limitations. Importantly, the electricity consumption of a household truly represents the occupants' evolving at-home behaviors during the pandemic. In other words, there are no concerns of inaccuracies due to self-reporting. Secondly, since the electricity consumption of all the homes in the community are metered regardless of their demographics, using electricity data to assess the populations' behavior will result in a more representative assessment. With this in mind, we study the Singaporean context, and analyze the electricity consumption of 10,246 households in the city-state from January to May 2020. By tracking how the households' electricity demands change during this period, we ascertain links between their behaviors and publicly available information about the progression of the pandemic. Our study shows that a strong correlation exists between the household peak consumption and new reported COVID-19 cases, and that there is a lagged effect by one day. While the Singaporean residential electricity consumption is typically influenced predominantly by the weather [19], we find that in the early stages of the pandemic, the disease progression has the most influence. This influence diminishes progressively as the country transitions into a strict lockdown—termed as the "Circuit Breaker"—in early April 2020, when people were only allowed to leave their homes for essential activities such as grocery shopping and exercise. Overall, our findings underscore the proactive response of Singaporean residents to the pandemic, taking steps to protect themselves even before a government-mandated lockdown.

It should be noted that we are not the first to study how electricity consumption has been affected by the pandemic. A recent study by Ruan et al. [17] has similarly examined the correlations between COVID-19 progression and the electricity consumption in different cities across the United States. However, in contrast to our study, their analysis was performed using the *aggregate* demand which includes not only the residential sector, but also the commercial and industrial counterparts. As we show later on, such an aggregation obfuscates trends in the residential demand, which is arguably the most direct indicator of the peoples' daily behaviors, especially in a period when people are increasingly staying at home. Other studies

(e.g., [20–26]) have also focused on the overall power sector in different countries during the pandemic, showing declining demand as lockdowns are enforced and commercial and industrial activities wind down. While these studies discern the power industry's response to the pandemic, they provide limited insight insofar as the objective is to adjust public health interventions by analyzing citizens' behaviors.

Results

We obtain the electricity consumption of 10,246 households in Singapore from smart meter data collected by their electricity service provider; see Methods. With this, we assess whether the residents proactively responded to public health authorities' calls to curtail the pandemic by avoiding crowded public places on a voluntary basis. Specifically, we study if citizens stayed at home in the evening to a greater extent as the pandemic progressed, which would be reflected as an increase in their home electricity consumption at that time. This, in turn, will result in an increased *peak* demand given that the residential peak consumption occurs in the evening hours (see Fig. 1(a)). Note that while all citizens may not have the flexibility to work from home before an official lockdown, everyone has available the option of avoiding crowded public places after work in the evening. To evaluate if this indeed happened in the initial stages of the pandemic in Singapore, we obtain the peak value of the aggregated residential consumption and study if any relationships exist between the daily peak consumption and the progression of the pandemic. In particular, we use two metrics for the latter: the number of *daily new COVID-19 positive cases* and the number of *daily recovered cases* announced by the Ministry of Health through daily situation updates [27] and subsequently reported by the news media. It should be noted that these two variables comprise of the only immediate information made available to the public that allow them to assess the progression of the disease. We selected both of these data for our analysis due to their potential opposing influences on the society's response—while the former may encourage people to be more cautious and stay at home, the latter may promote optimism and downplay the severity of the health crisis.

Fig. 1(a) shows the daily aggregated demand of all the households for the period beginning on 23 January 2020—which is when the first COVID-19 positive case was detected in Singapore—and ending on 31 May 2020, until which the electricity demand data is available to us. Clearly, the daily peak always occurs in the evening period from 8PM-11PM; the corresponding peak values are obtained and plotted in Fig. 1(b). From this figure, we observe that the peak demand continues to increase during this period. This trend would not be visible from analyzing the aggregate demand of the residential, industry, and commercial sectors. Indeed, such an aggregation would actually exhibit an opposite trend, given that residential demand only accounts for a small proportion of the total energy demand, about 14.9% in the Singaporean context [28]. Therefore, the overall national demand reduces as the commercial and industrial activities ramp down during the pandemic [29]. Similar declines in the overall demand were observed in other countries as well [17, 20–26]. Towards our goal of assessing whether citizens respond to the disease progression, we now plot the COVID-19 case numbers for the same period in Fig. 1(c) and study the cross-correlation between the daily new cases and the peak demand (see Fig. 1(d)), and that between the daily recovered cases and the peak demand (see Fig. 1(e)). The corresponding Pearson's coefficient r with the p-value are also depicted in the figures. Here, while we observe statistically significant correlations ($p << 0.05$) between the peak aggregate demand and both the daily new and recovered COVID-19 cases, we find that the correlation between the latter pair is weaker. Further, from Fig. 1(d), we find a maximum cross-correlation of 0.665 at a lag of one day, which suggests that the daily new case have a one-day-delayed impact on the peak demand. Meanwhile, Fig. 1(e) shows a maximum cross-correlation of 0.479 at a lag of five days, implying that peak aggregate demand leads daily recovered cases by 5 days. To verify whether these correlations are spurious, or represent a long-term relationship between the data, we test for cointegration using the Engle-Granger cointegration test [30]. For both new and recovered cases, the test indicates cointegration ($p = 1e^{-3} << 0.05$ for both τ and z tests) with the peak demand values. These results suggest that there is indeed a link between the response of the society

