The where, when, and how of EV charging: detecting and characterizing charging behavior with advanced meter data analytics

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ABSTRACT

Load from the home charging of electric vehicles holds the potential to cause significant strain on the grid, but its inherent flexibility is a powerful tool to mitigate those same impacts. Among customers on EV-specific electricity tariffs, past load shape analyses indicate widespread use of controlled charging, suggesting that such customers largely avoid charging during peak periods. But especially for EV drivers who are not on EV rates, the location, timing, and extent of uncontrolled charging—and its impact on system peaks—remain a blind spot and pose a challenge for grid planning. This study leverages a dataset compiled by the California Energy Commission containing hourly electricity meter data for more than ten million California residences. We apply a neural-network algorithm to detect EV charging directly at the meter, and we add additional criteria to identify Level 2 charging. We then carry out a two-stage clustering analysis to categorize EV drivers' daily load shapes into different characteristic charging behaviors. The categorization allows us to assess the frequency of undesirable charging patterns across subsets of the population. In particular, we investigate the relative frequency of afternoon charging among customers who are and are not on EV rates along with the size of the resulting loads. We finish by reflecting on the nature and size of the untapped load flexibility available from EV charging, and we discuss future approaches to unlocking it.

Introduction

Electric vehicle (EV) charging in residential buildings represents a substantial new load that is poised to drastically reshape energy usage in the residential sector. An EV driven 10,000 miles per year at a typical efficiency of 3.2 mi/kWh will add more than 3 MWh of consumption, increasing the 6 MWh annual consumption of an average California home (CEC 2019) by around 50%. Moreover, the power draw from 120V Level 1 charging, around 1 kW, exceeds the hourly average load from a California home, while the draw from 240V Level 2 charging, at 6 kW or higher, is larger than any other common residential load[1] by a wide margin. Level 2 charging has the potential to drive significant new peaks in residential demand on the grid, which could strain both generation capacity and distribution infrastructure.

In recent years, adoption of EVs in California has been growing at a rapid pace and growth is projected to continue through this decade and the next (CEC 2024). Understanding the size, location, and timing of the anticipated EV charging loads will be crucial to effective planning of the California energy system over this period. For this reason, refining forecasts of transportation energy consumption in the context of electrification has been a key focus of modeling efforts at the California Energy Commission (CEC) as part of development of the California Integrated Energy Policy Report (IEPR). It will also be important to gain an understanding of how EV charging loads can be shaped by incentives, such as EV-specific

[1] High-capacity electric tankless water heaters are a potential exception, but these are not common.

electricity rates, to aid in planning for the future of the energy system. The relative novelty of EV charging loads poses a challenge: although there are numerous modeling tools and survey instruments that can provide scenario-based insights into EV charging demand, actual EV owner consumption patterns are poorly understood, and there has been little ground-truth information derived from direct analysis of electricity meter data.

Several studies have developed approaches to detecting the presence of EV charging in advanced metering infrastructure (AMI) data using both machine learning (Elahe et al. 2022, Lin & James 2022, Kamoona et al. 2025) and training-free (Li et al. 2024) approaches; however, each of these studies has been limited by the relatively small datasets available for EV owners given low present-day adoption levels in the population. In recent years, however, the CEC has amassed a very large dataset of AMI data from large investor-owned utilities (IOUs) and publicly owned utilities (POUs) in the state, via its authority under California Assembly Bill 802. Our investigation aims to detect the presence of Level 2 EV charging directly in the AMI data from the residential sector, and to characterize typical patterns of charging, using machine-learning techniques. We utilized data from more than 10 million residential electricity meters, which we paired with vehicle registration data on the more than 1.5 million EVs registered in California. This represents a drastic increase in the available data for training and validating an EV detection model; its breadth also allows us to identify the variety of typical EV charging patterns that are present in the EV-owning population.

To detect EVs, we used Recurve's existing neural-network based classification model for EV charging detection, trained on the CEC AMI dataset combined with EV registration information from the California Department of Motor Vehicles (DMV). For the meters with detected EV charging, we also applied consumption-based threshold criteria to identify the presence of Level 2 charging. We then utilized a two-step clustering approach to the load shape data for meters with detected Level 2 charging, to identify typical patterns of charging in the EV-owning population. Load shape clustering has been successfully used in numerous other studies (see Murthy et al. 2022 and references therein) to identify representative behavioral and consumption patterns in the population; here we use it to focus specifically on Level 2 charging behavior. Finally, we consider how time-of-use (TOU) and EV-specific electricity rates appear to affect the frequency of different charging patterns, and we discuss implications for the effectiveness of rate design in influencing charging behavior. This study is part of an ongoing collaboration between Recurve and the CEC on end-use detection in the CEC's AMI data; in earlier work (Gerke et al. 2024), we presented an approach to detecting heating and cooling end uses in CEC's AMI dataset.

Data

The dataset utilized in this study is composed of the following two main components.

- **Meter data.** To detect and characterize EV charging patterns, we analyzed hourly whole-building AMI data and related metadata (e.g., address and net-metering status) collected by the CEC for over 10 million residential electricity meters in the service territories of Pacific Gas & Electric (PG&E), Southern California Edison (SCE), San Diego Gas &

Electric (SDG&E) and the Sacramento Municipal Utility District (SMUD)[2], covering a period from 2018 through 2024.
- **Vehicle registration data.** To support model training, we leveraged vehicle registration data provided to the CEC by the California DMV indicating the addresses and dates of registration for all registered EVs in the state (including battery-electric and plug-in hybrid vehicles) through the end of 2023.

In the remainder of this paper, we describe the procedure for training the EV detection model, assess its performance, and characterize the consumption patterns observed among meters with detected Level 2 EV charging. The model training was completed substantially prior to the load analysis, and so different data were available for use in the two steps.

Model training data. The meter dataset available at the time of EV detection model training included data from PG&E, SCE, and SMUD. Data quality issues prevented data from SDG&E from being used for model training. The available AMI data at the time covered a period in either Q3 or Q4 of 2023, depending on the utility; we performed model training and validation on the most recent year of available data for each meter analyzed. The DMV data included the original vehicle registration date, latest registration date, registration address, fuel type, and vehicle identification number (VIN), for approximately 1.5 million vehicles identified as fully electric or plug-in hybrid, with registration dates ranging from the early 1990s through the end of 2023.

