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The environmental impacts of green technologies in TX

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ABSTRACT

Using detailed electricity consumption and solar generation data from homes in an Austin TX neighborhood between 2013 and 2015, we calculate the environmental benefits of electric vehicles and rooftop solar panels. We estimate time-varying electric grid marginal emissions and water consumption rates in ERCOT through a regression based analysis, and find that emissions and water consumption rates are lowest at high demand times due to those hours' reliance on cleaner natural gas generators. We utilize these emissions and water consumption rates to estimate the avoided GHGs and water consumption from grid electricity that solar panels provide. For electric vehicles, we estimate the net effect of this technology, given the avoided gasoline consumption but increase in grid-related charging. We find that, on average, solar panels avoid approximately 75% of yearly grid-related emissions (0.7 tons CO_2/year per kW of solar capacity) and yearly grid-related water consumption (400 gal/year per kW of solar capacity), where the benefits depend on the orientation of the panels. We also find that electric vehicle deployment results in avoiding up to 70% of fuel-related emissions (3.5 tons CO_2/year) and 60% of fuel-related water consumption (1400 gal/year), though the benefits significantly decrease with the efficiency of the counterfactual vehicle.

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1. Introduction

Being "green" has become much easier for households with the evolution of technology, such as electric vehicles (EVs) and solar photovoltaic (PV) panels. These technologies allow consumers to maintain a traditional lifestyle while also reducing their environmental impact by reducing fossil-fuel consumption either on the electricity grid or from internal combustion vehicles. Governments recognize the environmental benefits of these technologies and thus have implemented myriad policies to spur their deployment.

However, the question remains as to what degree these technologies improve environmental outcomes as they depend on multiple complex factors including the time- and location-specific emission characteristics of the electricity generation displaced by solar PV or consumed by EVs. For example, an EV's environmental impact will depend on when and where the customer charges it. Similarly, the environmental impact of a household's solar PV system will vary depending on the type of generation from the electricity grid that is displaced. The temporal and spatial variation of these technologies' environmental impacts means that households can influence the magnitude of environmental benefits by engaging in certain behaviors associated with these technologies.

Utilizing household energy consumption and generation data from the Mueller residential neighborhood in Austin, TX and hourly generation data for the Texas electricity grid, we analyze how household solar PV and EV utilization patterns impact the CO_2 emissions and water consumption associated with consuming electricity from the grid. We then explore how the use of these technologies can be adjusted to maximize environmental benefits and whether these optimizing actions are indeed being taken.

Though several papers have investigated the environmental and electric system impacts of EVs (see Hadley and Tsvetkova, 2009; Doucette and McCulloch, 2011; Holland et al., 2016; Huo et al., 2015; Rangaraju et al., 2015) or solar PV (Spiegel et al., 2000; Connors et al., 2004; Sivaraman and Keoleian, 2010; Zhai et al., 2012), our paper's detailed, hourly household level dataset on energy consumption, PV generation, and EV charging fills several gaps in the literature. First, it allows us to identify hourly environmental impacts from actual charging patterns and identify whether households are charging during environmentally friendly times of day. Second, we are able to estimate the magnitude and existence of a solar rebound effect, and whether this rebound effect

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varies with EV ownership. Third, we can identify whether households are making environmentally optimal decisions with respect to these technologies. Though many engineering papers have been written on how to maximize solar capture through panel tilt and orientation (see for example Li and Lam, 2007; Zhao et al., 2010; Lave and Kleissl, 2011; Hong et al., 2014), to the best of our knowledge, ours is the first paper to estimate the environmental impact of solar panel orientation based on the marginal emissions profile of the system. Our use of a marginal (rather than average) emissions analysis also allows us to more accurately measure the environmental impact of the timing of charging and distributed generation. Thus, our detailed dataset and carefully constructed emissions analysis contributes a robust and disaggregated analysis to the growing literature on the environmental impacts of green technologies.

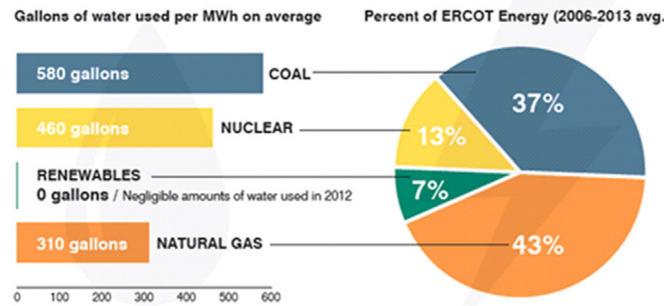

Fig. 1. Texas Energy-Water Nexus.
Source: Environmental Defense Fund (2015).

2. Environmental impacts of electricity

2.1. Emissions and water consumption of electricity generation

Generating electricity causes many types of environmental impacts. In the United States, electricity is predominantly generated through the combustion of fossil fuels (EIA, 2016a). Fossil fuel fired electricity generators emit many local air pollutants, such as NO_x, SO_2, and particulate matter, causing air quality effects in adjacent areas. These generators are also a significant source of greenhouse gas (GHG) emissions. Nationally, electricity generation is responsible for almost 40% of annual US CO_2 emissions (EIA, 2016b).

Fossil fuel based electricity generation is also a water intensive process. In 2015 over 1 trillion gallons of water were consumed for cooling during the production of electricity in the United States (EIA, 2015). Fig. 1 shows how many gallons of water are used in Texas for each MWh of electricity generated by generation source; renewables only utilize a negligible amount of water in producing electricity.

Generally, power plants withdraw water from a nearby surface source (e.g. river, lake, or coastal water). Most of the water is returned to the body of water; however, some may evaporate or otherwise not be returned to its original source. This water is considered to be consumed. Thus, the water impacts of electricity generation can be measured by both the *withdrawal* and *consumption* of water. These two water impacts are very different, and each type of generator may withdraw and consume a different amount of water. For example, natural gas combustion turbine generators do not require water for cooling, whereas natural gas or coal steam turbine generators must use large amounts of water to condense steam and thus have greater water withdrawal and consumption levels. Withdrawing large quantities of water is problematic for two reasons: it displaces water for other uses, such as drinking, and the water that is returned to nature may be heated, causing local concerns in terms of water quality. However, for purposes of this article, we reduce the scope of our analysis to the amount of water consumed, rather than withdrawn.[1]

It is also important to note that most generators do not pay for using this water, due to its extraction from a body of water rather than using piped water. Thus, there exists a negative externality associated with water extraction and consumption for electricity generation that is currently unpriced.

2.2. The time- and location-varying environmental impacts of grid electricity consumption

While the environmental impacts of electricity *generation* are fairly straightforward in terms of emissions and water consumption, the environmental impacts attributable to electricity *consumption* are more complex particularly when electricity is consumed from an electric grid with multiple generators. An electric grid must be coordinated by a balancing authority (e.g. independent system operator or regional transmission operator) to match electric supply and demand in real time. To keep generation costs low, the balancing authority will generally dispatch the generators with the lowest marginal cost first. As demand increases, more expensive generators are dispatched with the most expensive generators called upon at times of maximum peak demand. Additionally, when non-dispatchable generation like solar or wind fluctuate, various dispatchable generators such as coal and natural gas power plants must increase or decrease generation, accordingly.

For these reasons, the environmental impact of grid electricity consumption at any point in time is a function of the generator that responds to the change in electricity demand at that point in time (i.e., the marginal generator). Any change in demand will change the environmental impact at the marginal generator's rate of emissions and water consumption; this is referred to as the marginal emission and consumption rate. These rates can fluctuate as different generators with different emission characteristics operate on the margin.

Often, data on marginal emission rates are unavailable for particular areas or time periods, and studies will utilize daily or yearly average emission rates to estimate emission impacts of different grid usage patterns. The use of average emission rates, however, may bias emission impact estimates, as not all generators in a system will respond proportionally to a change in demand. In fact, many studies have found instances of over- or under-estimation of emission impacts when average emission rates are used (Novan, 2011; Kaffine et al., 2013; Jacobson and High, 2010). Specifically, in the ERCOT region, Holland et al. (2016) find that CO_2 emissions are overestimated by 19% when using an average rather than a marginal emissions methodology.

Marginal generators are almost always dispatchable generators—ones that can be ramped up or down in response to a change in demand. Renewable generation such as wind or solar almost never act on the margin as they cannot be ramped up and can only under certain occasions be curtailed.[2] Instead, if these renewables increase simultaneously with demand, other dispatchable resources can be curtailed. Kaffine et al. (2013) find that the intermittency of wind generation leads to an increased use of natural gas during high demand times, and a cycling of coal during low demand times (when natural gas generation is less

[1] For purposes of this analysis, we also focus only on downstream water consumption, rather than including upstream water consumption associated with the extraction and production of the input fuel. Hence, our water numbers will likely be an upper bound for EV and a lower bound for PV.

[2] The curtailment of wind farms has dropped significantly in TX over the years, with a maximum of approximately 17% of wind generation curtailed in 2009, dropping down to about 1.5% in 2013 (see Bird et al., 2014). This substantial decrease in curtailment was brought about by the development of the state's Competitive Renewable Energy Zones program, which helped expand transmission lines by over 3500 miles to accommodate the excess wind generation. http://www.eia.gov/todayinenergy/detail.cfm?id=16831. However, as wind farms continue to expand (wind capacity is expected to double over the next few years- see SNL Financial, 2016), this curtailment issue may become a more prominent factor, requiring an expansion of transmission lines. If transmission lines are built, then the curtailment issue may be alleviated as wind capacity expands.

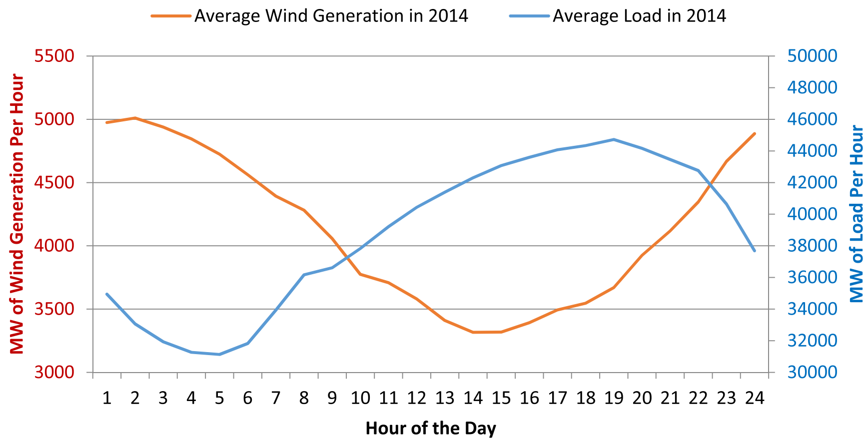

Fig. 2. Average wind generation and load in 2014 in ERCOT region.[a] [a]Data Source: http://www.ercot.com/gridinfo/generation/

available)[3]; resulting in different marginal emissions being avoided throughout the day from wind generation.

