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Cooling-related electricity consumption patterns for small and medium businesses in California: Current impacts and future projections under climate change

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ABSTRACT

As global temperatures rise, the need to cool commercial buildings will increase, and with it, electricity demand. In this research we focus on small and medium businesses (SMBs), which collectively employ half of the US workforce, and propose methods to identify responsiveness of an SMBs' electricity demand to warmer temperatures (temperature sensitivity). We also develop methods for projecting air conditioning adoption, temperature-related demand, and hourly demand patterns using future climate change scenarios. We applied these methods to a unique dataset of 60,000 SMBs from California containing one year of hourly electricity demand for each establishment. We found evidence that SMB temperature sensitivity is related to a variety of factors including business activities, climate zones, and daily usage patterns. Climate projections through 2100 reveal significant and heterogeneous impacts on both temperature-related demand and air conditioning adoption and that these impacts are unequal. Areas that are lower income, more rural, and have higher proportions of populations living in disadvantaged communities are projected to have comparatively higher increases in SMB demand. These findings suggest that climate-related impacts on SMBs and their employees could be substantial and disparate in the future, as well as a need for policies that can address these inequalities.

1. Introduction

Climate change is already having dramatic impacts on human populations, a trend that will continue without large-scale global efforts to curb greenhouse gas emissions [1]. Along with more frequent and severe extreme weather events, and more variability in temperature extremes, future projections estimate that the global surface temperature will increase between 1.6 and 2.4 °C by 2060 [2]. This changing climate will also likely contribute to the increased frequency and/or severity of extreme weather events, such as extreme heat and cold, precipitation, and droughts [3]. In terms of heatwaves alone, predictions suggest that their number and length will double by mid-century, and with it a doubling of heatwave-impacted populations [4]. However, future climate change impacts will not be universal in when, where, and who will be exposed, and it is likely that vulnerable populations are already being impacted disproportionately [5]. Understanding how climate change impacts will vary geographically and vary among populations within these geographies, both across and within U.S. climate regions, is critical to protecting the health, safety, and economic livelihoods of current and future populations.

Climate change is anticipated to impact the energy system by amplifying electricity demand growth [6], yet estimating the magnitude of these changes, particularly across geographies and within sectors, remains an on-going challenge. In our research, we examine an under-explored group of electricity users from the commercial sector that as group account for a substantial proportion of electricity demand and employ half the US workforce [7,8]: Small and Medium Businesses (SMBs). We focus on SMBs to better understand the impacts of temperature on current and future electricity demand. In doing so, we describe the relationship between warmer temperatures and electricity consumption for SMB establishments across different business sectors and climate zones, and then explore how future climate change

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projections might influence total and peak electricity demand related to cooling. We use the California context, with its wide range of climate zones, human development intensity, and population characteristics, to understand how projected cooling demand due to climate change may manifest across different geographies, climates, communities, and contexts. We find that the burden of increased electricity demand for SMBs are distributed unequally, with projected increases in demand higher for areas in California identified as disadvantaged communities.

1.1. Previous studies

The intersection of climate change with the energy system, including energy production, resilience and reliability is an active area of scholarship [9–12]. While climate change impacts on building energy demand has been previously explored (e.g., [13–15]), there has been less focus on commercial or business sectors. Previous studies have explored sensitivity of building cooling technology adoption to temperature [16] and how cooling behavior and demand may change under future climate scenarios [17–21]. These studies have found positive correlations between cooling demand and temperature with high levels of uncertainty related to future cooling impacts on increased electricity demand. However, these studies have been limited by the resolution of data and have focused on either residential users exclusively (e.g., [17]) or effects generalized across entire utility provider networks (e.g., [18]). Previous research has also found that for residential users the single greatest driver of total electricity use is weather, and this is primarily the result of heating, ventilation, and air conditioning (HVAC) [22]. For residential users, HVAC is estimated to contribute to 43% of all electricity usage, while for commercial buildings this is estimated to be 31% [23].

Previous work on the linkage between climate change and electricity use has considered residential users or combined demand from residential and commercial users [24–28]. However, very little research to date has specifically focused on the relationship between temperature patterns and small and medium business users (SMBs) (for an exception see [29]), although there are indications that from a global perspective the commercial sector will account for 80% of increases in electricity demand related to climate change by 2050 [6]. This gap in existing research is partly due to data availability. Previous research has been able to leverage information about electricity use from Advanced Metering Infrastructure (AMI) data collected from residential users or focus on grid-scale impacts, but datasets containing sub-daily electricity use for SMBs have been more challenging to access due to the potentially sensitive information they can reveal about individual business establishments. Additionally, the heterogeneity of business users can present its own set of analytical obstacles, making it difficult to generalize expectations for energy efficiency technology adoption and program design [30,31].

1.2. Research motivations and scope

Responses to temperature are a fundamental component of business operations, equipment purchase, and electricity consumption [32]. We focus on temperature response because of its relevance to how businesses will respond to climate change as well as its relationship to changing grid conditions, synergies with the adoption of energy efficiency improvements, and the deployment of distributed energy resources such as solar and storage. We also break new ground by exploring the effect of historical and future temperature on SMB electricity demand and adoption of cooling technologies. This is particularly important for understanding impacts on individual SMB establishments, impacts on SMBs with similar business operations, and impacts on the grid overall, all of which represent gaps in existing literature. We provide motivations for this inquiry as follows.

First, SMBs, as a sector, are responsible for large proportions of total electricity demand, with demand from the commercial sector, for which SMBs are a part, comprising at least one-third of total demand in the United States (with sectors of residential, industrial, and transportation demand comprising the other two-thirds) [8]. Second, compared to residential users, there are fewer overall SMB establishments with larger demand per user [8,33]. This makes them particularly important for load management through demand response energy programs as well as other efficiency programs that may have a larger proportional impact on system demand compared to the residential sector. Third, energy costs for SMBs can comprise a large proportion of total operational costs of the establishment, and decisions to make improvements or changes in electricity use patterns may have strong financial incentives. Indeed, research has shown that commercial mortgages for buildings certified as energy efficient (e.g., LEED) have lower default risk [34,35]. SMB establishments may therefore be inclined to view investment in energy saving technologies in the framework of financial costs and benefits and could be more likely to act on programs that promote efficiency improvements than residential users who spend a lower proportion of their household budgets on electricity.

Lastly, SMBs in certain geographical areas may be more exposed to impacts from climate change. Therefore, exploring the relationship between weather, climate change, and socioeconomics may have important implications for equity, distribution of energy resources, and programs that promote economic growth in these communities from an energy justice perspective [36,37]. Small and medium businesses consistently employ approximately half of the workforce in California and in the United States as a whole [7]. With such a large percentage of the workforce employed by SMBs, the successes and challenges of SMBs can have direct impacts on the livelihoods and well-being of their employees. In addition to economic impacts on employees, their households, and their surrounding communities, there can also be impacts on the health of SMB employees. As many employees will spend a large proportion of their lifetimes in work environments, the work environment itself can have implications for population health. Previous studies have identified that in the work environment, extreme outside temperatures are associated with negative occupational outcomes related to dehydration, fatigue and dizziness [38]. Exposure to extreme heat can lead to increased risk of occupational injuries with younger, male workers, as well as those working in agriculture, forestry, construction and manufacturing being more likely to be affected [39]. Given that we already know that the impacts from climate change, and by extension extreme heat events, will not be experienced equally across human populations, it is critical to understand how these impacts are distributed across society, not only from the perspective of where people live but also where they work.

Our research seeks to address the following research questions (RQs):

RQ1a: What is the relationship between temperature and electricity use for SMBs?

RQ1b: How does this temperature and electricity use relationship vary across business sector, energy use characteristics of establishments, and surrounding community context?

RQ2a: How will SMB electricity use change in response to future climate change?

RQ2b: How will changes in future SMB electricity use impact different business sectors, and adoption of cooling-related technologies, and what are their equity implications?

To address these research questions, we applied a dataset of electricity consumption from 60,000 SMB establishments in California. In the next section we describe the data sources and methods we apply in this research.

2. Data and methods

2.1. Data

We used multiple sources of data to understand the temperature sensitivity of SMB establishments, including hourly interval demand data for business establishments, temperature data, and future temperature projections. For electricity demand data, we were provided access to data from 60,000 small and medium business establishments that were identified and furnished by Pacific Gas & Electricity Company (PG&E), a utility company in California. This utility serves eight of California's sixteen climate zones and includes both majority urban and majority rural counties. Electricity demand in this dataset is recorded in one-hour intervals for 365 days spanning from August 1, 2010–July 31, 2011. Address and other identifying information were removed from the data prior to transmission to the authors. For each establishment we have metadata including the establishment's North American Industry Classification System (NAICS) code (a classification system for an establishment's economic activities, see [40] for more information), climate zone (defined by the California Energy Commission [41] and displayed in Fig. 1), ZIP code, and county.

We used two sources of temperature data in this research. First, we gathered historical hourly temperature data from the National Oceanic and Atmospheric Administration's (NOAA) Past Weather by ZIP Code dataset,[2] which we then associated to the business establishments in our dataset using ZIP code information provided by the utility. Next, we applied future climate projections from the Intergovernmental Panel on Climate Change (IPCC) Representative Concentration Pathways (RCP) 8.5 scenario, which was regionally downscaled using CNRM-CM5 from California's Fourth Climate Change Assessment [42]. RCP 8.5 is considered a high-emissions scenario where current emissions continue through the century at a business-as-usual rate, with average statewide warming for California of 4–7 °C by 2100. We associated these yearly climate projections to California ZIP codes by spatially averaging gridded temperature datasets to the extent of ZIP Code Tabulation Areas (ZCTAs). In Appendix A1 we provide additional detail about how these climate projections were mapped to ZIP codes.

