

**Supporting Information for**  
**Coordinated EV Adoption:**  
**Double-digit reductions in emissions and fuel use for \$40/vehicle-year**

Dong Gu Choi<sup>1,2</sup>, Frank Kreikebaum<sup>3,4</sup>, Valerie M. Thomas<sup>1,5</sup>, Deepak Divan<sup>3</sup>

**Affiliations:**

<sup>1</sup>School of Industrial and Systems Engineering, Georgia Institute of Technology, Atlanta, GA 30332.

<sup>2</sup>Present address: Korea Institute of Energy Research, 152 Gajeong-ro, Yuseong-go, Daejeon 305-343, Republic of Korea.

<sup>3</sup>School of Electrical and Computer Engineering, Georgia Institute of Technology, Atlanta, GA 30332.

<sup>4</sup>School of Economics, Georgia Institute of Technology, Atlanta, GA 30332.

<sup>5</sup>School of Public Policy, Georgia Institute of Technology, Atlanta, GA 30332.

\*Correspondence to: [vthomas@isye.gatech.edu](mailto:vthomas@isye.gatech.edu)

***Materials and Methods***

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This supplementary document presents data, assumptions, methods, and regional analysis for the primary document “Coordinated EV Adoption: Double-digit reductions in emissions and fuel use for \$40/vehicle-year” The data and models used to derive the results are presented in the order reported in the primary document: electricity and gasoline demand, electricity costs, greenhouse gas emissions, and total consumer expenditure. In addition, this document describes the sensitivity analysis and shows additional results that we could not include in the main manuscript. The final section shows regional results.

## ***Light-duty vehicle Model***

### **1. Estimation of the number of light-duty vehicles**

The NHTS surveyed the number of vehicles for some households over the entire United States and estimated the number of households in each state<sup>1</sup>. We calculate the share of households for each state. Based on the assumption that each household has the same number of vehicles on average, the share of households is the same as that of vehicles for each state, as follows: FRCC 6%, MRC 6%, NPCC 11%, RFC 20%, SERC 25%, SPP 2%, Eastern Interconnection total 71%. We use AEO 2011 projections for future light-duty vehicle (LDV) sales and LDV fleet size for the entire United States (*I*). Based on these projections, we calculate LDV sales and LDV fleet size for the Eastern Interconnection. We assume that LDV sales and LDV fleet size in each region of the Eastern Interconnection will be proportional to the current national distribution of vehicles.

### **2. Electric vehicle adoption**

We use three EV adoption scenarios for LDVs<sup>2</sup>. The first uses joint projections from the United States EPA and the National Highway Traffic Safety Administration (2), which is that EVs reach 10% market share by 2025. In addition, we consider two more scenarios: 20% and 100% market share by 2025 respectively. Based on an assumption that the market share of EVs will linearly increase, the number of EVs in the fleet stock will increase quadratically. For the 10% and 20% scenarios, this increase continues past 2025, resulting in a market share of 13.3% and 26.67% respectively in 2030. Consequentially, EVs comprise 8.4%, 16.8%, and 80.7% of the total fleet in 2030. Fig. S.1 shows the projection for number of LDVs and EVs in the Eastern Interconnection for this study.

### **3. Energy intensity and electric range of new electric vehicles**

The assumptions for EV energy intensities in the charging-depleting (CD) mode are based on the 2010 projection of Argonne National Laboratory (3). This likely inflates EV energy consumption in 2030 since ANL projects that battery-electric vehicle (BEV) and plug-in hybrid electric vehicle (PHEV) energy consumption will decline by 16.5-18.6% and 11.3-13.5% respectively, dependent on vehicle type. A number of previous studies have evaluated plug-in hybrid EVs with an all-electric range between 32 and 96 km (4-6). However, recently introduced full EVs, such as the Nissan Leaf, have a roughly 161 km range. We assume that battery-EVs sold between 2010 and 2030 have a 161 km range and plug-in hybrid vehicles have a 64 km all-electric range. The NHTS, AEO and ANL use different vehicle type categories. NHTS has automobile/car/station wagon, van, SUV, and pickup; AEO has car and truck, ANL has compact, midsized, small SUV, midsized SUV, and pickup. Since we are using data from all three studies<sup>3</sup>,

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<sup>1</sup>The Federal Highway Administration provides the National Household Transit Survey Data available at [nhts.ornl.gov/download.shtml](http://nhts.ornl.gov/download.shtml)

<sup>2</sup>We assume that no electric vehicle pickup trucks (NHTS-defined) will be adopted.

