

ENERGY FINDINGS

How Commute Time and EV Ownership Shape Residential Cooling Energy Load Profiles

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Findings

Commute duration and electric vehicle ownership influence hourly residential cooling demand through their effects on household occupancy patterns. Using data from 10,000 U.S. households, travel behavior was linked to building energy simulation through a co-simulation framework focused on Tucson, AZ, USA. Long commutes were associated with higher peak-to-valley load ratios, while electric vehicle households showed flatter demand profiles with increased early morning and evening loads.

1. Questions

This study examines how household transportation behaviors influence residential energy demand, with a focus on commute duration and electric vehicle (EV) ownership. We ask whether commute time affects home occupancy and cooling energy demand, and whether EV ownership shapes patterns of household energy use during the day. We also explore whether these behavioral patterns create differences in energy load profiles that may have equity implications under time-of-use (TOU) electricity pricing.

We hypothesize that longer commutes reduce daytime occupancy and lead to sharper swings in cooling demand, while EV ownership contributes to more distributed or flexible energy use. These differences may contribute to uneven impacts under TOU pricing structures. The analysis focuses on Tucson, Arizona, where cooling demand is a more significant factor compared to many other regions.

2. Methods

National Household Travel Survey (NHTS) 2017 data was used as the primary dataset for analysis. Trip-level data from NHTS 2017 was summarized into household travel diaries for integration with energy modeling.

The R statistical software (R Foundation for Statistical Computing 2023) was utilized to generate the travel diary. NHTS data was imported using the “summarizeNHTS” library (Transportation Research Board 2018) and trip information transformed using the “tidyverse” library (Wickham et al. 2019). The transformation involved considering the number of trips, the start and end times, and the vehicle ID for each respondent. Following, the

household and personal characteristics were merged with the travel diary. This integration ensured that relevant information from the household and personal files was combined with the travel data. Hence, a comprehensive dataset was developed that included the summarized travel information and the corresponding household and personal characteristics. Finally, subsets of data were generated for households that own electric vehicles and those that do not. All details of our modeling can be found in the supplemental document of this paper.

From this dataset, we identified 10,000 households that were stratified into four groups based on commute time (short vs. long) and electric vehicle ownership (EV vs. non-EV). Commute length was determined by filtering for work-related trips and calculating average one-way duration. Short commute times were defined as below the median time in the data, and long commute times were defined as above. EV ownership was defined based on vehicle fuel type codes included in the NHTS vehicle file. Additional features including number of household members, weather data, and temporal indicators (hour of day, day of week, month) were included from the merged dataset.

To estimate hourly occupancy, we trained a Multi-Layer Perceptron (MLP) model using the processed dataset. The MLP was fed household demographic variables (e.g., household size, number of workers, presence of children), hourly trip schedule indicators, and hourly outdoor temperatures from the TMY3 weather file for Tucson, AZ. The model was trained on a subset of NHTS households with sufficiently detailed travel data to allow inference of presence or absence at home. The model output was a binary hourly prediction of home occupancy.

To simulate energy use, we used the U.S. Department of Energy's prototype model of a single-family detached home (Goel et al. 2014), situated in Climate Zone 2B to represent Tucson, AZ. A typical meteorological year (TMY3) file for Tucson was used to model weather conditions. To represent a residential community, this prototype was replicated ten times. To introduce realistic variation, each home's floor area was randomly adjusted by $\pm 10\%$. This reflects typical size differences in planned residential developments, which often fall within a 5–15% range (Asabere and Huffman 2013; Yang et al. 2022).

Occupancy predictions from the MLP were then used to create customized occupancy schedules for each household. These schedules were input into EnergyPlus v9.5 (U.S. Department of Energy 2021) to simulate hourly cooling energy use over a representative summer design week in August. Simulations were managed using a Python-based co-simulation tool that links occupancy predictions with building simulation inputs. Simulated energy profiles were aggregated by commute and EV ownership group to examine differences in residential cooling demand.

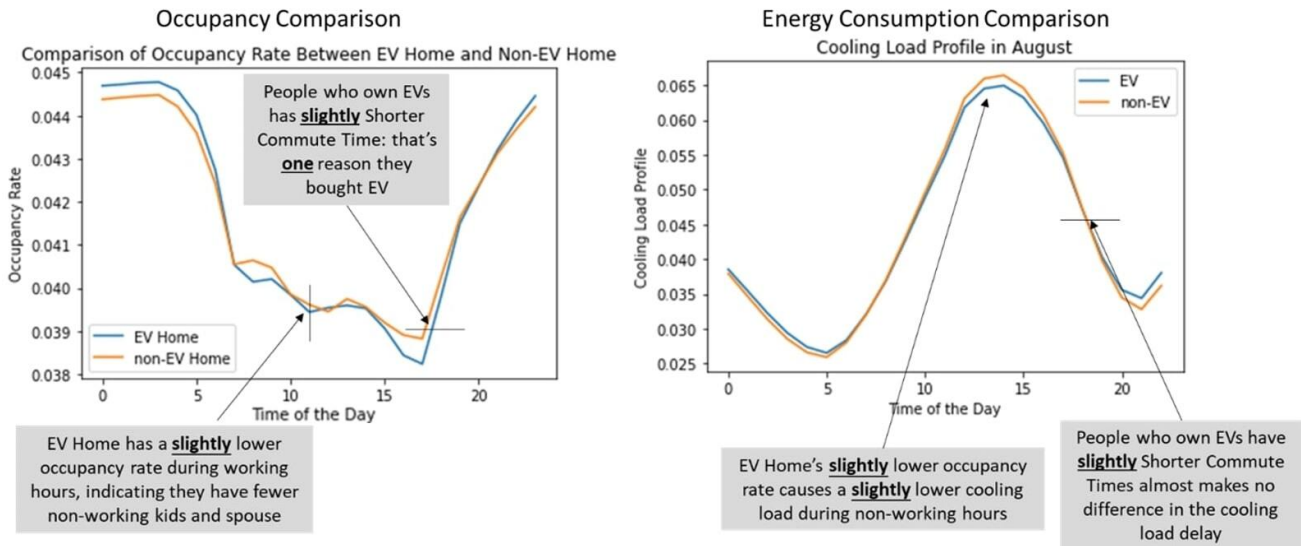


Figure 1. Comparison between occupancy rate and cooling load profile for long-commute and short-commute households

