
Supplementary information

Charging infrastructure access and operation to reduce the grid impacts of deep electric vehicle adoption

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Supplementary Information for: Charging Infrastructure Access and Operation to Reduce the Grid Impacts of Deep Electric Vehicle Adoption

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Supplementary Note 1: Expanded literature review

Driver Behaviour Model

Several large-scale models of charging demand have been used to study the Western US and California. These include EVI-Pro [1] which was used in recent California Energy Commission modeling [2] and which combines travel survey data with a model of drivers' economic decision making to simulate charging, BEAM which takes an agent-based approach using highly resolved mobility data for the California San Francisco Bay Area [3], and the proprietary agent-based model used by the consulting firm E3 [4]. Running a simulation of each individual driver's daily travel and modeling optimal decision-making, however, is expensive. Our proposed approach models driver decision making as probabilistic and is calibrated using a very large set of real charging data.

Time use and travel survey data are used in [2, 5, 6, 7, 8, 9, 10, 11, 12] to generate charging demand estimates. Data sets from small demonstration projects are used in others [13, 14]. GPS data from internal combustion engine vehicles are used in others [15]. In [16] the authors combine charging data with GPS data from internal combustion engine vehicles to study how mobility limits charging flexibility. In [17] the authors combined travel survey data with data from a small demonstration project. In most papers based on demonstration data, it is assumed that later adopters will exhibit the same behaviours and largely depend on home charging.

Clustering and other statistical methods are used increasingly in recent literature to reveal patterns in driver travel histories [18, 19] and charging data [14, 20, 21, 22, 23]. Several of these use very large data sets from the Netherlands [22, 20] or California [23, 16, 24, 25]. Ours is the first methodology to combine these elements for large-scale simulations connecting driver behaviour profiles, regional characteristics and policies on charging infrastructure to a data-driven model of real driver charging behaviours based on an extensive data set of charging sessions.

Grid Impact Modeling

Existing papers study many different aspects of EV grid impact.

The first category of papers focuses on the distribution grid. In [5] the authors model real-world distribution feeders in California to study distribution level impacts including voltage violations, line overloading, and peak capacity violations. In [6] the authors focus on residential power demand in California to study the increase in power demand driven by EV charging and impacts including transformer overloading. In [13] the authors used data from a demonstration project in the UK to study impacts including voltage violations and

transformer or feeder overloading. In [26] the authors focus on workplace charging to evaluate transformer aging.

The second category of papers focuses on the generation and transmission grid. In [3] the authors use PLEXOS, a unit commitment and economic dispatch model to study emissions and curtailment impacts in California. In [15] the authors use the California Low Carbon Grid Study outputs based on PLEXOS to analyze emissions for low levels of EV adoption. In [8] the authors use a capacity expansion model with transmission and generation co-optimization to study the economics of charging control in Chile. In [9] the authors use HiGRID to model dispatch and generation, including dispatch of controllable EVs, in California to study emissions and cost impacts. In [11] the authors similarly integrate EV demand into a dispatch model to study the generation-level impacts of managed overnight charging in Alberta, Canada. In [10] the authors study the demand and ramping impacts of different charging scenarios in the MISO US grid. In [12] the authors use a proprietary electricity sector market model to study the grid capacity, electricity price, and EV adoption impacts of centrally managed charging in Western Canada. In [27] the authors use a unit commitment model minimizing costs and curtailment to study the emissions and wind integration benefits of EVs in Beijing, China. In [23] the authors use an economic dispatch model to test the emissions impacts of extreme fast charging scenarios in the US.

The third category of papers studies combinations of the two. In [28] the authors evaluate the need for transformer upgrades under different charging control scenarios, and include analysis of charging emissions based on a marginal emissions profile. [7] is a large study on the Western US in which the authors consider both distribution and generation level impacts for EV adoption between 10- and 20%, using the GridView software from ABB to study capacity expansion planning and transmission congestion. In [17] the authors use rural, sub-urban, and urban test networks in OpenDSS to model the distribution system impacts and model transmission in Pandapower to study congestion in the United Kingdom under 100% EV adoption.

Control Modeling

Many papers studying grid impacts also model control. Central, grid-operator control is modeled in [7, 28, 3, 15, 17, 8, 10, 11, 12, 27], in many cases assuming the EVs are plugged in and participating at all times throughout the day. This assumption, however, does not represent current practice and can overestimate the load flexibility. In [9] the authors study the impact of a time-delay in updating central grid-operator control signals. In [16] the authors study shifted start times to understand the bounds of EV flexibility based on driver mobility needs. Site-level workplace control is modeled in [26, 24]. Driver responses to TOU rates are also considered in [2, 3].

On the Impact of Charging Infrastructure

A small number of studies include different charging infrastructure futures, comparing slow with fast charging [27, 29], modeling demand [2], and, for early adopters, evaluating emissions [30]. However, none of these assess reshaping the landscape of charging infrastructure as a tool or compare its effect against other types of control for reducing emissions and other grid impacts. They also focus on the charging patterns and options of early adopters. In a recent paper [23] the authors study the impact of extreme fast charging on emissions; a “gas-station” model of charging not represented in our data.

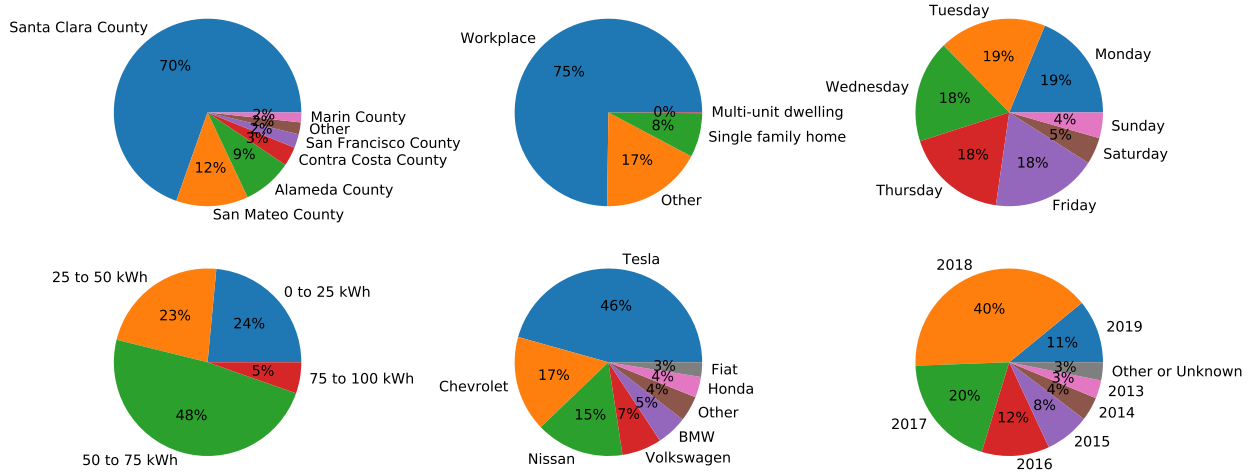
On EV Life Cycle Emissions

Our study focused on charging and grid impacts; another field of research looks at the life cycle emissions of electric vehicles and compares them to hybrid or internal combustion engine vehicles across different grids [31, 32].

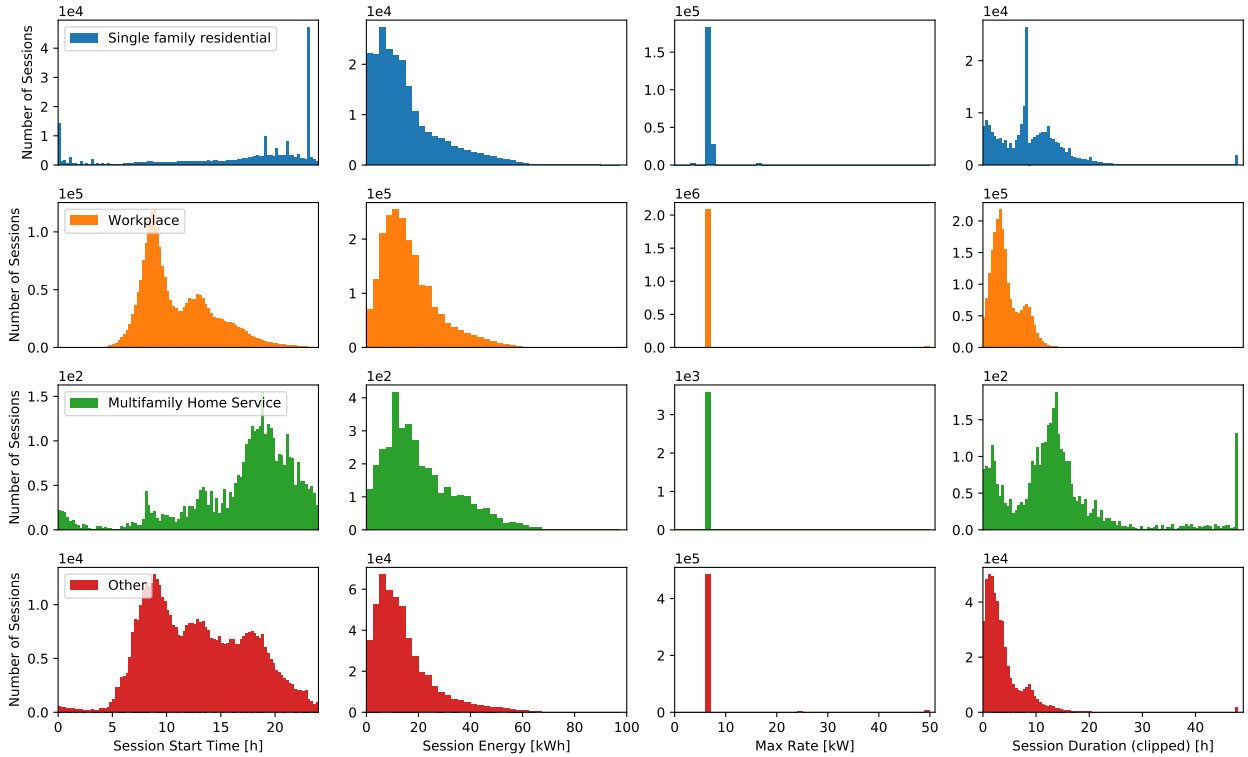
Another area of research considers EVs within much larger climate- and energy-systems models, e.g. [33].

Supplementary Note 2: Data Set Statistics

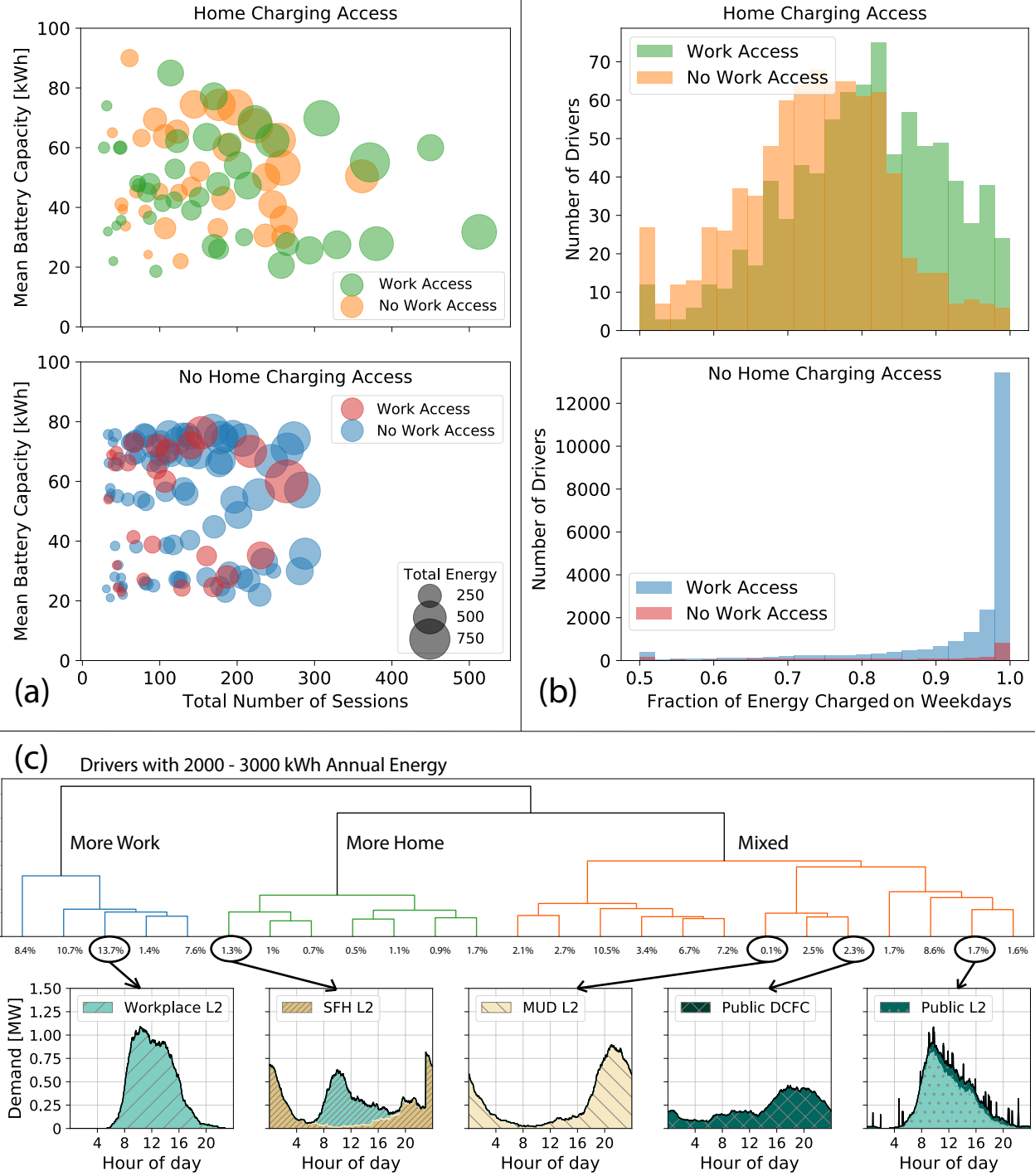
The charging data set used for this project includes over 2.8 million charging sessions recorded by 27.7 thousand battery electric vehicle drivers. The data was collected throughout 2019 in the San Francisco Bay Area. Supplementary Figure 1 illustrates the breakdown of the data by location, type, time of the week, and vehicle type. Supplementary Figure 2 illustrates the total distributions of session start times, session energies, session charging rates, and session durations for each of the four main charging segments.



Supplementary Figure 1: The breakdown of sessions (top row) and vehicles (bottom row) in the data. Most sessions occur in Santa Clara County, the county which includes the city of San Jose. Most sessions occur at workplaces, and the sessions are well distributed across weekdays. 8% of sessions occurred on weekends. Most of the vehicles have battery capacities larger than 50 kWh. The most common make is Tesla, followed by Chevrolet, Nissan, and Volkswagen. Finally, the most common model year is 2018, corresponding to the large number of Tesla Model 3's sold in California.



Supplementary Figure 2: These histograms illustrate the key charging session parameters from the data set. Each row shows one segment (from top to bottom): single family home, workplace, multi-unit dwellings, and public. Each column shows one parameter (from left to right): session start time, session energy, session charging rate, and session duration. The duration is clipped at 48 hours such that the last bin includes all sessions with longer durations. The session start time varies the most across segments. Home charging, either at single family homes or multi-unit dwellings, is more likely to last for longer than 12 hours. We also observe the impact of timers in the start times of single family home charging sessions, with a large number of sessions starting exactly at 11 pm.



Supplementary Figure 3: (a) The relationship between mean battery capacity, number of sessions, and total energy for each driver cluster: clustering revealed a clearer distinction between behaviours for drivers with small and large battery capacity vehicles when those drivers lacked access to home charging. The combination of home and workplace charging access also enabled more frequent charging, with some clusters (in green) charging more than once per day throughout the year. (b) This histogram of drivers reveals that the fraction of energy charged on weekdays is much higher for most drivers without home charging. (c) The clustering of driver behaviours illustrated in this dendrogram for one bin of annual energy use shows the many distinct, mixed-use charging behaviour patterns identified in the data. The sub plots illustrate the aggregate demand profile on a typical weekday for 1000 drivers from each of five sample clusters.