This paper focuses on Austin Energy's grid in Texas, whose independent system operator (ISO), the Electric Reliability Council of Texas (ERCOT), manages the flow of electricity and the wholesale market. Natural gas and coal have dominated the ERCOT generation mix from 2013 to 2015, with the share of natural gas increasing over the years and displacing some coal generation (see ERCOT 2013, 2014, 2015). Wind comprises about 11% of total generation in each year, but it generates much more during the night than during the day. Fig. 2 plots the average hourly wind generation and load over the course of 2014 in the ERCOT region. As can be seen in the figure, wind provides approximately 14% of the average load during the evening, but only about 7% in the middle of the day. Because wind is clean and does not consume or withdraw water, it is a great generation source in terms of environmental impact. However, it is important to keep in mind that any action that increases load during times of high wind generation (i.e., night) will not affect the amount of wind that is generated (though it could reduce the amount of wind curtailment during moments of very high wind generation, particularly in places that are located outside of the transmission constraint, near the wind generators, or on the Western side of TX[4]). Instead, it will require an increase in the generation of a dispatchable resource, such as natural gas or coal. Ensuring that these dispatchable generators are as clean as possible will help reduce environmental impacts from any actions that increase the demand for centralized electricity generation (such as electric vehicle charging).

This also speaks to the importance of relying on marginal rather than average analyses. By relying only on average analyses, a larger percentage of wind will appear to make EVs more beneficial for emissions reductions; however, if charging occurs when coal is on the margin, the environmental benefit of this charging pattern is significantly decreased if not totally negated. Our usage of a marginal analysis therefore will better represent the environmental impacts of charging EVs at different times of day.

3. Data

3.1. Pecan Street Inc.

Our primary dataset contains 141 households in Austin's Mueller neighborhood for the three-year period spanning October 1, 2012 to September 30, 2015. These data include demographic information (income, education, household composition); property information (such as number of bedrooms, existence of programmable thermostats and other appliances, etc.); solar PV array information (array size, tilt, azimuth, orientation); EV information (type, existence of charger at work); and hourly grid electricity consumption, solar PV generation, and EV charging. The dataset was obtained from Pecan Street Inc., an organization based in Austin, Texas that conducts research to support innovation in water and energy management.

For over 200 homes in Austin's Mueller neighborhood, Pecan Street has installed technology that allows for the precise measurement of load consumption and energy generation data. These technologies include dual-socketed utility-grade meters in the home and high-resolution data monitoring equipment that collects circuit-level energy consumption data and energy generation data for rooftop PV systems at one-second to one-minute intervals (our analysis relies on aggregated hourly intervals of these data). These meters record total electricity consumption within the household,[5] as well as circuit-level electricity consumption and/or generation data for appliances, electric vehicles, and solar PV arrays. The benefit of these data is that they are recorded from actual customers, rather than from approximations or averages, thereby differentiating our paper from the existing literature on the environmental implications of solar generation and EV usage.

Within our dataset, 135 households own PV systems (see Appendix A for data trimming discussion). Hourly generation data (in kWh) are recorded for over 95% of hourly intervals, where missing data result from data aggregation malfunctions and/or errors. PV generation can vary with the amount of cloud cover and maintenance—which would not show up in simulated estimates of solar production such as the PVWatts calculator or EnergyPLAN models (as used in Connors et al., 2004[6]; Zhai et al., 2012). Spiegel et al. (2000) also use observed data of various projects installed throughout the US; however, our model benefits from having all panels of a similar age and installed in the

[3] Increased cycling of coal plants not only causes the plant to be less efficient, it also increases operating costs, which could push the coal plants down the dispatch order. Hence, as greater amounts of renewables come online, coal plants will retire more quickly, resulting in a cleaner generation mix in the long run (Hanson et al., 2016).

[4] Importantly, in 2013, the percentage of 15 min intervals with negative day-ahead prices of electricity in the TX Western Hub was less than 3%, and less than 5% in TX Western Load Zone; these moments are ones where curtailment is most likely. Though these negative price intervals were more frequent at night for the Western Hub/LZ, the sporadic nature of these moments throughout the year implies that a tariff which incentivizes customers to plug in their EVs at night (such as "Free Nights and Weekends") would do little to ensure increased environmental benefits (see Historical DAM Load Zone and Hub Prices from http://www.ercot.com/mktinfo/prices). Projected increases in wind and solar penetrations could mean more curtailments and more frequent negative prices in the near future.

[5] To be precise, the data are not calculated on net- total consumption is recorded separately from total generation of PV arrays, rather than net consumption.

[6] Connors et al. (2004) utilize simulated data rather than household level data; the authors do have the data at the household level but are unable to rely on it primarily given a large number of missing PV production data hours.

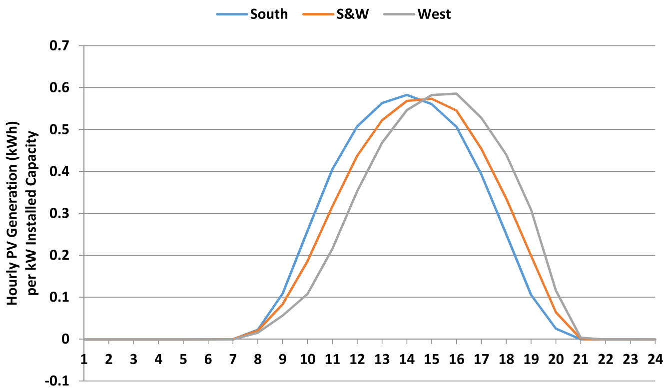

Fig. 3. Average generation by panel direction, summer.

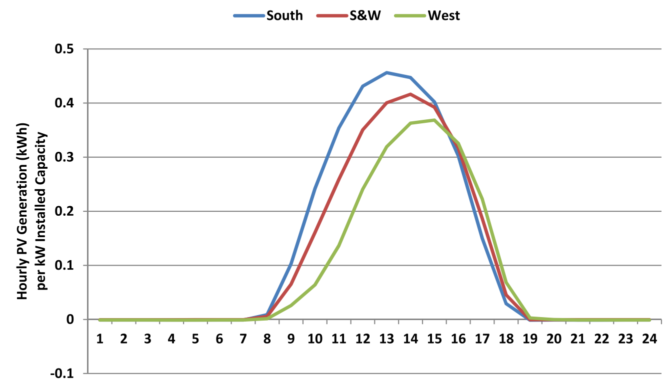

Fig. 4. Average generation by panel direction, winter.

same neighborhood, thus minimizing variation across weather patterns that may affect solar production. Furthermore, because we utilize household consumption data rather than average regional consumption data (such as in Sivaraman and Keoleian, 2010), we are able to test for the existence of a solar rebound effect.

With the Pecan Street data, we can also explore the implications of a panel's orientation on environmental impacts. Figs. 3 and 4 show how the panel's orientation affects its generation capacity in summer and winter respectively: facing the panel west provides more generation later in the day, whereas a south-facing panel maximizes generation around 1 pm. Notably, facing the panel south produces more generation during the winter than facing the panel west (see Section 5.3.1 for a deeper description of generation differences across panel orientation).

Within our dataset, 46 households have EVs that are primarily charged at home. A subset of the EVs in our sample is plug-in hybrid vehicles (Chevy Volts), which use both gasoline and electricity. Pecan Street has recorded details on how many trips the EV took, how many miles were driven, and on how many trips the Chevy Volts utilized gasoline. This further differentiates our paper from the existing literature. For example, Weiller (2011) utilized vehicle trip data from the National Household Transportation Survey (NHTS). Though NHTS updated their data in 2009, the survey lacks data for EVs because few were in use during the time period, forcing Weiller to extrapolate information from gasoline-fueled vehicle trips. Other papers are required to make assumptions about vehicle miles traveled (Holland et al., 2016) or avoid looking at miles travelled altogether (Huo et al., 2015). We use this subset of vehicles in the dataset to calculate the number of miles driven on gasoline, and vehicle usage is extrapolated to the remainder of the vehicles in the dataset.

For all households in our sample with EVs, we also know when they were charged, while most papers do not and instead utilize simulations (Sioshansi et al., 2010; Rangaraju et al., 2015), estimate the differences in emissions based on hour of the day (Hadley and Tsvetkova, 2009; Holland et al., 2016), or simply do not look at how the emissions vary over the course of the day (Doucette and McCulloch, 2011; Huo et al., 2015). Our household level data allow us to view the actual charging patterns of EV owners, rather than having to rely on simulations or representative descriptions of charging patterns. In addition – similar to our PV analyses – availability of data for total household electricity consumption and grid electricity consumption enable us to find that an income effect for EV ownership does not exist. Furthermore, given that many of the households owning EVs also have PV, we are able to estimate whether the solar rebound effect is affected by EV ownership.

Some summary statistics can be found in Table 1.

3.2. Electric grid data

Beyond Pecan Street's data, we estimate marginal CO_2 emission and water consumption factors using data from the EPA's Air Market Program Database (AMPD).[7] Hourly load (MW) and CO_2 emissions (short tons) data were retrieved for all generating units located in the ERCOT footprint within Texas for all hours in the study period. Generator type (combined cycle, combustion turbine, and several variations of steam turbines), primary fuel type (coal or natural gas), and locational information was also retrieved for all generators.[8]

The resulting dataset contains approximately 315 generating units representing 100 generating facilities.[9] Natural gas plants comprise the majority of these generators (87%) and contribute 51% of total GHG emissions in the region.

3.3. Other sources

We also utilize data from two other sources. First, data from US EIA (2011) and Argonne National Laboratory (2012) help derive the factor we use for converting gasoline usage to corresponding water consumption, as detailed in Appendix B.

Second, we utilize historical daily weather data and cloud coverage from Austin, TX for estimating the solar rebound equation in Section 4.1. These data come from Weather Underground (2016).

4. Methodology

We estimate the environmental impact (in terms of CO_2 emissions and water consumption[10]) of household solar PV and EV adoption utilizing household demographic and hourly electricity consumption and generation data. For PV, these benefits come from avoiding grid electricity consumption. For EVs, we estimate the net benefits resulting from an increase in grid electricity consumption and a reduction in gasoline consumption. For both PV and EVs, we account for the impact of PV and EV ownership on energy consumption and the time-varying emission and water consumption intensity of displaced grid electricity generation.

We estimate the hourly impact on grid CO_2 emissions and water consumption caused by solar PV generation and EV charging by multiplying the household's hourly PV generation or EV charging by the grid's hourly marginal emission and water consumption factor,

[7] The AMPD collates continuous emission monitoring system (CEMS) data from the EPA's emission trading programs, which generally require fossil-fuel fired generating units greater than 25 MW to report hourly load and emission information among other data.