<sup>3</sup>NHTS data is 2009 data. AEO contains real data for 2008 and 2009, but the data from 2010 are projected data. ANL report uses

we need to convert the energy intensities of electric vehicles from one category to another category. Based on the qualitative description provided for these vehicle types and on current LDV distributions, we create maps from one categorization system to the other. Based on the mapping we convert the energy intensities in ANL categories to those in the NHTS categories (Table S.1)

#### 4. Fuel economies of new conventional vehicles

The United States NHTSA and EPA regulate the Corporate Average Fuel Economy (CAFE) standard; the average fuel economy for new model year vehicles of each manufacturer are required to meet this standard. A manufacturer may comply with CAFE standards by ensuring that its current year fleet meets the fuel economy standard, purchasing credits from a manufacturer whose fleet exceeds the fuel economy standard, carrying forward or back credits, or paying penalties. Our model allows intra-year trading but assumes no inter-year trading or payment of penalties. The NHTSA sets the standard and then EPA calculates the fuel economy of each vehicle to determine manufacturer compliance. When setting the standard, the NHTSA does not consider EVs, use of the alternative fuel (i.e. electricity) by dual-fuel vehicles (i.e. PHEVs) prior to MY2020, carry-forward or transfer of credits. EPA relaxes many of these assumptions when calculating the fuel economy standard necessary to meet GHG emissions requirements and current MY fuel economy. This results in an NHTSA fuel economy standard that is lower than the EPA standard for GHG emissions.

EPA calculates the average fuel economy for new model year vehicles as Eq. S.1.

$$Fuel\ Economy\ (MPGe) = \frac{\sum n_i}{\sum \frac{n_i}{f_i}} \quad (Eq. S.1.)$$

where  $n_i$  is number of vehicles in type  $i$  and  $f_i$  is fuel economy of vehicles in type  $i$ . The EPA uses the petroleum equivalency factor (PEF) to calculate the mile per gallon equivalent (MPGe) of EVs for MY 2011-2025, as shown in equation Eq. S.2 (7,8). In the formula, E is the Wh/mi of electricity consumed by the vehicle when tested using the 2-cycle method.

$$PEF = \frac{1}{E} * 33705 * \frac{0.303}{0.830} * 6.6667 \quad (Eq. S.2.)$$

The EPA uses a utility factor (UF) to calculate the MPGe of PHEVs. The utility factor assumes the vehicle does not charge during the day but begins the day fully charged. The UF is roughly 0.35 for 20 mile range and 0.6 for 40 mile range (9). The formula for PHEV fuel economy is shown in equation Eq. S.3 (7), where UF is utility factor,  $FE_{CD}$  is fuel efficiency of charge depleting mode and  $FE_{CS}$  is fuel efficiency of charge sustaining mode. It is not clear if  $FE_{CD}$  is calculated in the same manner as an EV.

$$FE_{UFweighted} = \frac{1}{\frac{UF}{FE_{CD}} + \frac{(1-UF)}{FE_{CS}}} \quad (\text{Eq. S.3.})$$

The fuel economy standards are calculated by year by vehicle footprint, the footprint defined by the four contact points of the wheels. NHTSA assumes a given market share of vehicle footprints to calculate the fleet average CAFE standard. The market share of each footprint may change over time. We assume the market share by footprint and type is time-invariant and matches the footprint distribution of 2009-2010.

Since the CAFE standard is calculated using a harmonic mean, given the high fuel economy assigned to EVs by the EPA, scenarios with higher EV market share result in a lower required conventional vehicle (CV) fuel economy. Taken to the extreme, this would lead to falling CV fuel economy as EV adoption increases. Here, we impose the requirement that within a given scenario, CV fuel economies do not decrease as a function of time, even if an EV scenario leads to fleet-wide fuel economies higher than required by the CAFE standard. Fig. S.2 shows projections of required fuel economy of new conventional vehicles and their stock.

This analysis assumes that the fuel economy standard is binding and the EPA GHG standard is slack. The EPA GHG standard includes the impacts of upstream emissions. Therefore, it is possible that scenarios with high EV penetration would have a binding GHG standard and a slack fuel economy standard. This analysis also neglects the EPA multiplier incentives for EVs and PHEVs, which expire in MY 2021. These multipliers are in addition to the petroleum equivalence factor, and count one EV/PHEV as more than one vehicle when calculating GHG emissions. We neglect the limit prior to MY 2019 for maximum improvement in fleet fuel economy achievable with dual-fuel vehicles. We also assume that the EPA uses the UF when calculating fuel economy over the entire study period. We assume natural gas vehicles are not purchased.

Since higher adoption of EVs could be counter-balanced by less efficient gasoline-powered vehicles, we consider a policy change to unlink the fuel economy of conventional vehicle from EVs. In the unlinked cases, the fuel economy of new CVs alone is required to meet the CAFE standard, and EV adoption will not affect the required fuel economy of new CVs.