Supplementary Note 3: Driver Behaviours

Access to charging options at home and at work, total annual energy use, and battery capacity were each identified as key drivers behind different charging behaviour patterns. Separating the drivers in the data set along these lines reveals these divisions. Supplementary Figure 3 illustrates several of the key behavioural differences.

The mean per-session energy usage reveals interesting information about the behaviours of drivers in these categories, as shown in Supplementary Table 1. We see several interesting divisions: first, drivers with larger battery capacities tend to charge more at each session; second, comparing the first four columns with the last four, drivers with access to home charging tend to charge less at each session than drivers that depend on only work or public charging; and third, per session energies are relatively similar for drivers charging 1000 or 4000 kWh annually. Despite having battery capacities well over 50 kWh, drivers with large batteries and high energy needs only charge 23 - 29 kWh per session on average or 22 - 26 kWh per session when considering the median. This reflects the strong tendency to maintain a high state of charge and comes at the cost of needing to charge more frequently.

Annual EV Energy Use	No Home No Work		Only Work Access		Only Home Access		Both Home And Work	
	Sm. Batt.	Lg. Batt.	Sm. Batt.	Lg. Batt.	Sm. Batt.	Lg. Batt.	Sm. Batt.	Lg. Batt.
0-600 kWh	9.38	12.89	9.62	14.09	8.96	14.47	9.48	15.67
600-1000 kWh	11.28	20.42	10.83	19.28	10.72	19.93	10.04	16.65
1000-1600 kWh	12.28	24.91	11.42	21.09	10.76	24.62	10.24	21.92
1600-2000 kWh	12.52	24.71	11.89	21.60	11.40	22.56	11.47	20.72
2000-3000 kWh	13.41	26.71	12.98	22.04	10.71	25.10	11.30	22.41
3000-4000 kWh	14.65	26.17	15.25	22.24	12.13	24.22	12.50	23.83
4000 kWh +	16.37	28.46	16.38	24.07	12.26	25.38	12.88	23.00

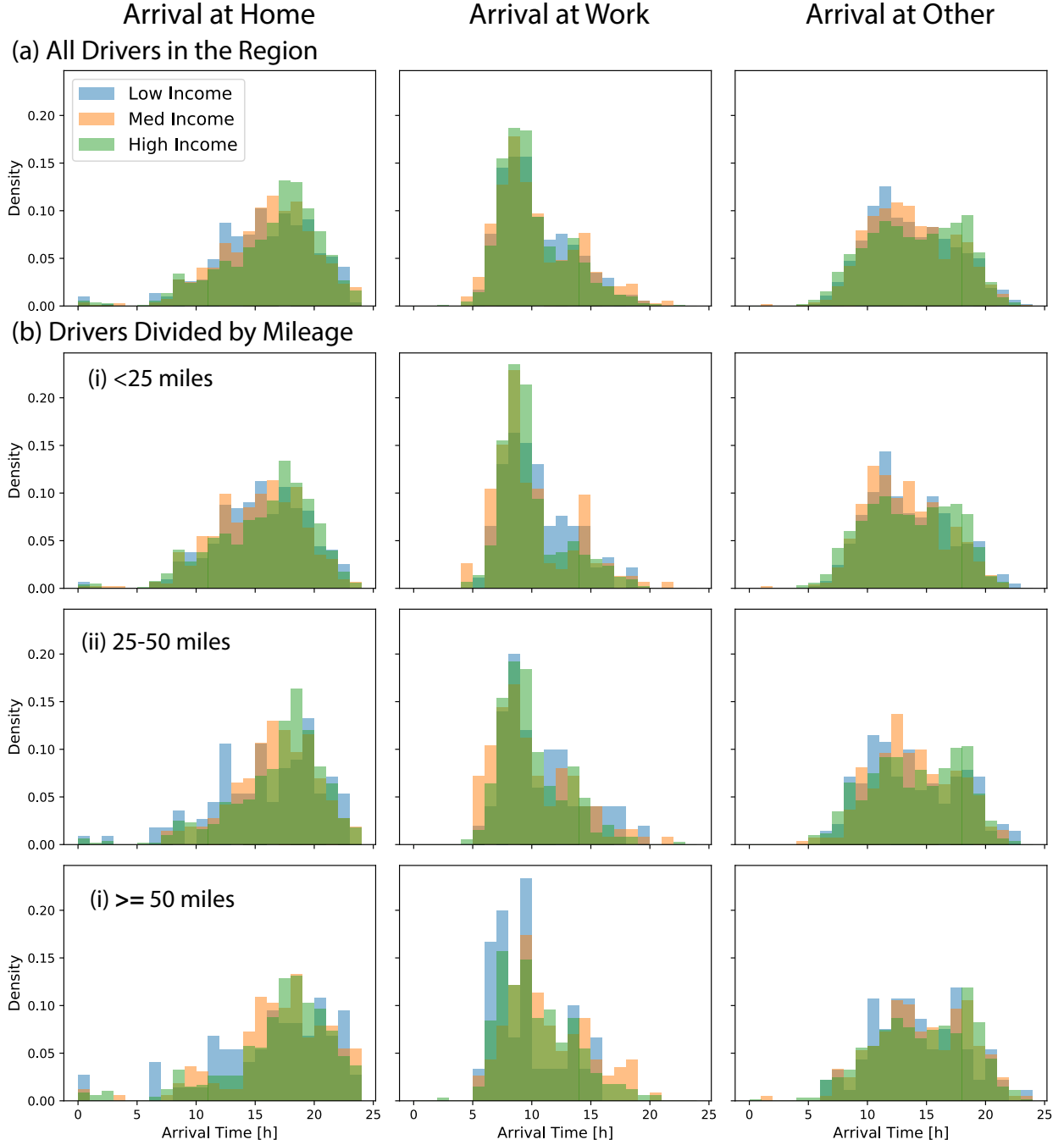
Supplementary Table 1: Average energy use per charging session, in kWh, for drivers in each division of access, battery capacity, and annual energy use. Small (Sm.) and Large (Lg.) Battery (Batt.) capacity is divided at 50 kWh.

Supplementary Note 4: Comparison with Travel Survey Data

The 2016-2017 National Household Travel Survey Data (NHTS) is conducted by the Federal Highway Administration in the US to capture travel patterns of a wide range of residents from across the country [34].

We did not observe large differences in travel patterns between income groups within the charging data. We used the NHTS data to validate this observation in two ways: first, studying the distributions of arrival times for different income groups within the Bay Area NHTS data; and second, rebuilding the charging model using only sessions compatible with the NHTS travel patterns.

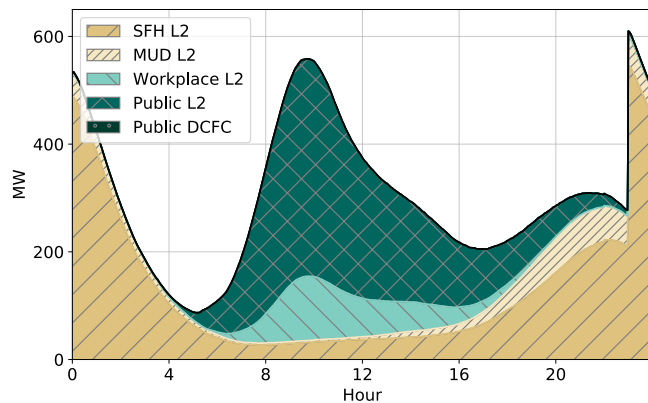
We focused on survey respondents located within the two regions most aligned with the charging data: “San Francisco-Oakland-Hayward, CA” and “San Jose-Sunnyvale-Santa Clara, CA”. To match the charging model as closely as possible, we binned the respondents’ income groups into low income (up to \$49,999 household income), medium income (from \$50,000 to \$99,999 household income), and high income (at least \$100,000 household income). Since the charging model also parameterizes charging behaviour on total energy needed, we considered additional divisions of the respondents by daily miles traveled.



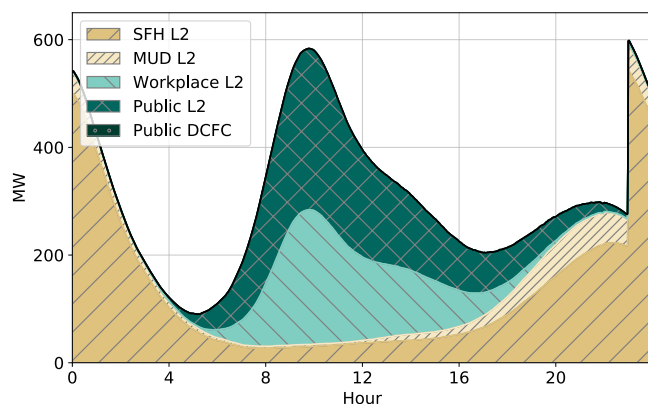
Supplementary Figure 4: Normalized histograms showing the distribution of arrival times at home, work, and other locations in the NHTS travel survey data [34]. The first row (part (a)) shows all drivers in the California Bay Area region together; the later rows (part (b)) show those drivers divided by daily mileage on the survey day. In each case, the drivers are divided into three income categories shown in blue, orange, and green: low income: low income (up to \$49,999 household income), medium income (from \$50,000 to \$99,999 household income), and high income (at least \$100,000 household income).

Using Sessions Feasible for Survey Respondents

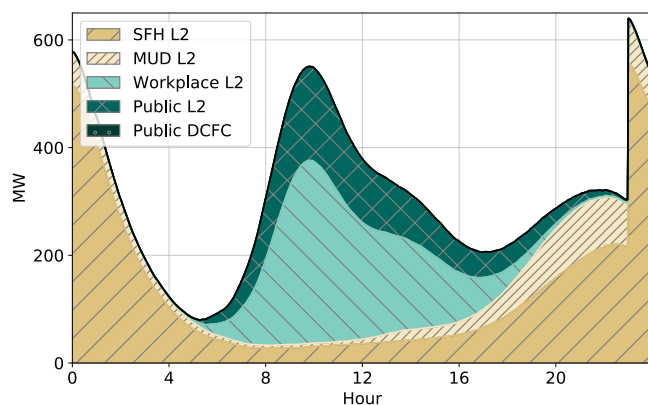
(a) Low Income



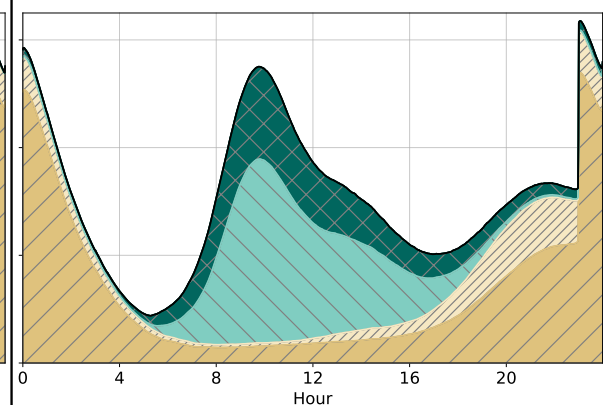
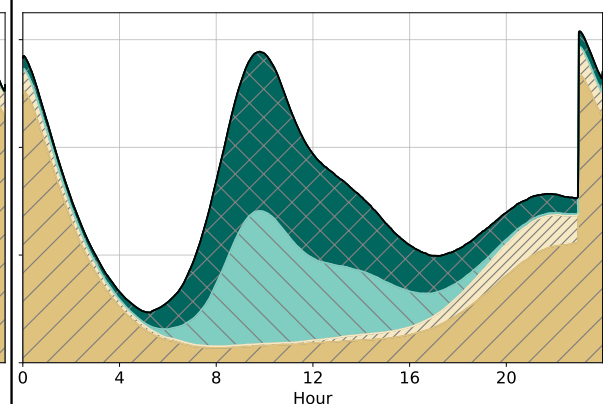
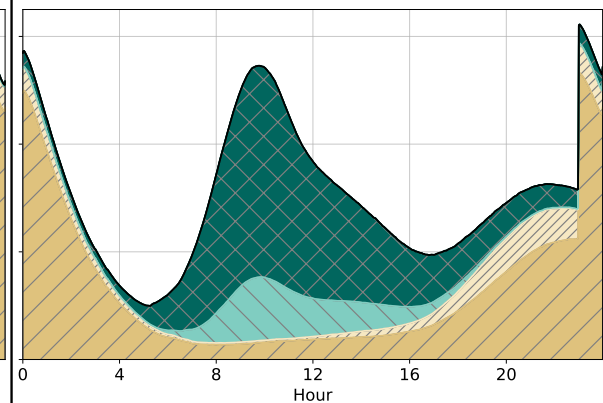
(b) Medium Income



(c) High Income



Using All Sessions



Supplementary Figure 5: Load profiles for a typical weekday under the “High Home Access” scenario. On the left, the sessions models were retrained using only charging sessions feasible for drivers in the low, medium, or high income subgroups of Bay Area travel survey respondents. On the right, the original model based on all the sessions was used. Each row models a different scenario for Santa Clara County, where all drivers are assumed to be in low (top row), medium (middle row), or high (bottom row) income households, rather than the distribution over incomes recorded by the census and used in the main results.

Supplementary Figure 4 shows the arrival time for all journeys taken by personal vehicle: arrival at home,

at work, and at other destinations are shown in the three columns respectively; all drivers in these two regions are shown in row 1; drivers with low, medium, and high daily mileage are shown in rows 2 to 4. Each plot is a density plot (a normalized histogram) so that the distributions can be compared across income groups. Out of the respondents from these two regions there are 651 households in the low income group, 772 households in the medium income group, and 1731 in the high income group. While there is some variation, we can confirm that the distributions of arrival times are quite similar across income groups.

Supplementary Figure 5 studies the weekday profile for Santa Clara County - the largest in the charging data set and in this region - using two different models. On the left, the sessions models were retrained using only sessions compatible with charging for a subset of survey respondents (the low, medium, and high income groups in the region as described above). On the right, the sessions models were trained using the full data set. In the main paper results, each county has a different distribution of incomes based on census data. Here, in each row we adjusted the distribution of income groups to isolate and compare the model’s performance separately on each population group: the first row shows the result if every household in Santa Clara County were low income; the second and third rows show the results if every household were medium and high income, respectively. Each scenario was run for the “High Home Access” scenario. These results clearly illustrate the higher use of workplace and multi-unit dwelling charging among high income drivers in the model.

Again, we see some small variation between the two models (comparing the left and right columns) - for example, there are fewer evening public charging sessions in the survey data - but the aggregate charging demand is very similar. The mean absolute percentage error for the total aggregate demand is 4.8%, 3.3%, and 3.2% for the low (top row), medium (middle row), and high (bottom row) income groups, respectively. This result confirms that the charging data largely captures the range of behaviours observed in the travel survey, even for lower income drivers who are less well represented among early EV adopters.

Supplementary Note 5: Driver Access and Energy Charged in Each Segment

Supplementary Table 2 shows the fraction of drivers with access to each type of charging, and the amount of energy charged in each segment, for each scenario.

Drivers with Access [%]	Universal Home	High Home	Low Home High Work	Low Home Low Work
SFH Charger	80	65	24	24
MUD Charger	20	7	3	3
Neither Home Charger	0	28	73	73
Energy Per Segment [%]				
SFH	62	50	18	19
MUD	24	8	4	4
Workplace	11	15	35	21
Public	3	27	43	56

Supplementary Table 2: The percentage of drivers with access to each type of home charging and the amount of energy charged in each segment, for each access scenario.

With Universal Home access, 62% and 24% of total electricity consumption is delivered through single family home (SFH) and multi-unit dwelling (MUD) charging, respectively. At the other end of the scenario range with Low Home High Work access, only 24% of drivers have access to SFH charging and 3% of drivers have access to MUD charging. In that scenario, 18% and 4% of total electricity consumption is delivered through SFH and MUD charging, while 35% and 43% is delivered through workplace and public charging, respectively.