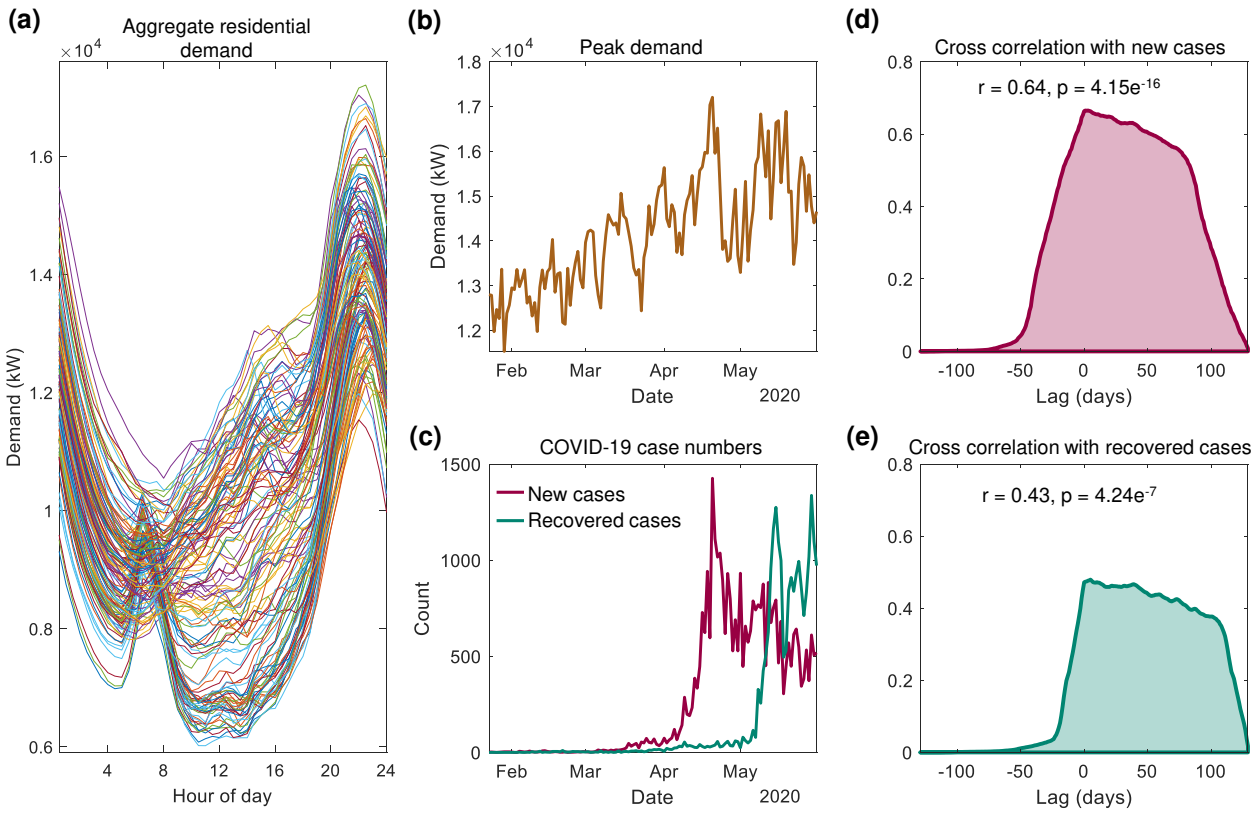

Fig. 1. Relationship between COVID-19 case data and residential electricity consumption in Singapore. **(a)** Aggregate demand of 10,246 households for the period of 23 January 2020 to 31 May 2020. **(b)** Daily peak values from (a). **(c)** Daily new COVID-19 cases and recovered cases announced by the Ministry of Health Singapore. **(d)** Normalized cross-correlation plot between the peak aggregate demand and new COVID-19 cases. **(e)** Normalized cross-correlation plot between the peak aggregate demand and recovered cases. For (d) and (e), the corresponding Pearson's correlation coefficient and p-value are indicated as well.

and disease progression. To examine this in more detail, we consider two distinct phases of the pandemic in Singapore: before the lockdown or Circuit Breaker which begins on 7 April 2020, and during the Circuit Breaker. Analyzing the correlations during the two phases, we find statistically significant correlations for the former but not the latter; see Supplementary Note 1.

Proactive citizen response before the Circuit Breaker

An important question now arises about the above observations: is it possible that the increase in the peak demand is not due to the response of Singaporeans towards COVID-19 progression, but only caused by changes in the weather? We ask this because studies in the past have shown that the Singaporean electricity consumption mainly depends on the weather, with the demand generally increasing with the temperature (e.g., see [19]). Therefore, do the correlations shown in Figs. 1(d) and 1(e) exist only because the weather becomes warmer, or is it also because of the social response to the COVID pandemic? To answer this question, we construct a vector error correction model (VECM) while considering weather as a contributing factor. More specifically, five weather parameters are obtained and subsequently reduced to 2 principal components that explain more than 99.9% of the variance; see Methods for more details. In addition to these two weather principal components, the VECM is also fed the daily new and recovered COVID-19 cases as inputs. We then train the model for the period beginning on 23 January 2020 until before 7 April 2020 when the government implemented the Circuit Breaker. Using this trained model, we forecast the error variance decomposition to assess how changes in each factor contribute to the changes in the peak aggregate demand; in other words, we analyze how important the influence of each factor is on the

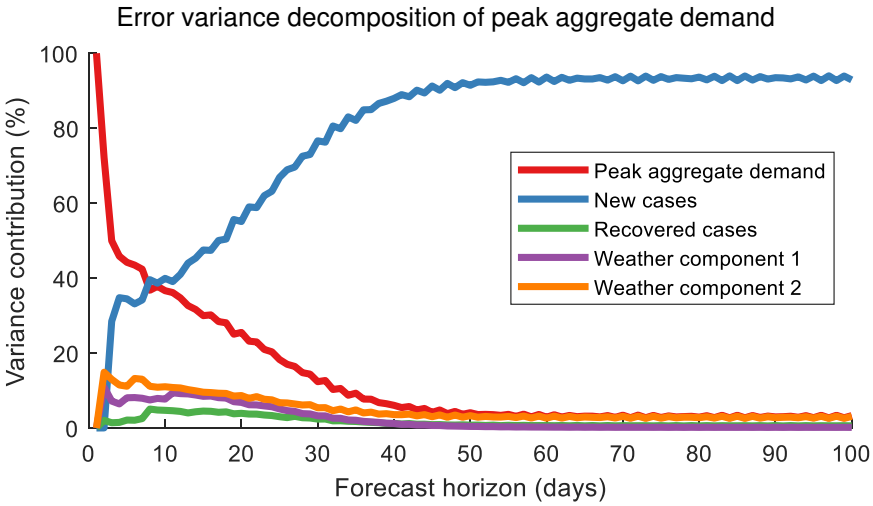

Fig. 2. Results from the VECM for the peak electricity consumption of 10,246 households in Singapore. The figure shows the error variance decomposition of the influencing factors—daily new and recovered COVID-19 cases, two weather components, and self-influence—on the electricity consumption. Each of these factors experience a one-standard-deviation shock at X-axis equals zero. The VECM was trained with data from the period 23 January 2020 to 6 April 2020, which is the pre-Circuit Breaker period. Results demonstrate that the household electricity consumption is most influenced by changes in the daily new COVID-19 cases.

households' electricity consumption. These results are presented in Fig. 2. Three important observations can be gleaned from the figure. First, it confirms that both COVID-19 progression and the weather influence the electricity consumption. However, the most significant factor is the new COVID-19 cases—contributing over 93% of the variance—while the weather plays a relatively minor role, with the two components contributing about 3% combined to the variance. Second, though the government did not force citizens to change their behavior before the Circuit Breaker, our results show that people *proactively* responded to the increasing new COVID-19 cases and stay at home during evenings to a larger extent. Finally, when comparing the roles played by the daily new COVID-19 cases and the daily recovered cases, we find that the influence of the latter is negligible (less than 1%). Recall that we initially hypothesized that the population's concerns may be alleviated by news of people recovering successfully from their infections. Yet, we find that this is not the case according to our VECM, suggesting that citizens respond more towards adverse news about the pandemic progression rather than successful patient recoveries.