Recurve cross-referenced the meter and DMV datasets by normalizing the address information in both and converting it to unique identifiers that allowed locations to be robustly matched. This procedure yielded some 790,000 residential electricity meters with one or more all-electric battery EVs (BEVs) or plug-in hybrid EVs (PHEV) registered at the same address, leaving more than 9 million meters without an identified EV registration. The remainder of the EV registrations were either commercial/government vehicles or had address information that could not be matched to a PG&E, SMUD, or SCE electricity meter. These are likely to be primarily LADWP, SDG&E, or small municipal utility customers, though some addresses were also incomplete or malformed, making matching impossible.

Load analysis data. When the load analysis was performed, additional meter data had been collected, yielding data for the above three utilities, plus SDG&E, covering a period through the end of November 2024. By applying the trained EV detection model to the most recent year of data in this refreshed dataset, we were able to identify EV charging across all four utilities' service territories using the most recent available data, allowing for a more up-to-date assessment of the rapidly growing fleet of EVs in California. The DMV data was primarily used to train and assess the model in the model training step; we did not make use of it for the load analysis.

Methodology

Detecting EV Charging

This study made use of Recurve's FLEX platform and its neural-net based EV detection model to identify meters having consumption patterns that are indicative of EV charging. The model

[2] The other large utility in the state, the Los Angeles Department of Water and Power (LADWP), does not have hourly AMI for residential customers and therefore cannot be used for EV charging detection.

integrates data preprocessing, feature engineering, and a neural network machine learning model, including a transformer encoder layer and a classifier layer, to identify EV charging activity in residential smart meter data. The result of applying the model to a single meter's consumption data is a numerical probability that EV charging is occurring on that meter. Figure 1 presents a high-level schematic diagram of the steps in the model. Full details of the model are proprietary.

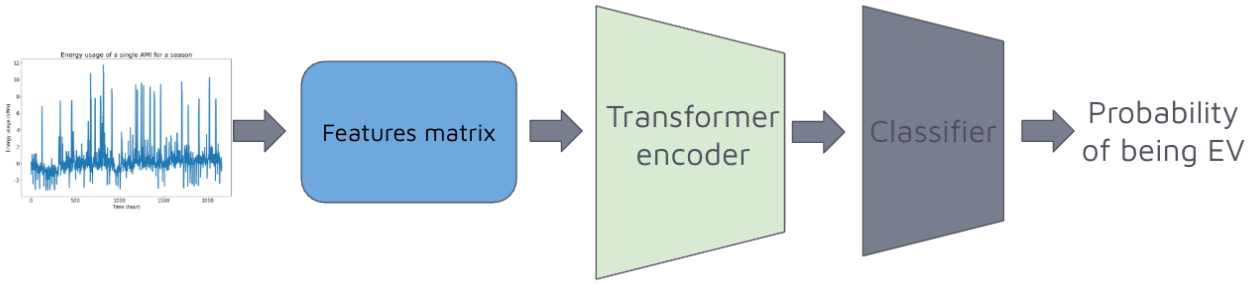

Figure 1. A schematic overview of the steps in Recurve's neural-net model for EV detection.

In the present study, we trained the model on a sample of meter data labeled using EV registration data from the California DMV and determined a probability threshold above which a meter was identified as an EV charging detection. Details of the training process and outcomes are presented in a later section of this paper.

Model Training

To ensure maximal effectiveness for this work, we trained Recurve's existing EV detection neural net model on a subset of the model training dataset described above before applying the trained model to the full dataset to assess its final performance. The training subset was composed of the most recent 365 days of consumption data for 100,000 meters with EVs registered at their address and 500,000 meters without such a registration. To ensure the model was trained on data that provided a complete representation of annual consumption patterns, the training data were randomly sampled from the set of meters with at least 365 full days between the first and last meter read available. In the case of meters with EV registration, the final meter read was required to be at least 365 days after the initial date of registration to ensure that the EV was registered at the site throughout the entire period covered by the meter data. 10% of the training data was held out of the training process as a test dataset to allow model performance to be assessed on an unseen dataset during the training process.

Training iterations and refinement. A challenge arises in training the model on this dataset, because EV *registration*, which we use to label our training data, is not necessarily indicative of EV *charging*, which is what we can detect in the meter data. Some EV owners might charge at different addresses than their registration address, while others might charge only at public charging stations. Thus, we expect that some fraction of meters with EV registrations will not have EV charging, and vice versa. Faced with these imperfect labels, we adopted an iterative approach to model training, in which we used an initial training run to identify and exclude meters that appeared likely to be mislabeled (i.e., registered EVs that were not commonly charged at their registered address), then retrained on the refined dataset to enhance the model's power to distinguish EV charging patterns.

The first iteration yielded a double-peaked probability distribution for meters with registered EVs, with peaks around 10% and 80%, which is qualitatively consistent with our expectations if some fraction of EVs are typically charged away from their registered address. The population without registered EVs had a strong single peak around 10% probability, with a long tail toward higher probability. These patterns are indicative of model confusion driven by imperfect labeling: some EV-labeled meters show identical consumption patterns to non-EV-labeled meters, and vice versa, so the model's distinguishing power is limited. To mitigate this, we removed from the training set all meters with registered EVs that had a detection probability below 20% in the first training iteration, re-trained the model on the reduced dataset, then applied the model to the full test dataset to assess the improvement. The probability distributions resulting from this second iteration showed a much clearer differentiation between the populations with and without registered EVs, indicating an improved classification fidelity.

Determining the Detection Probability Threshold. Because the model yields a probability that EV charging is present, our next step was to establish a probability threshold that could be used to claim a detection of EV charging. We examined the outputs of the model's confusion matrix, which breaks down the model's performance into true negatives, false positives, true positives, and false negatives. Examining the results of the model applied to the test data, we found that a clear trade-off between true positive and false negatives,[3] with the latter declining at the expense of the former at probabilities above 65%. Given that we expect many putative "false negatives" to in fact be accurate non-detections of EV charging (i.e., EV owners who do not charge at their registered address), we opted to keep the detection threshold below that level. Additionally, we analyzed the load shapes to determine at what probability threshold patterns resembling EV charging become clearly evident. Ultimately, we settled on a probability threshold of 60% to declare an EV charging detection.