The choice of RCP climate scenarios for predicting future conditions remains a subject of scholarly debate. While many researchers suggest that the earth's current climate trajectory likely falls between RCP 4.5, a moderate emissions stabilization pathway, and RCP 8.5 [43], others contend that RCP 8.5 remains an indispensable tool for quantifying potential physical climate risks, as evidenced by its near-perfect agreement (within 1%) with historical cumulative CO2 emissions [44]. In this study, we opt for RCP 8.5 to explore a worst-case scenario, thereby underlining the pressing need for robust mitigation strategies. For comparison purposes we have included alternative results under the RCP 4.5 scenario for selected analyses (see Appendix A4).

As the SMBs in our dataset are located in California, with relatively temperate weather and high proportions of gas heating, we focused on cooling degree days (CDD), or days where the average daily temperature is above a selected set-point in our exploration of temperature sensitivity [45]. We chose to apply the set-point temperature of 65°F as it is frequently applied in energy literature [17,46–48], although we also acknowledge that there will always be tradeoffs when choosing a fixed set-point to represent thermal comfort [49]. See Fig. 1 for total yearly CDD displayed for each climate zone in California.

Our data contains establishments from 20 different economic sectors (represented by the first two digits of a NAICS code[3]), as shown in Fig. 2. The number of users varies by business sector in our data, with *Other Services (except Public Administration)* having the greatest number of users (n = 12,138) while *Mining, Quarrying, and Oil and Gas Extraction* having the least (n = 150), and the median number of establishments in each business sector is 1,977.

As a focus of our research considers relationships to contextual characteristics, we also explored the sector-wise distribution of business establishments in our dataset across income strata, where income levels are derived based on ZIP code median household income corresponding to the establishment's location. Sectors such as Mining, Quarrying, and Oil and Gas Extraction, along with Agriculture, Forestry, Fishing, and Hunting, are notably more prevalent in areas with lower median household incomes. In contrast, sectors like Educational Services, Information, and Real Estate and Rental and Leasing are more commonly associated with higher-income regions. See Appendix A2 for additional information about establishment distributions across income strata.

In this research we occasionally focus on selected business sectors for illustrative purposes and when a larger number of establishments is required for subsample comparisons (i.e., so there is adequate within-category variation for analysis using geographic boundaries such as U. S. Census County designations). For these comparisons, we selected the five business sectors (*Accommodation and Food Services, Agriculture, Forestry, Fishing and Hunting, Health Care and Social Assistance, Real Estate and Rental and Leasing, and Retail Trade*[4]) with the highest number of establishments, excluding *Other Services (except Public Administration)*, which does not impart any information about the business-related activities associated with establishments within that sector. Further exploration and analysis including distribution of establishment counts across electricity demand levels, and distribution of demand across sectors and climate zones is provided in Appendix A2.

2.2. Methods

The methods applied in this study are described in detail in this section. First, we explain our approach for measuring user electricity demand responsiveness to temperature (Section 2.2.1). Next, we describe the method for identifying the relationship between SMB establishment characteristics and demand responsiveness to temperature (Section 2.2.2). Finally, we show how future climate scenarios are leveraged for simulating projected temperature sensitivity and adoption of cooling technologies in future periods (Section 2.2.3).

2.2.1. Deriving temperature response and sensitivity

We describe our method for deriving SMB CDD sensitivity as follows. Eq. (1) defines the model for CDD sensitivity for each individual SMB establishment where Y_W is the weekly demand on weekdays for week w, CDD_w and HDD_w are cooling degree days and heating degree days during week w calculated using a base temperature of 65°F, shown in Eqs. (2) and (3), where T_d is the average temperature on day d.

$$Y_w = \beta_0 + CDD_w\beta_{CDD} + HDD_w\beta_{HDD} + \epsilon_w \quad (1)$$

$$CDD_W = \sum_{d\in w} max(T_d - 65, 0) \quad (2)$$

$$HDD_W = \sum_{d\in w} max(65 - T_d, 0) \quad (3)$$

In our study we opt for a weekly resolution for both temperature and demand variables. This approach was chosen to reduce the impact of certain factors such as variations in specific days of the week and lagged temperature effects [50], which, for example, could be related to human responses (e.g., occupants might not instantly adjust their thermostats following a temperature change) and building dynamics (e.g., the thermal inertia of buildings may delay the adjustment of internal temperatures to external temperature changes). This methodology allows us to focus on the influence of external thermal variables, which we regard as the most important factors within this context.

We fit the model using ordinary least squares and performed a student t-test on the resulting coefficients β_{CDD} (namely CDD sensitivity),

[2] https://www.climate.gov/maps-data/dataset/past-weather-zip-code-data-table.

[3] Complete NAICS codes contain six digits, with each successive digit containing more specific information about the establishment. For example, the first two digits of the NAICS code represents the economic sector, third digit the economic sub-sector, the fourth digit the industry group, etc.

[4] Retail trade includes two 2-digit NAICS codes, 44 and 45.

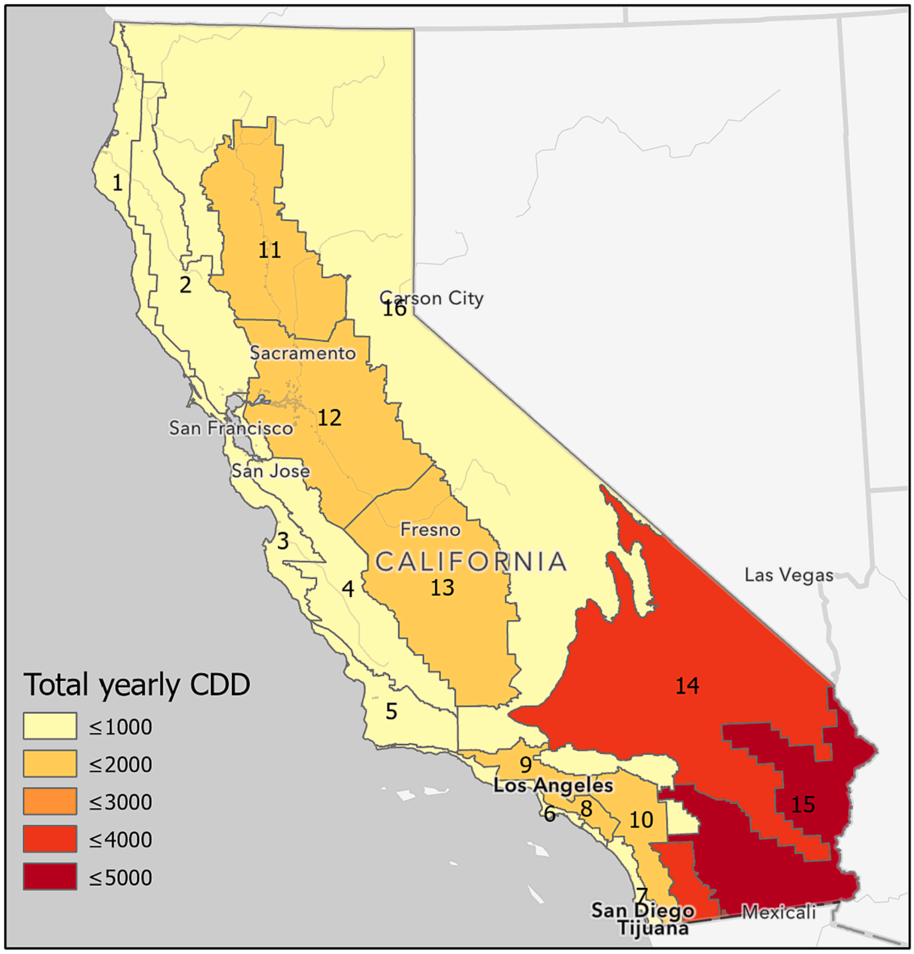

Fig. 1. California climate zones shown with total yearly CDDs averaged for reference cities within each climate zone. Climate zones are designated by numbers 1–16 for the state of California. In general, areas with warmer temperatures, such as those in southern California, have higher total yearly CDD compared to areas with cooler temperatures, such as northern California.