Impact of the Circuit Breaker

Having studied the pre-Circuit Breaker period, we now shift our attention to households' electricity consumption as the country implements a full lockdown. We consider three specific time periods as shown in Fig. 3(a) and explained below: (i) Period-1 corresponds to the pre-Circuit Breaker period, beginning on 23 January 2020 when the first positive COVID-19 case was reported and ending on 6 April 2020. (ii) Period-2 also covers the pre-Circuit Breaker period, beginning on 7 February 2020 when the Government of Singapore elevated the Disease Outbreak Response System Condition (DORSCON) to Orange, indicating high disease severity and potential community transmission [31]. (iii) Period-3 covers the Circuit Breaker period, beginning on 7 April 2020 and ending on 31 May 2020 until which the residential demand data is available to us. For each period, we train the VECM and plot the extent to which each influencing factor contributes to the variance of the peak aggregate demand. This is shown in Fig. 3(b).

Clearly, the influence of the new COVID-19 cases on the electricity consumption reduces as time progresses. Even during the pre-Circuit Breaker period—while it remains the most dominant factor—its influence on the peak demand during Period-2 falls to 89% from its original contribution of 93% in Period-1. Once the lockdown is implemented (i.e., during Period-3), however, its variance contribution is only 3.3%.

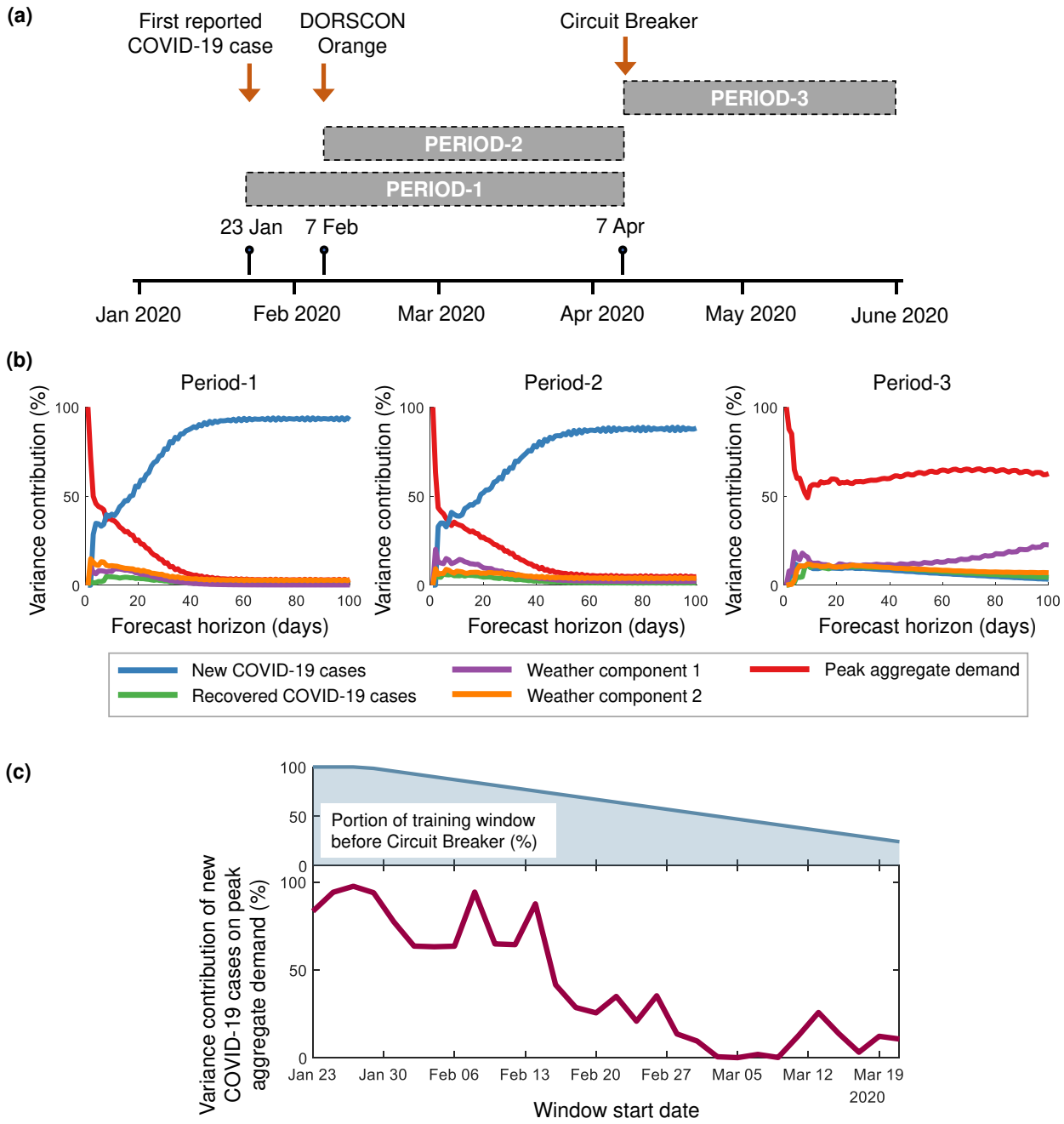

Fig. 3. **(a)** We trained the VECM on three specific periods in 2020. Period-1 covers the interval from the reporting of the first COVID-19 positive case to the start of the Circuit Breaker. Period-2 also covers the pre-Circuit Breaker period, but begins after the government elevated the Disease Outbreak Response System Condition (DORSCON) to Orange. Period-3 covers the interval after the Circuit Breaker begins. **(b)** Variance contributions of the different influencing factors on the peak residential consumption during the three periods indicated in (a). **(c)** Illustrating how the behavior of residents reaches a new normal during the Circuit Breaker. Each point on the X-axis indicates the starting date of a 10-week window whose data is used to train the VECM. The figure depicts the forecast variance contribution of the new COVID-19 case numbers to the peak residential consumption for each time window which moves forward in steps of two days each. It also depicts the portion of the training window that falls prior to the Circuit Breaker.