## **5. Generation of electric vehicle daily energy requirement, electric vehicle hourly demand profile, and electric vehicle hourly capacity profile**

The NHTS surveyed the trips made by all members of selected households for one day<sup>4</sup>. Travel via the light-duty fleet is a subset of the reported transit modes. We use the NHTS data to develop type-specific daily energy requirements per vehicle if an existing CV is replaced with an EV. We also develop type-specific hourly demand profiles for use with the uncontrolled charging scenarios, assuming the vehicle begins charging at the end of the last journey of the day. We develop type-specific hourly capacity profiles for the controlled charging case, assuming the vehicle is available for charging anytime it is parked at home. In all cases, we assume future light-duty fleet driving patterns match the NHTS 2009 survey. This neglects both recent data showing a decline in vehicle usage and the possibility that drivers may use increased efficiency to increase annual mileage (10,11).

To develop the EV daily energy requirement, EV hourly demand profile, and EV charge capacity profile, we remove the following data records: data sourced from households located in metropolitan statistical areas (MSAs) outside the Eastern Interconnection, data sourced from households with an undesignated MSA, data for transit modes other than car, van, SUV, or pickup truck, and data for a vehicle which had overlapping or duplicate trips. In addition, if a trip stop time was not specified, we assume the stop time was 11:59p. Similarly, if no trip start time was specified, we assume the start time to be 12:00a. We extract the following eight data samples from the filtered and repaired data: car weekend trips, car weekday trips, van weekend trips, van weekday trips, SUV weekend trips, SUV weekday trips, pickup truck weekend trips, and pickup trip weekday trips. For each of the samples, we generate the following for a representative EV:

- Daily energy demand: The average daily energy demand for a single vehicle. Calculated using the vehicle type specific energy intensities and the average daily driving distance for the sample. We neglected charging efficiency.
- Hourly demand profile: The charging demand of the average vehicle of the sample based on an uncontrolled charging scheme whereby the vehicle begins charging upon completion of the last journey of the day and charges at a given uniform rate until all energy used during the day has been restored. If the time which a vehicle stays at charging infrastructure is too short, then it is possible that the vehicle is not fully charged. However, based on the assumptions of 6.6 kW charging rate and the NHTS usage profiles, incomplete charging is rare.

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<sup>4</sup> Average annual vehicle mile travels (VMTs) : car - 25700 km (16000 mile), van - 37000 km (23000 mile), and SUV - 32200 km (20000 mile).

- Hourly capacity profile: The charging power the average vehicle of the sample can accommodate for every hour of the day if the vehicle is connected to charging infrastructure as soon as a journey is completed. The use of a fleet-wide capacity profile ignores car-level dynamics where the battery of a given vehicle may not be able to accommodate additional energy until later in the day.

Fig. S.3 shows the uncontrolled charging profile. For the controlled charging schemes, we generate charging capacity profiles with the assumption that home charging infrastructure and rate incentives ensure that drivers plug in vehicles whenever they are at home. A charging capacity profile is the fraction of the EV vehicle fleet that is connected to charging infrastructure, times the assumed charging power of 6.6 kW. Fig. S.4 shows the charging capacity profile. Comparing the average value of S.3 to S.4, we can see the abundance of flexibility in the capacity profile.

### ***Electric Power System Models***

The analysis uses four models: For each EV market share scenario, (i) a light-duty-vehicle fleet model determines the vehicle characteristics for CVs and EVs for each year over the study period; (ii) a least-cost capacity planning (CP) model determines the optimum electric generation capacity for each year over the study period; (iii) a unit commitment (UC) model optimizes the day-ahead selection of which power plants to run based on information available the day before the delivery of power; and (iv) an economic dispatch (ED) model optimizes the dispatch of generation and flexible loads during the operational hour. The CP model was programmed and implemented in the AMPL optimization package, and was solved using the ILOG CPLEX 11.1 solver. The UC and ED models were programmed in MATLAB and solved in MOSEK.

The models are run in series. We run the light-duty vehicle fleet model for the entire study period, 2010-2030. The output is input into the CP model, which is also run for the entire study period. The CP output is fed into the UC model, which is run for the first day of the sub-period of interest. The results from the first-day of the UC model are fed into the ED, which is run for every hour of the first day of the sub-period. The UC and ED models are then rerun for every day in the sub-period of interest. As our focus is on the metrics once EV market share has stabilized, we only run the UC and ED models in 2030. To reduce the computational burden, the UC and ED models are only run during time periods of demand or supply stress on the system: the weeks with the highest and the lowest projected annual hourly loads, the week with the highest daily wind potential production, and the week with the lowest daily wind potential production. We apply the models to these six regions separately. We aggregate the six regions' results to provide an overall assessment for the entire Eastern Interconnection.

## **6. Capacity Planning Model**

The Capacity Planning (CP) model minimizes the NPV of capacity changes and electricity production over a multidecade period. A 1-year time scale is segmented into three seasons

(winter, summer, intermediate), and we assume each season to have a representative hourly weekday load curve and a representative hourly weekend load curve. More detail on the six hourly load curves will be shown in Section 11. The CP model is run for each region for 50 years (2010 - 2060) and we use only the data for 2010-2035. Except for some wind generation, as described in Section 13, all capacity built in a given region is used to supply demand in that region.