Supplementary Note 6: Context for Storage Costs

Policies supporting a future with Low Home High Work access could translate into remarkable storage savings. With uncontrolled charging and 50% EV adoption, that scenario would yield savings of up to \$ 696 million or \$ 1.46 billion depending on the forecast cost of battery storage (see the main manuscript for more

details). To give added context to these numbers: the mean cost of electricity throughout 2035, including nonfossil fuel generation, is up to 7.8 \$/MWh and the mean marginal cost of generation on a mean weekday reaches up to 26.3 \$/MWh under Universal Home access charging (see Supplementary Tables 3, 4, and 5). These savings of \$ 696 million or \$ 1.46 billion would amount to over 10 and 21% of total annual generation costs. They also represent costs of \$ 28.62 or \$ 59.85 per EV driver in the region. This does not include the costs associated with grid emissions for each scenario.

Access Scenario	No Storage			10 GW Storage		
	Mean	Max on Mean Weekday	Max	Mean	Max on Mean Weekday	Max
Universal Home	26.34	52.74	649.84	24.17	28.65	49.33
High Home	25.35	44.73	647.88	24.08	27.76	45.67
Low Home High Work	24.60	39.01	647.88	23.96	26.90	43.49
Low Home Low Work	24.61	39.12	647.88	23.95	26.97	43.92
No EVs	23.01	29.25	346.95	22.63	25.67	40.98

Supplementary Table 3: The marginal generation cost in \$/MWh under each scenario, calculated from hourly results, in all cases with uncontrolled EV charging. On the right we show the results for the case where 10 GW of four-hour grid storage was operating to smooth net demand.

Access Scenario	No Storage		
	Mean Price [\$/MWh]	Total Cost [\$]	Total Demand [MWh]
Universal Home	7.78	6.8e+09	8.8e+08
High Home	7.69	6.8e+09	8.8e+08
Low Home High Work	7.58	6.7e+09	8.8e+08
Low Home Low Work	7.59	6.7e+09	8.8e+08
No EVs	6.87	5.7e+09	8.3e+08

Supplementary Table 4: The mean price of electricity, calculated by dividing total cost by total generation at each hour (including that from nonfossil fuel generation).

Access Scenario	10 GW Storage		
	Mean Price [\$/MWh]	Total Cost [\$]	Total Demand [MWh]
Universal Home	7.58	6.7e+09	8.8e+08
High Home	7.51	6.6e+09	8.8e+08
Low Home High Work	7.43	6.5e+09	8.8e+08
Low Home Low Work	7.44	6.5e+09	8.8e+08
No EVs	6.68	5.6e+09	8.3e+08

Supplementary Table 5: The mean price of electricity, calculated by dividing total cost by total generation at each hour (including that from nonfossil fuel generation), for the case where 10 GW of four-hour grid storage was operating to smooth net demand.

Supplementary Note 7: Additional Result Details

In Figure 6 we found that adding daytime charging decreased ramping. With 50% adoption, ramping on a mean day in the Low Home Access scenarios is no higher than 6.9 GW, 82% of the 8.4 GW ramping in Business as Usual and 71% of the 9.7 GW observed with Universal Home Access. With 100% EV adoption,

ramping on a mean day in the Low Home Access scenarios is even lower at 6.0 GW, just 65% of the 9.2 GW ramping in Business as Usual and just 51% of the 11.7 GW observed with Universal Home Access.

We also found that scenarios with high daytime charging used more of the excess renewable generation. The Universal Home Access scenario misses that opportunity and leads to up to 1.73 TWh of wasted clean energy: $1.84\times$ more than in the best case. At 100% EV adoption, Universal Home access leads to up to 940 GWh of excess generation: $3.29\times$ more than in the best case with Low Home Low Work access.

Supplementary Note 8: Emissions for Internal Combustion Engine Vehicles

Top-selling trucks in 2019 including the Ford F150, Dodge Ram, and Chevrolet Silverado trucks emit between 470 and 530 grams of CO_2 per mile; crossovers, the next most popular category, including the Toyota RAV4 and the Honda CR-V emit between 302 and 328 grams of CO_2 per mile; the 2019 Honda Civic, a popular sedan, emits approximately 276 grams of CO_2 per mile [35].

Supplementary Note 9: Cost of Charging Infrastructure

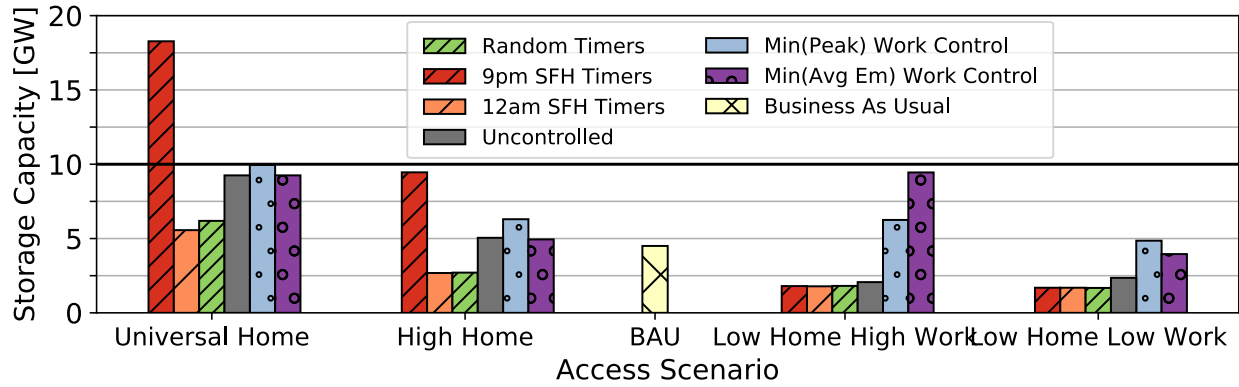
Like adding storage, adding extra generation capacity has a high price tag. Making changes to the grid should be weighed against the potential benefits from managed charging and from building daytime charging infrastructure.

The cost to install a level two charger is between \$800 and \$4000 at a home or between \$2200 and \$15,000 at work or at a public destination [36, 37, 38]. This range varies based on the amount of electrical work involved, whether a panel upgrade is needed, and, for workplaces, the data, control, and maintenance services included. Estimating the average cost for each type as \$1200 and \$7000, respectively, and assuming work and public chargers can be shared between at least two vehicles, the infrastructure for Low Home High Work access would cost \$16.85 billion more than the infrastructure for Universal Home access in a scenario with 50% EV adoption. If the emissions savings per year, number of EVs, and charging infrastructure were held constant over 10 years, with a discount rate of 10% those figures would mean an abatement cost of \$1.36 per kilogram of CO_2 . This is only a rough estimate, however, as the emissions benefit of switching to daytime charging would grow with increasing renewables. Adding charging infrastructure also increases drivers' likeliness to switch from internal combustion engine to electric vehicles [39], and the resulting drop in emissions from that increase in adoption should figure into these decisions. Grid modelers should reevaluate the use of these tools as they update their plans for capacity expansion.

Supplementary Note 10: Additional Results and Details

Storage Requirements in 2030

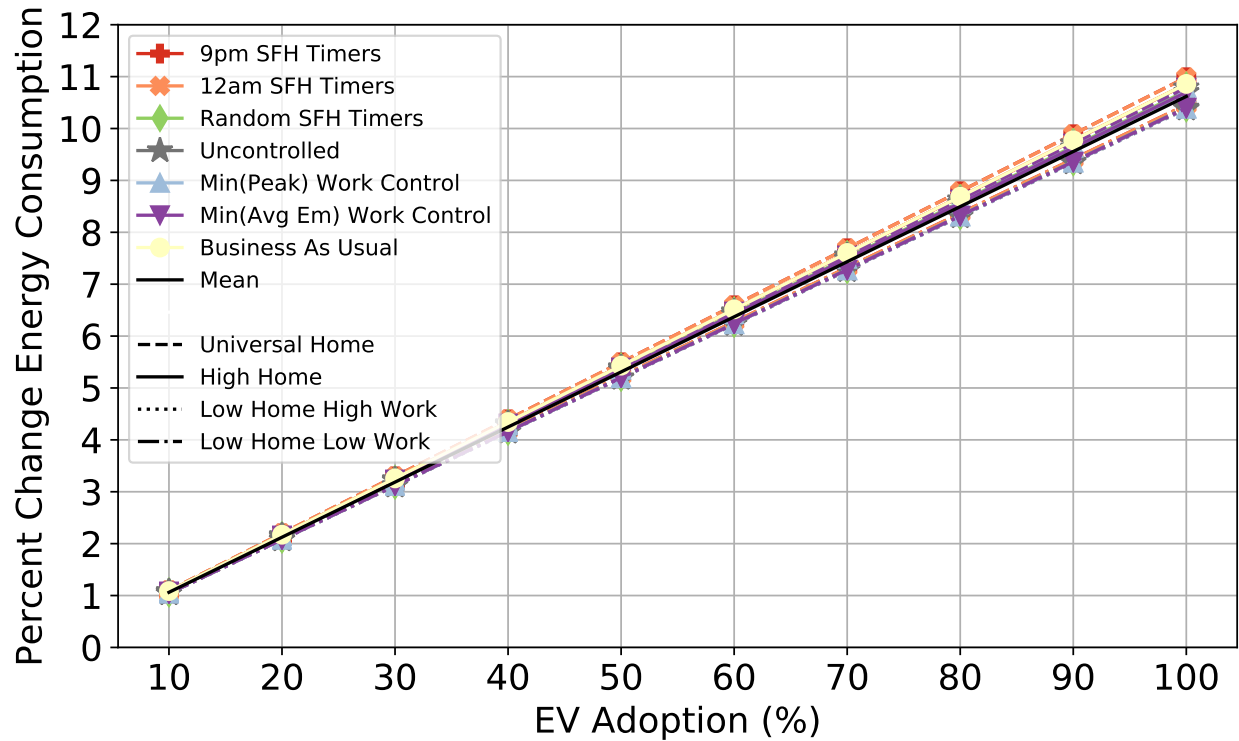
We model the grid in 2030 slightly differently than 2035: wind and solar are increased to $2.5\times$ 2019 levels, fewer fossil fuel generator retirements and additions occur, and baseline demand is increased by 10%. In a “stress” test with 100% EV adoption by 2030, the storage requirements are shown in Supplementary Figure 6. This is a version of the storage result shown in Figure 5 of the main paper. The important difference is in the average-emissions-minimizing workplace control with Low Home High Work access. That control in that scenario creates a very high midday peak in demand, and in 2030 with less solar, that leads to a higher peak net demand on many days and pushes up demand for storage significantly.



Supplementary Figure 6: Storage required to support 100% EV charging in 2030.

Energy Consumption with Increasing EV Penetration

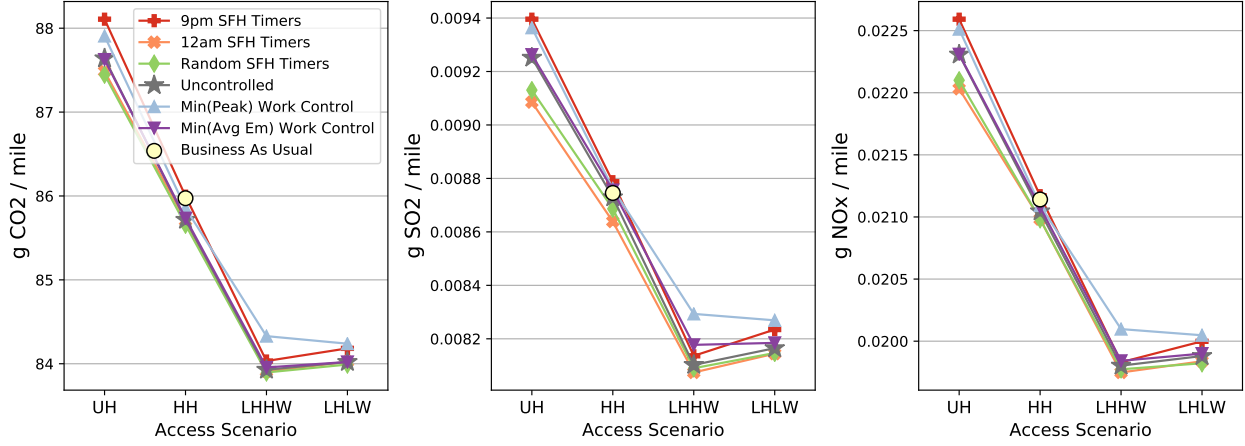
Supplementary Figure 7 shows the increase in energy consumption over a 2035 baseline with no EV adoption. Due to the open-loop nature of the model there is a small difference between the scenarios. The mean reaches a value of 10.6% with 100% EV adoption.



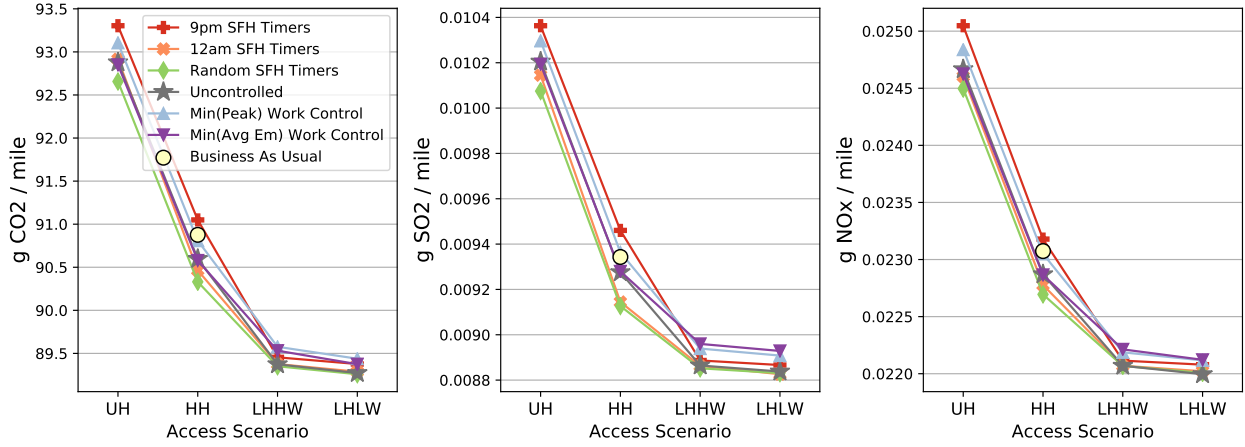
Supplementary Figure 7: Percentage increase in total electricity consumption (energy) with increasing EV adoption.

SO₂ and NO_x Emissions

Supplementary Figures 8 and 9 show the emissions per mile in terms of CO₂, SO₂, and NO_x for each charging scenario in a 2035 grid with medium renewables: solar and wind both at 3.5× and 3× 2019 levels respectively.