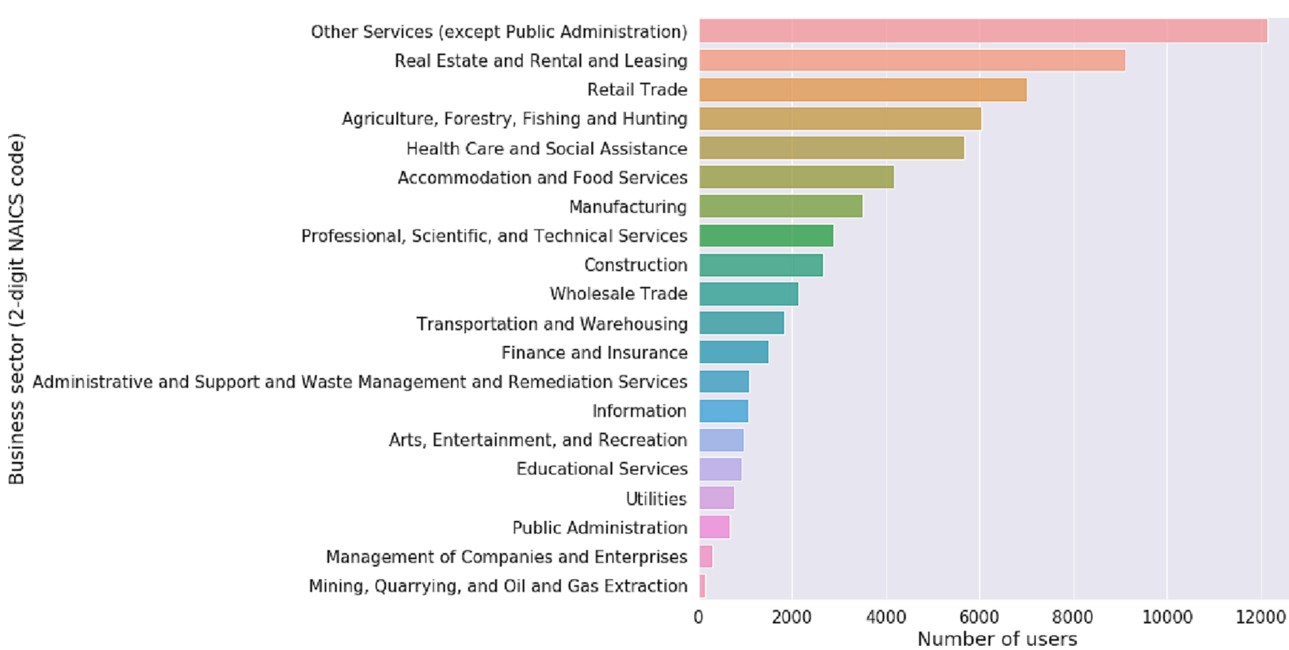

Fig. 2. Count of establishments in the dataset within each business sector, corresponding to each establishment's two-digit NAICS code. *Other Services (except Public Administration)*, *Real Estate and Rental and Leasing*, and *Retail Trade* have among the highest establishment counts in our dataset while *Public Administration*, *Management of Companies and Enterprises*, and *Mining, Quarrying and Oil and Gas Extraction* have the lowest.

with a probability value of 0.05 or lower indicating statistical significance. The intuitive meaning of a statistically significant and positive β_{CDD} is that there is a higher load associated with hotter days for this establishment (i.e., this SMB's demand is responsive to CDDs). For residential users, additional load during hot days is often associated with usage of cooling-related appliances, such as fans, central heating, ventilation, and air conditioning (HVAC) systems or window air conditioner units. However, the determinants of load increases during hot days could be more complicated for SMB establishments. For example, some SMBs—such as agricultural establishments—may have more active business operation days that coincide with warmer days of the year, such as during summer months.

An SMB whose demand is responsive to CDDs might not necessarily be responsive across all hours. Intuitively, demand during afternoon hours could be more responsive to CDDs as this is the time when building cooling technologies, such as A/C, may operate more intensively due to higher occupancy and warmer outdoor ambient temperatures. We thus define hourly CDD sensitivity for those users as follows:

$$Y_w^h = \beta^h{}_0 + CDD_w \beta^h{}_{CDD} + HDD_w \beta^h{}_{HDD} + \epsilon^h{}_w \tag{4}$$

where h is hour of the day and w is week, with Y_w^h is the average demand in hour h of all the days in week w. In Eq. (4), we utilize the same weekly independent variables as in Eq. (3), thereby establishing a consistent correspondence between the two equations. This uniformity enables an in-depth examination of the hourly fluctuations of temperature's influence on demand, aligning it with the daily demand impacts for a more coherent comparative analysis. Similar to Eq. (3), the decision to minimize the effects of variations on specific days of the week and lagged temperature impacts remains applicable in this hourly scenario.

2.2.2. Identifying characteristics related to temperature response and sensitivity

Once CDD response and CDD sensitivity are obtained, we next analyzed whether there is heterogeneity across different users and if so, what characteristics drive such heterogeneity. To do so, the following estimation was conducted for both CDD response and CDD sensitivity:

$$I_i = \sigma(\gamma_0 + NAICS_i \gamma_{NAICS} + CDD_i \gamma_{CDD} + D_i \gamma_D + r_i \gamma_r + m_i \gamma_m + \sum_{j=1}^{6} p_{ij} \gamma_{pj} + \epsilon_i) \tag{5}$$

$$\beta_i = \gamma'_0 + NAICS_i \gamma'_{NAICS} + CDD_i \gamma'_{CDD} + D_i \gamma'_D + r_i \gamma'_r + m_i \gamma'_m + \sum_{j=1}^{6} p_{ij} \gamma'_{pj} + \epsilon'_i \tag{6}$$

where I_i is the CDD response (which is 1 if the estimated β_{CDD} is statistically significant, and 0 otherwise), β_i is the CDD sensitivity, $NAICS_i$ is the 2-digit NAICS code, CDD_i is the average daily CDD, D_i is the average daily demand, m_i is the ZIP code level household median income, p_{ij} is the indicator of the most common time period during which daily peaks occur for each user i, either early morning (2am-6am), morning (6am-10am), afternoon (10am-2 pm), late afternoon (2pm-6pm), evening (6pm-10pm), or night (10pm-2am) (j is the index of the six periods), and $\sigma(z) = 1/(1 + exp(-z))$. Note that the estimation in Eq. (5) was fit across all users while the estimation in Eq. (6) was only fit for users that were CDD responsive.

2.2.3. Future projection of A/C adoption, demand, and daily demand patterns

As future climate change alters average temperatures, temperature-related electricity demand will also change accordingly. In many areas of California more frequent and higher temperature warm weather days are expected, meaning that users' sensitivity of demand to CDD will change. A/C adoption will also likely increase, which we interpret here as SMBs being responsive to CDD (CDD responsive = 1; CDD non-responsive = 0). We use these relationships to predict A/C adoption and temperature-related demand in the future based on projected future temperatures using regionally downscaled IPCC scenarios.

The approach we propose for future projection incorporates a recursive updating of CDD response, CDD sensitivity, and average daily demand. It is important to note that in addition to changes in CDD response (due to A/C adoption) and demand changes, CDD sensitivity is also anticipated to shift under future warming scenarios. The degree of this shift is derived from current data, employing temperature variations across different climate zones. Therefore, a caveat to this approach is that should future temperatures substantially exceed the present temperature range experienced in California, the accuracy of CDD sensitivity extrapolation may be diminished. In Section 3.3, we also illustrate that CDD sensitivity tends to decrease under elevated temperature conditions. We have described the specific steps for this approach as follows.

Future A/C adoption was projected by substituting future CDDs into equations estimated from Eq. (5). This update was only conducted for users who have not adopted A/C as we assume that once a user adopts A/C, the A/C will not be removed. For each user i in year y, we estimated the probability of having A/C, $\widetilde{I}_i$, by substituting the projected CDD of the year into (5). If $\widetilde{I}_i \geq 0.5$, we identified that user i will have A/C starting from year y. For each year y, the future CDD sensitivity was similarly updated by substituting future CDD into equations estimated from Eq. (6), but this updating was only applied to users who have already adopted A/C by year y.

We updated the average daily demand of user i in year $y+1$ based on projected CDD response and CDD sensitivity with the following equation (note that this only applies to users who have or are projected to have A/C in year y).

$$D_i^{y+1} = D_i^y + \beta_i^y \cdot (CDD_i^{y+1} - CDD_i^y) \tag{7}$$

This process of updating CDD response, CDD sensitivity, and average daily demand was continued until the final modeled year, 2100. Once we obtained the increased average daily demand for each year, the increase was allocated to each hour based on the difference in hourly CDD sensitivity as calculated in Eq. (4). Finally, we used this approach to demonstrate changes in load shapes across future projection periods.

3. Examining temperature response and sensitivity of SMBs

In this section, first, we calculated the temperature response and sensitivity of daily electricity demand for each individual SMB and summarized them by sector (Section 3.1). Next, we completed an hourly analysis of establishment load data, where temperature response and sensitivity of hourly electricity demand was explored to reveal patterns across different times of day (Section 3.2). Lastly, we examined if and how the temperature response and sensitivity of demand are correlated with features such as business sector, load pattern, weather, and other contextual characteristics (Section 3.3).

3.1. CDD response and sensitivity of SMBs

We examined SMB establishments' temperature response and sensitivity with respect to CDD. The regression described in Eq. (1) was applied to each SMB establishment and CDD response and sensitivity for each SMB was obtained. Since our focus is on SMBs—with working hours that may vary substantially on weekends—only weekday data was included in this analysis so that different sectors can be compared on a similar workday basis.