Generation and demand are characterized for generation technologies  $i \in I$ , wind supply curve  $j \in J$ , hours  $h = 1, \dots, 24$ , wind level  $w$  of 1, 2, or 3 for high medium and low wind level, seasons  $s = 1, \dots, 6$  for winter weekday, weekend, intermediate weekday, weekend, summer weekday, weekend, and time  $t = 1, \dots, T$ , the electricity demand (MWh),  $d_{s,h,t}$ , the EV charging demand (MWh),  $dev_{s,h,t}$ , the EV charging capacity (MWh),  $cev_{s,h,t}$ , and the number of days in season  $s$ ,  $\theta_s$ . A risk-adjusted real discount factor<sup>5</sup>,  $r$ , is applied. Electricity generation is limited by the maximum capacity factor of technology  $i$ ,  $\phi_i$ , the solar electricity potential at hour  $h$ , wind level  $w$  and season  $s$ ,  $\phi_{solar,s,h}$ , the wind electricity potential at hour  $h$ , wind level  $w$  and season  $s$ ,  $\phi_{wind,s,w,h}$ , and the upper bound generating capacity of technology  $i$  (MW),  $u_i$ . The cost parameters are the capital investment cost (\$/MW),  $C_i$ , annual fixed cost (\$/MW-yr) and variable cost of O&M plus fuel (\$/MWh) for technology  $i$ ,  $F_i$ , the levelized cost of potential wind power including transmission at the  $j^{th}$  step of the supply curve,  $LC_{wind,j}$ , and the peak demand multiplicative factor<sup>6</sup>,  $\delta_s$ . There are CO<sub>2</sub> emissions from technology  $i$ ,  $e_i$ , and the renewable electricity standard is  $res_t$ . The decision variables are capacity (MW),  $x_{i,t}$ , capacity expansion (MW),  $y_{i,t}$ , capacity retirement (MW),  $q_{i,t}$ , new wind capacity at the  $j^{th}$  supply curve level (MW),  $xwind_{j,t}$ , electricity generation for EV charging (MWh),  $zev_{i,s,w,h,t}$ , and non-EV use (MWh),  $z_{i,s,w,h,t}$ , and electricity generation from new wind capacity in the  $j^{th}$  supply curve level (MWh),  $zwind_{j,s,w,h,t}$ .

The objective function is shown in Eq. S.4.

$$\min \sum_t \frac{1}{(1+r)^t} \left\{ \sum_i (C_i y_{i,t} + F_i x_{i,t}) + \sum_i V_{i,t} \sum_s \frac{\theta_s}{3} \sum_w \sum_h (z_{i,s,w,h,t} + zev_{i,s,w,h,t}) \right. \\ \left. + \sum_j LC_{wind,j} \sum_s \frac{\theta_s}{3} \sum_w \sum_h zwind_{j,s,w,h,t} \right\} \quad (\text{Eq. S.4.})$$

<sup>5</sup>The United States DOE expected that the annual yield on the 10-year United States Treasury bond would average 5.4% and annual consumer price inflation would average 2.1% from 2009 to 2035 (EIA 2011a). We obtain a risk-free discount factor rate of 3.2%. With about 4% risk-premium, we use 7% real risk-adjusted discount rate to account for the time value of money.

<sup>6</sup>Please see section 11 for the details.

*Capacity Change Constraint.* Based on the existing power plant capacities, the total capacities of each technology will vary over time as a function of retirements of existing plants and new construction. Some technology options, including biomass and hydro, are physically and/or economically limited, so we assign these technologies maximum capacity limitations.

$$x_{i,t} = x_{i,t-1} - q_{i,t-1} + y_{i,t} \quad \forall i, \forall t \quad (\text{Eq. S.5.})$$

*Generation Constraint.* The power output generated by each technology must not exceed its maximum available capacity.

$$z_{i,s,w,h,t} + zev_{i,s,w,h,t} \leq x_{i,t} \quad \forall i, \forall s, \forall w, \forall h, \forall t \quad (\text{Eq. S.6.})$$

$$\sum_s \frac{\theta_s}{3} \sum_w \sum_t (z_{i,s,w,h,t} + zev_{i,s,w,h,t}) \leq \varphi_i x_{i,t} \times 8760 \quad \forall i, \forall t \quad (\text{Eq. S.7.})$$

However, the maximum power output of wind technology at each time is determined by wind speed as well as capacity.