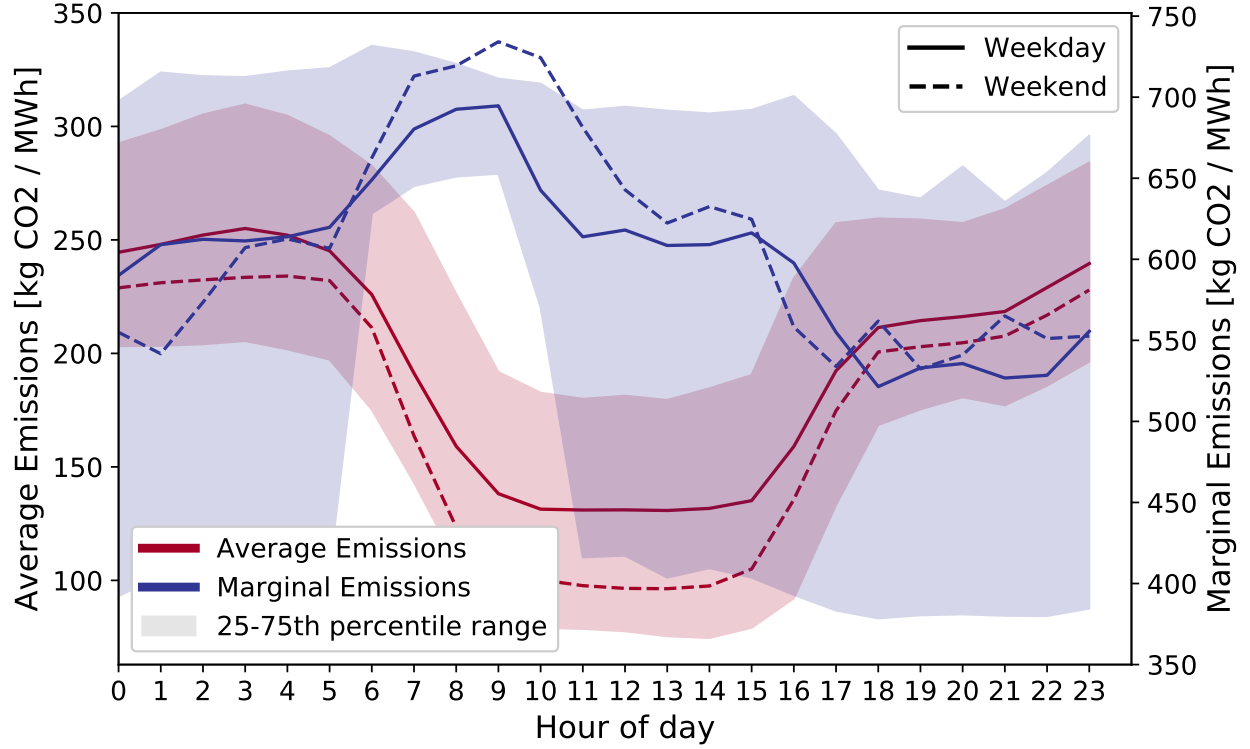
Supplementary Figure 8: CO_2 , SO_2 , and NO_x emissions per mile in the Medium Renewables scenario of 2035 with 50% EVs. The x-axis in each subplot shows the four base EV charging scenarios: Universal Home Access, High Home Access, Low Home High Work Access, and Low Home Low Work Access.



Supplementary Figure 9: CO_2 , SO_2 , and NO_x emissions per mile in the Medium Renewables scenario of 2035 with 100% EVs. The x-axis in each subplot shows the four base EV charging scenarios: Universal Home Access, High Home Access, Low Home High Work Access, and Low Home Low Work Access.

Marginal vs Average Emissions

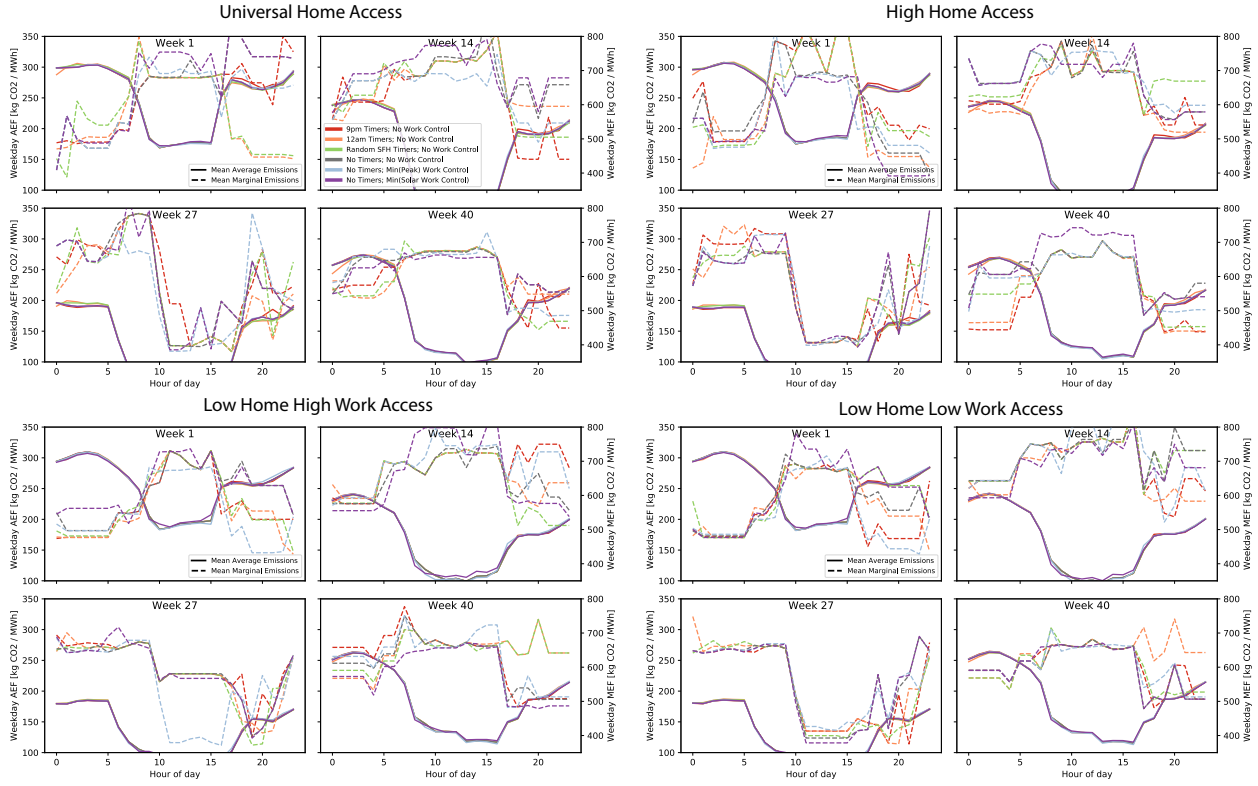
Average emissions are calculated at each hour of the year by dividing the total emissions by the total electricity consumption. Marginal emissions depend on the emissions rate of the marginal power plant operating at each hour. Supplementary Figure 10 uses the Business As Usual charging scenario to show that these two are different, on average, with the midday period experiencing lower average but higher marginal emissions. There is substantial variability, however, as shown by the 25-75th percentile bands.



Supplementary Figure 10: The median (50th percentile) marginal and average hourly CO2 emissions over the full simulation year, divided into weekdays and weekend days. This is shown for the Business As Usual scenario with 50% EVs. The shaded bands show the 25th and 75th percentile values.

Supplementary Figure 11 shows these profiles for all the other scenarios in different weeks of the year. The average emissions factor reflects the average emissions intensity of electricity generation and is consistently lower in the middle of the day during times of high solar generation.

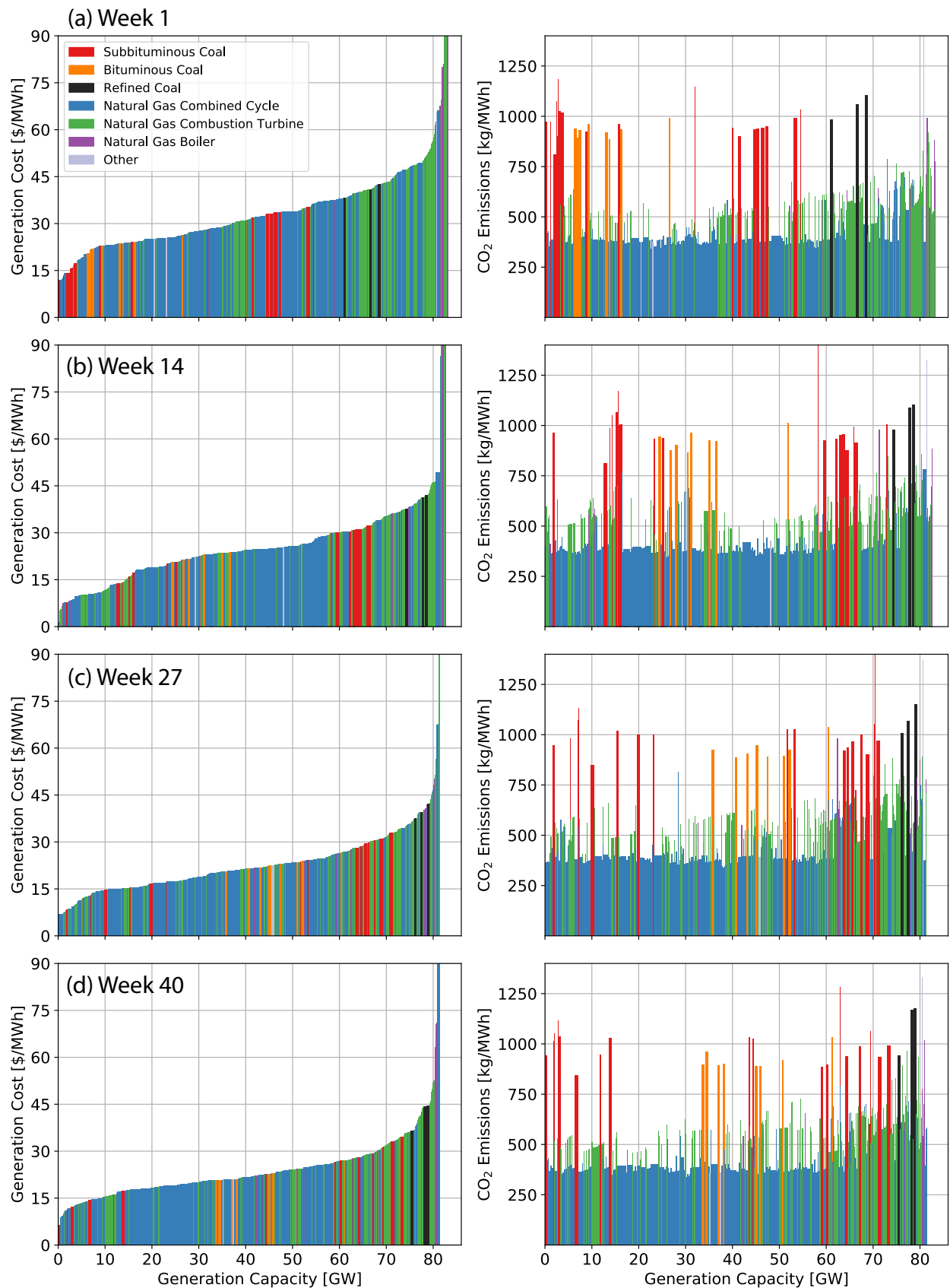
We find the marginal emissions factors are typically high during the day in the Universal Home Access and High Home Access cases. The profiles are noisier in the two scenarios with Low Home Access, but often higher during the middle of the day. This unpredictability and misalignment between when marginal and average emissions are lowest poses a challenge for control. In Figure 7 in the main text we found that controls based on average emissions, pushing charging demand toward peak solar hours, could increase emissions by pushing demand toward times of higher marginal emissions. That effect would be exacerbated on days of low solar generation and improved in scenarios with higher solar generation.



Supplementary Figure 11: Mean weekday marginal and average emissions factor profiles for each scenario for four weeks in the year.

Dispatch Variability

The merit order of generators is based on reported fuel costs which varied throughout the year. Supplementary Figure 12 shows the merit order for four sample weeks spread evenly throughout the year.

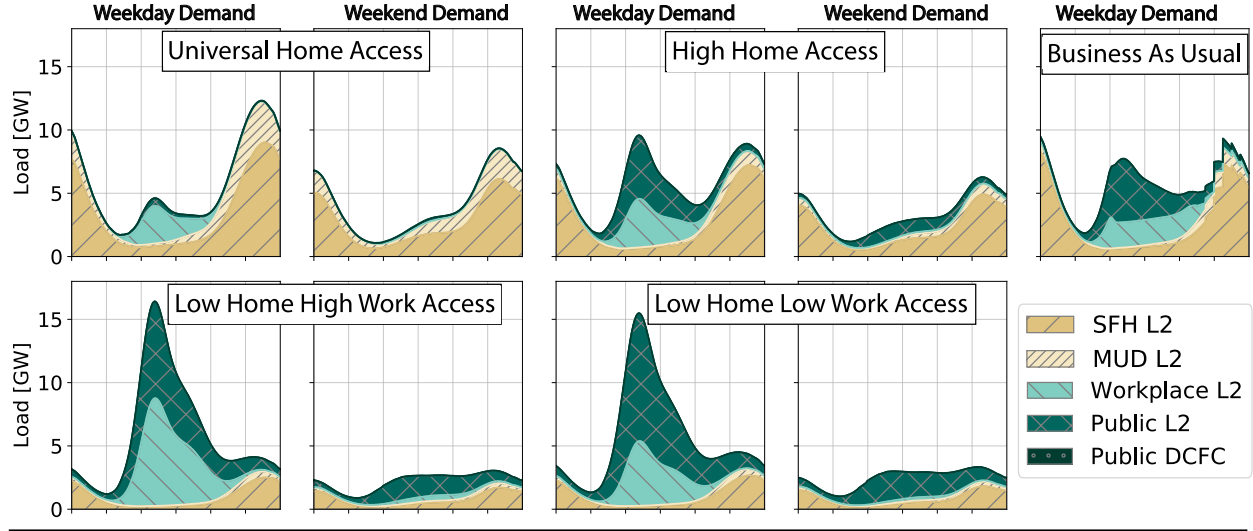


Supplementary Figure 12: The merit order of fossil fuel generators in week 14 (top row) and week 40 (bottom row) of the year. The left subplots show the generating units arranged by cost and the right subplots show their respective emissions rates.

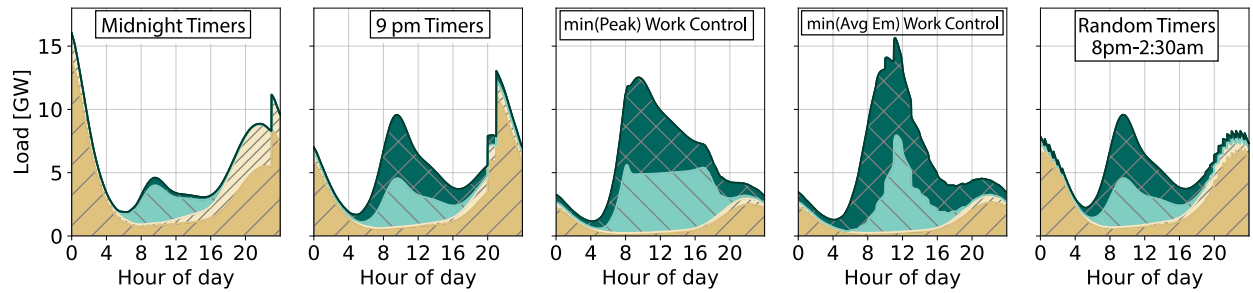
Version of Figure 2 Showing Time Zone Effect

Supplementary Figure 13 is another version of Figure 2 showing the load profiles for WECC at 50% EV adoption and illustrating the effect of the two timezones in WECC, visible from the multiple timer spikes.