[8] Generators less than 25 MW generally are not required to report emissions data as part of the EPA's emissions trading programs. However, a relatively small proportion of ERCOT's generators are less than 25 MW. Approximately 0.36% of ERCOT fossil fuel generator capacity results from generators less than 25 MW.

[9] A generating facility may have multiple generating units. The number of generation units and facilities are not static across the study period as some facilities begin operation or retire.

[10] To narrow our focus for this paper, we do not estimate the impact on local air pollutants; thus, our calculated environmental benefits are likely a lower bound for PVs. Holland et al. (2016) estimate both carbon and localized air pollution impacts across the nation at the county level, and find an overall positive environmental benefit from EVs in Texas.

Table 1
Summary statistics pecan street data.

	Variable name	Min	Max	Average (Std. Dev.)
Demographics (141 households)	Total household income	\$27,500	\$1,000,000 +	\$151,000 (\$125,000)
	Education level	Unknown	Postgrad	College degree (NA)
	# Females in HH	0	5	1.39 (0.86)
	# Males in HH	0	5	1.28 (0.91)
Household electricity consumption data (141 households)	Consumption/h (kWh)	−4.08	24.00	1.26 (1.21)
	Grid consumption/h (kWh)	−9.00	24.00	0.49 (1.62)
Solar data (135 households with PV)	PV gen/h (kWh)	−0.01	9.45	0.81 (1.28)
	PV array (kW)	2.94	9.05	5.61 (0.94)
	PV tilt (degrees)	20	35	27.5 (3.90)
	PV azimuth (degrees)	150	295	209.42 (29.02)
	PV orientation	South/East, South, South/West, West, West/East		
Vehicle data (33 households with EVs)	Charging/h (kWh)	0	6.76	0.24 (0.78)

respectively, as represented in Eqs. (1) and (2).

$$GridEmissions_{i,t} = ElectricityUse_{i,t} * Marginal\ CO2\ Emissions\ Factor_t \quad (1)$$

$$GridWater_{i,t} = ElectricityUse_{i,t} * Marginal\ Water\ Consumption\ Factor_t \quad (2)$$

where t references each hour over our sample period and i references each household; $GridEmissions_{i,t}$ and $GridWater_{i,t}$ represent the household's hourly amount of grid emissions and grid water either consumed from the EV charging or avoided from the PV Generation; $ElectricityUse_{i,t}$ refers to the amount of electricity either consumed by the EV or generated by the PV in each hour; and the Marginal Factors are the marginal emissions rates estimated in Section 4.2.

For estimating the net environmental impact of EV usage, we also estimate the avoided emissions and water consumption resulting from the corresponding reduction of gasoline consumption.

The remainder of Section 4 describes the methodology for accounting for PV and EV ownership on electricity consumption, and calculating marginal CO_2 emission and water consumption rates as well as avoided CO_2 emissions and water consumption from reductions in gasoline consumption.

4.1. Solar rebound effect

Eqs. (1) and (2) assume that each kWh produced by the PV system displaces one kWh of grid electricity. However, this assumption may not hold given the household's behavioral response to having a PV system and an EV. Given that solar PV reduces the household's monthly utility bills, households might increase their total electricity consumption after installing solar PV such that one kWh of PV generation offsets less than one kWh of grid electricity. This phenomenon has been referred to as the "solar rebound" effect, analogous to the effect observed with respect to energy efficiency (Morakinyo et al., 2016) and improvements in vehicle fuel economy (Linn, 2016). However, there has been little empirical research conducted on the rebound effect to date with respect to rooftop solar ownership and usage. Paetz et al. (2011) find anecdotal evidence that customers increase consumption during moments of lots of sunshine, as they consider the electricity to be free, and Haas (1994) describes the theoretical basis for this shifting of consumption to midday times. However, neither of these papers fully test this theory due to lack of sufficient data.

Due to our highly disaggregated household demographic and energy data, we are able to estimate the existence and magnitude of a solar rebound effect by conducting the following random effects regression model:

$$grid\_electricity_{i,t} = \gamma_1 generation_{i,t} + \gamma_2 EV_i + \gamma_3 EV_i * generation_{i,t} + \Gamma X_i + \varepsilon_{i,t} \quad (3)$$

where $grid\_electricity_{i,t}$ is the total amount of grid electricity consumed by household i at time t; $generation_{i,t}$ is the amount of PV generated by household i at time t; EV_i is an indicator variable for a household that has an electric vehicle that is regularly charged; X_i is a vector of controls, including daily maximum temperature, household size, and home square footage[11]; and $\varepsilon_{i,t}$ is an i.i.d. error term.

This regression allows us to test whether there is a one-to-one relationship between PV generation and grid consumption. If there is no rebound effect, then we expect γ_1 to equal −1, signifying that one kWh of solar PV generation perfectly offsets one kWh of grid electricity consumption. Furthermore, we can test to see if there is an income effect associated with EV ownership. An income effect would occur if having an electric vehicle causes the household to consume less (more) electricity for other non-charging purposes due to the tightening (loosening) of the budget constraint. A tightening would occur if the need to charge the EV increases the electricity bill, essentially restricting the budget; alternatively, a loosening would occur if the avoided gasoline payments shifts the budget constraint out. Finally, the EV and generation interaction term allows us to test whether the solar rebound effect varies with EV ownership.

In order for us to be able to include the presence of an electric vehicle in our rebound regression, we are unable to include household fixed effects in our primary regression. Thus, we conduct some robustness checks, including a fixed effect regression in order to test out the direct solar rebound effect.

The results of the regressions are presented in Table 2:

Consistent across all three regressions, we identify a rebound effect associated with solar generation of approximately 9% (the coefficient

Table 2
Regression testing for rebound and income effect.

Variable	1. Coefficient (Std. Err.)	2. Coefficient (Std. Err.)	3. Coefficient (Std. Err.)
Generation	−0.915 (0.001)	−0.912 (0.001)	−0.903 (0.001)
Electric vehicle indicator	0.214 (0.065)	–	0.220 (0.001)
EV*generation	0.015 (0.001)	0.015 (0.001)	0.004 (0.001)
Household square footage	3.62e-4 (6.1e-5)	–	3.57e-4 (1.36e-6)
Household size	0.123 (0.026)	–	0.129 (0.001)
Maximum daily temperature	0.023 (4.1e-5)	0.023 (4.3e-5)	0.023 (4.5e-5)
Cloud cover	0.009 (2.5e-4)	0.009 (2.5e-4)	0.009 (2.6e-4)
R^2	0.523	0.523	0.519
Number of observations	2,855,853	2,845,643	2,845,643
Number of households	114[a]	114	114
Household fixed effects	No	Yes	No
Random effects	Yes	No	No

[a] The number of households here is reduced below the 141 total households; households are dropped from the regression if we do not have the full information on household characteristics. As a matter of reference, Pecan Street has identified 23 households as being the threshold number of households for estimating statistically significant regressions.

[11] Other household characteristics were included in the regression (such as education and income) but these were not significant and are therefore not shown in Table 2. Results available upon request.

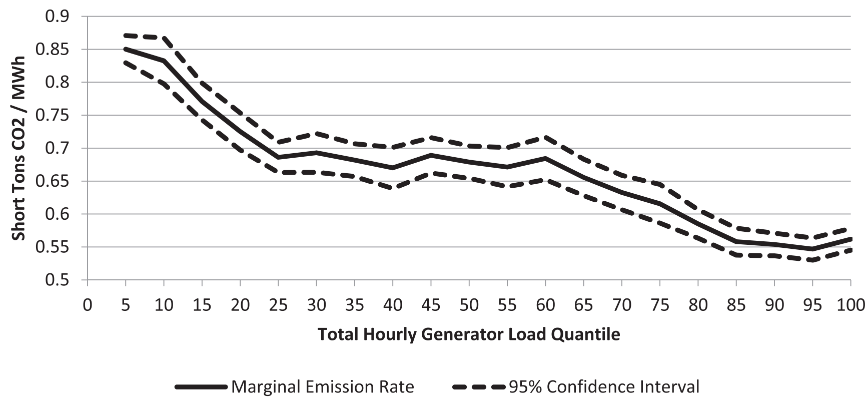

Fig. 5. Average CO_2 marginal emissions rates as function of total hourly generator load for fiscal year 2014.

on solar generation is statistically significantly different from −1, with a p-val of 0). Here we assume that the rebound effect occurs uniformly across all hours.[12] Interestingly, having an electric vehicle increases that effect by 1.5%. Thus, electric vehicle owners will have a slightly larger increase in grid consumption – as the household avoids having to purchase expensive gasoline, the household budget constraint is shifted out (even after accounting for charging costs), allowing for an increase in grid consumption.

However, the coefficient on EV ownership, though statistically significant, is not statistically different from the average EV consumption. Thus, we do not find an income effect related only to EV ownership; rather, that effect comes through the interaction with solar. Essentially, households that both own an EV and generate will increase their total consumption by 1.5% (based on our preferred specification) during hours when generation is greater than zero. This amount is smaller under the standard OLS regression (column 3), but the results are qualitatively similar.

Though we find evidence that a rebound effect exists for households that generate their own electricity, its magnitude is small. Compared to most rebound effect estimates for other technologies (such as energy efficient appliances and vehicles), this rebound effect is on the lower end of the spectrum. Gillingham et al. (2016) find that most estimates for the rebound effect associated with appliances and vehicles are between 5 and 25%. Hence, the direct environmental benefits of PV and EVs still remain quite large, even when accounting for the rebound effect.

To account for the solar rebound effect, we adjust Eqs. (1) and (2) by the calculated solar rebound factors, thereby shifting up or down hourly consumption by 8.5 or 10% depending on whether the household owns an EV (thus, we assume that the rebound effect occurs uniformly across all hours).

We can then calculate the monthly and yearly avoided emissions and water consumption (See Section 5 for results).

Finally, we calculate the average avoided carbon emissions and water usage for a 1 kW PV array as well as for the average PV array in our sample, 5.61 kW.

4.2. Time-varying grid CO_2 emissions and water consumption intensity

4.2.1. Average marginal CO_2 emission rates

There are a number of methods in the literature for estimating marginal emission rates, ranging from complex system dispatch models to simpler merit ordering methods. Dispatch models use a variety of inputs to simulate actual generator dispatch patterns. These models may incorporate fuel prices, transmission constraints, and other factors to produce granular estimates of marginal emission rates. Merit ordering uses historical or cost data to determine dispatch order. This method orders the generation units based on capacity factors or marginal costs and assumes units are dispatched first if they have higher capacity factors or lower marginal costs; finally, it identifies the marginal generator needed to fulfill demand based on this order.