Identifying Level 2 Charging

Because the neural-net model identifies EV-charging consumption patterns in a holistic way, it can identify both Level 1 and Level 2 charging, although detections of the former are likely to be less complete, since the relatively small loads involved are more difficult to distinguish. In this study, we are primarily interested in understanding Level 2 charging, so we performed a post-processing step on the meters with detected EV charging, to identify meters that appear to have Level 2 charging. Although the distinction between Level 1 and Level 2 charging is technically one of voltage not power, the vast majority of Level 2 chargers operate at power levels at or above 6 kW. It is also expected that most Level 2 charging sessions last for longer than one hour. Given these assumptions, we identified EV-charging detections as Level 2 charging based on the frequency with which they exhibited apparent charging events, defined as periods of hourly consumption exceeding 6 kWh for at least one hour.

To establish a meaningful threshold for the number of apparent charging events, we examined the distribution of meters by their annual count of such events, for meters with and

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[3] All probability thresholds had low false-positive and high true negative rates. This simply reflects the unbalanced nature of the classification: the vast majority of customers do not have EVs, and the model assigns significant probability to a small fraction of customers, so these metrics are essentially guaranteed to show good performance.

without EV charging detected by the trained machine learning model in the training dataset. We observed stark differences between the two populations. Among meters where no EV charging was detected, roughly two thirds had zero hours exceeding 6 kWh, and the proportion of customers exceeding a given number of instances declines rapidly as the number increases. By contrast, among meters with EV charging detections, the overwhelming majority (92%) had at least one hour in excess of 6 kWh, and the proportion of customers with a given number of instances declined much more slowly.

These results indicate that the EV detection model is highly effective in detecting consumption patterns consistent with Level 2 EV charging. However, it is also clear that exceeding 6 kWh for an hour or more is not a sufficient indicator on its own to claim a detection of Level 2 charging, since a third of the general population also exhibits at least one such instance. Therefore, to detect Level 2 charging, we require two elements to be in place: first, the EV detection model must have yielded a detection, and second, the site must have a large enough number of high-load instances to be reasonably indicative of regular Level 2 charging. In this study we used a threshold of 26 annual high-load instances, which would correspond to charging at Level 2 once every two weeks on average. Lower frequencies than this could reflect sporadic EV charging; on the other hand, more than 10% of the general population exhibits high-load events on this frequency, so a lower threshold would yield an elevated false-detection rate for Level 2 charging, even among customers with EV charging detected.

Characterizing Level 2 Charging Patterns

A primary focus of this study is characterizing patterns of charging, understanding their relative frequency, and exploring the drivers of different behaviors. To identify discrete patterns of charging in the population, we applied a two-step clustering strategy to the 24-hour daily consumption profiles of meters with detected Level 2 charging, making use of the clustering technique from the open-source GRIDmeter 2.0 project (which has now been subsumed into the Linux Foundation Energy's OpenDSM project[4]). The underlying clustering algorithm is described in a report from Recurve (2024). In brief, the clustering algorithm normalizes each daily load shape; performs a dimensional reduction using functional principal component analysis (FPCA), and identifies clusters of load shapes in the FPCA feature space using the bisecting k-means algorithm. The transformation of the data into functional space effectively sidesteps some of the challenges encountered in prior clustering studies like Murthy et. al. (2022) which required manual human intervention to distinguish similar clusters in hourly space.

Our usage of the clustering algorithm here differs in a few ways from its application in GRIDmeter. First, we clustered daily load shapes, rather than weekly averages. Second, in the load shape data for Level 2 detections it was evident that charging sessions frequently occur around midnight. This tended to spuriously create two clusters representing midnight charging when the input load shapes covered the period from midnight to midnight: one cluster for charging sessions starting in the evening and a second for charging sessions ending in the early morning. In fact, these clusters represented the same charging behavior. To eliminate this confusion, we applied a six-hour shift to the daily load shapes, so that each "day" in the clustering inputs ran from 6 am to 6 am. A shift of six hours was selected based on our observation that meters with EV detections tended to have the lowest load at around 6 am.

[4] www.opendsm.energy

The clustering analysis for this study proceeded in two steps. In the first step, we clustered the 24-hour daily load shapes for each individual meter over the most recent available 365 days of hourly data. We allowed the number of clusters to range between 4 and 20 for each meter and determined the optimal number of clusters for each meter via the commonly used silhouette metric. (We set the minimum cluster number at four based on the expectation that charging and non-charging behaviors would typically be different on weekends and weekdays, yielding at least four distinct patterns.) Figure 2 shows the resulting load shape clusters for three example meters. Typically the clustering algorithm identified one or two non-charging patterns, with hourly consumption below 6 kWh throughout the day, and several charging patterns with charging occurring at different periods of the day.