$$z_{wind,s,w,h,t} + zev_{wind,s,w,h,t} = \varphi_{wind,s,w,h} x_{wind,t} + \sum_j z_{wind,j,s,w,h,t} \quad \forall s, \forall w, \forall h, \forall t \quad (\text{Eq. S.8.})$$

$$z_{wind,j,s,w,h,t} = \varphi_{wind,s,w,h} x_{wind,j,t} \quad \forall j, \forall s, \forall w, \forall h, \forall t \quad (\text{Eq. S.9.})$$

$$x_{wind,j,t-1} \leq x_{wind,j,t} \quad \forall j, \forall t \quad (\text{Eq. S.10.})$$

*Demand constraints.*

Case 1: Uncontrolled charging

$$\sum_t z_{i,s,w,h,t} \geq d_{s,h,t} \quad \forall s, \forall w, \forall h, \forall t \quad (\text{Eq. S.11.})$$

$$\sum_t zev_{i,s,w,h,t} \geq dev_{s,h,t} \quad \forall s, \forall w, \forall h, \forall t \quad (\text{Eq. S.12.})$$

$$\sum_{i \in I \setminus \{hydro, wind, solar\}} x_{i,t} \geq \delta_s \times \max_h (d_{s,h,t} + dev_{s,h,t}) \quad \forall s, \forall t \quad (\text{Eq. S.13.})$$

Case 2: Controlled charging

$$\sum_h \sum_t zev_{i,s,w,h,t} \geq \sum_h dev_{s,h,t} \quad \forall s, \forall w, \forall t \quad (\text{Eq. S.14.})$$

$$\sum_t zev_{i,s,w,h,t} \leq cev_{s,h,t} \quad \forall s, \forall w, \forall h, \forall t \quad (\text{Eq. S.15.})$$

$$\sum_{i \in I \setminus \{hydro, wind, solar\}} x_{i,t} \geq \delta_s \times \max_h (d_{s,h,t}) \quad \forall s, \forall t \quad (\text{Eq. S.16.})$$

*Renewable standard constraint*

$$\begin{aligned} & \sum_s \frac{\theta_s}{3} \sum_w \sum_h \left( \begin{aligned} & z_{biomass,s,w,h,t} + z_{solar,s,w,h,t} + z_{wind,s,w,h,t} + \\ & z_{other\_ren,s,w,h,t} + zev_{biomass,s,w,h,t} + zev_{solar,s,w,h,t} + \\ & zev_{wind,s,w,h,t} + zev_{other\_ren,s,w,h,t} \end{aligned} \right) \quad \forall t \\ & \geq res_i \sum_{i \in I} \sum_s \frac{\theta_s}{3} \sum_w \sum_h (z_{i,s,w,h,t} + zev_{i,s,w,h,t}) \end{aligned} \quad (\text{Eq. S.17.})$$

## 7. Unit Commitment Model

In actual power system operation, a Unit Commitment model (UC) is run before the operating hour to determine which units will be online during the operating hour and determine an initial schedule for how much power each unit will produce. In many systems, the UC run spans a 24-hour period, called an operating day, and is run 12 hours before the start of the operating day, resulting in decisions made up to 36 hours before the operating hour. The uncertainty in generator availability, maximum potential production of intermittent generators, and transmission capacity for periods 12-36 hours in advance requires conservative UC. We adopt the convention of 24 hour UC runs performed the day before the operating day.

Since UC is normally performed over the course of one operating day, dispatchable, capacity-factor-limited resources such as hydro are not optimized over the course of the year. To resolve this, most power systems employ a coarser hydro UC period on the order of months to years to optimize hydro usage. We do not employ a long-term hydro optimizer.

To provide the system maximum flexibility to maintain security, our UC does not limit the amount of renewable curtailment which can occur. This is consistent with actual operating practice which strives to minimize cost. For systems with limited load controllability, high levels of intermittent renewables, and/or inflexible generation, this can result in curtailment of renewable resources. Should the curtailment be severe enough, RES requirements satisfied in the CP may not be fulfilled in practice, which would lead to penalties and incentives for utilities to build more capacity.

Our UC uses a perfect load forecast and a 24-hour-ahead wind potential production forecast. A solar forecast was not used since the CP did not build any solar. Also, the solar capacity factor was assumed to be 1, allowing solar plants to be dispatched at full capacity around the clock. FRCC, the only region with pre-existing solar, had 110 MW of solar capacity at the start of the study period. The crudeness of solar modeling results in the frequent commitment of solar generation to run at full capacity around the clock. This has minimal impact on the final results as solar represents less than 0.23% of FRCC capacity.

Assuming UC is run 12 hours before the start of the operating day and wind forecasts are generated two hours before the UC is performed, wind forecasts used in the UC extend 38 hours into the future. However, we only have access to 4, 6, and 24 hour-ahead wind production forecasts. Therefore, the 24 hour-ahead was used to represent the forecast input to the UC. Compared to the forecasts used in an actual UC, this likely leads to artificially poor forecasts for operating hours 1-10 and artificially accurate forecasts for operating hour 11. While most actual UC processes include reserve and ancillary service requirements, we did not consider them in our UC. In addition, while the model calculates the carbon emissions by unit and by hour that

will result if the UC solution is followed, it does not include emissions associated with startup and shutdown.