Other approaches use linear regression of historical generation and emission data to estimate marginal emission rates (see for example Hawkes, 2010; Siler-Evans et al., 2012; Zivin et al., 2014). Both Hawkes (2010) and Siler-Evans et al. (2012) regress generator emissions data onto load data to estimate marginal emission rates for Great Britain and the eight regions of the North American Electric Reliability Corporation, respectively.

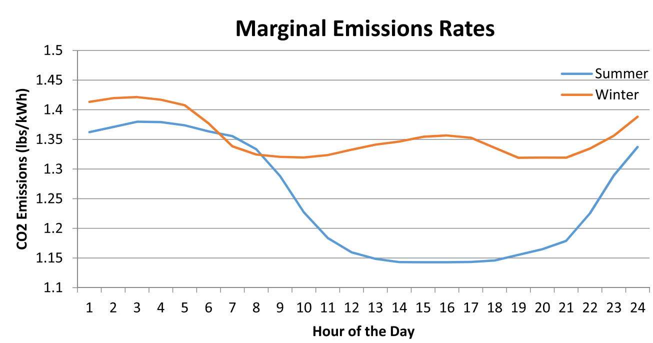

Fig. 6. Marginal emissions rates during summer and winter.

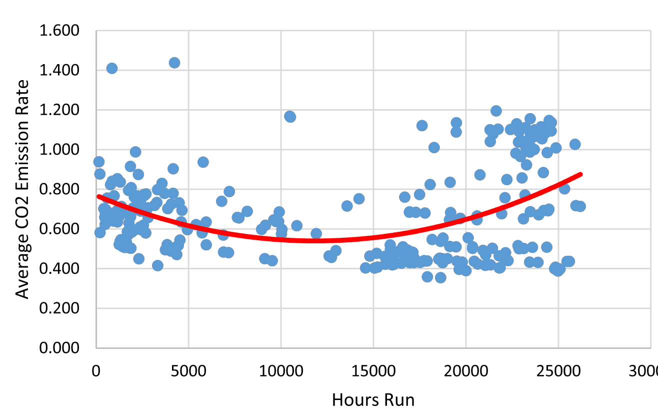

Fig. 7. Average CO2 rates by hours of generation.

[12] We assume that the solar rebound effect is constant throughout the day and the year, as the household will likely see the electricity bill and react to a lower overall price by increasing consumption. This is a simplifying assumption, but is not likely too far from the truth- households can increase vehicle charging at night and increase their A/C usage during the day, for example. Identifying how this coefficient changes over time is not possible, especially because PV generation is zero at night and thus interacting PV generation with hourly dummies would not provide correct results during evening hours.

Table 3
Water consumption by generator technology and cooling system in 2011.

Fuel	Generator technology	Cooling system	2011 net generation	2011 water consumption	Weighted average water consumption
Coal	Steam turbine	Pond	110.7	0.54	0.57
		Tower	47.9	0.65	
Natural gas	Steam turbine	Pond	17.6	0.44	0.48
		Tower	6.8	0.71	
		Cogen – with water consumption	0.9	0.12	
		Cogen – no water cons. reported	1.3	0.06	
	Combined cycle	Pond	10.2	0.18	0.19
		Tower	83.7	0.22	
		Cogen – with water	36.2	0.17	
		Cogen – no water cons. reported	15.6	0.16	

Note: net generation and water consumption columns are presented as in Scanlon et al. (2013).

We adapt Hawks and Siler-Evans et al.'s methodology by regressing the hourly change in grid generator load onto the hourly change in CO_2 emissions for generators using hourly generator load and CO_2 emission data. Siler-Evans et al. regress the aggregate hourly change in load onto emissions for all generators within the region of interest; we instead regress the sum of the absolute value of each individual generator's hourly change in load and emissions. Our method accounts for generators that may be on the margin within a given hour but exhibit opposite changes in load due to intra-hour load changes and/or transmission constraints. Utilizing aggregate hourly data without accounting for individual generator trends could erroneously exclude the influence of certain generators in the estimation of the average marginal emission rate during certain hours.

Similar to Hawks and Siler-Evans et al., we also restrict the generators to those located within ERCOT. Though this ignores electricity imports and exports from outside ERCOT, the amount of imported and exported electricity in ERCOT is very low (in 2015, net imports and exports averaged 0.1% of total daily electricity consumption; see ERCOT, 2015).

The first difference of the grid generator load and CO_2 emission vectors (i.e. $x_t - x_{t-1}$ for $t = 2 \dots n$) is determined for each generator to create vectors of $n-1$ observations of the change in hourly generator load and CO_2 emissions. The absolute value of these differences are then summed by each hour to produce vectors for change in hourly generator load ($\Delta load_t$) and change in hourly emissions ($\Delta emissions_t$) for all hours. We regress the vector of hourly change in grid generator load onto the vector of hourly change in emissions to estimate average marginal emission rates.[13] The generalized specification is shown in Eq. (4).

$$\Delta emissions_t = \beta_0 + \beta_1 \Delta load_t + \varepsilon_t \quad (4)$$

The coefficient β_1 is interpreted as the average marginal emission rate for the given set of data.

To derive average marginal emissions rates for each hour of household data, we disaggregate the data into tranches according to total hourly grid generator load. We sum grid generator load for each hour and segment observations into twenty quantile bins.[14] We then apply the linear regression model to each quantile bin to estimate an average marginal emission rate for each bin. Finally, to derive hourly average marginal emission rates to apply to Eqs. (1) and (2), we assign an average marginal emissions rate to each hour of our household dataset based on the grid generator load quantile bin of the given hour ($\beta_{1,bin[t]}$).

Fig. 5 shows the estimated average marginal emissions rates by quantile bin for Fiscal Year 2014. The marginal carbon intensity of the grid generally declines as total hourly grid generator load increases. This is likely due to the marginal generator switching from coal-fired generators to natural gas-fired generators as more generators are dispatched to fulfill increasing demand.

Fig. 6 shows how average marginal emission rates vary across the hours of the day in summer and winter. As load grows during the summer mid-day, more natural gas is on the margin, leading to lower marginal emissions rates during those hours relative to winter mid-day. Thus, given the current grid composition, summer marginal emissions are highest during the evening hours of low demand.

Because the marginal emission rates are derived from data that excludes non-fossil fuel fired generators and generators less than 25 MW regardless of fuel type, the model assumes that a fossil fuel fired generator greater than 25 MW is operating on the margin at all times. This is generally true as non-dispatchable generators like solar and wind do not respond to changing demand, and other non-fossil fuel generators such as hydroelectric and nuclear generators generally operate as base load generation due to very low marginal costs. Additionally, deriving and assigning average marginal emission rates based on total hourly grid generator load quantile bins is utilized because the relative position in the generator dispatch order at any given time—as represented by the quantile bins—will more directly determine the marginal emission rate than other parameters such as overall system demand, time of day, or season.

While the observed marginal emission rates generally decline with increasing load, the analysis may not reflect an increase in marginal emission rates during the small number of hours of the highest demand when particularly inefficient and dirty natural gas plants are dispatched to fulfill load. Because the methodology is regression-based, it measures average marginal emissions for a relatively large block of hours (approximately 438 h per quantile bin). Thus, it would not adequately capture the fact that during "critical peak" hours (i.e., a number of small hours throughout the year where demand spikes very rapidly, such as in heat waves), very dirty and inefficient natural gas plants may be dispatched to provide for this spike in demand. Fig. 7 plots the average CO_2 rates for generators depending on how many hours they operated during the study period. As demonstrated in the figure below, generators that run only a few hours per year produce greater CO_2 emissions.[15]

However, due to the limited hours that these dirty generators run, the emissions associated with these plants will have only a small impact on the average marginal emissions rate calculated for the top 95% centile bin of demand; thus, we find that on average, high demand hours are associated with lower marginal emission rates.

[13] We refer to these rates as "average marginal"- different than the merit ordering, which is able to identify the last marginal unit, we instead identify the amount of emissions that are, on average, on the margin every hour. For example, both coal and natural gas may be on the margin during a specific hour on different days of the year. This method would therefore average the emissions from both sources (weighted by their respective load) to create an average marginal emission.

[14] For example, the first bin consists of the observations during the 5% of hours when total hourly generator load is the lowest (i.e., up to the 5th percentile). The next bin consists of observations between the 5th and 10th percentile of hours when total hourly generator load is the lowest. This is repeated until the final bin contains the 95th percentile of hours, when total hourly generator load is the highest.

[15] Generators that operated during the most hours showed increased average CO_2 rates as well reflecting the fact that coal generators generally have high capacity factors.

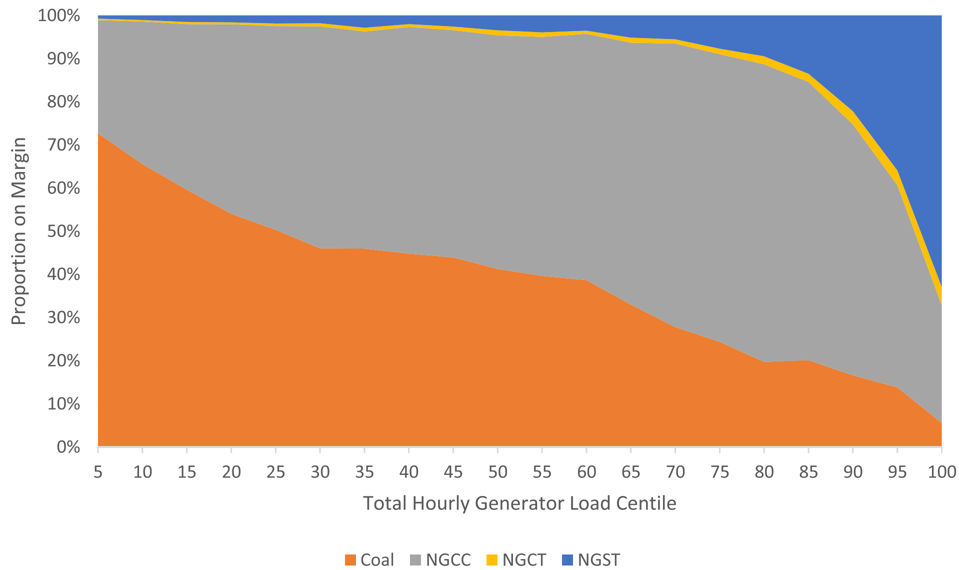

Fig. 8. Average fuel/technology type marginal proportion as function of total hourly generator load for fiscal year 2014.

4.2.2. Average marginal water consumption rates

To estimate average marginal water consumption rates, we derive weighted water consumption rates based on the proportion of various generator types operating on the margin in each hour.