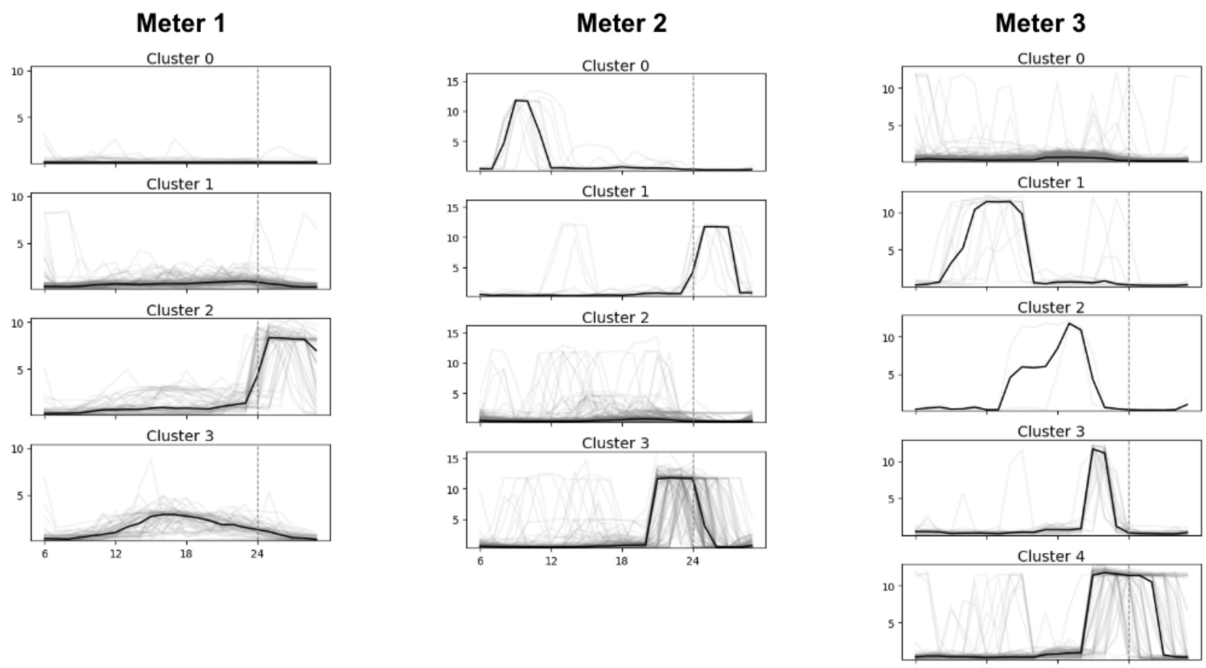

Figure 2. Load shape clusters identified for three example meters in the first step of clustering. Each column represents a single meter, and each panel is a single cluster. The median load for each cluster is a heavy black curve, and individual daily load shapes are light gray curves; clusters may contain different numbers of individual load shapes. Each load shape runs from 6 am to 6 am; a vertical dashed line indicates midnight.

In the second step of clustering, we calculated the median load shape for each individual meter's clusters, which reduced each individual meter down to a handful of load shapes that represented its basic daily consumption patterns. We then applied the clustering algorithm to these representative load shapes, which yielded typical daily consumption patterns across the entire population of meters with Level 2 charging detections. To determine the ideal number of clusters, we repeated the clustering exercise with different target cluster counts and selected a number that distinguished among different charging patterns of interest (e.g., differentiating between charging during midday hours and charging in the afternoon upon arrival at home). Ultimately, we found that creating twelve clusters yielded an appropriate differentiation. Results of this final clustering step are presented in the Findings section.

Findings

Characterizing EV and Level 2 Detections

Running the trained neural net model on the entire labeled training dataset allowed us to assess the fidelity of our detections. We expect that some proportion of registered EVs will go undetected for one of several reasons:

- The vehicle is charged exclusively (or nearly so) away from home
- The vehicle is charged exclusively at Level 1 on a meter whose other sources of load are large enough to obscure the roughly 1 kW of additional demand
- The vehicle was acquired during the analysis period, making charging harder to detect
- The vehicle has been retired or moved out of state.

The California Vehicle Survey (NREL 2024) indicates that, around the time of our analysis, 30% of BEV owners and 53% of PHEV owners had access only to Level 1 charging at home, while 5% of EV owners had no access to home charging at all. All of this constrains the fraction of registered EVs we can expect our algorithms to detect.

The training dataset contained some 791,000 addresses with registered EVs, of which 563,000 were BEVs and the remainder PHEVs. Around half of these vehicles were registered for the entire year analyzed; of these, the model detected 58% of the BEVs and 23% of the PHEVs. BEV detection rates drop precipitously for vehicles with shorter registration periods, with only 30% detection for BEVs registered in the last quarter of 2023. PHEV detection rates remained relatively stable regardless of registration date, which may indicate that detected PHEVs have highly regular charging patterns. Applying our Level 2 charging thresholds, we found that 92% of the detected BEVs and 58% of the detected PHEVs appeared to have Level 2 charging. These values are much larger than the Level 2 charging penetrations in the California Vehicle Survey, indicating, unsurprisingly, that our detections are strongly biased toward Level 2 charging.

We also detected EV charging at 135,000 locations that did *not* have registered EVs, and 70% of these detections appeared to have Level 2 charging. It is to be expected that some EVs will be charged at residences other than their place of registration, since some owners will have multiple households, vacation homes, etc. It is also probably that some fraction of these detections are false positives. That false-positive rate is difficult to constrain, but depending on where it falls, our EV detections here are enough to account for between 49% and 69% of the expected count of home-charging EVs, including 24% to 34% of PHEVs and 61% to 85% of BEVs, when limiting to vehicles that were registered for the full analysis period. Our Level 2 charging detections account for 68% to 90% of the expected total, including 27% to 35% of PHEVs and 80% to 100% of BEVs charging at Level 2.

We then ran the detection model on the more recent (circa 2024) load analysis dataset, which covered a broader population (including SDG&E) over a more recent period (through November 2024). The model detected some 602,000 meters with EV charging. Of these, 81% appeared to be charging at Level 2 based on our high-load-event threshold, nearly identical to the proportion of detections that appeared to have Level 2 charging in the training dataset.

Load Shapes by EV Detection and Solar Status

Figure 3 shows daily average load shapes for meters in the load analysis dataset with detected Level 2 EV charging, other (presumably Level 1) EV charging, and no EV charging detected, by electric utility and the presence or absence of behind-the-meter solar. Several differences are evident among the different subpopulations. Most apparent is the sharp peak in consumption at midnight for Level 2 (and, to a lesser extent, Level 1) meters across most utilities, with an earlier peak around 9 pm occurring in SCE service territory. This likely indicates that EV charging occurs preferentially at certain hours of the day, likely in response to price signals from EV-specific electricity tariffs. We will explore the relation between rates and charging behavior in more depth in the following section, but it is worth noting that SCE's EV rates are at their lowest starting at 9 pm, whereas the other three utilities have the lowest EV rates starting at midnight.