As for the weather, we observe the opposite trend, with the combined influence of the two weather components growing with time. While only contributing to 3.2% and 5.9% of the variance in the peak demand during Periods-1 and 2, respectively, their combined influence grows to 29.6% during the Circuit Breaker period. This results in weather becoming the dominant factor influencing the residential electricity consumption (excluding its own self-inertia). This is understandable given the fact that the lockdown in Singapore was enforced strictly, and even first-time violators received substantial penalties [32]; as such, the residents' behaviors do not change significantly in this period due to the pandemic progression.

Until here, we have restricted our study to three specific time periods. Alternatively, we could employ a sliding time window, and repeat the above analysis using VECMs trained for each of these windows. To this end, we consider a window 10 weeks long, which iteratively advances in steps of 2 days. The results are presented in Fig. 3(c), which depicts the variance contribution of the new COVID-19 cases towards the peak aggregate demand. The figure also depicts the proportion of the training window that falls prior to the Circuit Breaker—this value reduces as the window moves forward. Our results indicate that the influence of the new COVID-19 cases remains high as long as the VECM training window lies outside the Circuit Breaker period. As the training window overlaps more and more with the Circuit Breaker period, the influence reduces. This implies that citizens no longer respond to the pandemic progression by changing their behaviors, and/or have grown accustomed to their new lifestyles under lockdown.

Influence of demographics

Social response during the pandemic may be very different for different sections of the population. To understand if demographic factors played a role in determining peoples' response in the Singaporean context, we classify the 10,246 households into six different dwelling types: 1-room/2-room HDB, 3-room HDB, 4-room HDB, 5-room/executive HDB, private apartment/condominium, and landed property; see Methods. (HDB here refers to residential apartments constructed by the Housing and Development Board, Singapore.) Results of this classification are summarized in Fig. 4(a). For each dwelling type, we aggregate the demands of all the households belong to that type. Subsequently, we employ the VECM that was described previously, but now train six different instances—each instance is trained with the peak aggregate demand of the corresponding dwelling type along with the weather components. Fig. 4(b) presents the error variance decomposition results, and shows that there are no significant differences in the reactions of the households based on the dwelling type. For each dwelling type, the overarching trend is consistent—the peak value of the electricity demand depends more on the disease progression during the initial stages of the pandemic than later on during the Circuit Breaker period. Referring to Fig. 4(b), we observe a drop in the plot corresponding to households living in 1- or 2-room HDB apartments for the period 25 – 31 January 2020. The overlap of this drop with the Chinese New Year holidays from 25 – 27 January 2020 suggests that any variation in the peak aggregate demand for these households is owing to the holidays rather than the disease progression. We also analyze the cross-correlation between new and recovered COVID-19 numbers and the aggregate demand for each dwelling type, which again shows similar responses by households regardless of their demographics; see Supplementary Note 2.

We now study another aspect of daily electricity-use behavior, and assess *when* the peak demand occurs for the different dwelling types. With this, we can capture significant changes in the lifestyle of the residents; if the peak demand advances in time, it suggests that residents perform their chores or turn on heavy appliances earlier on in the evening. A potential reason for the latter is changes in the weather—as the weather becomes warmer, residents rely on air-conditioning earlier in the evening. Given the fact that air-conditioners are high power appliances, the evening peak advances. Alternatively, the peak demand could occur later in the evening if the residents stay up later, a plausibility when residents work from home and do not have to report to their workplace on the following day. For the Singaporean households involved in this study, regardless of their dwelling type, we find that the peak demand generally advances in the period before the Circuit Breaker; see Fig. 4(c). Interestingly, this trend reverses during the Circuit Breaker period