3. Findings

As demonstrated in [Figure 1](#), homes with long-commute residents experience a steeper and earlier decrease in occupancy during morning hours compared to homes with short-commute residents. Similarly, in the evening, the occupancy of long-commute homes surges more drastically than that of short-commute households. These variations in home occupancy directly influence the home's energy profile. Specifically, homes with long-commute residents exhibit more dramatic changes in their load profiles, characterized by a larger peak-to-valley ratio. Nevertheless, it is noted that the timing of the peak and valley periods remains consistent across both groups. Thus, we found that at the community level, commute time exerts a more substantial influence on the building's peak-to-valley ratio. Yet, it appears to have a lesser impact on the timing of the load shape's peak and valley periods, as evidenced by the consistent peak and valley times in homes with both long and short commutes.

Previous research finds that low-income households often live on city outskirts, and high-income households may commute farther for jobs or preferred neighborhoods (Blumenberg and King 2019; Sandow and Westin 2010). In both scenarios, during these extended commutes, the occupancy rate within the households is likely to decrease as more members are away. In contrast, groups with shorter commutes, especially those residing in city centers or close to their workplaces, are likely to experience higher household occupancy rates, as their members spend less time commuting.

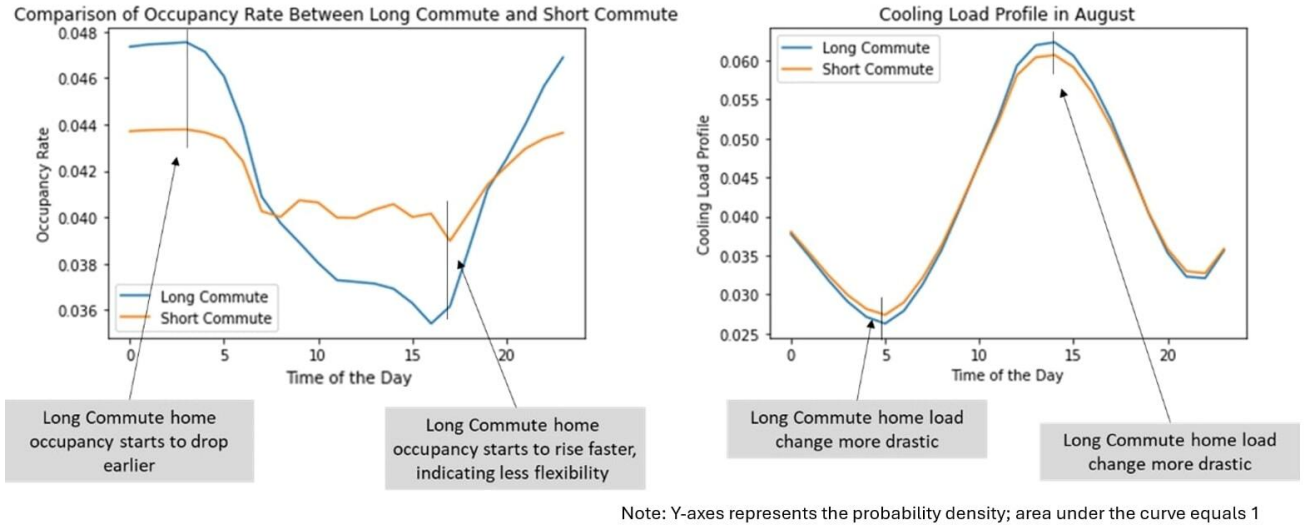


Figure 2. Comparison between occupancy rate and cooling load profile for households that own an EV and households that do not own an EV

As illustrated in [Figure 2](#), there is a minor difference in travel patterns and home occupancy between homes with EVs and those without. Observations during the morning hours reveal a higher occupancy rate in EV homes compared to non-EV homes. This suggests that EV homeowners tend to depart from their homes later than non-EV households. Consequently, EV homes experience a higher cooling energy consumption during these morning hours. During non-working hours, it is noted that EV households exhibit a lower occupancy rate compared to non-EV homes. This directly correlates with lower cooling energy consumption during these periods for EV homes. Around 5 pm, there is a trend of later commute times for residents of EV homes compared to their non-EV counterparts.

Overall, EV households use more energy in the morning and evening, while non-EV homes consume more during daytime hours and exhibit a higher peak-to-valley cooling load ratio. The data further shows that households with EVs tend to have shorter commute times. This can be at least partially attributed to the higher ownership of EVs among urban households residing in city centers, where shorter commutes are common. On the other hand, rural households have lower EV ownership and longer commute times, which is typical of suburban and rural areas (Baatar et al. 2019). Additionally, the findings reveal that EV-owning households have lower occupancy rates compared to those without EVs. This discrepancy can be likely linked to the relatively higher cost of EVs, making them more prevalent among higher-income households, often with dual incomes (Xing, Leard, and Li 2021). Lastly, our findings align with (Acosta-Sequeda et al. 2023), who found that long commutes influence electricity consumption patterns.

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SUPPLEMENTARY MATERIALS

Supplemental Information File

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