We first estimate the proportion of coal steam turbines, natural gas steam turbines, natural gas combustion turbines, and natural gas combined cycle power plants operating on the margin using a similar methodology as employed to estimate average marginal CO_2 emission rates. To do so, we calculate the change in total hourly grid generator load by generator type ($\Delta load_{g,t}$), where g represents generator type and t represents hour. By generator type, we then regress the vector of hourly change in each combination's load onto the vector of total hourly change in load. The generalized specification is shown in Eq. (5).

$$\Delta load_{g,t} = \theta_{g,0} + \theta_{g,1}\Delta load_t + \varepsilon_{g,t} \tag{5}$$

The coefficient $\theta_{g,1}$ is interpreted as the average proportion of generator type g operating on the margin for the given set of data. Similar to how we estimated average marginal CO_2 emission rates, we apply the linear regression model to each grid generator load quantile bin to estimate an average generator type marginal proportion for each hour. Finally, we assign average marginal proportions ($\theta_{g,1,bin[t]}$) for each generator type to each hour based on the quantile bin of the given hour of the given fiscal year.

Using water consumption rates reported by Scanlon et al. (2013), we derive average marginal water consumption rates for each hour weighted by the average marginal generator type proportions. Scanlon et al. provide water consumption and withdrawal at a more detailed level than our data provide including water consumption rates by power plant cooling system (pond or tower). However, our data do not specify cooling system type. Thus, we calculate weighted average consumption and withdrawal for the overall technology type (coal, natural gas combined cycle, natural gas combustion turbine, and natural gas steam turbine) weighted by the 2011 net generation for that source in TX as shown in Table 3. Importantly, natural gas combustion turbines consume no water, and therefore do not appear in the table below.

Given the numbers in Table 3, we calculate the marginal water consumption weighted by the generator technology was producing in that particular hour:

$$\Theta_t = \frac{\sum_g \theta_{g,1,bin[t]} * WAWC_g}{\sum_g \theta_{g,1,bin[t]}} \tag{6}$$

where t refers to the hour of the day, g refers to the generator type, Θ_t is the marginal water consumption at time t, $WAWC_g$ refers to the Weighted Average Water Consumption from the last column in Table 3, and $\theta_{g,1,bin[t]}$ refers to the marginal proportions as described earlier.

Fig. 8 shows the estimated average fuel/technology type marginal proportion as a function of total hourly generator load for Fiscal Year 2014. As generator load increases, natural gas represents a larger proportion of the marginal fuel. At very high levels of load, natural gas steam turbine (NGST) is used more than natural gas combined cycle

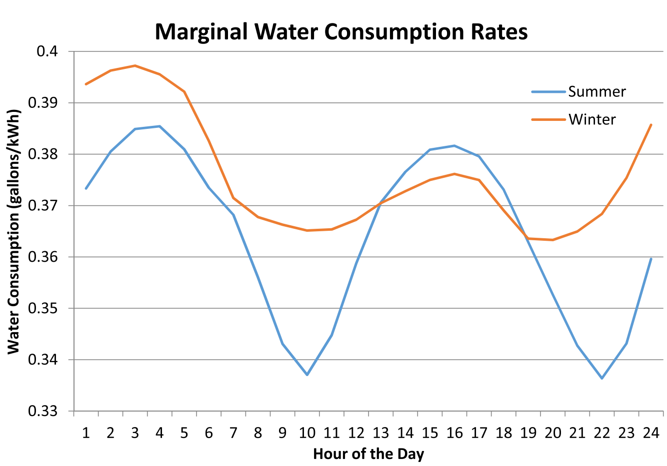

Fig. 9. Marginal water consumption rates during summer and winter.

Table 4
Upper and lower bound gasoline-fueled emissions.

	Counterfactual vehicle	MPG	VMT	Gallons/year	lbs CO_2/year
Upper bound	Average light-duty vehicle	21.6	11,400	527.78	10,340.91
Lower bound	Chevy Volt (gasoline powered)	37	11,804	319.02	6250.39

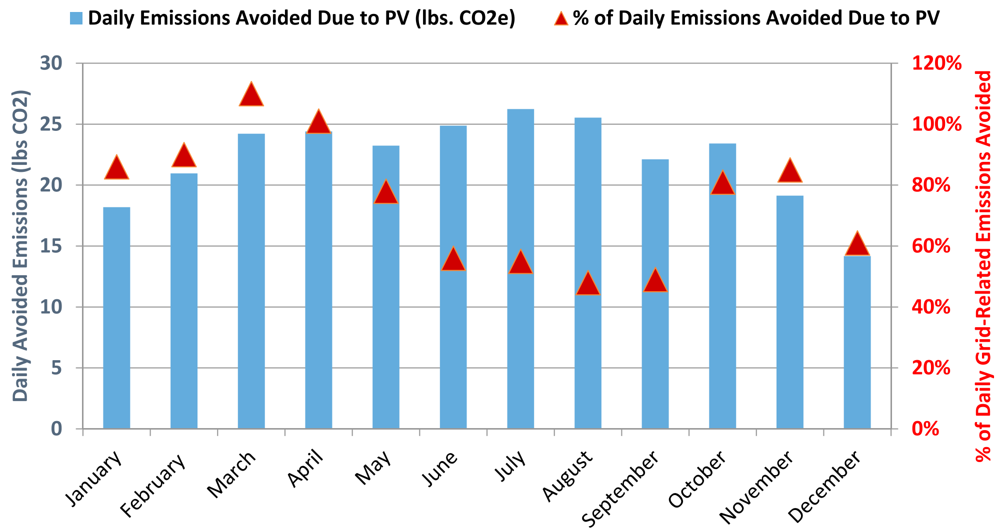

Fig. 10. Daily CO_2 grid emissions avoided due to a 5.61 KW PV array in absolute and percentage terms, by month.

(NGCC); as described in Table 2, NGST uses much greater quantities of water per kWh than NGCC, on par with water consumption from coal generation. Thus, given the current composition of the grid, during times of greatest demand and load, water consumption peaks.

Fig. 9 shows marginal water consumption rates for summer and winter. During the winter, when demand and generation are low, coal is on the margin more frequently; thus, water consumption is overall high hour to hour. However, during the highest moments of generation – summer midday – NGST is currently being utilized much more frequently; therefore, we see a spike in water consumption during these hours of the summer, climbing above winter's midday water consumption (times when coal and NGCC are on the margin).

4.3. Estimating avoided emissions from electric vehicle ownership

To calculate the avoided emissions from EVs, we first estimate the amount of increased grid electricity due to charging. Households charge their vehicle during different times of the day, leading to different levels of CO_2 emissions and water consumption. Given the results from Table 2, during generating hours, grid consumption will increase by 1.5% of the amount generated. Thus, for all households with EVs, we use the following equations to calculate household hourly emissions (in lbs) and water consumption (in gallons/kWh) associated with the charging of EVs:

$$Grid\ Emissions_{i,t} = (0.015 * gen_{i,t} + EVcharging_{i,t}) * \beta_{1,t} \quad (7)$$

$$Grid\ Water_{i,t} = (0.015 * gen_{i,t} + EVcharging_{i,t}) * \Phi_t \quad (8)$$

Although EVs increase grid emissions through charging (exacerbated by the solar rebound effect), the benefit they provide is by reducing the amount of gasoline that otherwise would have been consumed through driving a gasoline vehicle. However, choosing the correct counterfactual vehicle takes some thoughtful consideration. Two factors are key in choosing a counterfactual vehicle: that vehicle's fuel efficiency and how many miles it is driven.

With respect to the counterfactual vehicle's fuel efficiency, using an average mile per gallon (MPG) of all passenger light-duty vehicles would not be a conservative approach. Essentially, when households choose to purchase a vehicle, they need to choose amongst a portfolio of different options, each with a different bundle of attributes. At the same production price point, there is a technical tradeoff between fuel efficiency and other attributes, such as horsepower, weight, and size of the vehicle (Klier and Linn, 2016). This means that for the same price, vehicle buyers are likely going to have to choose between a more efficient vehicle and a more powerful one. To illustrate this tradeoff, we utilize a range of efficiencies starting from the 2012 average light duty efficiency and ending at the Chevy Volt's efficiency when it is driven on gasoline alone (recall that the Chevy Volt is a PHEV and thus can be driven on gasoline; when done so, it achieves a combined efficiency of 37MPG[16]).[17]

The second consideration has to do with the miles driven, which is important given the existence of a rebound effect, whereby households with more energy efficient vehicles may drive longer distances due to the lower utilization cost. We utilize a range of vehicle miles traveled (VMT), and assign different miles to the different MPG range. For the low MPG range, we utilize a VMT of 11,400, the average distance driven by passenger vehicles in 2012 (US EPA, 2014). For the high MPG range, we instead apply the U.S. Department of Energy's 2012 annual average vehicle miles traveled by hybrid and plug-in EVs: 11,804 (United States Department of Energy, 2015a, 2015b).[18]

Using the EPA's estimate of 8887 g of CO_2 emissions per gallon of gasoline consumed (US EPA, 2014), we calculate the range of lbs. of CO_2/year consumed by the alternative gasoline vehicles, as reported in Table 4.

In our sample from the Pecan Street dataset, there are 6 Nissan Leafs and 27 Chevy Volts. Pecan Street monitored four of these Chevy Volts during the sample period to record information on 1447 vehicle trips, including total VMT and the usage of gasoline on each trip. They report that the Chevy Volts utilized gasoline on 17.03% of the trip miles traveled; however, we do not have information on whether gasoline was used for the entire trip or only for a fraction of the trip. To be conservative, we assume that gasoline was utilized fully on the trip miles that record *some* usage of gasoline, and multiply 17.03% by 11,804 to calculate the average number of miles the Chevy Volts in our sample[19] would be driven on gasoline (2010 miles/year). Given the MPG of 37 for the gasoline-powered Volt, this corresponds to 54 gal gasoline/year, or 1064.35 lbs. CO_2/year, consumed by each Volt-owning household.

[16] https://www.fueleconomy.gov/feg/noframes/31618.shtml.

[17] All Chevy Volt model years (from 2012 to 2015) have a combined MPG of 37 when driven on gasoline.

[18] A slightly higher VMT for more fuel efficient vehicles is consistent with a small rebound effect, or a moderately elastic demand for gasoline (Gillingham et al., 2015).

[19] Nissan Leafs are fully electric and therefore no extra analysis needs to be conducted on these households.