(a) Uncontrolled Charging Demand



(b) Controlled Charging Examples

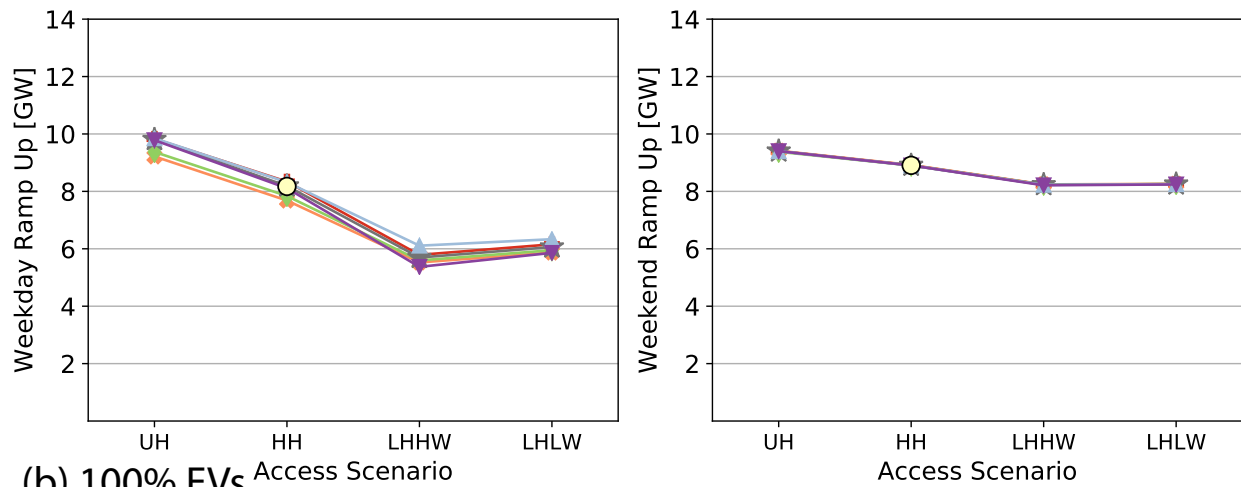


Supplementary Figure 13: Weekday or weekend demand profiles under different scenarios for 50% adoption in the US states in WECC. Part (a) illustrates the uncontrolled weekday and weekend demand for each of the four charging infrastructure access scenarios (see Methods). Part (b) shows an example of each of the five types of controlled charging studied. The aggregate WECC demand is shown in Pacific Time: the timer spikes from states in WECC on Mountain Time can be seen at 8 pm Pacific in the 9 pm Timer case and at 11 pm Pacific in the midnight timer case.

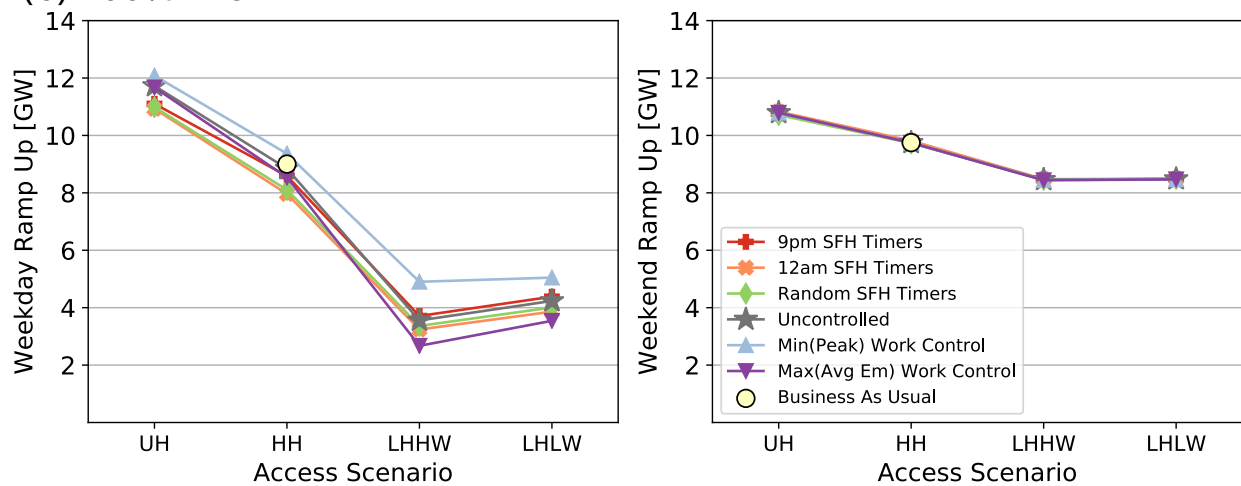
Ramping

Supplementary Figure 14 shows ramping broken down by weekday and weekend day. The trends are the same, as the Low Home Access scenarios (LHHW and LHLW) have the lowest ramping. These results reflect the net demand after applying 10 GW of grid storage.

(a) 50% EVs



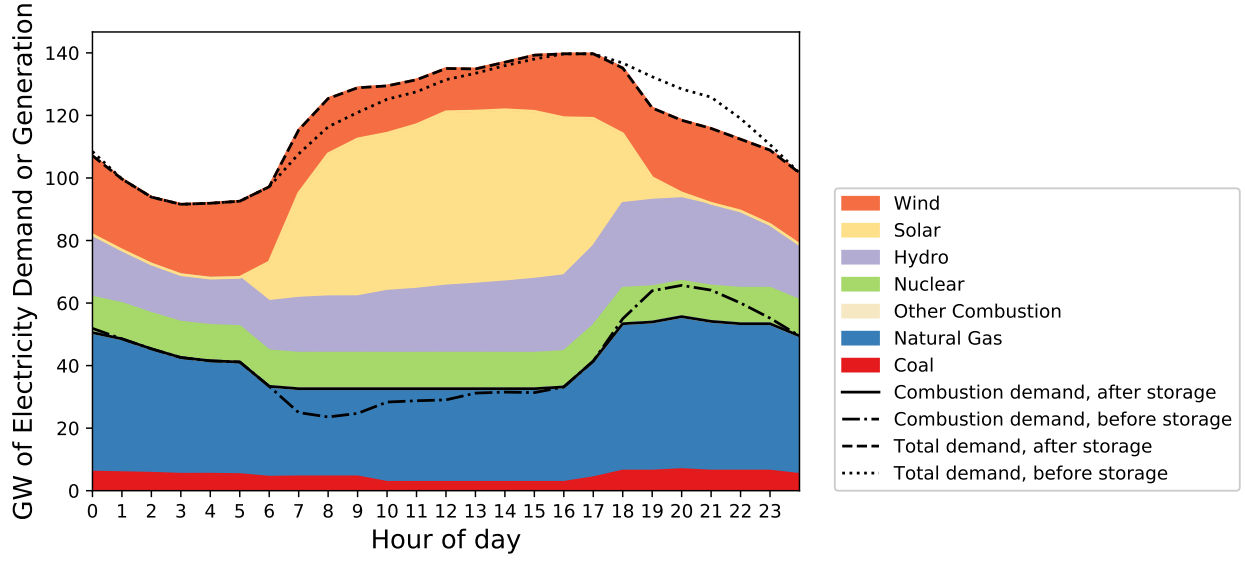
(b) 100% EVs



Supplementary Figure 14: The largest one hour ramp-up on a mean weekday (left) or weekend day (right) in each scenario.

Example dispatch

Supplementary Figure 15 shows how the demand was dispatched across generation resources for a sample summer weekday in the Business As Usual charging scenario.

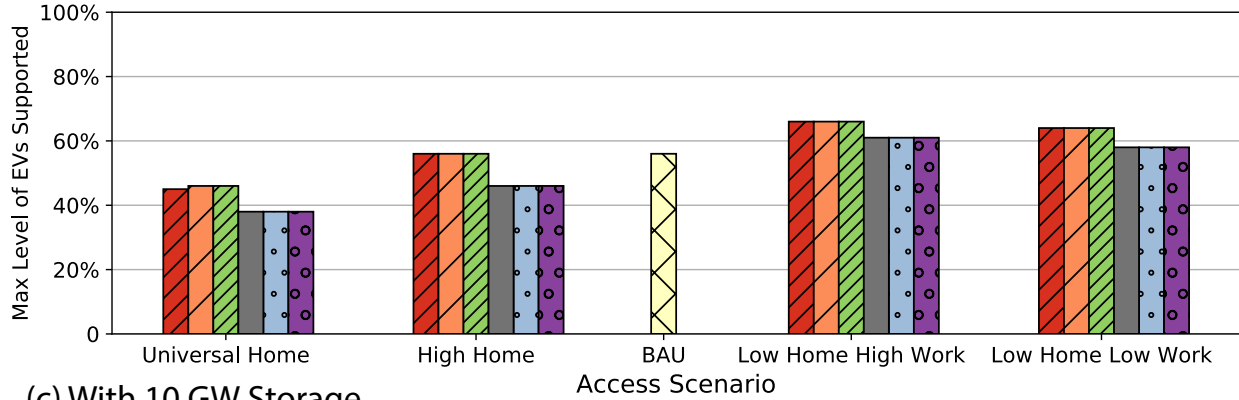
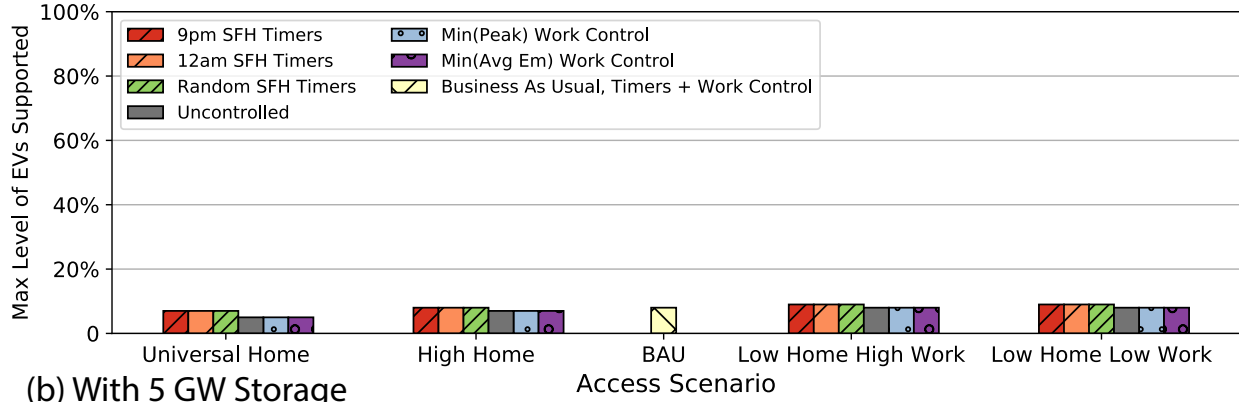


Supplementary Figure 15: Example of dispatch for the Business As Usual and Medium Renewables scenario with uncontrolled charging on Friday, July 20th, 2035. The baseline grid battery storage of 10 GW operates on the net demand such that the finale profile dispatched to the fleet of fossil fuel generators is flattened.

Supplementary Note 11: Sensitivity Tests

Sensitivity of Capacity

In the capacity results shown in Figure 4 in the main text, we found grid capacity insufficient if the demand could not be supported for at least one hour in the year. In Supplementary Figure 16 we show the sensitivity of this result to using different amounts of grid storage, in each case operated to smooth net demand.

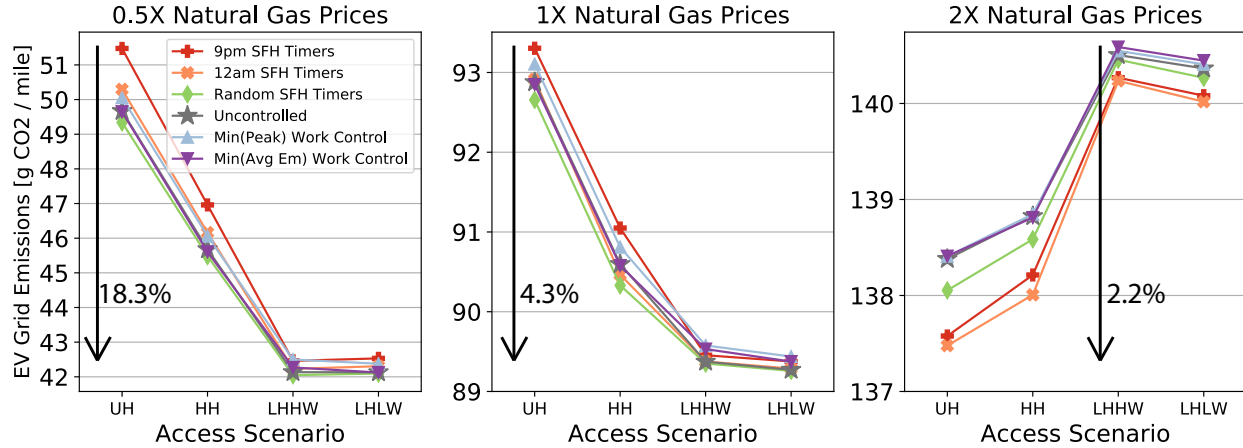


Supplementary Figure 16: Grid capacity, considering different levels of grid storage.

Sensitivity to Gas Prices

In Supplementary Figure 17 we show the sensitivity of our emissions results to changing gas fuel prices. Changing the fuel price of gas generating units does not change the capacity or ramping results, but does affect the total emissions by reordering the merit order in the generator dispatch model.

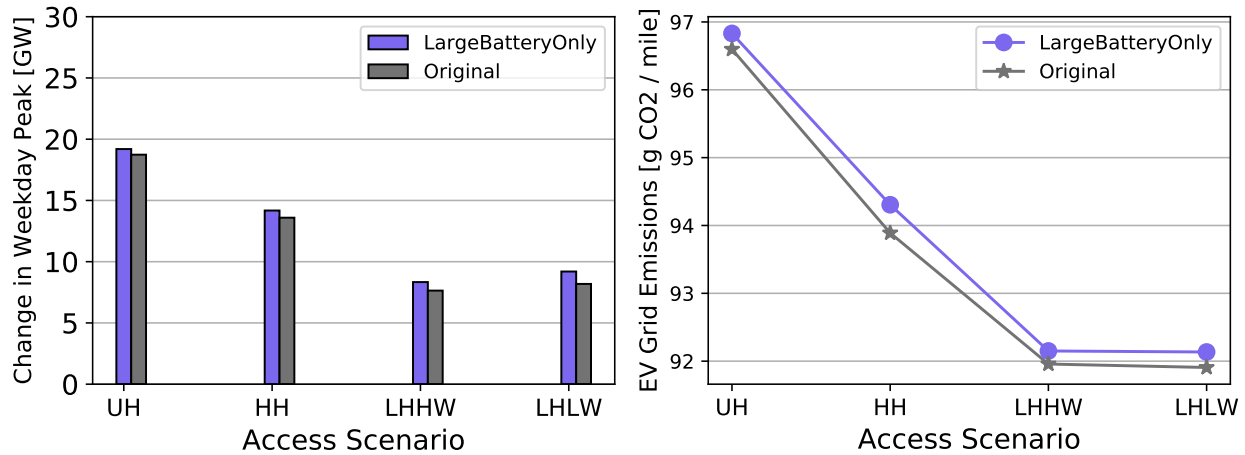
We see that the absolute value of emissions is much higher with high gas prices and much lower with low gas prices. This is because gas generators are lower emitting than coal generators. The trends across charging scenarios change little, except in the $2\times$ gas price test. Here, daytime charging has higher per mile emissions, but the difference between scenarios is very small and may not be significant given model error.



Supplementary Figure 17: Grid CO_2 emissions to support added 100% EV charging in each scenario. From left to right we test the sensitivity to 0.5 $\times$, 1 $\times$, and 2 $\times$ gas generator fuel prices.

Large battery scenario

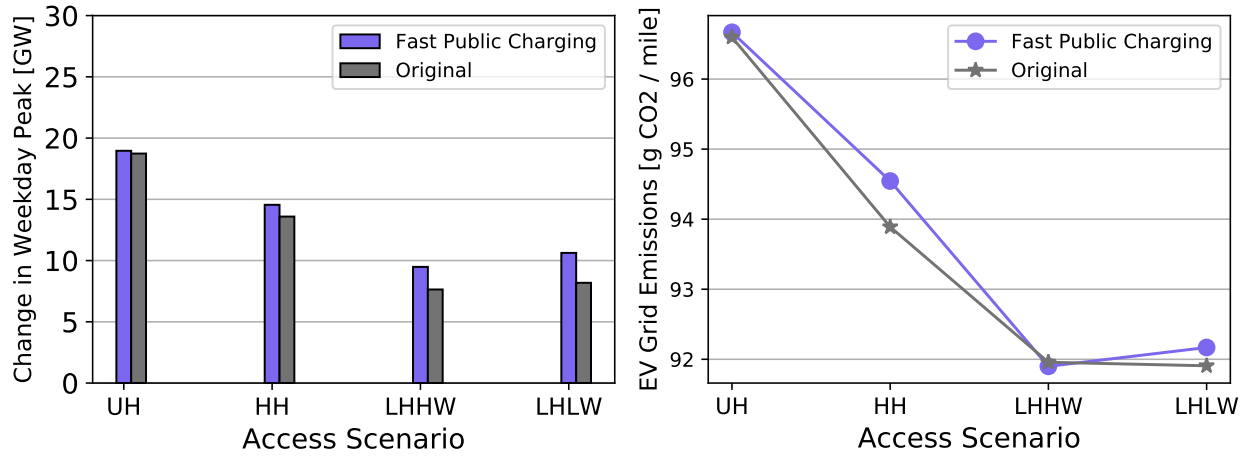
The model of charging demand models the probability with which each driver has a large or small battery EV as a function of their income. Here we test the sensitivity to that assumption by giving large battery EVs to all drivers. The result, shown in Supplementary Figure 18, is similar to the mixed battery result, as battery capacity has a smaller impact on charging profiles than other factors such as control and charging infrastructure access.