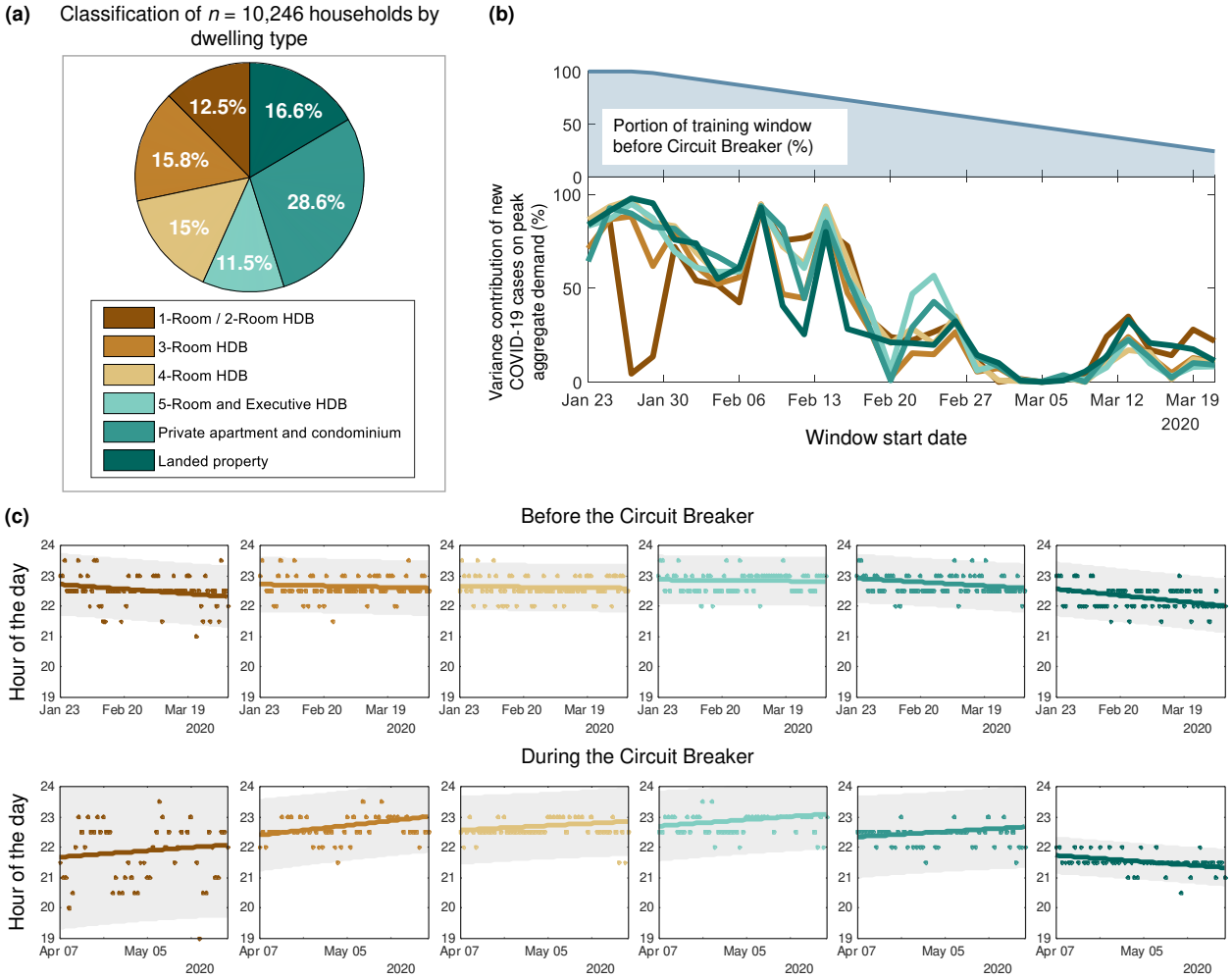

Fig. 4. Influence of demographics on the citizens' response to the pandemic. **(a)** Classification of 10,246 Singaporean households by dwelling type. **(b)** The same as Fig. 3(c) but for the aggregate demand of households belonging to different dwelling types. **(c)** The period at which the aggregate electricity consumption of the different types of households attains its peak. The top row corresponds to the pre-Circuit Breaker period of 23 January to 6 April 2020, while the bottom row corresponds to the period of 7 April to 31 May 2020, which is during the Circuit Breaker. The solid line in these figures is the result of a linear regression performed for each category of households, with the grey shaded areas representing the 95% confidence intervals.

for households of all demographics except Landed properties, underscoring their lifestyle changes during the lockdown. The opposing trend observed for Landed properties suggests that the weather seems to be the dominant influencing factor rather than the lifestyle changes during the Circuit Breaker for these residents. This reasoning is also supported by the fact that such households generally have higher average incomes and more occupants [33], and may prefer to maintain their comfort in the warmer weather by advancing their air-conditioning usage.

Discussion

Our study has several implications. First, while residential electricity consumption data have traditionally been used only for billing and planning purposes, we have demonstrated that these data can capture peoples' at-home behaviors in real time during a pandemic, adding to the list of bespoke data that are available for researchers and policymakers for this purpose. Specific to the Singaporean case study, our results can augment the behaviors captured through the TraceTogether contact-tracing mobile application [14]. Second,

while ours is a retrospective study, the analyses can be performed in real time to inform public health decision making. Importantly, policymakers can anticipate the speed of response of the community to their interventions—our study has shown that Singaporean households respond to news of new COVID-19 cases with a delay of one day. Moreover, policymakers can gain crucial insight into whether populations belonging to specific demographics require additional assistance in managing the crisis. On another note, our findings suggest that people respond more to public health updates that focus on the extent of the disease spread during the pandemic, i.e., the number of newly infected patients, rather than the number of successful recoveries; this may prove useful while tackling future waves of this, and other, pandemics. Third, our study suggests that public health efforts at the beginning of the pandemic were indeed effective in persuading Singaporeans about the severity of the disease and the need to effect immediate behavioral changes to tackle its spread. In this context, another factor that may have contributed to the active response of Singaporeans is their prior experience with the 2002-2004 SARS outbreak [34], during which Singapore was a major epicenter. Lastly, by studying electricity consumption behaviors across all the demographics—specifically, dwelling types—we found that *all* residents responded in a cohesive manner. Given that to protect oneself during an infectious disease outbreak is to protect the society-at-large, this broad response could have contributed to the effectiveness of Singapore's response to COVID-19.

Methods

Data collection

Electricity consumption data. We obtained the smart meter data of 11,901 unique residential consumers who are supplied electricity by SP Group [35] with the consent of the Energy Market Authority (EMA), Ministry of Trade and Industry, Singapore [36]. This dataset consists of the kWh consumption of the anonymized individual households at a half-hourly resolution for the period 1 November 2019 to 31 May 2020. From this dataset, we discarded households with missing entries. As a result, we obtained the complete electricity consumption data for 10,246 households over the seven-month period. While the original dataset did not specify the class of the households, i.e., the dwelling type, we used the average monthly electricity consumption statistics [37] from the EMA to classify the households into six categories: 1-room/2-room HDB, 3-room HDB, 4-room HDB, 5-room/executive HDB, private apartment/condominium, and landed property. In more detail, each consumer's average consumption during the months of November 2019, December 2019, and January 2020 was determined, and three separate classifications were performed by assigning to each consumer the dwelling type with the nearest average consumption as reported by the EMA. The final classification was obtained as the majority of the three previous classifications. However, if all three classifications happened to be distinct, the consumer was assigned the dwelling type based on their November 2019 consumption.

Weather data. Since the Singaporean electricity consumption is influenced by the weather [19], we included weather as an influencing factor while analyzing the change in the residential demand using our VECM. The weather data used in this study was obtained from Meteoblue [38]. In particular, we obtained five different weather parameters at an hourly resolution for the time period under consideration: temperature, relative humidity, total cloud cover, solar irradiation, and wind speed. The first two parameters are measured at 2 meters above the ground, while the wind speed is measured 10 meters above the ground. Since these five parameters are highly correlated with each other, they were converted into 2 principal components which explain over 99.9% of the variance, which serves to reduce the number of dimensions of the data.

COVID-19 case data. We obtained COVID-19 case numbers released by the Ministry of Health Singapore to the media [39]. Specifically, these consist of the new positive COVID-19 cases and new recovered number of patients every day from January to May 2020.

Vector error correction model

Vector error correction models (VECMs) are used to capture complex relationships between multiple time-series data [40]. An extension of vector autoregression models [41], VECMs are used when the time series to be analyzed are cointegrated, which is indeed the case for our analysis. Cointegration between variables exists when they are driven by a common stochastic trend; in such cases, there exists one or more linear combination of these variables which is stationary. The number of such linear combinations is referred to as the number of cointegration relations, and is a parameter of the VECM. Another key component of the VECM is the degree of the multivariate autoregressive polynomial composed of the first differences of the time series, $(p-1)$. Here, p is the order of the vector autoregression model representation of the VECM.