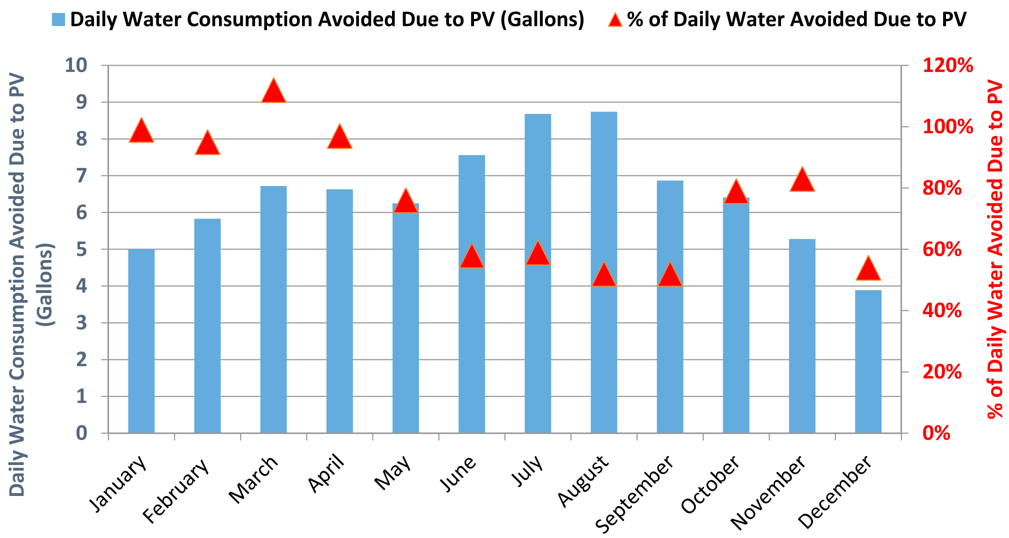

Fig. 11. Daily grid-related water consumption avoided due to a 5.61 KW PV array in absolute and percentage terms, by month.

Thus, the overall change in yearly emissions for each EV household is the following:

$$AvoidedEmissions_{i[volt]} = GasolineEmissions_{AV} - (GasolineEmissions_{volt} + GridEmissions_{i[volt]}) \quad (9)$$

$$AvoidedEmissions_{i[leaf]} = GasolineEmissions_{AV} - GridEmissions_{i[leaf]} \quad (10)$$

$GasolineEmissions_{AV}$ is the lbs. of CO_2 emitted by alternative gasoline powered vehicles, $GasolineEmissions_{volt}$ is the lbs. of CO_2 emitted by the Volt on 17% of VMT that use gasoline, and *GridEmissions* is the yearly summed total lbs. of grid CO_2 emissions induced from charging the vehicles as calculated in Eq. (7).

To calculate the avoided water consumption, we need to take into account not only the water consumed by the charging of the vehicle (see Eq. (8)), but also the water consumed in creating the gasoline used to fuel the Chevy Volts and the gasoline-powered alternative vehicles. Appendix B calculates the water intensity of gasoline production; we find that average total water usage for US gasoline production is 4.27 gal of water per gallon of gasoline.[20] Thus, we use the following equations to calculate the amount of water consumed by the Volt and the Leaf:

$$CarWater_{i[volt]} = 4.27 * (Gasoline_{AV} - Gasoline_{volt}) - GridWater_{i[volt]} \quad (11)$$

$$CarWater_{i[leaf]} = 4.27 * Gasoline_{AV} - GridWater_{i[leaf]} \quad (12)$$

where $Gasoline_{AV}$ and $Gasoline_{volt}$ are the gallons of gasoline used by the alternative vehicle and the Volt, respectively, and *GridWater* is the amount of water consumed from charging the vehicle as calculated in Eq. (8).

5. Results and discussion

5.1. Solar PV

5.1.1. Avoided CO_2 emissions

We find that solar PV households in our sample were able to avoid between 2049 and 13,635 lbs. of CO_2/year, with a mean of 8029 lbs. of CO_2/year. This translates to an average of 1453 lbs. per kW of installed capacity. On average, we find that PV systems avoid 75% of yearly emissions generated by the household's grid consumption. There is substantial variation across the months and seasons of the year, as some months have greater emissions. As can be seen in Fig. 10 (see Appendix C for the numbers underlying the figure), though more absolute emissions are avoided during summer months, household summer electricity usage is far higher than during other months. Therefore, PV offsets the lowest proportion of households' grid electricity consumption and emissions during the summer. Of note, during March and April, households' PV generation exceeds their total grid electricity consumption (likely due to decreased demand for A/C), such that PV contributes clean electricity to the grid during these months, helping avoid the consumption of grid electricity by other Austin Energy households.

5.1.2. Avoided water consumption

Solar PV households in our sample are able to avoid between 606 and 4013 gal of water consumption per year. Per kW of installed capacity, the annual average amount is 424 gal; hence, the average PV array of 5.61 kW conserves 2379 gal/year.[21] On average, PV deployment allows the household to avoid 77% of its annual grid-related water consumption.

This amount varies over the course of the year, as demonstrated in Fig. 11 (see Appendix C for the numbers underlying the figure). The greatest amount of daily reductions occurs during the summer, due to greater PV output.

5.2. Electric vehicles

The households with EVs in our sample are able to avoid 566 to 8409 lbs. CO_2/year (or 9–81% of emissions relative to a gasoline-fueled vehicle), whereas the gallons of water saved (in terms of water consumption from electricity generation) varies between −196 and 1393 gal/year (or −14 to 77% of water otherwise consumed by a gasoline-fueled vehicle). Figs. 12 and 13 show the total amount of CO_2 emitted and water consumed by all four vehicle types (Chevy Volt, Nissan Leaf, Average light-duty vehicle, and all-gasoline run Chevy Volt), while Figs. 14 and 15 show the yearly percentage avoided CO_2 and water from shifting to the EV depending on the counterfactual vehicle. On average, EVs are able to avoid 42%–70% of CO_2 emissions and 30%–62% of water. This range of average avoided emissions and water

[20] This fits in well with other estimates; see for example Harto et al. (2010) who estimate a water intensity of 2–6 gal of water/gal of gasoline.

[21] As a point of comparison, a family of four on average consumes 8000 gal per month for domestic purposes, such as washing and drinking (http://www.sbunet.com/customer_services/default.asp?CategoryNumber=8&SubcategoryNumber=4).

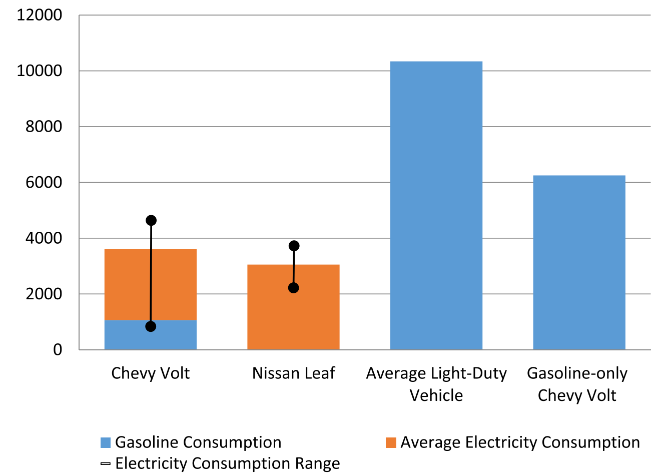

Fig. 12. Yearly total CO2 emissions by vehicle type (pounds).

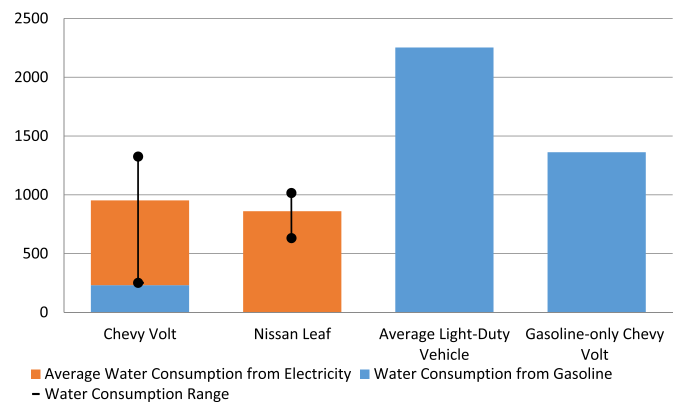

Fig. 13. Yearly total water consumption by vehicle type (gallons).

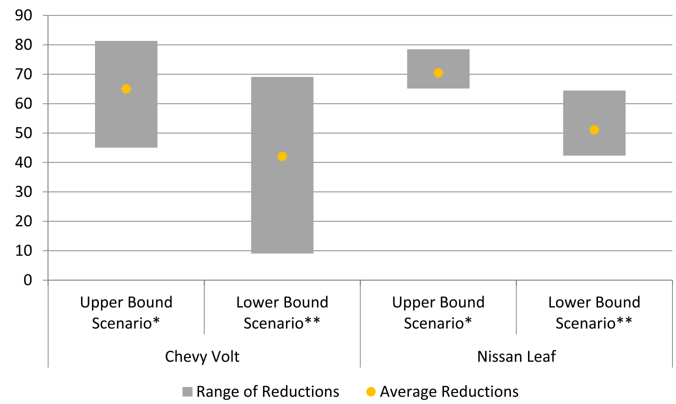

Fig. 14. Average yearly % reductions of CO_2 by vehicle type and counterfactual vehicle. *Note: *Upper bound scenario = Counterfactual vehicle is average light-duty vehicle; **Lower bound scenario = Counterfactual vehicle is gasoline-driven Chevy Volt.*

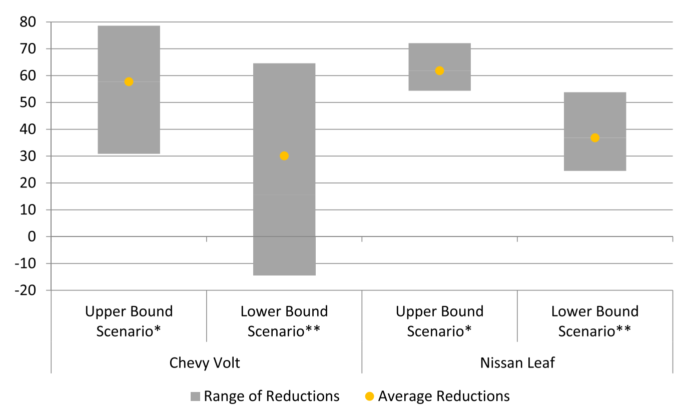

Fig. 15. Average yearly % reductions H_2O by vehicle type and counterfactual vehicle. *Note: *Upper bound scenario = Counterfactual vehicle is average light-duty vehicle; **Lower bound scenario = Counterfactual vehicle is gasoline-driven Chevy Volt.*

depends on the fuel efficiency of the counterfactual vehicle: the benefits will be larger by 4091 lbs. CO_2/year and 891 gal/year if the counterfactual vehicle has the efficiency of an average light-duty vehicle (such as a Ford Escape) instead of the fuel efficiency of a gasoline-fueled Chevy Volt. Thus, consumer preference for vehicle type can have a statistically[22] significant effect on both emissions and water consumption. Importantly, this means that to maximize the environmental benefit of electric vehicles, policies should focus on incentivizing customers who would have otherwise chosen less efficient vehicles to purchase an electric vehicle instead. Some manufacturers are now producing electric SUVs, making the shift to a more efficient vehicle less of an attribute tradeoff for these customers. Furthermore, as SUVs tend to be more expensive (see kbb.com for a comparison across vehicle types), these households may very well be the ones who can most afford the electric vehicles. Thus, as technology advances, the ability of policymakers to incentivize owners of inefficient vehicles to shift to EVs may improve.