For generation technologies  $i \in I$ , generator unit identifier  $g \in G$ , index of operating hours solved in a single UC run  $h = 1, \dots, 24$  ( $T=24$ ), the demand parameters are uncontrolled electricity demand at hour  $h$  (MWh),  $d_h$ , energy required over the UC period to meet controlled EV demand<sup>7</sup> (MWh),  $d_{EV}$ , EV charging capacity at hour  $h$ , only applicable to controlled charging (MW),  $cEV_h$ . Electricity generation is limited by the maximum capacity factor of technology  $i$  during UC period,  $\phi_{\max i}$ , the minimum capacity factor of technology  $i$  during UC period,  $\phi_{\min i}$ , the forecasted wind energy maximum potential during hour  $h$  for a forecast produced before the UC model is run,  $\phi_{\text{forecasted\_wind},h}$ , the wind energy maximum potential during hour  $h$ ,  $\phi_{\text{actual\_wind},h}$  and the upper bound for generating capacity of unit  $g$  of technology  $i$  (MW),  $u_{i,g}$ . The cost parameters are the variable cost (O&M + fuel cost) of unit  $g$  of technology  $i$ ,  $V_{i,g}$ , and the startup cost of unit  $g$  of technology  $i$  (\$/start),  $S_{i,g}$ . There are CO<sub>2</sub> emissions from technology  $i$ ,  $e_i$ . The decision variables are the electricity generation from unit  $g$  of technology  $i$  at hour  $h$  (MWh),  $z_{i,g,h}$ , the startup of unit  $g$  of technology  $i$  at hour  $h$  (1 = startup occurs, 0 = no startup occurs),  $start_{i,g,h}$ , and the state of unit  $g$  of technology  $i$  at hour  $h$  (1 = online, 0 = offline),  $state_{i,g,h}$ .

The objective function minimizes the variable costs and startup costs of the entire generator fleet over the period of the Unit Commitment

$$\min \left\{ \sum_i \sum_g \sum_h V_{i,g} z_{i,g,h} + \sum_i \sum_g \sum_h S_{i,g} start_{i,g,h} \right\} \quad (\text{Eq. S.18.})$$

#### *Demand constraints*

##### Case 1: Uncontrolled charging

For uncontrolled charging, the total generation during any hour must equal the total demand. In this case, total demand includes conventional load as well as EV charging load.

$$\sum_i \sum_g z_{i,g,h} = d_h \quad \forall h \quad (\text{Eq. S.19.})$$

##### Case 2: Controlled charging for cost minimizing

For controlled charging, the conventional demand ( $d_h$ ) must be met during each operating hour, as shown in Eq. S.20. In addition, the energy required by the EV fleet over the UC period must be provided over the course of the UC period, as shown in Eq. S. 21. Finally, the amount of power which can be directed to the EV fleet in any given hour cannot exceed the fleet charging capacity of that hour, as shown in Eq. S.22.

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<sup>7</sup>Only applicable to the controlled charging

$$\sum_i \sum_g z_{i,g,h} \geq d_h \quad \forall h \quad (\text{Eq. S.20.})$$

$$\sum_i \sum_g \sum_h z_{i,g,h} \geq \sum_h d_h + dEV \quad (\text{Eq. S.21.})$$

$$\sum_i \sum_g z_{i,g,h} - d_h \leq cEV_h \quad \forall h \quad (\text{Eq. S.22.})$$

*Minimum Output Constraint.* The power output generated by each unit must not be less than its minimum power output if the unit is online.

$$-z_{i,g,h} + \varphi_{\min i} u_{i,g} \text{state}_{i,g,h} \leq 0 \quad \forall i, \forall g, \forall h \quad (\text{Eq. S.23.})$$

*Maximum Capacity Factor Constraint.* The capacity factor of the unit over the operating day must not be larger than the unit's maximum capacity factor.

$$\sum_h z_{i,g,h} \leq T \varphi_{\max i} u_{i,g} \quad \forall i, \forall g \quad (\text{Eq. S.24.})$$

*Unit Startup Constraints.* A unit offline in the prior hour but online in the current hour must be started in the current hour.

$$\text{state}_{i,g,h} - \text{state}_{i,g,h-1} - \text{start}_{i,g,h-1} \leq 0 \quad \forall i, \forall g, \forall h \quad (\text{Eq. S.25.})$$

An offline unit must not supply energy and an online unit must not be supply more energy than its nameplate capacity (Eq. S.26 for non-wind units) or its forecasted maximum capacity (Eq. S. 27 for wind units).

$$z_{i,g,h} - \varphi_{\max i} u_{i,g} \text{state}_{i,g,h} \leq 0 \quad \forall i \in I \setminus \{\text{wind}\}, \forall g, \forall h \quad (\text{Eq. S.26.})$$

$$z_{i,g,h} - \varphi_{\text{forecast\_wind},h} u_{i,g} \text{state}_{i,g,h} \leq 0 \quad \forall i \in \{\text{wind}\}, \forall g, \forall h \quad (\text{Eq. S.27.})$$

The UC was run for four weeks for each region in 2030. The four weeks are the periods with highest peak hourly load, lowest peak hourly load, highest wind production, and lowest wind production.