In our study, the MATLAB econometrics toolbox is used to implement the VECM [42]. The inputs to the model are the following: peak aggregate electricity demand, daily new COVID-19 cases, daily new recovered cases, and the first two principal components obtained from the five weather variables. Here, while the initial weather data is at an hourly resolution (i.e., 24 data points per day), the two components are averaged over each day in order to obtain a single data point per day per component. The following steps are performed to train a VECM with data for a specific time period. Each of the input series is differenced, and their stationarity verified using the Augmented Dickey-Fuller test [43]. Next, the number of cointegrating relations between the set of time series is found using the Johansen cointegration test [44]. The VECM is then fit to the inputs using maximum likelihood [41]. For each set of inputs, we vary the model parameter p in $[0, 6]$, and choose the value of p that minimizes the Akaike information criterion (AIC) [45]. Finally, with this model, we forecast the error variance decomposition [40] considering a forecast horizon of 100 steps. The parameters of the optimal VECM used for different simulations in this study are presented in Supplementary Note 3.

Data and code availability

The electricity consumption data used in this study are obtained with approval from the Energy Market Authority, Ministry of Trade and Industry Singapore. The codes used for our analyses will be made available online upon publication.

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Author contributions

G.R. and J.C.-H.P. conceived and designed the experiments. G.R. performed the analyses and generated the figures. G.R. and J.C.-H.P. wrote the manuscript.

Competing interests

The authors declare no competing interests.

Materials and correspondence

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Figures

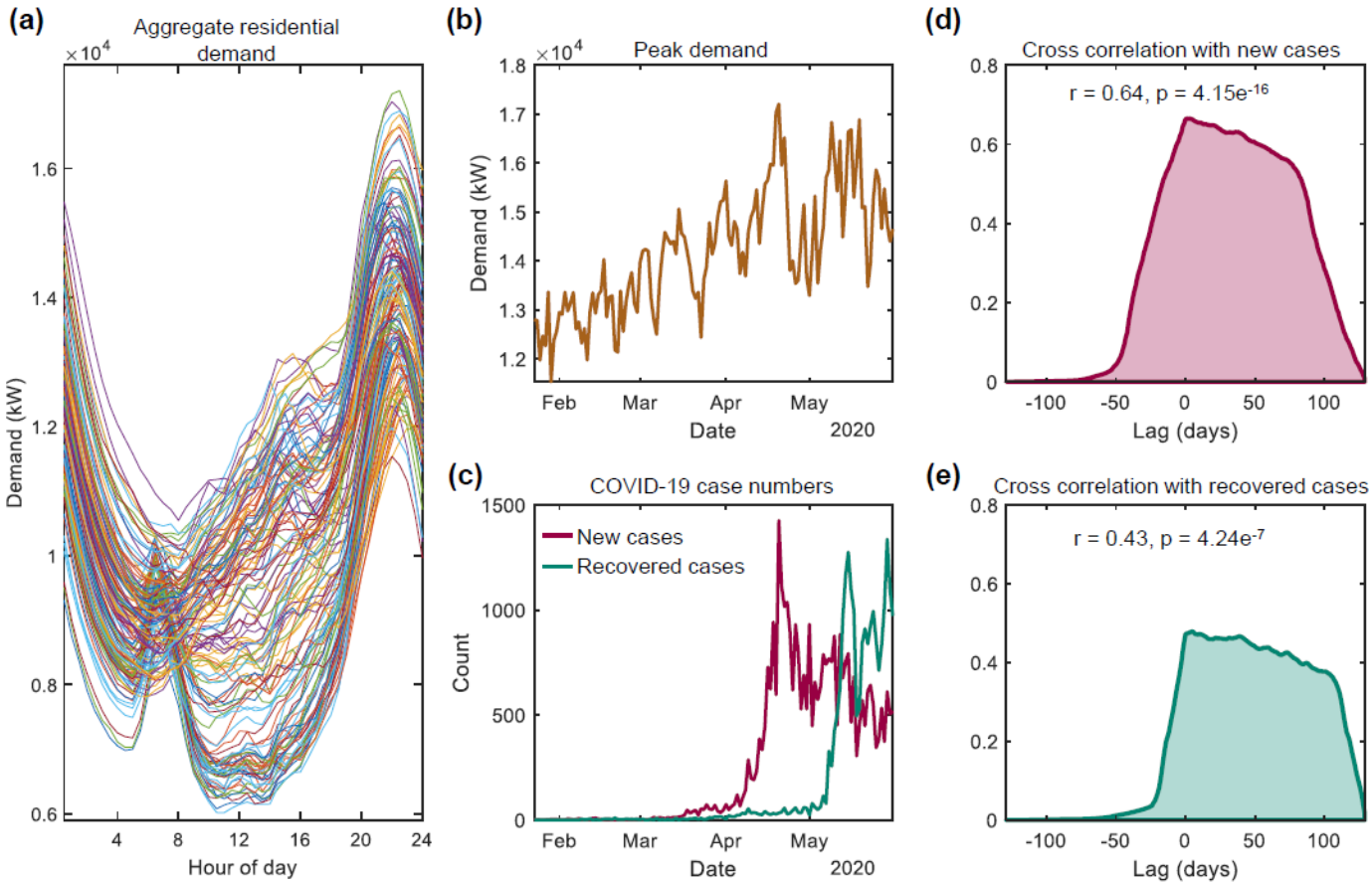

Figure 1

Relationship between COVID-19 case data and residential electricity consumption in Singapore.(a) Aggregate demand of 10,246 households for the period of 23 January 2020 to 31 May 2020. (b) Daily peak values from (a). (c) Daily new COVID-19 cases and recovered cases announced by the Ministry of Health Singapore. (d) Normalized cross-correlation plot between the peak aggregate demand and new COVID-19 cases. (e) Normalized cross-correlation plot between the peak aggregate demand and recovered cases. For (d) and (e), the corresponding Pearson's correlation coefficient and p-value are indicated as well.