Estimated CDD response is summarized by sector and by climate zone in Figs. 3 and 4. In Fig. 3, we show the percentage of SMBs that are CDD responsive summarized by sector. The percentages of CDD responsive SMBs in these sectors range from 36.5% to 81.3%. Three sectors have percentages of CDD responsive SMBs over 70% including

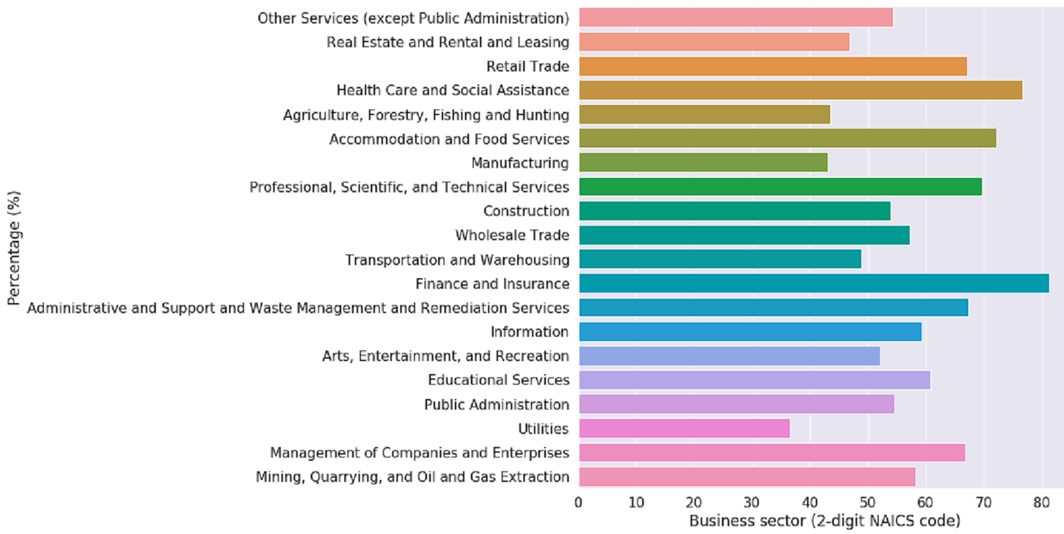

Fig. 3. Percentage of establishments in the dataset that are CDD responsive (e.g., adopted A/C) across different business sectors, corresponding to each establishment's two-digit NAICS code. *Finance and Insurance, Health Care and Social Assistance, and Accommodation and Food Services* have among the highest percentage of CDD responsive establishments, while *Agriculture, Forestry, Fishing and Hunting, Manufacturing*, and *Utilities* the lowest.

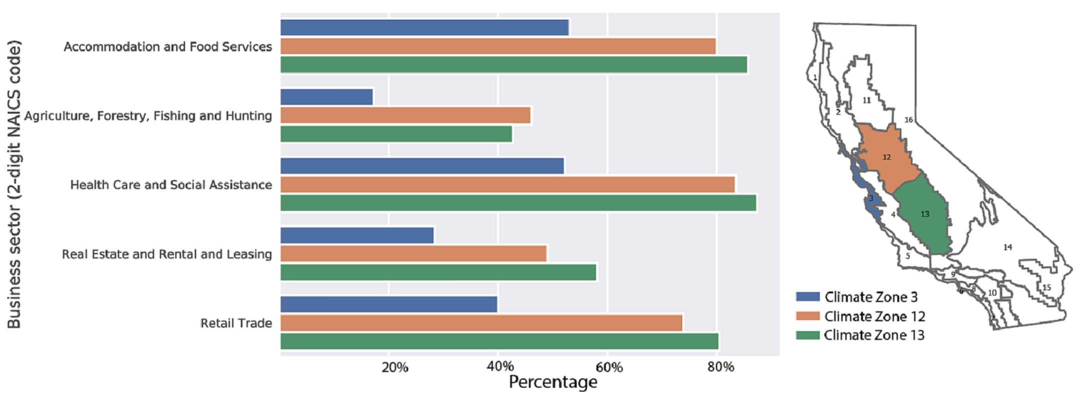

Fig. 4. Percentage of establishments that are CDD responsive (e.g., adopted A/C) for selected business sectors (left). Colors correspond to Climate Zones 3, 12, and 13 which are visualized on a California wide map (right).

Finance and Insurance (81.3%), *Health Care and Social Assistance* (76.7%), and *Accommodation and Food Services* (72.1%). These high percentages could reflect one or more of many potential built environment needs, such as thermal comfort in an indoor office, serving medical patients with certain healthcare requirements, or customers desiring a comfortable overnight stay or dining experience. Four sectors have percentages of CDD responsive SMBs below 50%, which are *Utilities* (36.5%), *Manufacturing* (43%), *Agriculture, Forestry, Fishing and Hunting* (43.6%), and *Real Estate and Rental and Leasing* (46.9%). Some potential reasons for these low A/C adoption percentages could be due to the inefficient cost of cooling these establishments or that employees are not always working inside, reducing their cooling requirements. While self-generation could also potentially influence the low percentage of CDD responsiveness in certain sectors, its impact is likely minimal in this setting for two main reasons. First, our dataset spans from 2010 to 2011, a period during which deployment of behind-the-meter solar or wind power was relatively scarce. Second, our dataset predominantly consists of small to medium-sized establishments and even within the manufacturing sector 95% of our sampled businesses consume <1MWh on average daily. Thus, the prevalence of non-renewable on-site generation, like gas or diesel generators, is likely much lower compared to larger establishments that were not included in our dataset.

A deeper look into the percentages of CDD responsive SMBs in different climate zones is shown in Fig. 4. We found percentages to be lower in a cooler zone (Climate Zone 3) compared to warmer zones (Climate Zone 12 and 13). This observation is consistent with expectations since A/C is more likely to be deployed in climates with more frequent high temperature days throughout the year. Additionally, we further extended some of this analysis by investigating three-digit NAICS subsectors nested within selected two-digit NAICS sectors that have either high or low percentages of CDD responsive establishments. Within certain two-digit NAICS sectors, there was substantial variation in CDD responsiveness among subsectors, while in others, subsector responsiveness was similar. For example, consider the Accommodation and Food Services sector, where the Food Services and Drinking Places subsector, often equipped with ovens/grills, has a higher share of CDD-responsive SMBs compared to the Accommodation subsector. In contrast, within the Agriculture, Forestry, Fishing and Hunting sector, all subsectors consistently had a low proportion of CDD responsiveness. These results are presented in detail in Appendix A3.

CDD sensitivity is shown in Fig. 5 for CDD responsive SMBs to display the magnitude of their response. For the sake of comparison, we normalized each SMB's CDD sensitivity by its average weekday daily electricity demand. This normalization parameter was chosen because CDD sensitivity is positively correlated with demand and the demand distributions are vastly different across sectors, as shown in Fig. 3. Thus, normalized CDD sensitivity can be interpreted as the portion of the demand that is responsive to CDD.

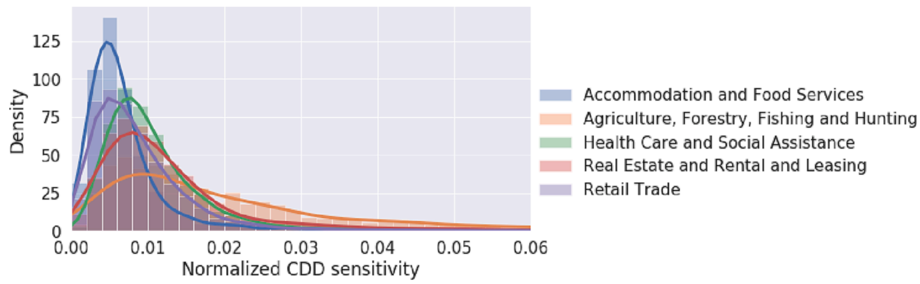

Fig. 5. Distribution of normalized CDD sensitivity across selected business sectors. *Accommodation and Food Services* has the most concentrated distribution while *Agriculture, Forestry, Fishing and Hunting* has the most dispersed distribution.

The distribution of normalized CDD sensitivity for each sector is similar in appearance to a lognormal distribution whose probability density function is 0 for negative normalized CDD sensitivity and has a single peak. The distribution of normalized CDD sensitivity is centered around lower values and has relatively low standard deviations for *Accommodation and Food Services* and *Retail Trade*. In contrast, the density of normalized CDD sensitivity for *Agriculture, Forestry, Fishing and Hunting* is more evenly distributed with a higher density on larger normalized CDD sensitivity values compared to the other sectors. When comparing the median of normalized CDD sensitivity, *Agriculture, Forestry, Fishing and Hunting* was the highest, *Accommodation and Food Services* and *Retail Trade* was the lowest, and *Health Care and Social Assistance* and *Real Estate and Rental and Leasing* was in the middle of the range. One possible explanation is that although *Agriculture, Forestry, Fishing and Hunting* and *Real Estate and Rental and Leasing* tend to be less likely to have cooling technologies, once they have adopted these cooling technologies, the electricity needed to cool the establishment can be large compared to the demand from other electrical appliances.

3.2. Hourly CDD sensitivity of SMBs

Having first explored CDD response in terms of daily demand, we next investigated the CDD response and sensitivity of hourly demand. We have provided an example of hourly CDD sensitivity results for SMB establishments in Health Care and Social Assistance, displayed in Fig. 6 (see Figs. A5–A8 in Appendix B for these hourly CDD sensitivity results of other sectors). The upper panel displays box plots for hourly CDD sensitivity across different hours alongside the average demand profile of SMBs. The lower panel displays the percentage of SMBs that were CDD responsive in each hour.