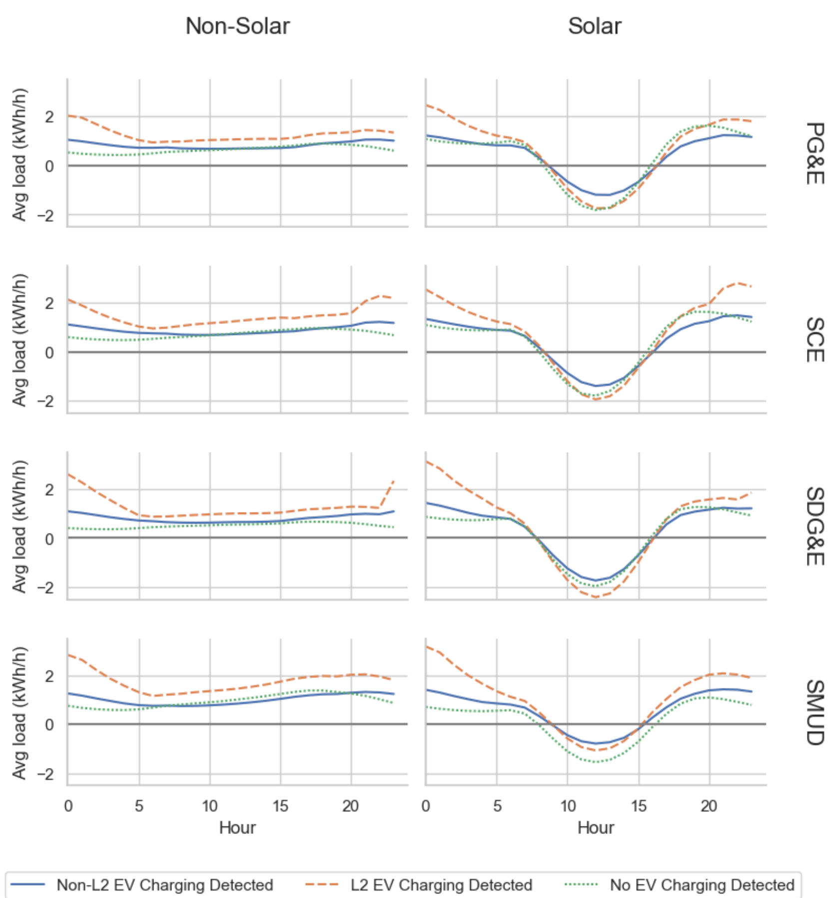

Figure 3. Daily average load shapes by EV detection status, solar status, and electric utility. Plots are shown over a 24-hour day starting at midnight.

It is also noteworthy that non-solar meters with Level 2 charging have higher consumption than their non-EV counterparts in all, likely reflecting that such meters are associated preferentially with larger single-family homes. By contrast, Level 1 EV charging detections have similar loads to their non-EV counterparts during daytime hours, indicating that they may be a more representative cross-section of the population.

Consumption Patterns in the Level 2 Charging Population

Figure 4 shows the representative daily consumption patterns revealed by running our two-step clustering algorithm on meters with Level 2 charging detected in the load analysis dataset. Recall that these cluster load shapes have been computed over a 24-hour cycle that starts at 6 am. We have assigned each cluster a descriptive name to indicate the specific behavior that it represents. Because we are interested in understanding what drives customer charging behavior, our naming aims to reflect the customer's decision about when to charge their EV.

We can broadly subdivide the clusters into days with and without EV charging. The non-charging patterns are as follows:

- **Low usage.** Consumption is well below 1 kWh in all hours of the day, indicating little usage, such as when occupants are at work or away from home.
- **Moderate usage.** Similar to the low-usage pattern, with higher usage indicative of higher occupancy but not high enough to reflect significant cooling usage.
- **High usage.** Usage levels are higher but do not reach a level indicative of Level 2 charging. The clustering identifies distinct patterns related to early and late usage.

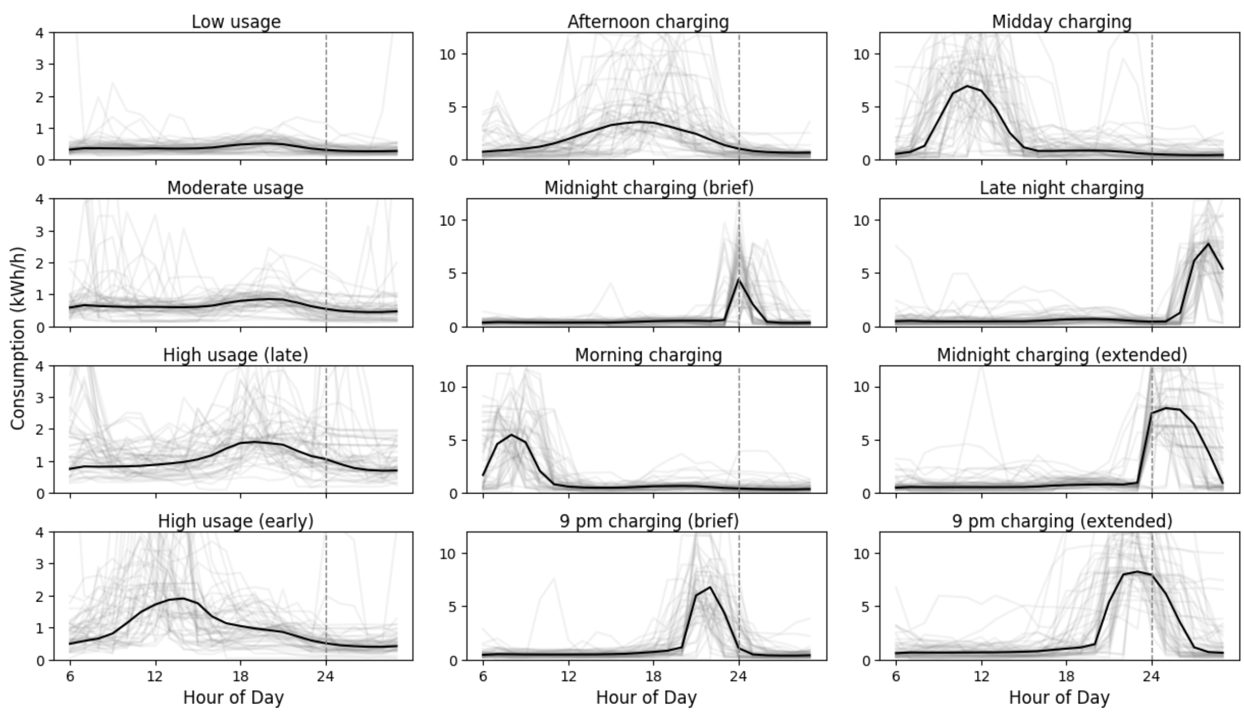

Figure 4. Representative consumption patterns for meters with Level 2 charging detected in the load analysis dataset. Gray curves show meter-level cluster load shapes for a sample of meters, while black curves show the median shape for each cluster. Plots run over a 24-hour period starting at 6 am; vertical lines indicate midnight.