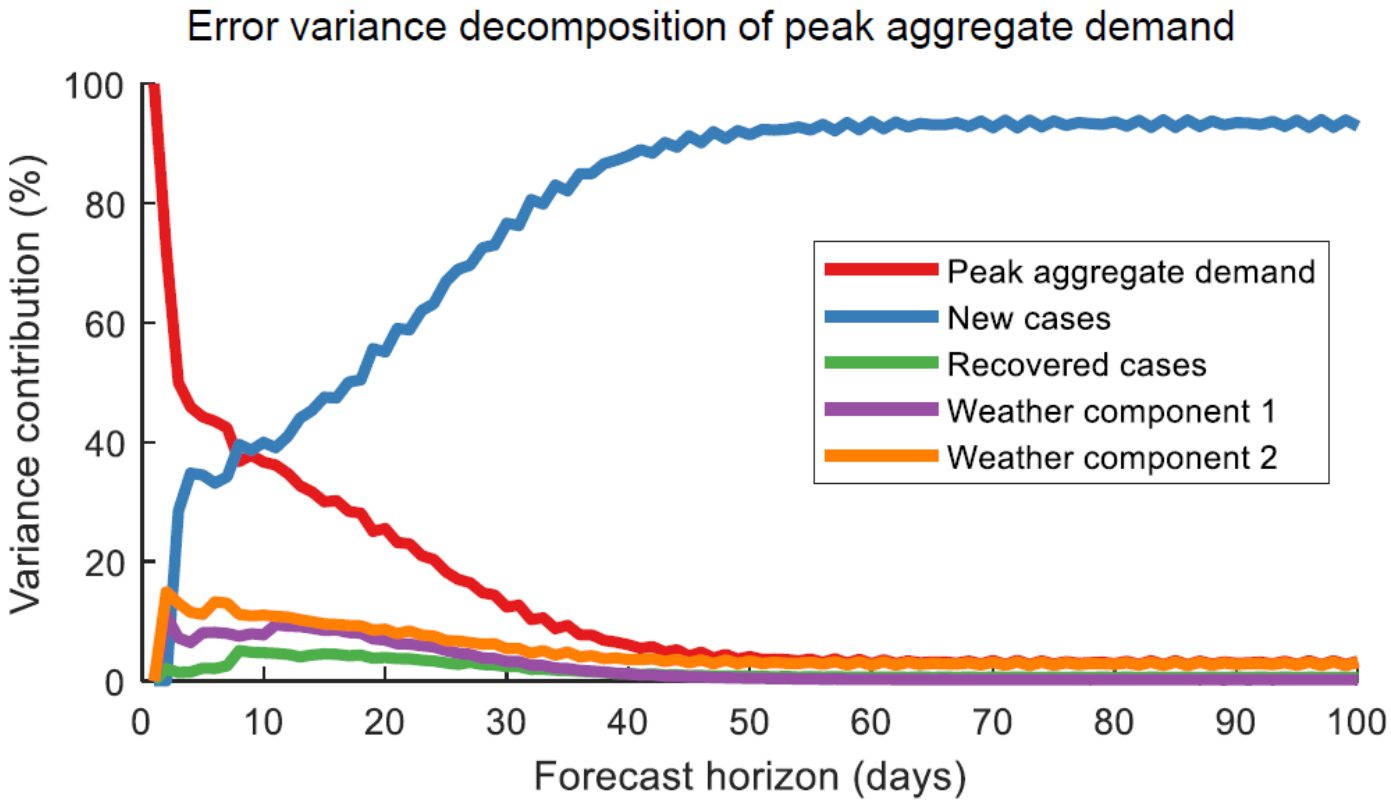

Figure 2

Results from the VECM for the peak electricity consumption of 10,246 households in Singapore. The figure shows the error variance decomposition of the influencing factors—daily new and recovered COVID-19 cases, two weather components, and self-influence—on the electricity consumption. Each of these factors experience a one-standard-deviation shock at X-axis equals zero. The VECM was trained with data from the period 23 January 2020 to 6 April 2020, which is the pre-Circuit Breaker period. Results demonstrate that the household electricity consumption is most influenced by changes in the daily new COVID-19 cases.