Supplementary Figure 18: Sensitivity of key results on net demand increase and grid emissions to giving all drivers large battery EVs.

High fast charging scenario

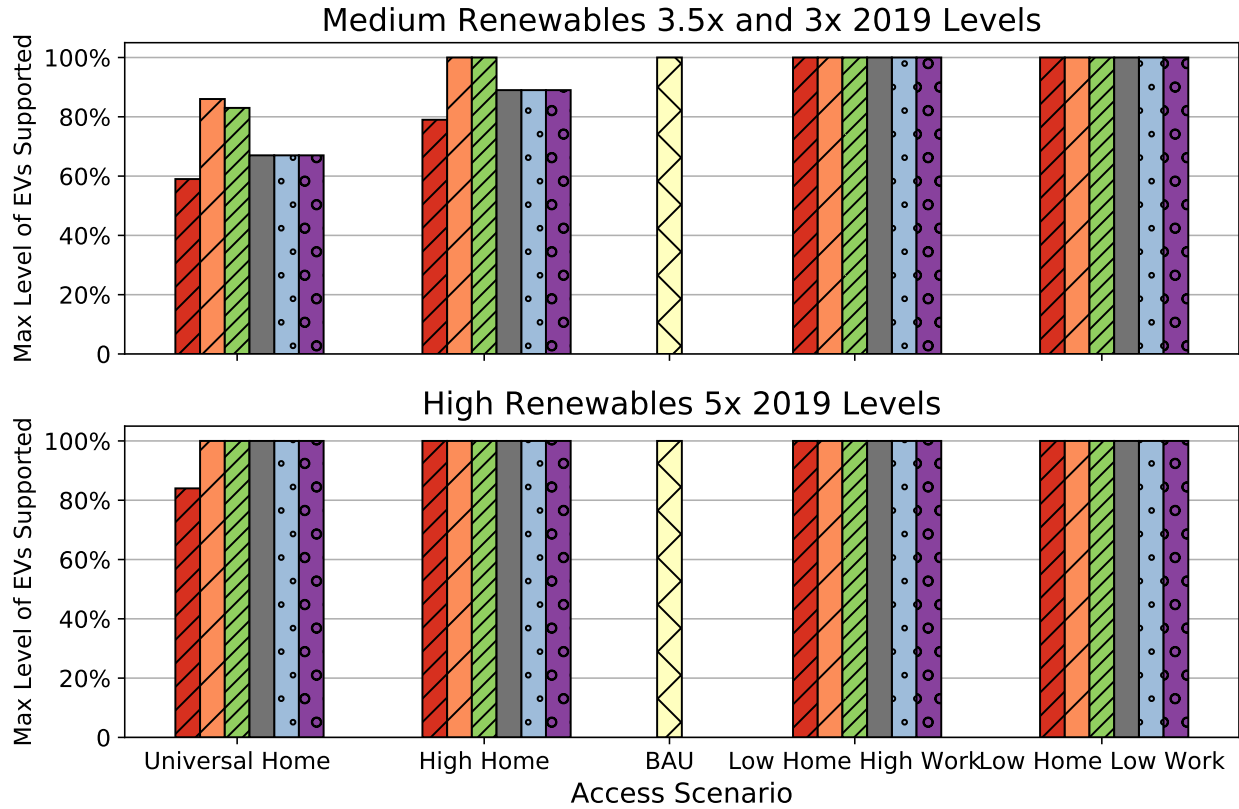
The model of charging demand is based on a charging data set in which most public charging is level 2 (L2). Here we test the sensitivity to that assumption by making all public charging fast charging (DCFC). The result, shown in Supplementary Figure 19, is similar to the original result, as the profile of fast and slow charging in aggregate is similar, and charging speed varies the profile less than other factors such as control and charging infrastructure access.



Supplementary Figure 19: Sensitivity of key results on net demand increase and grid emissions to making all public charging fast charging rather than level 2.

Sensitivity to Renewables Scenarios

We found substantial sensitivity to renewables scenarios in the level of EV penetration for which the grid had capacity to support charging. Supplementary Figure 20 shows maximum level under High Renewables with $5\times$ 2019 levels for wind and solar. The Medium Renewables scenario with $3.5\times$ and $3\times$ 2019 levels of solar and wind was shown in the main results. The High Renewables scenario presents another extreme: all scenarios could be supported without storage, except with the use of 9 pm timers in the Universal Home Access scenarios.

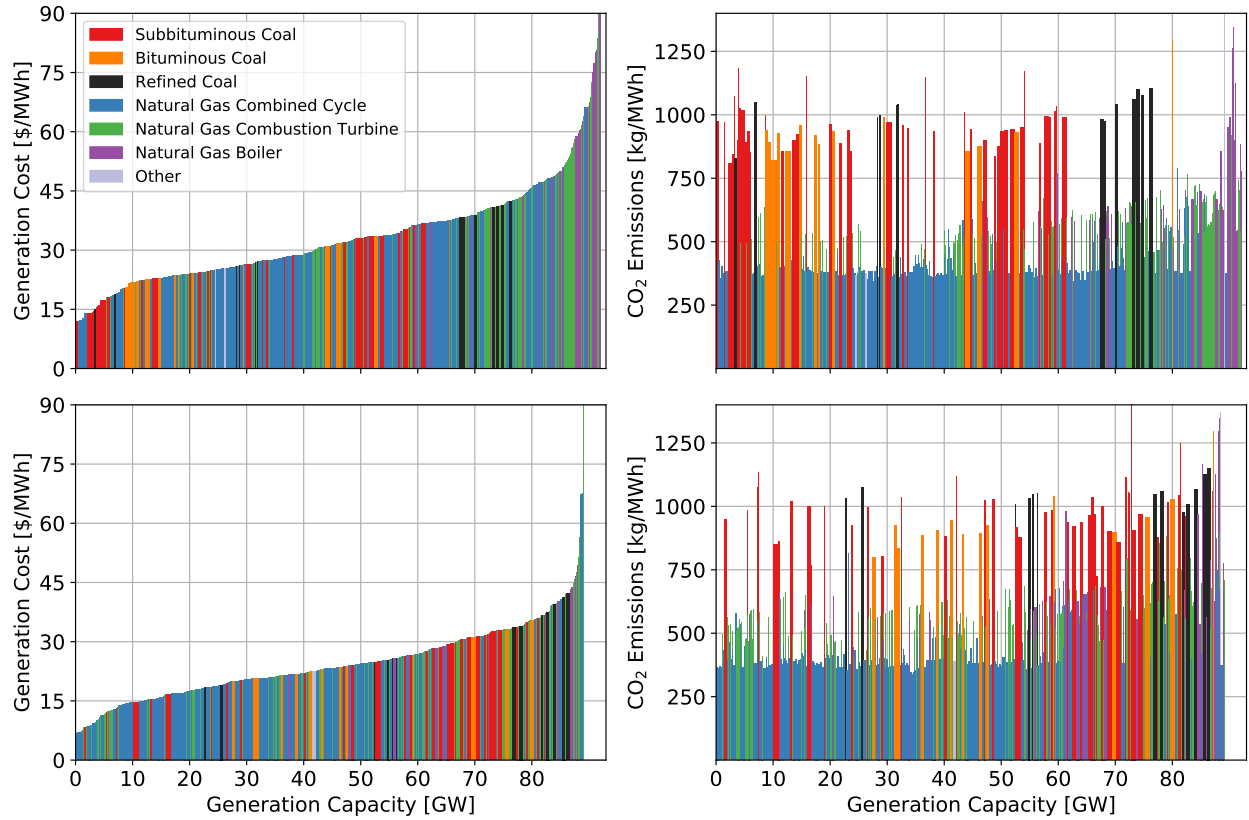


Supplementary Figure 20: Sensitivity of grid capacity to higher renewables scenarios.

Supplementary Note 12: Parallel Results for the 2019 Grid

2019 Dispatch

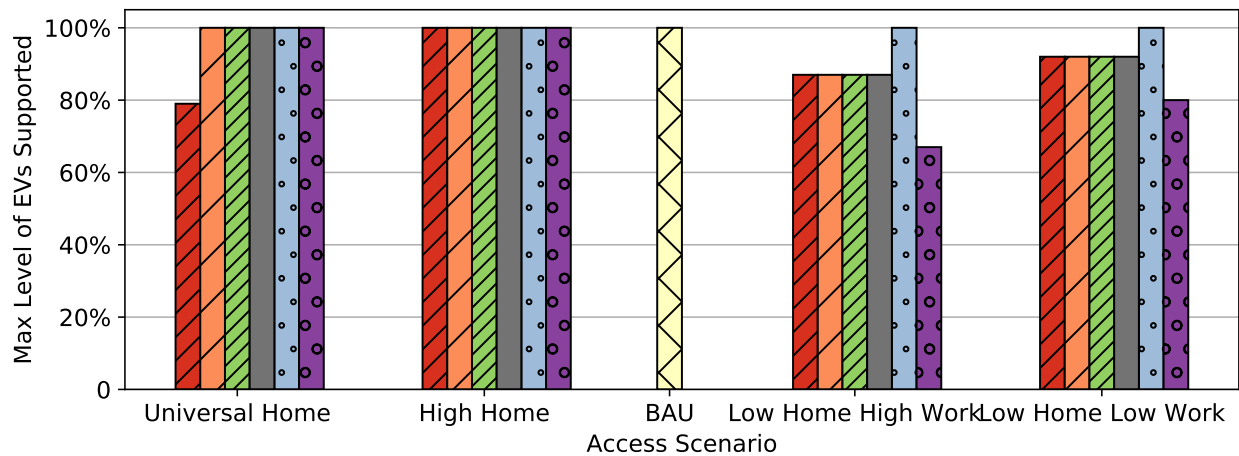
Supplementary Figure 21 shows the merit order of fossil fuel generating units used by the dispatch model in 2019, before any upgrades were applied to the grid model. Compared with 2035, there are substantially more coal plants. Many coal plants and and gas plants will be retired before 2035, with only gas plants added. We also see in 2019 that there are many high emitting generators distributed throughout the order.



Supplementary Figure 21: Merit order of generators for weeks 1 (top row) and 27 (bottom row) in 2019, without any upgrades to the grid. The left subplots show the generating units arranged by cost and the right subplots show their respective emissions rates.

2019 Grid Capacity

Supplementary Figure 22 shows the highest level of EV adoption for which charging could have been supported with the 2019 grid. In 2019, the daytime charging scenarios would have been harder to support than the home charging scenarios. The 2019 grid had more dispatchable generators and less renewable generation, resulting in a different crunch time of day.

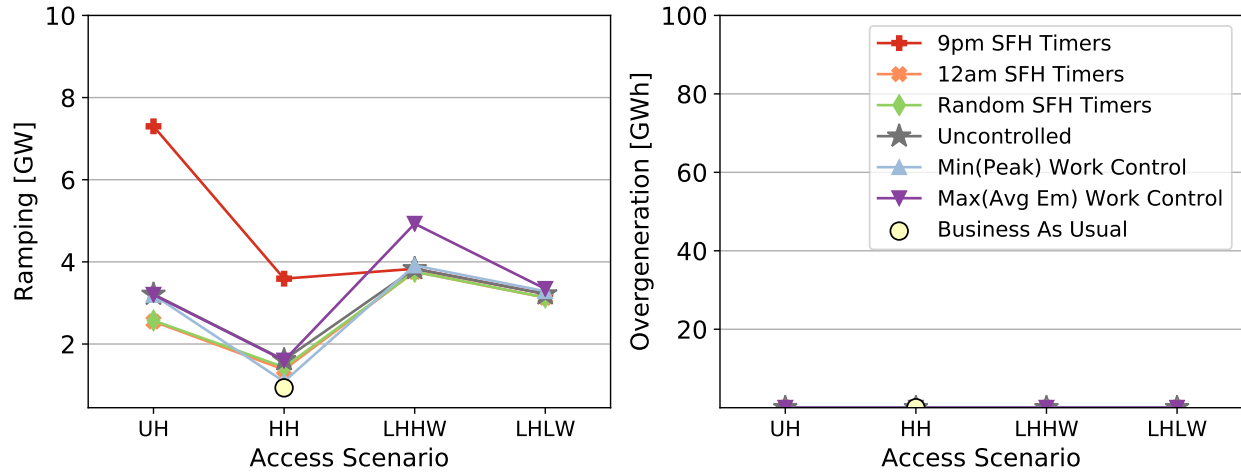


Supplementary Figure 22: Capacity to support EV charging in the 2019 grid, without any additional storage.

2019 Ramping and Overgeneration

Supplementary Figure 23 repeats part (a) of Figure 6 from the main paper, using the 2019 grid instead of the 2035 grid model. We see that there would have been zero overgeneration in the 2019 grid with 100% EVs charging, due to lower levels of renewable generation.

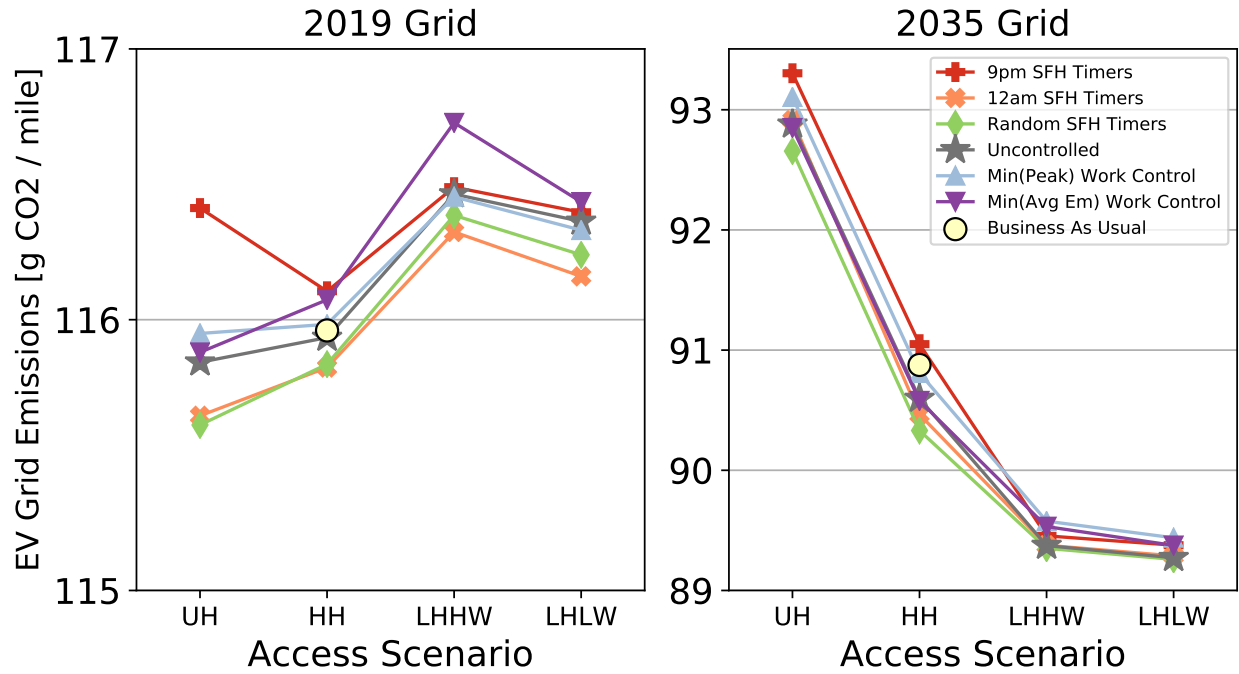
Without control, ramping is lowest in 2019 in the High Home Access charging scenario and highest in the Low Home High Work Access charging scenario, as with less solar generation in 2019 the daytime charging scenarios increase midday net demand. We also see that 9 pm SFH timers stand out as a cause of high ramping.