## 8. Economic Dispatch Model

The economic dispatch (ED) model determines how much power will be dispatched from each generating unit for the current hour and future hours of the operating day. For every UC solution, the ED model is run once for each hour of the operating day. So, at 12am the ED finalizes the dispatch for 12am-1am but also updates the estimated dispatch for the remaining hours of the day. When run again at 1am, the ED takes the outcomes from 12am-1am as fixed, finalizes the outcomes for 1am-2am and re-estimates the dispatch for the remaining hours of the day.

When finalizing the dispatch for the current hour, the maximum potential production of wind generation is set to the observed potential production rather than the day-ahead forecasted value. This is based on with the assumption that intra-hour wind forecasts of aggregate, multistate

potential wind production are perfectly accurate. We make this assumption given the geographic diversity of a multistate wind generation portfolio and the accuracy of near-term forecasts. However, maximum production of wind generator's in subsequent hours is still based on the day-ahead forecast used in the UC.

Like the UC, the ED does not limit the amount of renewable curtailment so the ED may curtail wind to minimize the cost of securely operating the system. Should the curtailment be severe enough, RES requirements satisfied in the CP may not be met in the ED. Like the UC, the ED does not utilize solar forecasts or capacity factor limits. Thus, production of the ED predicts the FRCC pre-study period solar resources operate around the clock at rated capacity. Reserve and ancillary service requirements are not considered in the ED. In addition, while the ED calculates carbon emissions by unit by hour, it does not include emissions associated with startup and shutdown.

The ED model is the same as the UC model, except state variables related to unit state and startup are constrained to the solutions determined in the UC. In addition, variables for prior hours are constrained to the values solved in prior ED runs. The ED was run for four weeks for each region in 2030. The four weeks are the periods with highest peak hourly load, lowest peak hourly load, highest wind production, and lowest wind production.

## **9. Parameters for Capacity Planning Model**

The parameters used for the CP model are shown in Table S.2. The parameters for costs, heat rates and maximum capacity factors are sourced from the assumptions used to generate the Annual Energy Outlook (AEO) 2010 (12). The capital cost figures are listed after multiplying the AEO figures by an investment factor greater than one, to account for the NPV impacts of construction time (13). The investment factors are shown in Table S.3. Since the parameters in AEO 2010 are based on 2008\$ and costs in this study are based on 2009\$, we adjust by the United States consumer price inflation (CPI) from 2008 and 2009, which is 2.7%<sup>8</sup>. The maximum capacity factors for coal technologies are based on the historical national average<sup>9</sup>. The maximum capacity factors for natural gas technologies are assumed to be higher than the coal technologies. The capacity factors for oil, pumped storage, hydropower, and others (municipal waste, etc.) are calculated by dividing total regional electricity generation by total regional capacities in 2009, and, therefore, these numbers are different in different regions (1). The maximum annual capacity factors for other technologies are based on our previous study (14). We do not allow the CP to build more pulverized coal, oil, pumped storage, or municipal generation. For the fuel costs, we use the projection of AEO for the costs of coal, natural gas, and

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<sup>8</sup>Consumer Price Index (CPI) from United States Department of Labor. Available at <ftp://ftp.bls.gov/pub/special.requests/cpi/cpiiai.txt>

<sup>9</sup> eGRID database from United States Environmental Protection Agency. Available at [www.epa.gov/cleanenergy/energy-resources/egrid/index.html](http://www.epa.gov/cleanenergy/energy-resources/egrid/index.html)

oil in each reliability region (1). In addition, cost estimates for nuclear fuel are from the World Nuclear Association website<sup>10</sup> with real cost escalation of 0.5% per year. We assume that biomass costs are constant, in real terms, over the study period. More details for biomass costs are shown in Section 15. Fig. S.5 shows sample fuel cost projections for the SERC region. We derive the GHG emissions rates for fossil fuel-based technologies by weight-average values from EPA's survey of the United States generation fleet<sup>9</sup> and we assume zero emission rates for nuclear and all other renewable technologies.

Newer sources indicate that actual capital costs for onshore wind and PV are lower than the AEO 2010 values. Additional reductions in real cost are possible. However, to ensure the analysis is internally consistent, we chose to retain AEO values throughout. Additional parameters with respect to wind generation cost and variability are described in more detail in Sections 13 and 14. Unlike other generation types, the cost of wind includes the cost of new transmission.