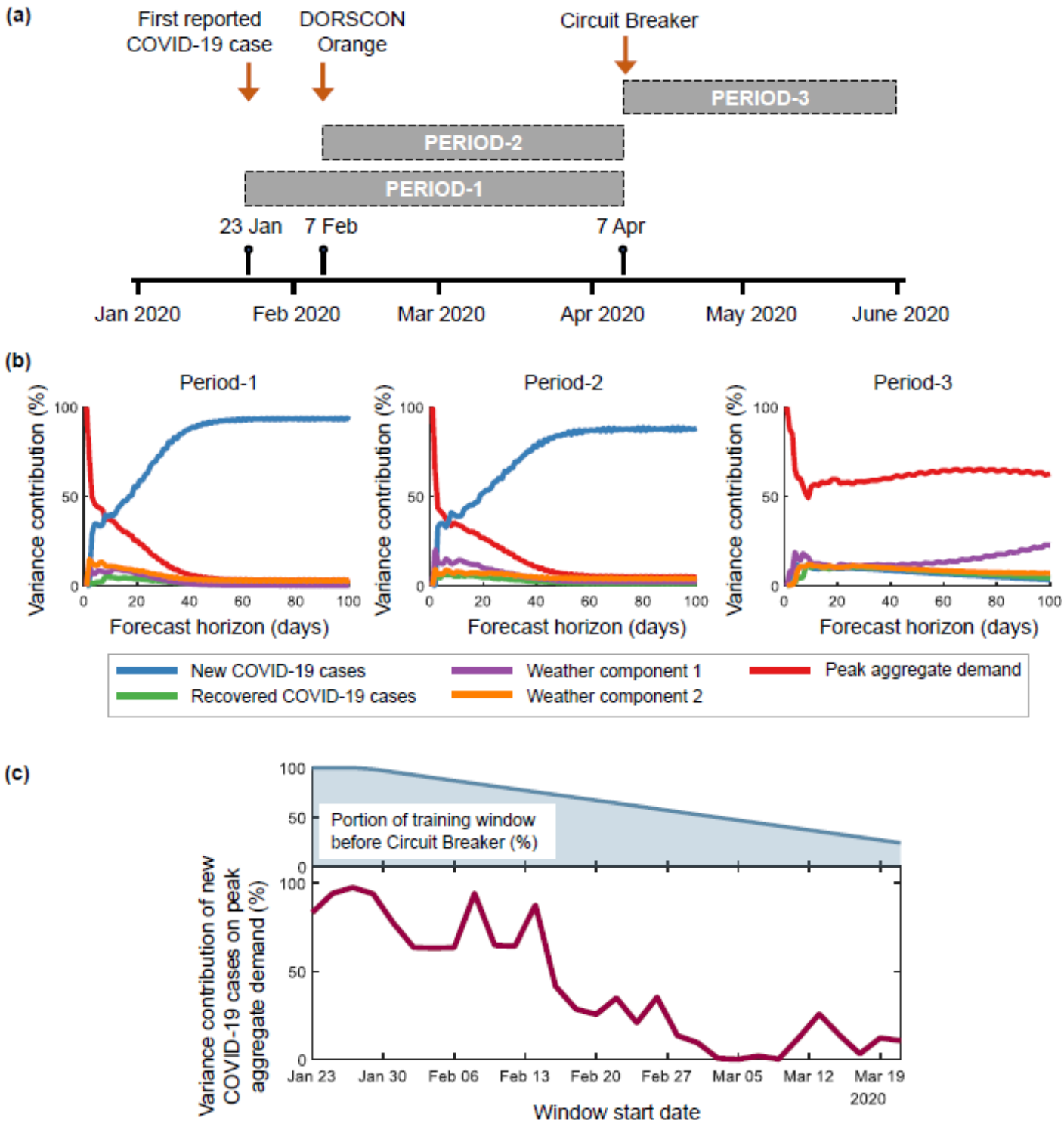

Figure 3

(a) We trained the VECM on three specific periods in 2020. Period-1 covers the interval from the reporting of the first COVID-19 positive case to the start of the Circuit Breaker. Period-2 also covers the pre-Circuit Breaker period, but begins after the government elevated the Disease Outbreak Response System Condition (DORSCON) to Orange. Period-3 covers the interval after the Circuit Breaker begins. (b) Variance contributions of the different influencing factors on the peak residential consumption during the three

periods indicated in (a). (c) Illustrating how the behavior of residents reaches a new normal during the Circuit Breaker. Each point on the X-axis indicates the starting date of a 10-week window whose data is used to train the VECM. The figure depicts the forecast variance contribution of the new COVID-19 case numbers to the peak residential consumption for each time window which moves forward in steps of two days each. It also depicts the portion of the training window that falls prior to the Circuit Breaker.

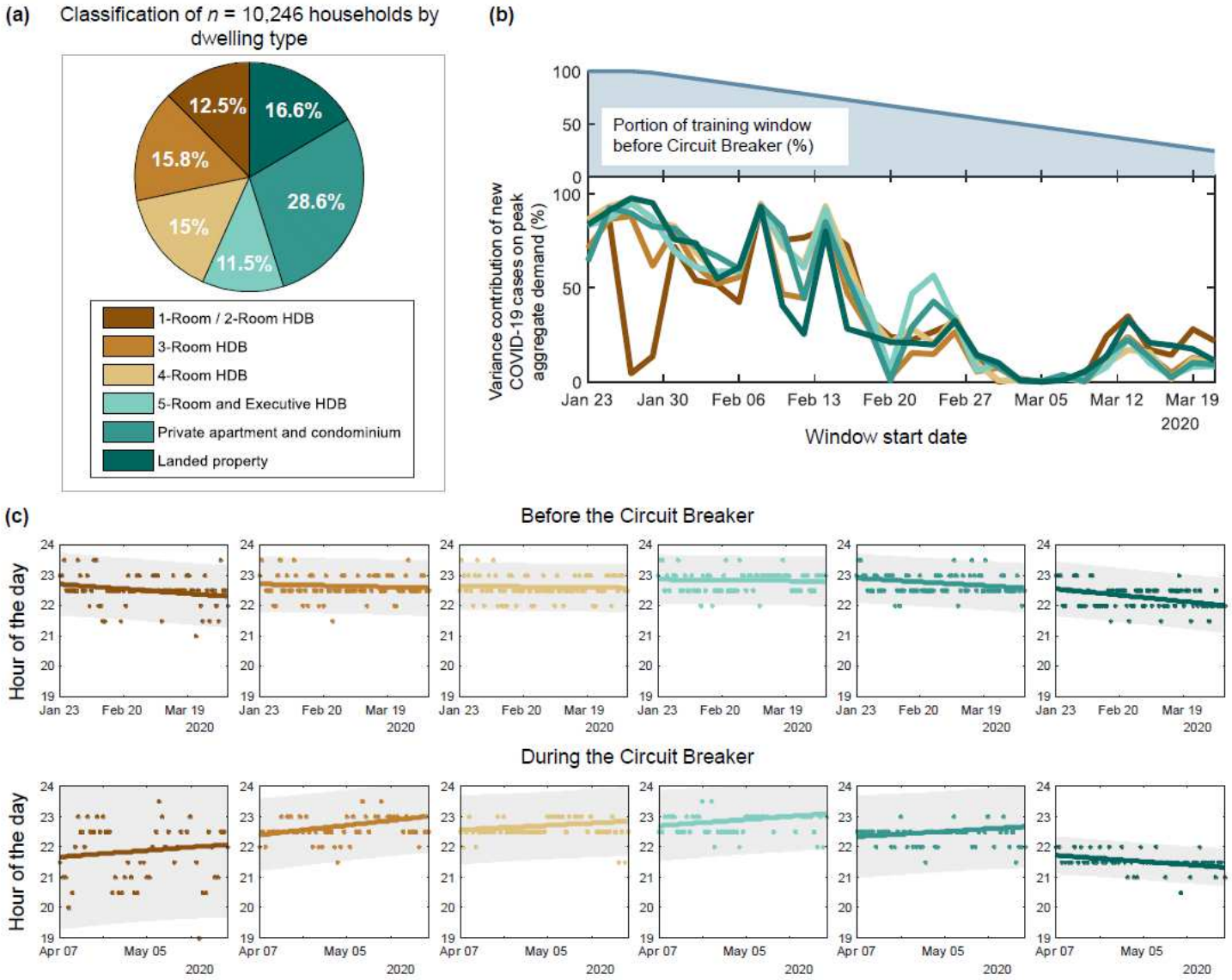

Figure 4

Influence of demographics on the citizens' response to the pandemic. (a) Classification of 10,246 Singaporean households by dwelling type. (b) The same as Fig. 3(c) but for the aggregate demand of house-holds belonging to different dwelling types. (c) The period at which the aggregate electricity consumption of the different types of households attains its peak. The top row corresponds to the pre-Circuit Breaker period of 23 January to 6 April 2020, while the bottom row corresponds to the period of 7 April to 31 May 2020, which is during the Circuit Breaker. The solid line in these figures is the result of a

linear regression performed for each category of households, with the grey shaded areas representing the 95% confidence intervals.

Supplementary Files

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- SupplementaryMaterials.pdf