Supplementary Figure 23: Grid impacts with 100% EV adoption charging in the 2019 grid. Ramping (left) is defined as the largest one-hour ramp up in net demand on a mean day in 2019, and overgeneration (right) is defined as the total annual electricity from nonfossil fuel generation that went unused in 2019.

2019 Grid Emissions

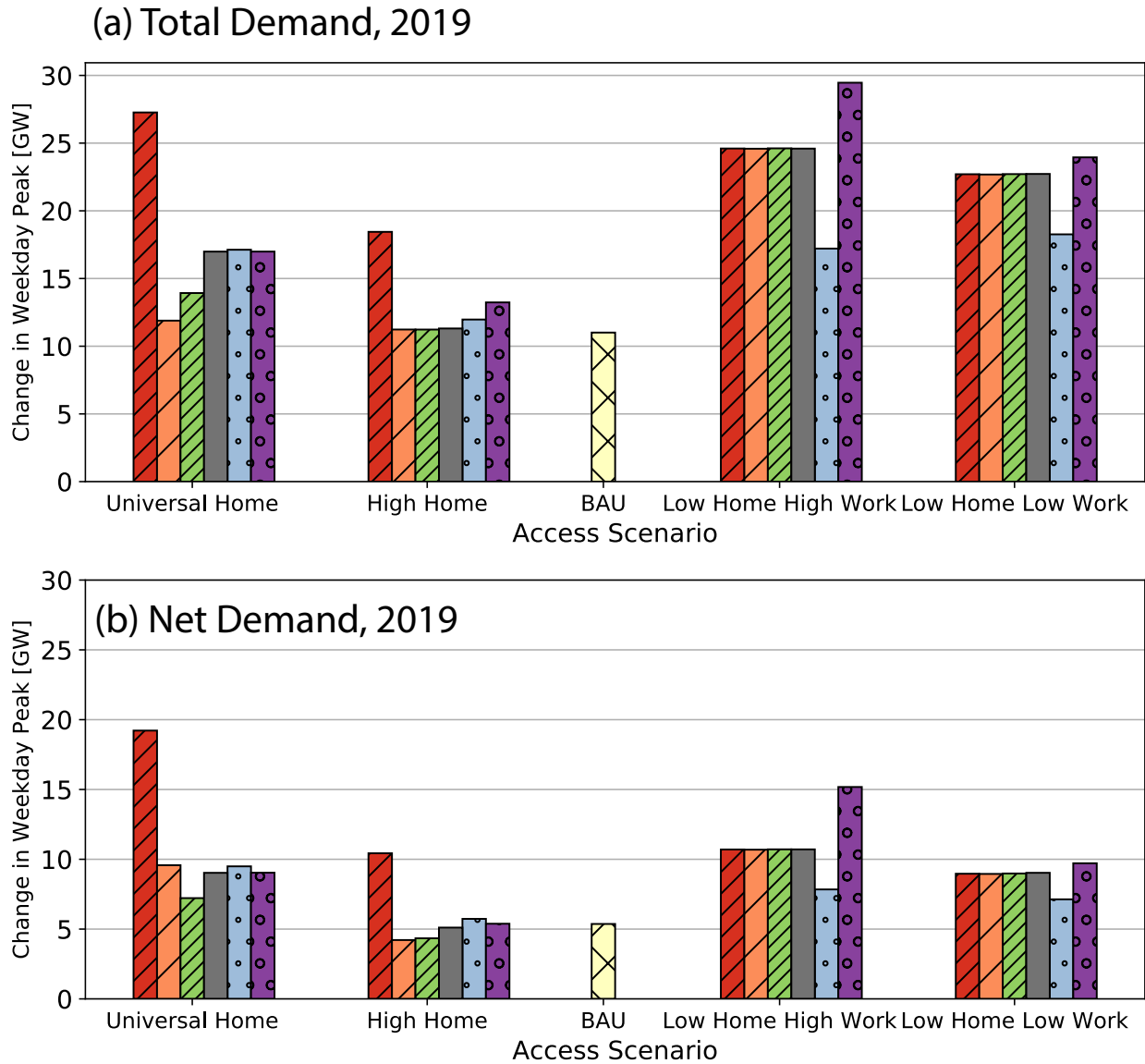
Supplementary Figure 24 compares the grid CO_2 emissions per mile traveled to support 100% EVs in the 2019 vs 2035 grid. We see grid emissions are substantially higher in the 2019 scenario thanks to the larger number of high emitting coal-fired plants present in the 2019 fleet.



Supplementary Figure 24: Grid emissions to support EV charging with 100% EV adoption, comparing the 2019 and 2035 grids.

2019 Peak Total Demand and Peak Net Demand Change

Supplementary Figure 25 shows the increase in peak total and net demand if 100% EVs were charged in the 2019. Compared with 2035, there is very little difference in 2019 between the trends in total and net demand.



Supplementary Figure 25: Change in peak total and net demand in the 2019 grid to support 100% EVs.

Supplementary Tables

Here we include the exact values plotted in figures in the main paper. Supplementary Tables 6 and 7 show the peak total demand changes reported in Figure 4. Supplementary Tables 8 and 9 show the peak net demand changes reported in Figure 4. Supplementary Tables 10 and 11 show the storage results reported in Figure 5.

Incr Peak Total Demand [%]	Universal Home	High Home	Low Home	High Work	Low Home	Low Work
Random SFH Timers	4.76	3.42		6.77		5.91
12 am SFH Timers	4.57	3.42		6.76		5.89
9 pm SFH Timers	7.85	3.82		6.77		5.90
Uncontrolled	6.23	4.33		6.77		5.91
Min(Peak) Work Control	6.45	5.09		6.60		5.43
Min(Avg Em) Work Control	6.20	4.29		9.38		6.86
Business As Usual	-	4.64		-		-

Supplementary Table 6: The percent increase in peak *total* demand on a typical day over a 2035 baseline with each charging scenario at 50% EV adoption. These are the same values plotted in Figure 4 in the main paper.

Incr Peak Total Demand [%]	Universal Home	High Home	Low Home	High Work	Low Home	Low Work
Random SFH Timers	12.13	9.18		21.40		19.66
12 am SFH Timers	10.60	9.18		21.37		19.64
9 pm SFH Timers	23.79	15.73		21.39		19.65
Uncontrolled	14.93	10.13		21.38		19.67
Min(Peak) Work Control	15.05	10.73		14.64		15.60
Min(Avg Em) Work Control	14.93	11.10		25.92		20.89
Business As Usual	-	9.41		-		-

Supplementary Table 7: The percent increase in peak *total* demand on a typical day over a 2035 baseline with each charging scenario at 100% EV adoption. These are the same values plotted in Figure 4 in the main paper.

Incr Peak Net Demand [%]	Universal Home	High Home	Low Home	High Work	Low Home	Low Work
Random SFH Timers	14.55	9.69		6.61		7.12
12 am SFH Timers	12.63	9.37		6.50		7.01
9 pm SFH Timers	24.89	16.56		6.52		7.00
Uncontrolled	17.45	12.14		7.48		8.01
Min(Peak) Work Control	17.58	12.77		8.93		8.89
Min(Avg Em) Work Control	17.45	12.04		7.20		7.85
Business As Usual	-	11.71		-		-

Supplementary Table 8: The percent increase in peak *net* demand on a typical day over a 2035 baseline with each charging scenario at 50% EV adoption. These are the same values plotted in Figure 4 in the main paper.

Incr Peak Net Demand [%]	Universal Home	High Home	Low Home	High Work	Low Home	Low Work
Random SFH Timers	32.42	21.78		13.12		14.12
12 am SFH Timers	35.79	21.67		12.89		13.91
9 pm SFH Timers	49.99	39.87		13.32		15.18
Uncontrolled	36.37	26.38		14.83		15.89
Min(Peak) Work Control	36.59	26.71		17.95		17.60
Min(Avg Em) Work Control	36.37	26.31		14.28		15.55
Business As Usual	-	27.11		-		-

Supplementary Table 9: The percent increase in peak *net* demand on a typical day over a 2035 baseline with each charging scenario at 100% EV adoption. These are the same values plotted in Figure 4 in the main paper.

Grid Storage [MW]	Universal Home	High Home	Low Home	High Work	Low Home	Low Work
Random SFH Timers	5544	4550		3906		4034
12 am SFH Timers	5473	4537		3908		4041
9 pm SFH Timers	7087	4541		3914		4041
Uncontrolled	7152	5450		4230		4374
Min(Peak) Work Control	7397	6347		6322		5624
Min(Avg Em) Work Control	7126	5420		4156		4329
Business As Usual	-	5447		-		-

Supplementary Table 10: The amount of four-hour grid storage required to support charging for 50% EV adoption. These are the same values plotted in Figure 5 in the main paper. The value reported is the capacity in MW.

Grid Storage [MW]	Universal Home	High Home	Low Home	High Work	Low Home	Low Work
Random SFH Timers	14673	8833		7424		7680
12 am SFH Timers	14214	8686		7427		7694
9 pm SFH Timers	24540	15721		7439		7693
Uncontrolled	18194	11424		8072		8359
Min(Peak) Work Control	19221	12305		12256		10860
Min(Avg Em) Work Control	18193	11317		7923		8270
Business As Usual	-	10897		-		-

Supplementary Table 11: The amount of four-hour grid storage required to support charging for 100% EV adoption. These are the same values plotted in Figure 5 in the main paper. The value reported is the capacity in MW.

Supplementary Methods

Data cleaning

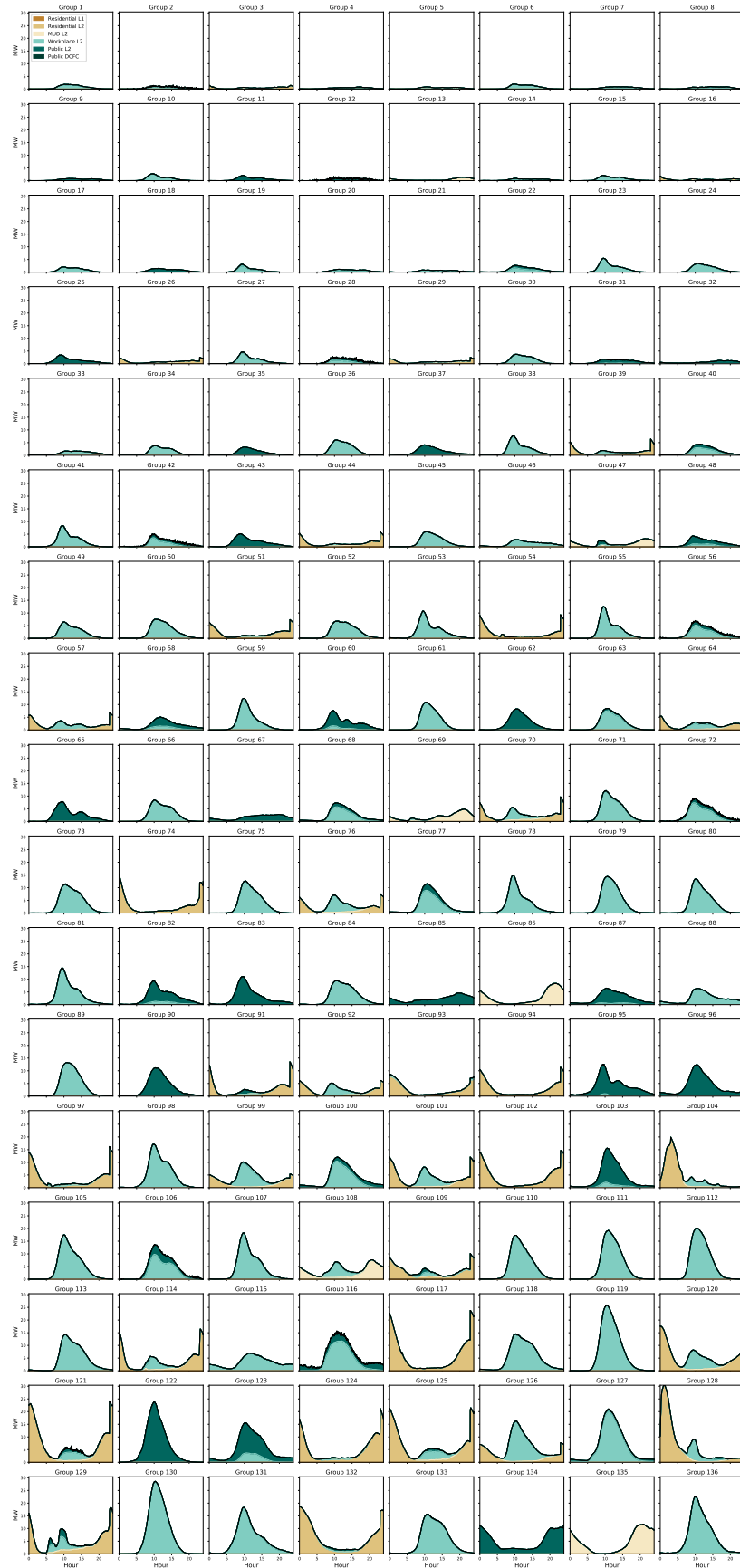
This paper used a large data set of real charging sessions. The charging session data was cleaned to remove sessions with impossible energy or charging power values, sessions that lasted less than one minute or delivered no energy, and sessions with missing data in the key categories of start time, date, or driver ID.

For this study, only vehicles labeled as “PLUGIN” type were used, not “HYBRID”. Unlabeled vehicles were categorized as “PLUGIN” if their battery capacity was larger than 20 kWh. Only drivers with known vehicle battery capacity were used. This left 73,449 drivers in the data set. To ensure only drivers were used for whom we captured all or most of their charging sessions in the network, we excluded drivers with less than 250 kWh (< about 1000 miles) of annual charging energy. We also excluded drivers with sessions in the fleet (commercial) category. This left a total of 28435 drivers in the data set. Finally, drivers in the extreme 0.01% of key columns like number of sessions were removed. This left a final 27,730 drivers to be used in the clustering.