The fact that EVs can consume more water from charging than their gasoline-fueled counterpart highlights the importance of increasing the amount of cleaner electricity used to power the central grid, especially as EVs become more prevalent in society.

[22] The differences between the upper and lower bounds in avoided CO_2 and water (representing the difference in counterfactual vehicle) are statistically significant, with a p-val of 0 for both differences not equaling zero (including separately for each type of vehicle).

5.3. Implications for households

5.3.1. Solar panel decisions

Because households can choose which direction to face their solar panels, the orientation of the panels will substantially impact a household's level of PV generation and corresponding total emissions avoided. Pecan Street records orientation of the solar panels ("South & East" facing panels implies that one panel faces south and another faces east; "South & West" and "West & East" orientations are labeled correspondingly). We show in Table 5 the breakdown of total emissions avoided for households with panels facing south and east, south, south and west, and west. In the second column, we present the avoided emissions per 1 kW capacity, as homes with panels facing south and west tend to have larger PV arrays.

In comparing the generation capability of different panel orientations, we proceed with some caution, as malfunctions of panels occasionally happen and panels can have different efficiency levels. Thus, it may be the case that the two households with south & east facing panels happened to have had fewer panel malfunctions during FY2013 and/or they could have panels that are relatively more efficient than those of PV owners whose panels face other directions. Therefore, although we report these values, we do not attempt to draw conclusions from the south & east facing panel outcomes. Given the relative sample sizes of the different panel orientation categories, we will therefore only compare panels of three orientations: south & west; south; and west. Table 5 demonstrates that, per each kW of installed capacity, south-facing panels result in greater avoided emissions and water than facing

Table 5
Avoided emissions by panel orientation.

	Avg yearly avoided lbs. CO_2 emissions	Avg yearly avoided lbs. CO_2 emissions/kW capacity	Avg yearly avoided gallons of water	Avg yearly avoided gallons of water/kW capacity	Number of households
South & east	9931.97	1537.00	2896.65	448.24	2
South & west	8586.41	1461.93	2511.62	427.60	72
South	7740.93	1529.52	2253.65	445.17	33
West	7116.42	1354.84	2093.35	398.43	17
West & east	7897.50	1215.00	2299.80	353.82	1

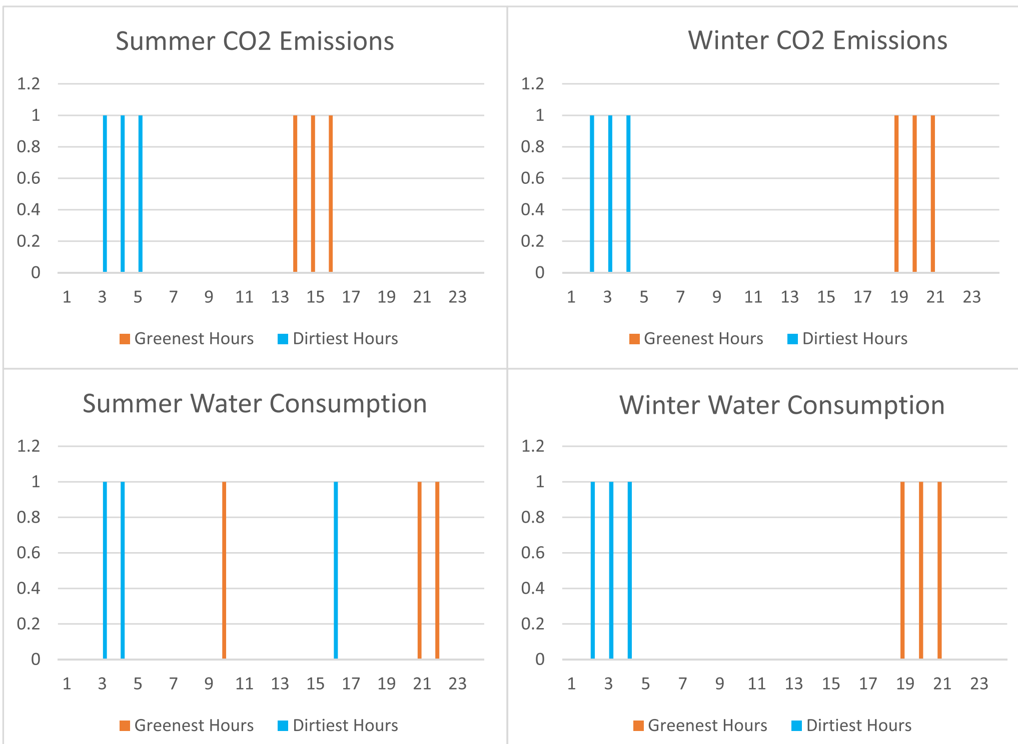

Fig. 16. CO_2 emissions and water consumption in summer and winter.

panels south & west or west. Per kW of installed capacity, this orientation avoids 4.4% more emissions and 3.9% more water than facing the panel south & west,[23] and 11.4% more emissions and 10.5% more water than facing the panels west.[24] This is likely due to the fact that a south-facing panel will maximize overall generation, as well as generating more power during the winter than do panels facing other directions, and winter is the season during which marginal emissions rates are highest (see Fig. 6 in Section 4.2.1).

However, it is important to note that other reasons may drive the orientation of solar panels (apart from rooftop viability). For example, it can be beneficial to the distribution system to have panels facing west; given that residential demand may spike in the afternoon/evening, having west facing panels can help reduce the reliance on grid electricity at times of higher demand. In 2013, Pecan Street conducted a study to estimate the benefits of different panel orientations, and identified a much larger total benefit from west-facing solar, due to its ability to reduce more peak demand (54% vs 65%) during the summer months (McCracken et al., 2013). This reduction at peak due to solar generation can have many benefits to society, such as reduced investment in infrastructure to meet peak demand. In fact, due to this benefit of west-facing solar, Pecan Street incentivized these households to have west-facing panels, by providing a $0.75/watt rebate to these customers (compared to a $0.50/watt rebate for south-facing panels).[25] Because of the large system benefits that west-facing solar can provide, it remains to be seen whether the increased environmental benefits of south-facing solar are enough to overcome the benefits of facing the panels west. Importantly, if west-facing rooftop solar can provide a significant direct benefit to utilities, there may be less resistance to PV deployment from these distribution companies, resulting in greater PV adoption overall; and thus, greater environmental benefits in the long run.

5.3.2. EV decisions

With respect to EVs, households can reduce their emissions by choosing when to charge their vehicle. In our sample, charging a vehicle for a full hour will require between 3.72 and 6.75 kWh[26] (not taking into account any rebound effects), with an average consumption of 3.76 kWh. For this part of our analysis, we utilize the average amount to represent what it takes to charge a vehicle over the course of an hour. In the summer, with respect to CO_2 emissions, the cleanest hour

[23] The differences in both CO_2 and water are significant, with p-vals of 0.06 and 0.08 respectively.
[24] The differences in both CO_2 and water are significant, with p-vals of 0.01.
[25] Monetary incentives verified over email by Pecan Street staff, 9/7/2016.
[26] Hourly EV charging varies based on a number of different factors, including the size of the vehicle's battery. We do not have data on battery size, and therefore calculate average hourly consumption as the average maximum hourly battery consumption at the household level.

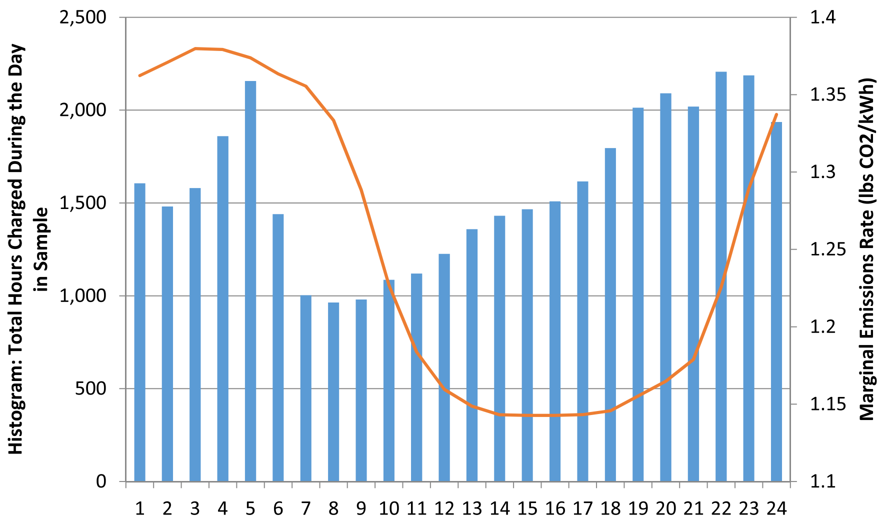

Fig. 17. Histogram of hourly charging and summer hourly CO_2 emissions.

on average is currently 2 pm (with average marginal emissions rate of 1.14 lbs/kWh), and the dirtiest hour is currently 2 am (the marginal emissions rate at that hour is 1.38 lbs/kWh). Consuming 3.76 kWh at 2 pm instead of consuming 3.76 kWh at 2 am avoids 0.90 lbs of CO_2. However, the situation looks different during the winter, where the marginal emissions rate has less variation across the hours but is higher in levels than during the summer – marginal emissions rates range between 1.32 at 8 pm to 1.42 at 2 am. This difference results in a benefit of only 0.38 lbs. CO_2 from shifting one hour of charging from 8 pm to 2 am, about a third of the benefit than during the summer.

On average, a household in our sample charges its EV for three full hours in the day.[27] Given this amount of charging, we can calculate the potential maximum amount of emissions avoided. To do this, we choose the 3 dirtiest hours, calculate the total lbs. CO_2 and gallons of water from grid charging; then we do the same with the 3 cleanest hours of the day, and take the difference between these two sums. Fig. 16 shows summer and winter's three cleanest and dirtiest hours of the day for both CO_2 emissions and water consumption.

If an EV owner were to somehow signal to its vehicle when the greenest times of the day occur, and charge during these times instead of dirtier times, it could save 2.58 lbs CO_2 and 0.49 gal per day in the summer and 1.10 lbs CO_2 and 0.36 gal per day in the winter; if the vehicle is charged every day, then yearly these savings increase to an average (across summer and winter savings) of 672.82 lbs CO_2 and 156.10 gal of water. There is a tradeoff during the summer for water and CO_2 (as the greenest hours of the day do not align as well as during the winter), though a household could do well by avoiding the dirtiest hours of the day, which align for both emissions and water consumption. Greatest savings could be achieved by implementing technology that sends a signal to the vehicle to charge during the cleanest moments of the day, thereby automating this action by the customer. Of course, this would also require customers to have charging stations at work, where they are able to plug their vehicle to charge if those moments coincide with the cleanest times of day. Austin Energy now has over 300 charging stations and rate plans that make charging while at work increasingly doable.[28] However, the charging stations do not yet provide information about the cleanest times of the day for charging.