There were six distinct patterns on charging days, some of which are split into two clusters:

- **Afternoon charging.** Charging sessions start between roughly 2 and 6 pm, consistent with expected arrival times at home from daily activities. Given California's evening peak, this is a particularly undesirable pattern from the grid perspective.

- **Midnight charging.** Charging sessions start at midnight, with two clusters representing brief and extended charging sessions.
- **Morning charging.** Charging sessions start between 6 and 9 am.
- **Midday charging.** Charging sessions start in the late morning through early afternoon.
- **9 pm charging.** Charging sessions start around 9 pm, with two clusters representing brief and extended charging sessions.
- **Late night charging.** Charging sessions start several hours after midnight.

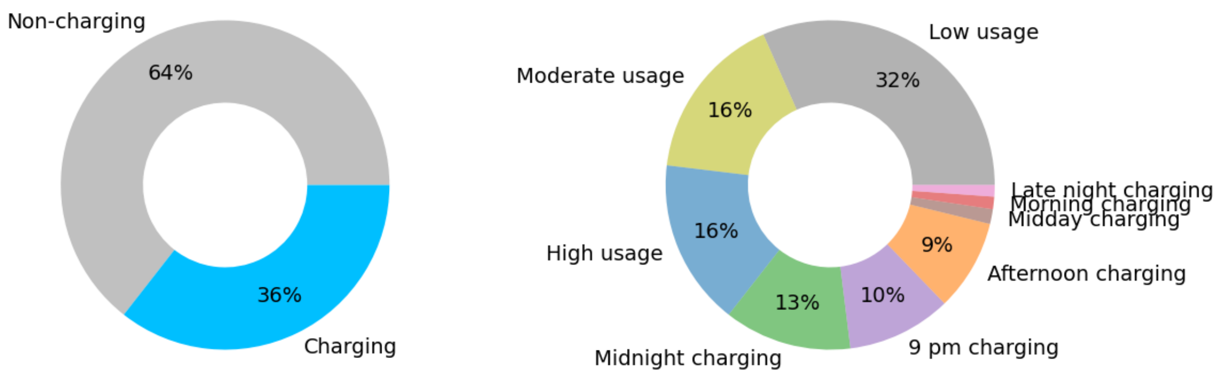

Figure 5. Breakdown of meter-days for Level 2 charging detections into charging and non-charging categories (left) and into the cluster groupings shown in Figure 4 (right). Labels are suppressed for percentages below 2%.

Clustering our 486,000 Level 2 charging detections yields roughly 175 million individual meter-days that can be categorized into these representative patterns. Figure 5 shows their breakdown into charging and non-charging subgroups and, further, into the more detailed patterns listed above. Meters with detected Level 2 charging engage in charging behaviors on slightly more than one third of the days, with most of the charging days falling into the midnight, 9 pm, and afternoon charging patterns. Figure 6 shows the breakdown of charging days alone. Midnight charging is the most common pattern, accounting for more than one third of charging days, followed by 9 pm charging. Afternoon charging is also a strong contributor, accounting for a quarter of charging days. All other patterns are relatively uncommon accounting for only 10% of all charging days in aggregate.

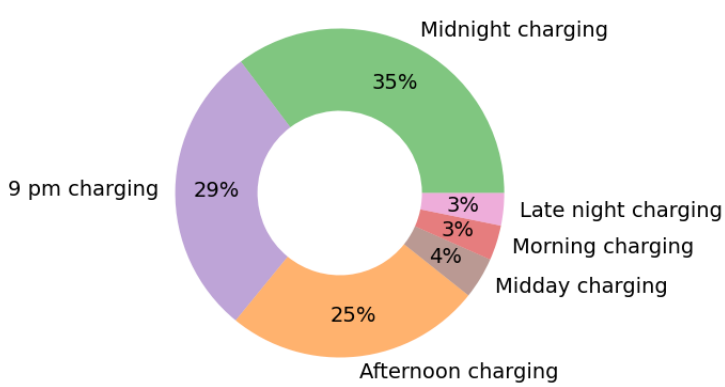

Figure 6. Breakdown of charging meter-days into the charging behavior clusters.

It is interesting to consider the implications of the results above for EV charging load on the grid at different times of day. These findings imply that, on an average day, 9% of our 486,000 detected Level 2 EV chargers exhibit the afternoon charging pattern. If each Level 2 charger draws 6-7 kW of power, then we can estimate that there was as much 250-300 MW of load—the capacity of a medium-sized power plant—arising from Level 2 EV charging during afternoon peak hours as of 2024. This load may be mitigated somewhat if the afternoon sessions do not all coincide in time on any given day; nevertheless, these results indicate that the potential to mitigate peak loads by shifting EV charging is already considerable. In the case of midnight charging, where nearly all charging sessions are expected to coincide exactly at midnight, we can estimate that EV charging was already contributing nearly half a GW of load in 2024. Monitoring and responding to the growth of this load spike will be important for effectively managing the future grid impacts of EV charging.

Consumption patterns by utility and rate grouping

EV-specific electricity tariff structures are a key tool for managing the significant and growing load from Level 2 EV charging. By correlating the load shape clusters identified in this study with the different types of rates available to California utility customers, we can assess the effectiveness of EV rates in driving shifts in customer charging behavior. To do this, we subdivided the rate codes available in the load analysis dataset into three subtypes as follows.

- **EV/Electrification rates** are specific to EV ownership or to broader adoption of electrification technologies. These rates are typically lowest starting at midnight, except for SCE's rates, which are lowest starting at 9 pm. They generally have the largest price differentials between peak and off-peak periods.
- **TOU rates** other than EV/Electrification rates typically reach their lowest values starting at 9 pm, except that SMUD's lowest rate starts at 8pm in the winter, and SDG&E has a TOU rate option that includes a super off-peak rate starting at midnight. These rates generally have smaller peak/off-peak differentials than EV/Electrification rates.
- **Non-TOU** rate structures are assumed for all other rate codes in the dataset.