Based on the example presented in Fig. 6, as well as patterns from other business sectors presented in Appendix B (Figs. A5–A6), we have drawn the following conclusions. First, SMB establishments whose daily demand is CDD responsive may not be responsive to CDD in each hour. In fact, the percentage of establishments that are CDD responsive per hour ranges from 40% to 100%, with more SMB establishments that are CDD responsive in the daytime with a peak at 2 pm for the *Health Care and Social Assistance* business sector. Moreover, the hourly CDD sensitivity was not the same in each hour and was higher during the day with a peak median at 3 pm. Note that the peaks of CDD responsive percentages or CDD sensitivity are not in the same hour as the peak of the average demand profile (dual peak, 12 pm and 4 pm). This difference in timing could be due to the peaks of CDD response and CDD sensitivity being more closely related to the temperature of each hour while peak

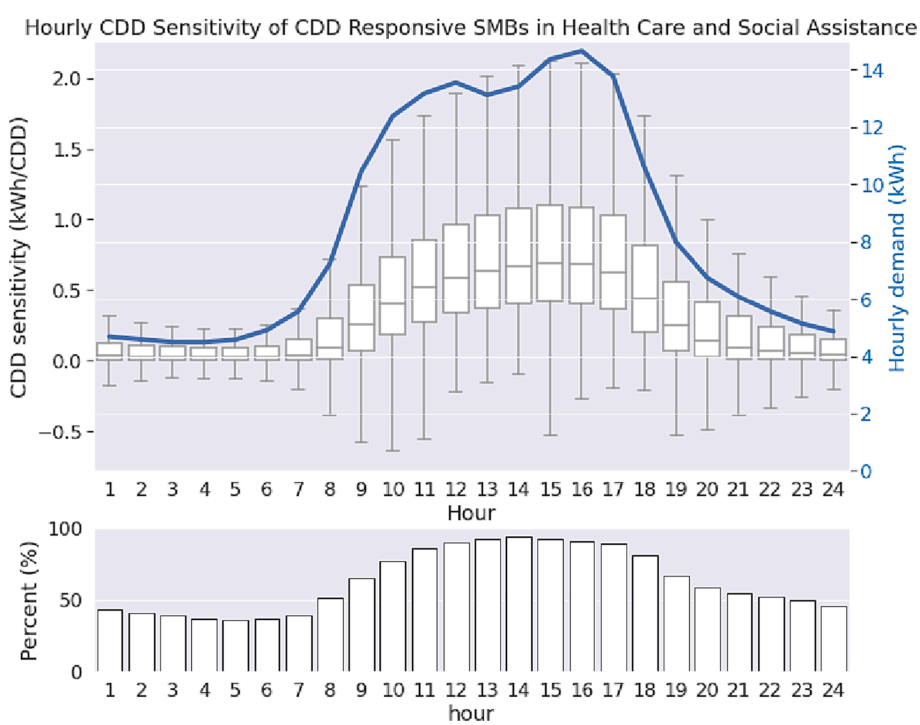

Fig. 6. Hourly CDD sensitivity (top) and CDD response (bottom) for *Health Care and Social Assistance* on a 24-hour clock, where 1 is midnight – 1am, 2 is 1am – 2am, etc. The blue line represents the average hourly demand (kWh) per hour (top). Higher levels of CDD sensitivity and response occur between 1 pm and 5 pm, which generally coincides with warmer outside temperatures.

load is more closely tied to the time when the establishment conducts more energy intensive business operations.

3.3. Relationship of CDD response and sensitivity with respect to other SMB characteristics

We have shown in Section 3.1 that both CDD response and sensitivity are related to the business sector and the climate zone of an SMB. Here we further demonstrate how business sectors and other establishment characteristics are associated with CDD response and sensitivity of SMB establishments.

We ran the logistic regression model defined in Eq. (5) over all SMBs with CDD response as the binary response variable. For easier interpretation of average daily demand and ZIP code level household median income, a contextual characteristic, we normalized them by a division of 100 and 10,000 respectively. Therefore, a one-unit change in average daily demand translates to a change of 100 kWh and one unit change in ZIP code level median household income corresponds to a change of $10,000. The underlying correlations between the median household income at the ZIP code level, average daily demand, and CDD responsiveness are presented in Appendix A3. The inclusion of these variables in our regression models is supported by these observed correlations.

Logistic regression results predicting CDD response (i.e., A/C adoption) are displayed in Fig. 7. We found that when controlling for other factors, CDD response varies by sector, with SMBs in *Health Care* and Social Assistance having the highest likelihood of being CDD responsive while SMBs in Agriculture, Forestry, Fishing and Hunting having the lowest likelihood, all compared to the baseline category of Accommodation and Food Services. We also found that SMBs in warmer areas (i.e., with higher average daily CDD) had a greater likelihood of being CDD responsive compared to users in cooler areas. This may be attributed to higher A/C adoption among SMBs that experienced higher temperatures more often. We also found that larger load and lower base/peak ratio was associated with a higher likelihood of an SMB being CDD responsive, with a practical interpretation that either larger physical establishments, or at least those establishments with comparably high electricity consumption, were more likely to have adopted A/C. In terms of peak period metrics, we found that the late afternoon peak was associated with the highest likelihood of being CDD responsive, while the night peak had the lowest likelihood. One explanation for such a peak period relationship could be that SMBs whose working hours cover the hottest time of day were more likely to have adopted A/C. Finally, we found that median household income of the ZIP code for which the SMB establishment was located was not associated with CDD response, suggesting that at least for our sampled areas, residential income was not a driver of A/C adoption.

We next ran the linear regression model defined in Eq. (6) with CDD sensitivity as the dependent variable. This model was run over the subset of SMBs who are CDD responsive (i.e., have adopted A/C) and the results are shown in Fig. 8. We found that after controlling for other factors, CDD sensitivity varies by sector with SMBs in *Agriculture, Forestry, Fishing and Hunting* having the highest CDD sensitivity while SMBs in *Accommodation and Food Services* having the lowest. Additionally, SMBs in warmer areas have lower CDD sensitivity than in cooler areas. One potential explanation for this discrepancy is that for establishments located in warmer areas, their A/C might already be operating at full capacity with little room to further increase the cooling power in response to high temperatures. Similar to our previous modeling of CDD response (Fig. 6), establishments with larger loads and lower base/peak ratio were associated with higher CDD sensitivity.

When estimating the relationship to peak usage periods, we found that a late afternoon peak has the largest CDD sensitivity while early morning and night peak have the least. However, unlike the logistic regression results, we found that establishments located in ZIP codes with lower median household incomes have higher CDD sensitivity. This finding can be difficult to fully unpack with our available data, as we only have a ZIP code-level information and not more specific information about individual businesses (e.g., finances, count of employees, age of building, etc.), but it could be related to establishments in these regions having lower energy efficiency A/C systems installed, for example.

4. Understanding future A/C adoption, electricity demand, and daily usage patterns of SMBs

In this next section, we present projections of future change in A/C adoption, temperature-related demand, and daily load shape using climate change scenarios (Section 4.1 and 4.2).

4.1. Projecting A/C adoption and electricity demand using future climate scenarios

Under the RCP 8.5 scenario introduced in Section 2.1, we projected A/C adoption, average daily demand and demand during system peak periods for SMBs for the following four sectors: *Real Estate and Rental and*

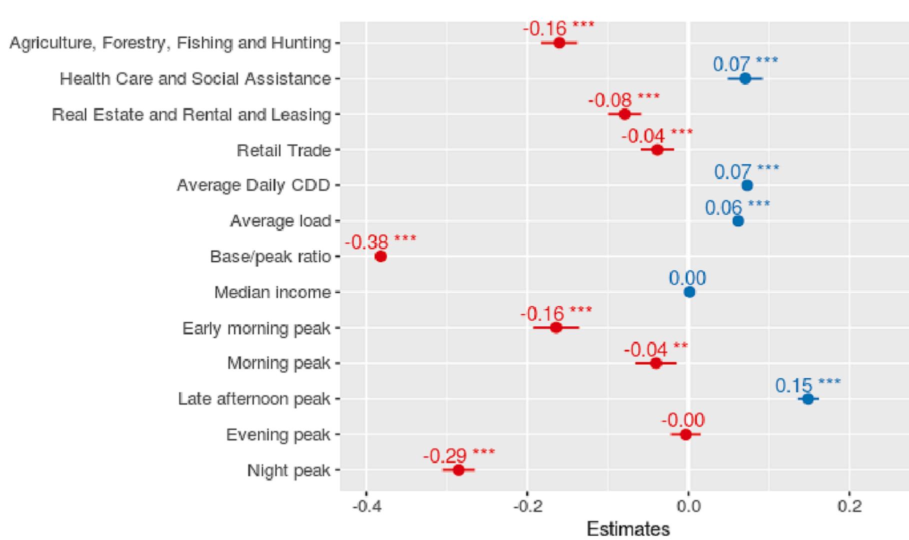

Fig. 7. Coefficient plot of logistic regression predicting CDD response (CDD responsive = 1; CDD nonresponsive = 0). Points represent estimates, lines the 95% confidence interval with statistical significance levels indicated by *p < 0.05, **p < 0.01, ***p < 0.001. Positive coefficient estimates are associated with features that contribute to higher probability of CDD response (i.e., A/C adoption), negative estimates are associated with lower probability of CDD response.