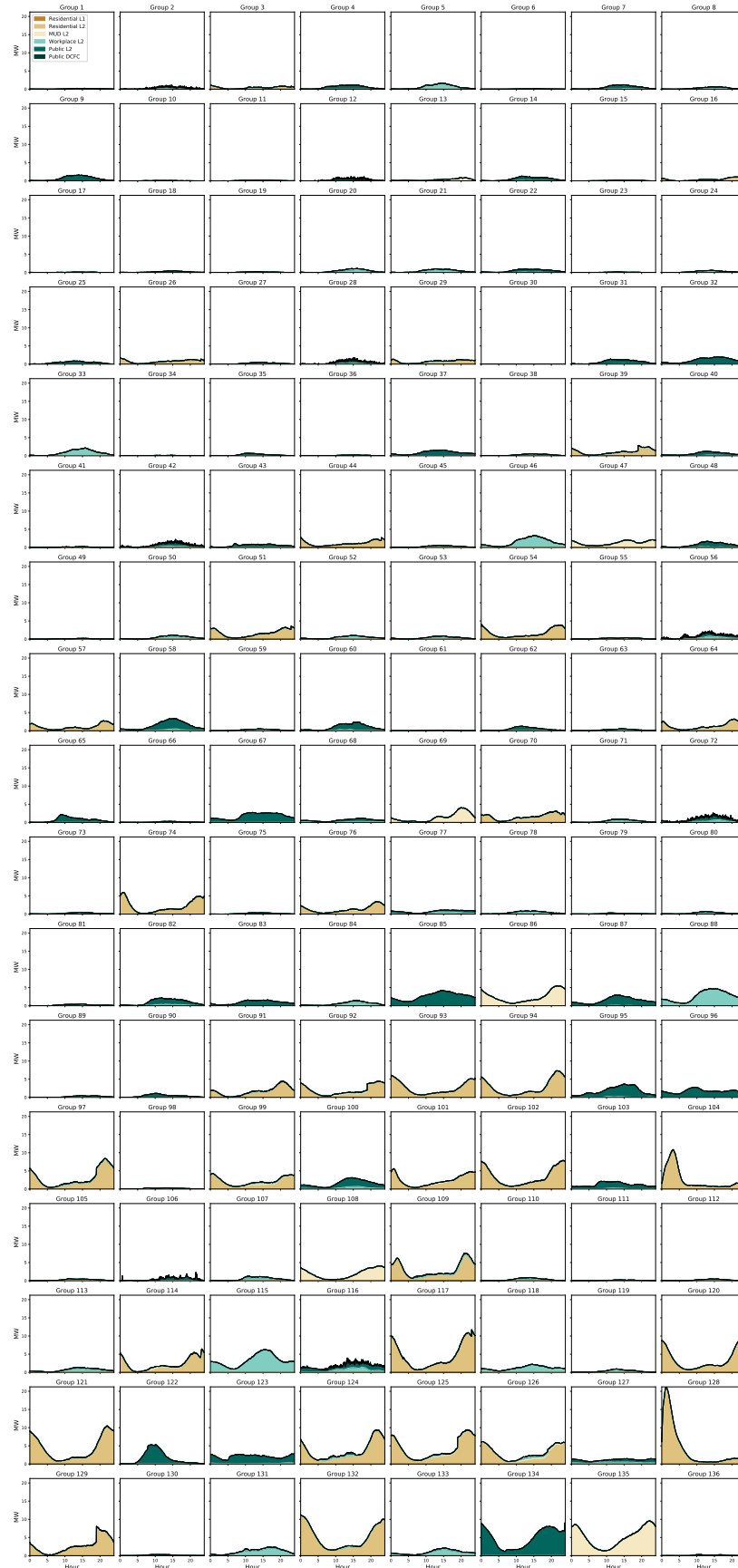
The census data was also cleaned to ensure all distributions added to 1. For example, in many counties the sum of the fraction of residents in each income group would amount to 99% instead of 100%. In those cases, the distribution was normalized by that value to ensure it summed to 100%. For one county missing mileage data, the missing value was filled using the mean of other counties in its state. The data processing code is included in the Github repository.

Group load profiles

Supplementary Figures 26 and 27 show the typical weekday and weekend load profile for 1000 drivers in each of the 136 driver behaviour groups. Note the method found groups for each bin of energy use separately, which can be seen by comparing the earlier and later group profiles in this set.



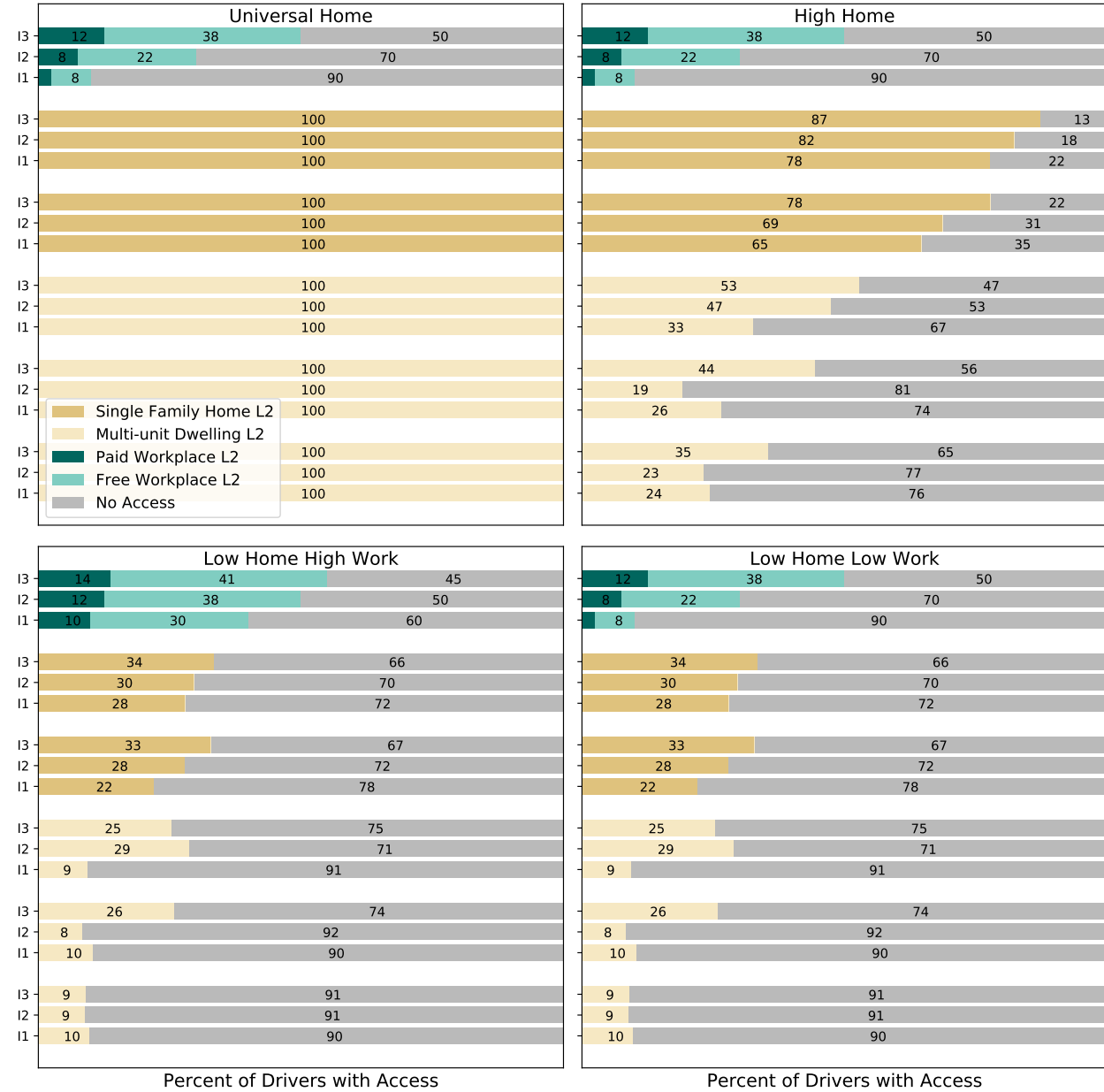
Supplementary Figure 26: Weekday profiles for 1000 drivers in each group.



Supplementary Figure 27: Corresponding weekend day profiles for 1000 drivers in each group.

Access scenario details

Supplementary Figure 28 illustrates the mapping from driver income and housing type to charging access used in each of the four access scenarios.



Supplementary Figure 28: Percentage of drivers with access to residential and workplace charging, divided by income and housing type. 'I1', 'I2', and 'I3' represent low, medium, and high annual household income groups.

Supplementary References

- [1] E. W. Wood, C. L. Rames, M. Muratori, New evse analytical tools/models: Electric vehicle infrastructure projection tool (evi-pro), Tech. rep., National Renewable Energy Lab.(NREL), Golden, CO (United States) (2018).

- [2] Assembly bill 2127 electric vehicle charging infrastructure assessment (revised staff report), Tech. rep., California Energy Commission, available at: <https://www.energy.ca.gov/programs-and-topics/programs/electric-vehicle-charging-infrastructure-assessment-ab-2127> (2021).
- [3] J. K. Szinai, C. J. Sheppard, N. Abhyankar, A. R. Gopal, Reduced grid operating costs and renewable energy curtailment with electric vehicle charge management, *Energy Policy* 136 (2020) 111051.
- [4] Energy, I. Environmental Economics, Benefit-Cost Analysis of Transportation Electrification in the Xcel Energy Colorado Service Territory, 2020.
- [5] J. Coignard, P. MacDougall, F. Stadtmueller, E. Vrettos, Will electric vehicles drive distribution grid upgrades?: The case of california, *IEEE Electrification Magazine* 7 (2) (2019) 46–56.
- [6] M. Muratori, Impact of uncoordinated plug-in electric vehicle charging on residential power demand, *Nature Energy* 3 (3) (2018) 193–201.
- [7] M. Kintner-Meyer, S. Davis, S. Sridhar, D. Bhatnagar, S. Mahserejian, M. Ghosal, Electric vehicles at scale—phase i analysis: High ev adoption impacts on the western us power grid, Tech. rep. (2020).
- [8] F. Manríquez, E. Sauma, J. Aguado, S. de la Torre, J. Contreras, The impact of electric vehicle charging schemes in power system expansion planning, *Applied Energy* 262 (2020) 114527.
- [9] A. J. Cheng, B. Tarroja, B. Shaffer, S. Samuelsen, Comparing the emissions benefits of centralized vs. decentralized electric vehicle smart charging approaches: A case study of the year 2030 california electric grid, *Journal of Power Sources* 401 (2018) 175–185.
- [10] C. Zhang, J. B. Greenblatt, P. MacDougall, S. Saxena, A. J. Prabhakar, Quantifying the benefits of electric vehicles on the future electricity grid in the midwestern united states, *Applied Energy* 270 (2020) 115174.
- [11] G. Doluweera, F. Hahn, J. Bergerson, M. Pruckner, A scenario-based study on the impacts of electric vehicles on energy consumption and sustainability in alberta, *Applied Energy* 268 (2020) 114961.
- [12] M. Wolinetz, J. Axsen, J. Peters, C. Crawford, Simulating the value of electric-vehicle-grid integration using a behaviourally realistic model, *Nature Energy* 3 (2) (2018) 132–139.
- [13] J. Quiros-Tortos, L. Ochoa, T. Butler, How electric vehicles and the grid work together: Lessons learned from one of the largest electric vehicle trials in the world, *IEEE Power and Energy Magazine* 16 (6) (2018) 64–76.
- [14] J. Quirós-Tortós, A. Navarro-Espinosa, L. F. Ochoa, T. Butler, Statistical representation of ev charging: Real data analysis and applications, in: 2018 Power Systems Computation Conference (PSCC), IEEE, 2018, pp. 1–7.
- [15] J. Zhang, J. Jorgenson, T. Markel, K. Walkowicz, Value to the grid from managed charging based on california’s high renewables study, *IEEE Transactions on Power Systems* 34 (2) (2018) 831–840.
- [16] Y. Xu, S. Çolak, E. C. Kara, S. J. Moura, M. C. González, Planning for electric vehicle needs by coupling charging profiles with urban mobility, *Nature Energy* 3 (6) (2018) 484–493.
- [17] C. Crozier, T. Morstyn, M. McCulloch, The opportunity for smart charging to mitigate the impact of electric vehicles on transmission and distribution systems, *Applied Energy* 268 (2020) 114973.
- [18] C. Crozier, T. Morstyn, M. McCulloch, A stochastic model for uncontrolled charging of electric vehicles using cluster analysis, *arXiv preprint arXiv:1907.09458* (2019).
- [19] M. Sodenkamp, J. Wenig, F. Thiesse, T. Staake, Who can drive electric? segmentation of car drivers based on longitudinal gps travel data, *Energy Policy* 130 (2019) 111–129.

- [20] N. Sadeghianpourhamami, N. Refa, M. Strobbe, C. Develder, Quantitative analysis of electric vehicle flexibility: A data-driven approach, *International Journal of Electrical Power & Energy Systems* 95 (2018) 451–462.
- [21] M. G. Flammini, G. Pretticco, A. Julea, G. Fulli, A. Mazza, G. Chicco, Statistical characterisation of the real transaction data gathered from electric vehicle charging stations, *Electric Power Systems Research* 166 (2019) 136–150.
- [22] J. R. Helmus, M. H. Lees, R. van den Hoed, A data driven typology of electric vehicle user types and charging sessions, *Transportation Research Part C: Emerging Technologies* 115 (2020) 102637.
- [23] A. Jenn, K. Clark-Sutton, M. Gallaher, J. Petrusa, Environmental impacts of extreme fast charging, *Environmental Research Letters* 15 (9) (2020) 094060.
- [24] S. Powell, G. V. Cezar, E. Apostolaki-Iosifidou, R. Rajagopal, Large-scale scenarios of electric vehicle charging with a data-driven model of control, *arXiv preprint arXiv:2105.12234* (2021).
- [25] S. Powell, G. V. Cezar, R. Rajagopal, Scalable probabilistic estimates of electric vehicle charging given observed driver behavior, *Applied Energy X* (2022) X, accepted.
- [26] S. Powell, E. C. Kara, R. Sevlian, G. V. Cezar, S. Kiliccote, R. Rajagopal, Controlled workplace charging of electric vehicles: The impact of rate schedules on transformer aging, *Applied Energy* 276 (2020) 115352.
- [27] X. Chen, H. Zhang, Z. Xu, C. P. Nielsen, M. B. McElroy, J. Lv, Impacts of fleet types and charging modes for electric vehicles on emissions under different penetrations of wind power, *Nature Energy* 3 (5) (2018) 413–421.
- [28] N. Brinkel, W. Schram, T. AlSkaif, I. Lampropoulos, W. van Sark, Should we reinforce the grid? cost and emission optimization of electric vehicle charging under different transformer limits, *Applied Energy* 276 (2020) 115285.
- [29] S. Sachan, S. Deb, S. N. Singh, Different charging infrastructures along with smart charging strategies for electric vehicles, *Sustainable Cities and Society* 60 (2020) 102238.
- [30] J. McLaren, J. Miller, E. O’Shaughnessy, E. Wood, E. Shapiro, Co2 emissions associated with electric vehicle charging: the impact of electricity generation mix, charging infrastructure availability and vehicle type, *The Electricity Journal* 29 (5) (2016) 72–88.
- [31] T. Yuksel, M.-A. M. Tamayao, C. Hendrickson, I. M. Azevedo, J. J. Michalek, Effect of regional grid mix, driving patterns and climate on the comparative carbon footprint of gasoline and plug-in electric vehicles in the united states, *Environmental Research Letters* 11 (4) (2016) 044007.
- [32] M. Miotti, G. J. Supran, E. J. Kim, J. E. Trancik, Personal vehicles evaluated against climate change mitigation targets, *Environmental science & technology* 50 (20) (2016) 10795–10804.
- [33] Y. Ou, N. Kittner, S. Babaei, S. J. Smith, C. G. Nolte, D. H. Loughlin, Evaluating long-term emission impacts of large-scale electric vehicle deployment in the us using a human-earth systems model, *Applied Energy* 300 (2021) 117364.
- [34] F. H. Administration, 2017 national household travel survey, Tech. rep., U.S. Department of Transportation, Washington, DC, available online: <https://nhts.ornl.gov> (2017).
- [35] US Department of Energy and United States Environmental Protection Agency, www.fueleconomy.gov the official us government source for fuel economy information, <https://fueleconomy.gov/feg/Find.do?action=sbsSelect>, accessed: 2022-04-10 (2022).
- [36] B. Meffert, How much does it cost to install a home charging station?, <https://www.getneocharge.com/blog-post/cost-to-install-a-home-charging-station>, accessed: 2022-04-14 (2022).

- [37] J. Potter, P. Cappers, Demand response advanced controls framework and assessment of enabling technology costs, Tech. rep., Lawrence Berkeley National Lab.(LBNL), Berkeley, CA (United States) (2017).
- [38] Chargepoint quote to slac national accelerator laboratory for fully managed l2 charging (2022).
- [39] C. Ledna, M. Muratori, A. Brooker, E. Wood, D. Greene, How to support ev adoption: Tradeoffs between charging infrastructure investments and vehicle subsidies in california, Energy Policy 165 (2022) 112931.