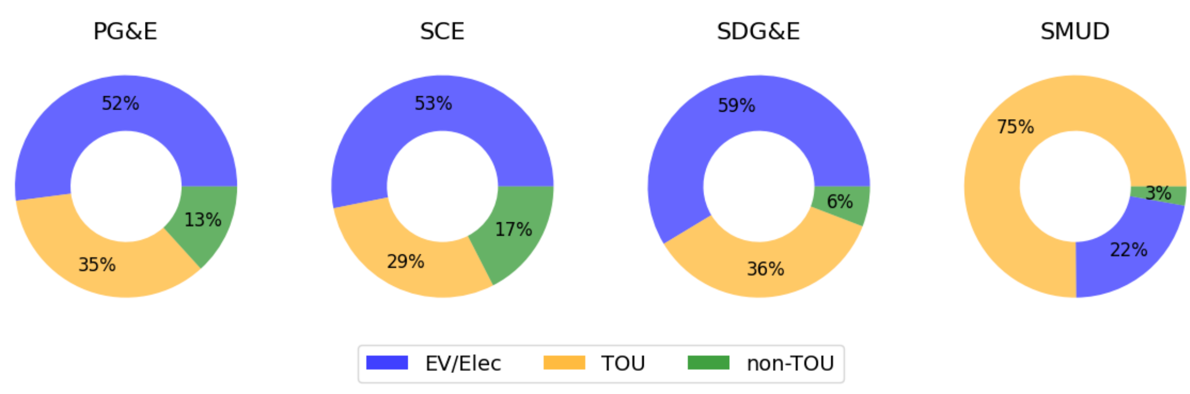

Figure 7. Breakdown of meters with Level 2 charging detections by utility and rate category.

Figure 7 shows the distribution of these rate categories, by utility, across the population of meters with Level 2 EV charging detections. In all three IOUs, most Level 2 detections are on EV rates, while adoption of SMUD's EV discount is considerably lower at less than one quarter of Level 2 detections. This difference may be driven by the smaller nighttime discounts available on SMUD's EV rate, ranging from 6 to 24 cents/kWh depending on the season, compared to the 20-40 cent discounts available on IOU EV rate plans.[5] Overall, across all utilities considered, 51% of Level 2 detections are on EV rates and 35% are on non-EV TOU rates. All four utilities also have a nonzero fraction of Level 2 detections on non-TOU rates, despite the fact that TOU is now the default rate type for all utilities considered.

In Figure 8, we show the proportion of days that are charging days among meters with detected Level 2 charging. The frequency of charging days increases somewhat as the available discount increases, with customers on EV rates charging on 37% of days, as compared to 29% of days for customers on non-TOU rates. This indicates that adoption of EV rates is driven to some degree by the salience of the available discount to the customer: customers who charge at home frequently have more savings opportunity and may therefore be more attentive to their rate selection. This effect appears to be relatively weak as a function of charging frequency, although it is possible that customers not on EV rates also have lower charging volume (i.e., fewer kWh of charging per session). Additional analysis of the results shown here may be able to address this point but is beyond the scope of the present study.

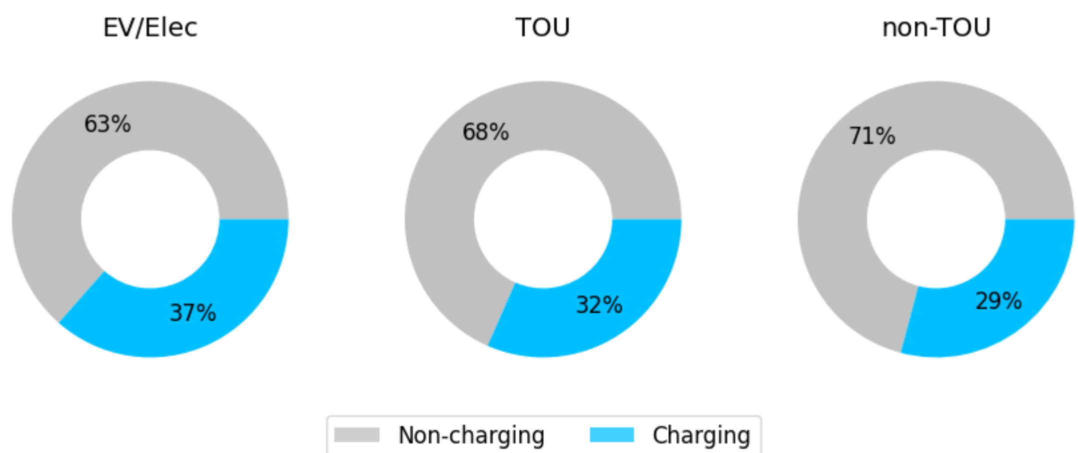

Figure 8. Proportion of days that are charging days, for meters with Level 2 charging detections, by rate category.

Finally, Figure 9 shows the distribution of the various charging patterns identified on charging days, by utility and rate category. Among the different subgroups we can see drastic variation in the proportion of customers engaging in different charging behaviors. For instance, consider the leftmost column, representing PG&E customers. For customers on non-TOU rates, the most common charging pattern is afternoon charging, and the majority of charging sessions occur in the afternoon and evening, while only 23% of charging days exhibit midnight charging. Customers on TOU rates shift this balance slightly, with modest increases in charging starting at 9 pm and midnight, but afternoon charging still accounts for more than a quarter of charging days. For customers on EV/Electrification rates, however, nearly two thirds of charging days exhibit the midnight-charging pattern, which is consistent with customers' capturing the savings

[5] It is important to recognize, however, that SMUD's rates are considerably lower than the IOUs' overall, making a large absolute off-peak discount more difficult to achieve.

available from the available rate discount. Further, the frequency of afternoon charging has been reduced by almost two thirds compared to what is observed on non-TOU rates.

SDG&E's EV/Electrification rates show similar impacts to PG&E's but may be even more effective in reducing afternoon charging. Furthermore, even SDG&E's non-EV TOU rates drive a strong increase in midnight charging, likely owing to the super-off-peak midnight option. SMUD's EV and TOU rates drive similar shifts, but the effects are less pronounced, with a third of charging days for meters on EV rates still exhibiting afternoon charging patterns. This likely reflects the smaller savings that SMUD customers can capture by shifting their charging, compared to IOU customers. For example, with a three-hour wintertime charging session at 7 kW, an SDG&E customer on an EV rate stands to save about $8.60 by shifting from peak hours to midnight, whereas a SMUD customer would save around $1.30. Given the lower savings, however, the effectiveness of the SMUD rate remains noteworthy.