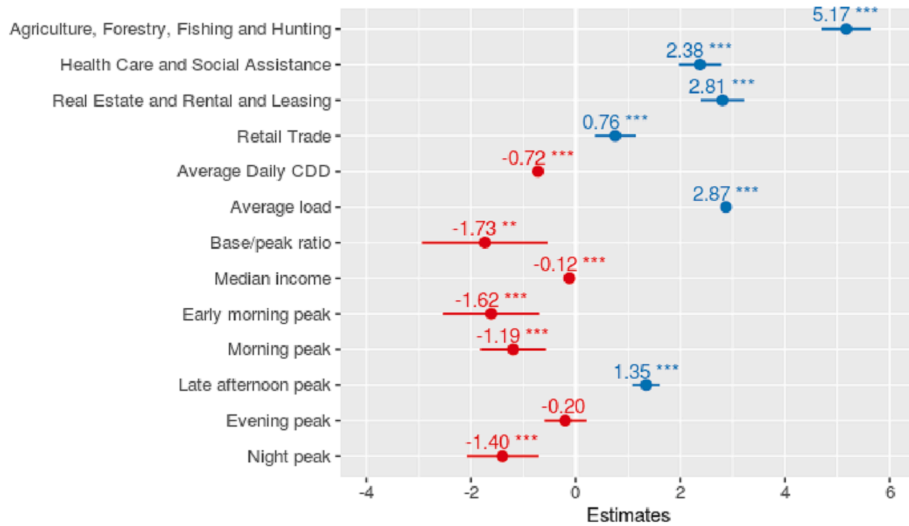

Fig. 8. Coefficient plot of linear regression predicting CDD sensitivity. Points represent estimates, lines the 95% confidence interval with statistical significance levels indicated by *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$. Positive coefficient estimates are associated with features that contribute to higher CDD sensitivity, negative estimates are associated with lower CDD sensitivity.

Leasing, Retail Trade, Accommodation and Food Services, and *Health Care and Social Assistance*. We did not include the sector of *Agriculture, Forestry, Fishing and Hunting* in this part of the analysis because CDD responsiveness in this sector are more likely to be affected by factors outside of A/C adoption, such as agricultural activities that consume electricity and coincide with warmer seasons of the year [51]. The system peak time period as defined by the utility (PG&E) is from 4 pm to 9 pm, which coincides with the time when the grid has the most operational burden due to increased system demand and diminishing generation from solar. We aggregated the results of A/C adoption, average

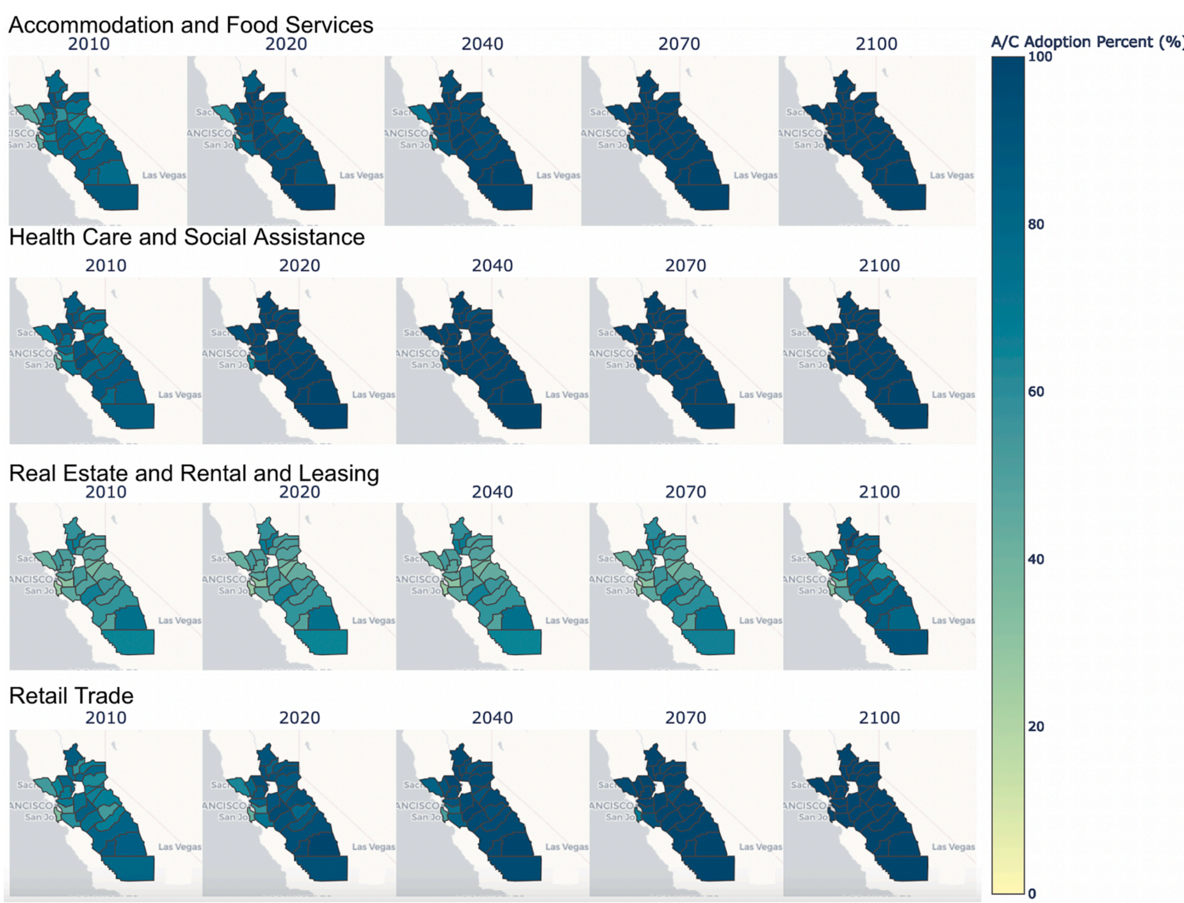

Fig. 9. Projected county-level A/C adoption for *Accommodation and Food Services, Health Care and Social Assistance, Real Estate and Rental and Leasing, and Retail Trade* for 2010, 2020, 2040, 2070, and 2100. Each panel contains a unique sector and year combination for selected counties in California. The color fill of counties corresponds to the A/C adoption rate percentage, with lighter colors representing lower adoption percentages and darker colors higher adoption percentages.

daily demand, and demand during system peak periods at the county-level (see statewide maps in Figs. 9, 12, and 13). For comparative analysis, we have projected the average daily demand for the four sectors under RCP 4.5 and generally found similar patterns but at lower magnitudes. These comparative results are provided in Appendix A4.

We first examined how the county-level A/C adoption percentage changed in our four selected sectors by projecting A/C adoption for existing SMB establishments in our dataset (in 2010) for 2020, 2040, 2070, and 2100 (displayed in Fig. 9). We observed that nearly all counties reached 100% A/C adoption for three out of four sectors, with only *Real Estate and Rental and Leasing* having establishments that do not all adopt A/C systems by 2100, with some counties even having less than a 50% adoption rate. In contrast, *Health Care and Social Assistance* and *Accommodation and Food Services* had relatively faster rates of A/C adoption, with most counties projected to have more than 75% A/C adoption by 2040. Such a difference in adoption rates could be related to business operations. For example, in the *Real Estate and Rental and Leasing* sector, the need for A/C utilization may be lower because some core business functions are performed off-site. This is different from establishments in *Health Care and Social Assistance*, which may require cooling for a variety of functions ranging from patient comfort to the storage of medications and medical supplies.

Fig. 10 shows the percentage increase in average daily demand at the county-level from 2010 to 2100 for the four selected business sectors. Overall, the sectors vary in percent demand change. *Health Care and Social Assistance* had the largest percentage change while *Accommodation and Food Services* and *Real Estate and Rental and Leasing* had the least. Within the same NAICS code, we also observed heterogeneity in demand increases across counties, with the largest variation occurring in *Real Estate and Rental and Leasing* while the least variation was in *Accommodation and Food Services*.

Fig. 11 shows the percent increase in demand during system peak time periods for the four sectors at the county-level from 2010 to 2100. In general, we found that the percentage of increased demand in the system peak period was higher than that of increased demand. We also observed substantial heterogeneity across sectors and counties (14% – 69%), which was more significant than for the total demand (10% – 36%).

4.2. Future projections of SMB daily usage patterns

To further investigate how SMBs' future demand changes are reflected in different hours and thus understand the changes in the timing of demand across business sectors, we examined the average load shape change for four sectors in different climate zones from 2010 to 2100 in 10-year increments (Fig. 12). The projections for Climate Zone 13 had a similar pattern to Climate Zone 12 and are not shown. See Fig. A9 in Appendix B for the remainder of the climate zones.

Some key observations from Fig. 12 are as follows. First, while all load shapes displayed some changes over the yearly range, variation emerged by sector and climate zone. Second, increases in demand primarily occurred during typical working hours, mostly concentrated within the 9am–9pm time window. Third, load shape changes did not have the same rate of change for different Climate Zones across time. For example, for the Bay Area (Climate Zone 3), relatively small changes occurred between 2010 and 2040, but large changes were observed after 2050. In contrast, load shape changes for establishments in warmer areas, such as Climate Zone 12, occurred almost immediately (by 2030).