Fig. 17 shows a histogram of the charging in the sample over the course of the day, overlaid with the marginal emissions rate per hour. A large portion of charging occurs after 6 pm and in the morning, when emissions are highest, given the current generation mix.

The fact that charging during the day currently produces fewer emissions than at night may seem counterintuitive given the large amount of wind being produced at night in TX. However, as discussed earlier, because wind cannot be ramped up or down in response to changes in load, any increase of load during the night will only result in changes in dispatchable load (e.g., coal and natural gas). It is possible that wind curtailments will decrease if there is greater load at night, especially in Western TX near the wind farms; but given the sporadic nature of these curtailments throughout the year and the low percentage of hours when this occurs (see Footnote 4), incentivizing customers to charge at night will likely not have a large enough benefit from reduced curtailments to offset the increase in marginal emissions that occur during moments of non-curtailment.[29,30]

It is important to point out in any case that the largest CO_2 savings for EVs comes from avoiding driving a gasoline-fueled vehicle, and they are largest when a household switches from a large, inefficient vehicle to an EV. Furthermore, multi-vehicle households may own both an EV and an SUV, serving very different purposes within the household (such as using the EV for commuting and using the SUV to take the kids to soccer practice). In this case, households can do very well in terms of reducing emissions by using the EV as much as possible and reducing the SUV's yearly miles traveled. Austin Energy has a rate structure for EV's that further incentives using the EV as much as possible.[31]

6. Conclusions and policy implications

The Pecan Street dataset provides a unique exploration of a variety of demand-side resources that households can adopt to reduce their environmental footprint. This paper contributes to the current literature by analyzing a granular PV generation and EV charging dataset from actual usage of these technologies. More specifically, due to this dataset, we are able to estimate the following: both the lbs. of CO_2 emissions and gallons of water consumption that a household can avoid by investing

[27] We define "full charging hours" to be the number of hours where the vehicle is plugged in for the entirety of the hour.
[28] See http://austinenergy.com/wps/portal/ae/green-power/plug-in-austin/!ut/p/a0/04_Sj9CPykssy0xPLMnMz0vMAfGjzOINjCyMPJwNjDzdzY0sDBzdnZ28TcP8DC09DfWDU4v1C7IdFQF4CNQ8/.
[29] Unless the customer is located outside of a transmission constraint zone, such as in Western TX near a wind farm.
[30] Note the previous discussion about the possibility of increase curtailment as more wind comes on line in the next few years.
[31] See link in Footnote 28.

Table 6
Avoided CO_2 emissions due to PV in select literature.

Source	Avoided Lbs of CO_2/kW of installed capacity	Region of study	Emissions methodology employed
Siler-Evans et al. (2013)	1500–2400 lbs/kW[a]	TX	Marginal emissions analysis
Connors et al. (2004)	1780 lbs/kW	ERCOT	Hourly emissions rates, simulated PV production
Zhai et al. (2012)	1931 lbs/kW	TX	EnergyPLAN simulation
Spiegel et al. (2000)	2760 lbs/kW	29 PV sites across US	Range of emissions profiles,[b] predominantly average

[a] These values are estimates based on a heat map of impacts across TX; accurate numbers not provided in source, but the Austin region is on the lower end of the spectrum in terms of avoided emissions.
[b] Emissions profiles were provided (or not) by the relevant utility; generally these were average emissions, with the exception of Scottsdale, AZ. The large difference in findings may be due to either the use of average emissions and/or the inclusion of non-TX regions.

in clean technologies, the existence and magnitude of a solar rebound effect, and the emissions and water consumption impact of solar panel orientation and strategic charging behaviors.

We find that solar panels allow residential customers to avoid a substantial amount of emissions: on average, a household with PV avoids 8107 lbs of CO_2/year (or 1453 lbs/kW of installed capacity on average).[32] Framed another way, on average, households can avoid 75% of yearly grid-related emissions. Though our results are within a reasonable range of numbers found in the literature (see a selection of literature in Table 6), our results are on the lower end of the spectrum. However, our methodologies and data employed are quite different from what is used in the literature, in that we have paired actual PV performance with a marginal emissions analysis. Most closely related to our paper is Siler-Evans et al. (2013) who use a marginal emissions analysis similar to ours; they estimate approximately 1500 lbs. avoided CO_2/kW of installed capacity in Austin (see Table 6 footnote a).

With respect to water consumption, we find that on average, households avoid 2369 gal of water consumption per year, or 77% of yearly grid-related water consumption, from installing solar panels. The literature related to the avoided water consumption benefit of solar panels is extremely limited, and to the best of the authors' knowledge, this is the first study to estimate the impact of actual installed household distributed solar panels.[33]

We also find that households can further decrease their emissions by 11.4% and their water consumption by 10.5% (relative to the average avoided emissions and water consumption) by choosing to face the panels south instead of west; however, the large majority of the homes (71%) in our sample choose to face their panels west or south & west instead, potentially due to the larger system savings that a western orientation provides. To the authors' knowledge, this paper provides the first estimate of realized (as opposed to simulated) environmental benefits of panel orientation for distributed solar.[34]

For electric vehicles, we find that a household will avoid on average between 2631 and 7285 lbs. CO_2/year (42–70% of yearly fuel-related emissions). These results are comparable to other estimates found in the literature for studies in the US; see Table 7.

We also find that households can save between 410 and 1393 gal of water usage per year (30–62% of yearly fuel-related water consumption) by shifting to an EV, depending on the efficiency of the counterfactual vehicle. The literature on this topic is limited, where most of the papers attempt to estimate only the water consumption associated with gasoline production (e.g., King and Webber, 2008; Wu et al., 2009), or with vehicle manufacturing (e.g., Berger et al., 2012; Bras et al., 2012). A few papers look at lifecycle water impacts of electric vehicles. For example, Harto et al. (2010), Onat et al. (2014) and Kim et al. (2016) estimate vehicle lifecycle water consumption and/or withdrawals,[35] and find that EVs have a higher water footprint than their gasoline counterparts.[36] However, none of these papers have utilized information on actual charging patterns and have not relied on marginal water consumption analyses, and are therefore likely overestimating the water consumption associated with observed vehicle use.

However, we do find that an EV has the potential to *increase* a household's fuel-related water consumption by up to 14% depending on the counterfactual gasoline-powered vehicle's efficiency. Although customers can improve their environmental footprint by charging during low marginal emissions times, the greatest impact a household can have on emissions is by shifting away from their secondary, gasoline-fueled vehicles and using their EVs instead (especially if that alternative vehicle is very inefficient). This also supports the idea that policies incentivizing the purchase of electric vehicles should be targeted to customers who would have otherwise purchased inefficient vehicles. Understanding what vehicle a potential buyer would otherwise have chosen may be difficult, but some programs can directly target these customers (such as a specially-designed clunkers exchange program; See Li et al., 2013 for a description and analysis of the 2009 "Cash-for-Clunkers" program).

A finding of our paper is that strategic timing – whether it involves charging an EV at hours with low marginal grid emissions and water rates, or facing one's solar panels south to maximize generation during the grid's emissions- and water-intensive times – can improve environmental outcomes. However, it is important to note that these findings are dependent on the current generation mix. As the grid becomes cleaner and more renewables come online, the marginal emissions profile will change. Specifically in TX, ERCOT foresees a drop in coal generation, though the magnitude of the drop depends on market dynamics and the implementation of the Clean Power Plan and Regional Haze Regulations (ERCOT, 2016).[37] As a result, gas' role as a marginal generation fuel will likely increase while coal's will decrease, and these fuels' timing as marginal power sources could shift both hourly and seasonally.

[32] Importantly, these environmental impacts are short-run effects only, as in the long run, the fuel mix is subject to change; as more DERs are deployed and integrated the grid, there can be less reliance on dirty generators, leading to a cleaner and more efficient grid.

[33] Wiser et al. (2016) simulate the avoided water consumption from the implementation of NREL's SunShot Vision Study's solar penetration, and find that solar panels decrease water consumption by 9% relative to a baseline. Though this number is much smaller than our findings, it is difficult to compare the two, as the Wiser et al. study is a result of a policy, based on simulations, and utilizes different methodologies. Deetjen et al. (2016) also attempt to estimate water consumption from solar panels, but only compare across three different solar panels located in three different locations; see Footnote 34 for a more in-depth description.

[34] One exception is Deetjen et al. (2016). However, they simulate solar generation from PVWatts rather than using observed solar panels as in this paper; they assign different capacities to each solar panel; and place each solar panel with a different orientation in different parts of TX (the west-facing panel is located in Western TX, the south facing panel is in Central TX, and the east-facing panel is in Eastern TX). Furthermore, they do not describe how they calculate avoided water consumption, making it very difficult to compare our results with theirs. Given our dataset with observed distributed solar panels located in the same neighborhood, we are able to minimize the differences across each panel that may affect the results from Deetjen et al.

[35] Water withdrawals associated with electricity generation are much higher than water consumption; the latter are estimated in this paper.

[36] Lifecycle analysis will also increase the amount of water related to EVs, as it includes water for creating the vehicle and battery, as well as water used for creating the solar panels or other generators used to power the EV.

[37] This remains a somewhat conservative prediction, as ERCOT assumes that the percentage of wind capacity will only increase by 2 percentage points over the next 15 years. A more ambitious advancement of wind capacity could increase the renewables percentage of the grid mix over time well beyond 37.1%.

Table 7
Avoided emissions due to EVs in select literature.

Source	Avoided emissions	Region of study	Emissions methodology
Archsmith et al. (2015)	2220–3980 lbs CO_2/year for EVs relative to gasoline vehicle	TRE NERC region	Marginal emissions
Doucette and McCulloch (2011)	90% reduction in CO_2 emissions for EV relative to gasoline vehicle	USA	Average emissions
Sioshansi et al. (2010)	25% reduction in CO_2 emissions for PHEV relative to gasoline vehicle	Ohio	Marginal emissions
Blumsack et al. (2008)	2094–2931 lbs CO_2/year for PHEV relative to gasoline vehicle	ERCOT	Average emissions
Duvall et al. (2007)	40–65% reduction in CO_2 emissions for PHEV relative to gasoline vehicle	USA	Marginal emissions

Such a re-shuffling of fuels on the margin will lead to changes in optimal environmentally beneficial behaviors. Thus, utilities, regulators, and policymakers should develop incentives for maximizing environmental behaviors that consider the future, and, if feasible to do in a transparent manner, dynamically adjust based on the composition of the marginal generation mix.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2017.09.009.

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