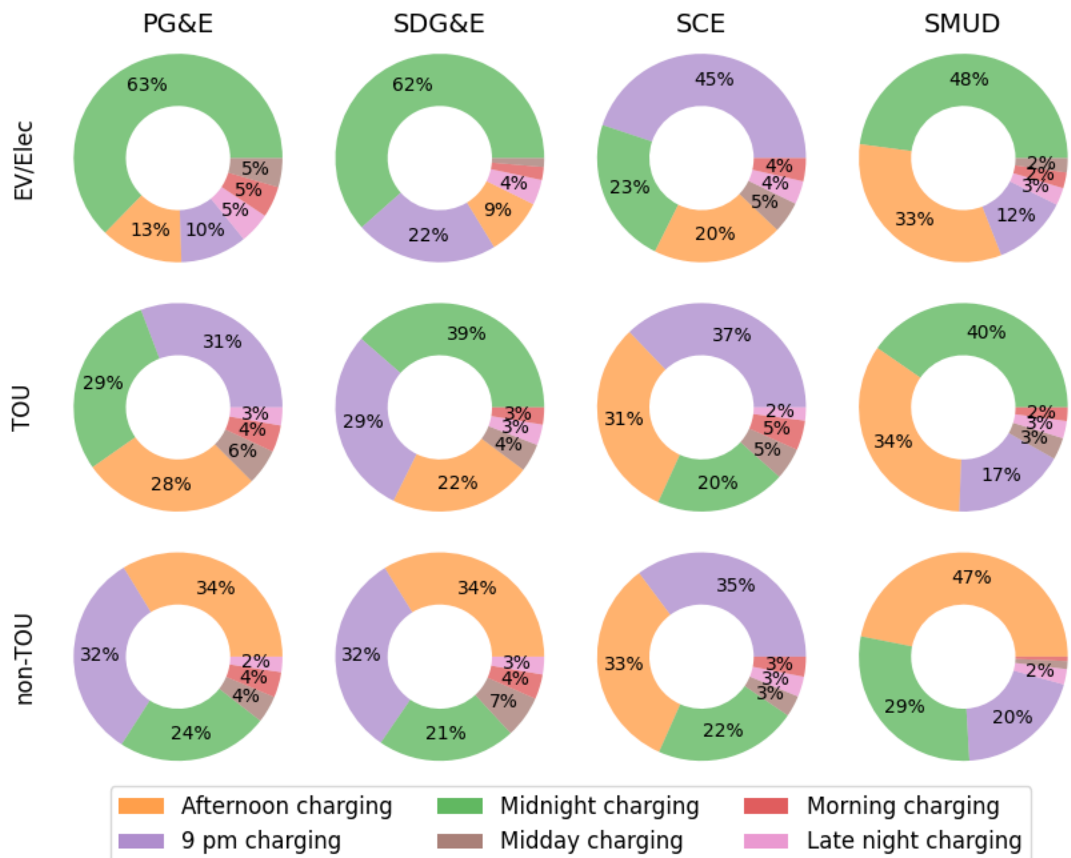

Figure 9. Distributions of charging-day patterns for meters with Level 2 charging detected, by utility and rate category.

SCE's rates drive different charging behaviors than the other utilities'. Customers on EV/Electrification rates exhibit an increased frequency of 9 pm charging and a modest reduction in afternoon charging, while ordinary TOU rates appear to drive only a slight reduction in afternoon charging. The preference for charging at 9 pm is expected, given that the lowest prices begin at that time. The limited effectiveness of both the EV and TOU rates in reducing afternoon charging may reflect the fact that, in both cases, customers can expect a partial discount for an afternoon charging session, if the session lasts past 9 pm.

Overall, these results indicate that EV rates can be highly effective in shaping EV charging behavior. To ensure maximal effectiveness, it is important to ensure that the available savings is large enough to capture the customer's attention and that the discounted period is well separated in time from the period when charging is being discouraged.

Conclusion

We applied the EV detection model from Recurve's FLEX platform to more than 10 million California residential AMI meters and applied criteria for identifying Level 2 charging. The resulting detections accounted for 49% to 69% of all registered EVs (both BEVs and PHEVs) and 80% to 100% of BEVs charging at Level 2, including a significant number of detections at addresses without registered EVs. These results confirm the model's effectiveness in identifying EV charging in large AMI datasets as well as the value of direct detection at the meter relative to vehicle registration alone. Most of the remaining undetected EVs are likely either charging primarily at Level 1or away from home.

We applied a two-step load shape clustering process to identify representative charging patterns among the population that does Level 2 charging. We identified six such patterns, distinguished by the time at which charging begins: morning charging, midday charging, afternoon charging, 9 pm charging, midnight charging, and late-night charging. Of these patterns, afternoon charging is especially problematic for the grid, since it reflects charging that coincides with peak demand hours. We estimate that, circa 2024, the load contribution from this mode of charging during peak hours is roughly 250 MW, which is significant.

We then investigated the effectiveness of different electricity tariff structures in disincentivizing afternoon charging. The results indicate that EV owners are quite sensitive to their electricity rates when deciding when to charge their vehicles. Both EV-specific rates and ordinary TOU rates were associated with a reduced incidence of afternoon charging , but, importantly, a rate's effectiveness in reducing peak-period charging depended significantly on the details of the rate structure. The most effective rates were those with the largest discounts for off-peak periods and those where the off-peak period was separated in time from the peak period by an intervening mid-peak period. These findings indicate that EV specific rates are highly effective in shaping behavior and that minor rate design improvements, coupled with efforts to increase uptake, hold the potential to provide additional value to the present-day power system.

More broadly, our results indicate that this analytical framework—automated EV detection and load shape clustering—holds great promise for characterizing the impacts of EV charging behavior on the energy system. By classifying each day's consumption into different typical patterns at the individual customer level, this approach should also enable assessment of EV charging impacts during specific grid emergencies, variability in customer charging behavior, and analysis of specific customer-level behavioral shifts in response to changing incentives. We will explore many of these topics in future work.

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