4.3. Factors related to projected demand increase percentage

We next examined what factors were related to the heterogeneity in projected demand increase percentages, illustrated in aggregate across sectors and counties in Fig. 10. To do so, we modeled projected demand increase percentage from 2010 to 2050 using the following factors: business sectors of the establishment, ZIP code level contextual variables (household median income, race/ethnicity information, land cover, population density, percentage of disadvantaged communities, solar installation per capita), and Rural-Urban Continuum Codes [52–55]. The results of this modeling are shown in Fig. 13, where Accommodation and Food Services is the reference for listed business sectors, percentage of those identifying as white alone as a measure of race/ethnicity, and land cover represented as a percentage in area of three land class designations (water, developed, and forest).

The key observations from Fig. 13 are as follows. First, the sector effect on demand increase percentage of Health Care and Social Assistance, Retail Trade, Real Estate and Rental and Leasing, and Accommodation and Food Services followed a descending order compared to Accommodation and Food Services. While the high demand increase percentage of Health Care and Social Assistance persisted, this ordering differed from the direct intuition gained from Fig. 10, as sector coefficients demonstrated the sector effect after controlling for other included factors. Second, establishments in areas that are lower-income, more rural, and had higher proportions of disadvantaged communities were projected to have higher levels of demand increase percentage in 2050. Upon examining the distribution of the four sectors addressed in Fig. A1, we found that these sectors' spread across ZIP code level median income groups are consistent with the overall user population. Notably, our data does not demonstrate an overrepresentation of these sectors in lower-income areas. This consistency lends further credibility to our results. One possible explanation is that those areas are more vulnerable to climate change and establishments in those areas are less prepared due to lower A/C adoption. Third, establishments located in areas with more water and forest and less developed tended to have lower levels of demand increase percentage. This could be related to urban heat island effects where areas with more features of urban development (buildings, asphalt, etc.) experience comparatively higher temperatures. Moreover, water and forest are also known to help reduce temperature through evaporation and evapotranspiration [56]. Lastly, we observed a higher projected demand increase percentage for establishments in areas where there were more photovoltaics deployed. This indicates the potential ability of mitigating the effect on electricity demand increase due to climate change through the adoption of renewable resources such as solar.

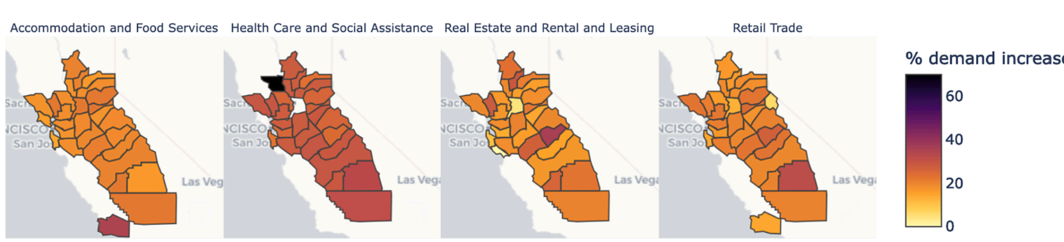

Fig. 10. Projected county-level demand increases between 2010 and 2100 for *Accommodation and Food Services, Health Care and Social Assistance, Real Estate and Rental and Leasing, and Retail Trade*. The color fill of counties corresponds to the demand increase percentage, with lighter colors representing lower demand increase percentages and darker colors representing higher demand increase percentages.

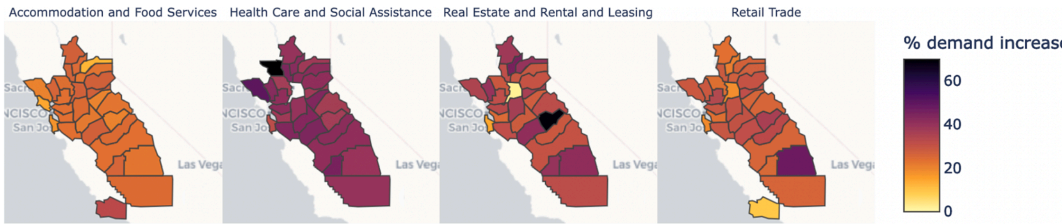

Fig. 11. Projected system peak-period county-level demand increased between 2010 and 2100 for *Accommodation and Food Services, Health Care and Social Assistance, Real Estate and Rental and Leasing, and Retail Trade*. The color fill of counties corresponds to the peak-period demand increase percentage, with lighter colors representing lower peak-period demand increase percentages and darker colors higher peak-period demand increase percentages.

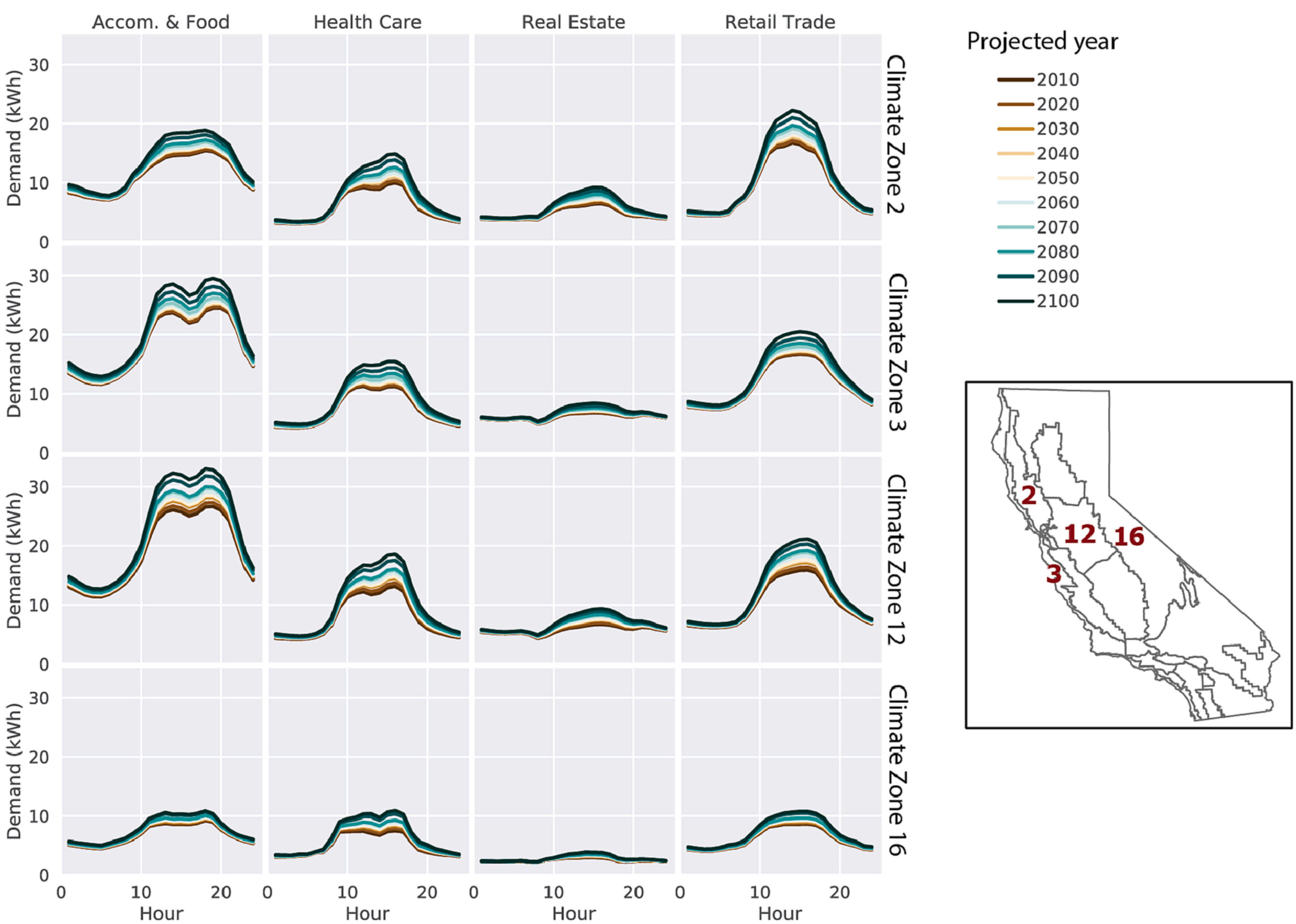

Fig. 12. Projected daily load shape change for *Accommodation and Food Services, Health Care and Social Assistance, Real Estate and Rental and Leasing, and Retail Trade* across four selected climate zones: Climate Zone 2, 3, 12, and 16. Locations of Climate Zones are displayed on a California wide map (right). Each panel contains a unique sector and climate zone combination (left). The color of the lines corresponds to projected daily load shapes in 10-year increments from 2010 to 2100.

5. Discussion and policy implications

We found evidence of substantial variation in electricity demand in response to warmer temperatures for SMBs in California. Some of this variation can be explained by the presence of cooling technologies, such as A/C, while other variation was related to the economic sector, and yet other variation was related to the climate zone that the business establishment was located in. When we used climate models to project changes in temperature into future periods, we found dramatic increases in electricity demand related to increased temperature, and for some sectors and in some climate zones, near complete saturation of A/C adoption. However, these projected increases were not distributed equally across California. Establishments' contextual surroundings – measured at the ZIP code level – were associated with comparatively higher increases in projected demand for lower income, more rural, and disadvantaged areas.

When examining the contextual factors associated with change in electricity demand through 2050, our analysis found disparities related to disadvantaged communities, an environmental justice measure developed by the state of California [55]. California's disadvantaged communities are areas that have been identified as having disproportional pollution and other environmental hazards while at the same time containing populations that are more vulnerable to these hazards. Communities with a disadvantaged status can also receive investments generated from California's Cap-and-Trade program to help promote economic opportunities, improve public health, and reduce other population burdens. In this respect, insights about disadvantaged communities can have policy-relevant implications. Our findings suggest that in

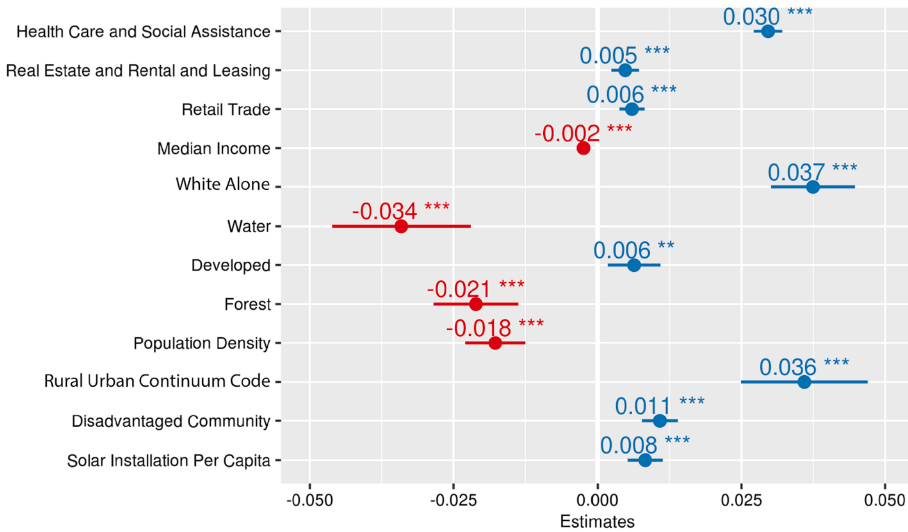

Fig. 13. Coefficient plot of linear regression predicting projected demand increase percentage in 2050 compared to 2010. Points represent estimates, lines the 95% confidence interval with statistical significance levels indicated by *p < 0.05, **p < 0.01, ***p < 0.001. Positive coefficient estimates are associated with features that contribute to larger increases in projected demand percentage change, negative estimates are associated with lower increases in projected demand percentage change.

addition to other challenges, disadvantaged communities may now also be confronted with impacts from climate change via SMBs, with businesses in disadvantaged communities projected to have higher levels of SMB demand increase compared to non-disadvantaged communities. This disparity may result in financial burdens that have implications on business viability and economic development, and, by extension, their employees. Another area of concern is if in response to increased energy costs, businesses may have more difficulties meeting the thermal comfort needs of employees and customers. Research has already found that just being located in an area with high temperatures is associated with higher risk of workplace injuries [39], and these types of impacts on employees could potentially be exacerbated if working environments are not adequately cooled. Our research highlights a clear need for policy that is specific for SMBs in disadvantaged communities, as well as lower income and rural areas, to mitigate some of these projected energy-related impacts from climate change. This could include subsidizing the deployment of new and more efficient cooling systems or updating existing inefficient systems so they are appropriately sized. Relatedly, programs that incentivize other energy efficiency improvements such as solar and storage [57], should consider incorporating temperature-related demand projections in their design.

From a grid-level perspective, our findings estimate a demand magnitude related to temperature for a large proportion of a utility's overall load footprint and attribute these estimates to economic sectors. Using information such as daily average load, location of business establishments, and business sector, our work provides some intial insights into how additions or removal of SMBs within a utility footprint may impact system demand. Moreover, our research suggests that as the average daily temperature increases due to climate change, and with it increases in A/C utilization, there will be increased demand related to temperature which could be exacerbated during extreme heat days or heatwaves. As these impacts will not be equally distributed, our work provides estimates for the magnitude of demand increases across different SMB sectors and across different climate zones. Such information may include how the patterns in hourly electricity consumption may change across different hours of the day, in different locations, and for various business sectors.

There are some important limitations to note for this research, first of which is related to the data itself. Given that this data was collected in 2010–2011, and is now over a decade old, new advances in building cooling efficiency and other patterns in cooling technology adoption will not be reflected in our analysis. At the same time, however, during the time period of our data there were far fewer behind-the-meter energy resources deployed, so meter consumption was not obfuscated from generation sources such as rooftop solar. Additionally, our data does not cover recent changes to California energy standards for residential and nonresidential buildings that came into effect in 2023 [58]. These new energy standards encourage adoption of electric heat pumps for space heating, electric water heating, solar PV and battery storage, as well as other energy efficiency and decarbonization-related technologies. While our expectation is that these standards will change the magnitude and timing of electricity demand in the future for business establishments, we are unable to produce such forecasts from our data.

While our data includes NAICS information about the establishment, we do not have any additional information about the types of technologies deployed, building characteristics, ownership, employee count, finances, etc. This makes it challenging to draw more specific establishment-level insights and instead we must rely on the aggregation of establishments by sector, as well as the surrounding context of the establishment (e.g., ZIP code-level population characteristics), when drawing conclusions. Relatedly, we do not have any specific information about the cooling technologies employed in these buildings, how they are deployed and when they are scheduled, nor other appliances that may also be influenced by outside temperatures, such as refrigeration units. Having a subset of buildings with load monitored appliances would certainly help us better disentangle these effects, and a caveat to this current research is that appliances not directly related to building cooling may be captured in temperature demand response that we estimate in our analysis.

While the analysis we conducted in this study was restricted to California SMBs, a logical next step for this research is to extend it to other areas of the United States, especially in places with differing climates and anticipated impacts from climate change. Given our findings, understanding whether disparities in demand impacts exist elsewhere, and the extent of the disparities, are a critical first step in informing adaptation policies that can help balance some of the unequal societal burdens related to future climate change impacts. More recently collected data that reflects emerging trends in the adoption of solar and storage systems, and where this adoption is occurring and among which business sectors, would also be important for identifying resiliency, access, and equitability issues. Moreover, insight into how businesses have been responding to increasingly high temperatures, with 2016 and 2020 being the hottest years on record [59], may provide new understanding into the behind-the-meter and HVAC adoption decisions that businesses are currently making in response to a changing climate.

An important future extension of this research is exploration into not only how electricity demand responds to hot weather (cooling degree days) but also projecting future demand sensitivity to cold weather (heating degree days). Currently, an overwhelming majority of deployed heating technology in California buildings uses natural gas, however, California has updated their building standards and now require newly constructed homes to be electric-ready (e.g., space heating, water heating, etc.) and have introduced heat pump standards for businesses such as offices, banks, and retail stores [58]. As electrification-related policies are more widely adopted in California, as well as other areas across the U.S., electricity and the thermal regulation of buildings will become inextricably linked, further increasing the importance of understanding how weather and climate is coupled with both electricity demand and supply in future periods.

6. Conclusions

We presented a first look at a critical, yet understudied, segment of energy users on the grid: small and medium businesses. In doing so, we have uncovered the following insights, addressing our first set of proposed research questions (RQ1a-b). We proposed temperature sensitivity as a measure to characterize the relationship between temperature and electricity use, and we explored its correlation with the demand for cooling. We found that there is substantial variation across business sectors in the sensitivity of electricity demand to temperature. We also found that some business sectors, on average, are characterized by higher levels of A/C adoption, such as *Healthcare* and *Accommodation and Food Services*, yet still display heterogeneity by climate zone, with establishments in warmer climate zones also having greater deployment of A/C. Lastly, we found that sensitivity to warmer temperatures among those establishments with A/C tends to follow a pattern of increased temperature sensitivity during working hours, often when outside ambient temperatures tend to be highest.

Using this information, we developed a series of models that predict A/C adoption and temperature sensitivity using both establishment-level and contextual features. We found that the two-digit NAICS code and average cooling degree days were important predictors of A/C adoption and temperature sensitivity to demand, as well as features specific to the energy use characteristics of the establishments, such as average load and peak period of day. However, while ZIP code level household income was not an important factor in predicting establishment-level A/C adoption, we did find it to be important for understanding temperature sensitivity—with lower income areas having establishments with higher temperature sensitivity to demand. Such a finding suggests that A/C use in these areas might be less energy efficient or that overall energy efficiency of the buildings could be lower.

Lastly, we applied future climate projections from the IPCC to model adoption of A/C and temperature-related demand—using our sample of SMBs as a baseline—to address our second set of research questions (RQ2a-b). We found that there is substantial heterogeneity across sector and county for adoption of A/C in California, with some sectors, such as *Health Care and Social Assistance*, reaching 100% A/C adoption saturation by 2100 and other sectors, such as Real Estate and Rental and Leasing, only reaching 50% A/C adoption by 2100 for some of the counties included in our analysis. We also observed heterogeneity in the impacts on projected load shapes across both sector and climate zone and found that change in load shapes mainly occurred during working hours. Using these projections, in our final analysis we examined factors associated with change in demand through 2050. We found that areas with lower income, more rural areas, and those areas designated as disadvantaged communities were associated with higher projected future demand.

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.

Data availability

The authors do not have permission to share data.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enbuild.2023.113301.

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