We assume that some existing power plants are retired during the study period (2010 - 2035). Particularly, most existing coal power plants are operating beyond their design life of 50 years (14), so we assume that those will be gradually retired over the future thirty years from 2012 at a constant rate. Similarly, we assume that existing conventional combustion turbines for natural gas will start to retire in 2020. Lastly, since we consider that the maximum lifetime of wind turbines is 20 years, existing wind turbines are retired before 2029.

## **10. Unit Parameters for Unit Commitment and Economic Dispatch Model**

The unit parameters by technology used for the UC and ED are shown in Table S.4 and S.5. Heat rates, emissions rates, and O&M costs for each technology are derived from the same sources as the CP model. We derived unit nameplate capacities for thermal units using technology-average values from EPA's survey of the United States generation fleet<sup>11</sup>. Unit minimum power during operation was found by averaging values across (15,16) for CT, (15-18) for CC, and (16,18) for coal. We assume minimum power values for nuclear, biomass, oil, and municipal units. The cycling cost includes the cost of a cold startup as well as a shutdown. Cold startup times are 10 hours for a coal plant, 6 hours for a CC, and 0 hours for a CT plant. We used cycling cost data for coal and gas plants from (15), assuming a long-run euro-to-dollar conversion rate of 1.3:1. We used cycling cost for nuclear plants from (18) using the 2003 euro-to-dollar conversion rate. In practice, nuclear plants are not shutdown except for refueling and emergencies; we assume the UC does not shut them down.

We assume biomass and municipal waste facilities have a cycling cost equivalent to the average of the coal and CC cycling cost. We assume advanced coal and gas technologies (SCPC, IGCC,

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<sup>10</sup>The Economics of Nuclear Power, World Nuclear Association. Available at [www.world-nuclear.org/info/inf02.html](http://www.world-nuclear.org/info/inf02.html).

<sup>11</sup> Available at [www.epa.gov/cleanenergy/energy-resources/egrid/index.html](http://www.epa.gov/cleanenergy/energy-resources/egrid/index.html)

Advanced CC, and Advanced CT) have the same minimum power and cycling costs as conventional units of the same fuel type. We adjusted the nameplate capacities of hydro units and intermittent renewable units so there was no more than one unit of each technology in each regional system. This improves solution time and is reasonable given the lack of transmission constraints and much shorter cycling time constants than the temporal resolution of the UC and ED. Although some references indicate that hydro, intermittent renewable and pumped hydro have zero start-up cost, we assume cycling cost of \$1 to avoid overzealous startups. This requirement is fulfilled automatically for the thermal units as part of the cost minimization process. To represent variability within the fleet of units of a specific technology, we determine the energy and cycling costs of a given unit by adding a uniformly distributed +/- 10% random value to the parameters in Tables S.4 and S.5. Given the low amount of pumped storage in each scenario and small capacity factor, we model pumped storage as a dispatchable renewable resource. Additional parameters with respect to wind generation cost and variability are described in more detail in Sections 13 and 14. The marginal cost for onshore wind, offshore wind, and solar production is set to the variable O&M cost.

## 11. Hourly Non-EV Load Profiles

The Federal Energy Regulatory Commission (FERC) Form No. 714<sup>12</sup> provides hourly load data of most utilities in the United States. By aggregating the 2010 hourly load data of some representative utilities in each region, we develop a regional hourly non-EV load profile spanning an entire year.

For the CP model, we segment this representative data into a single weekday and a single weekend day for each of three seasons (winter - Jan. to Feb. and Dec., intermediate - Mar. to May and Sept. to Nov., summer - June to Aug.). By averaging the data of all days in each segment, we develop representative 24-hourly conventional load profiles for each segment. Using the averaged hourly data can underestimate the capacity requirement. The electric power system must have more total capacity than the highest peak demand over the entire year. Therefore, from the aggregate 2010 hourly data, we calculate the ratios of the highest peak demand over the given season to the peak demand of each season's representative hourly load profile, and we define them as 'peak demand multiplicative factors'. The CP model uses these factors in the demand constraints.

By multiplying the ratio between the projection of annual demand and total annual generation in given aggregate load data, we develop the 24-hourly load profiles of non-EV load for every year. The UC and ED models sample specific periods from the representative hourly non-EV load profile. Each period contains a contiguous period of hours. We assume demand is inelastic.

## 12. Renewable Electricity Standards

We calculate the effect of each reliability-region-wide RES mandate based on the load-weighted average RES mandate of each state. The Department of Energy (DOE) provides information about states with renewable electricity standards. Currently there are 24 states plus the District of Columbia that have RES policies in place. The Database of State Incentives for Renewables & Efficiency (DSIRE) from DOE provides more details on each state's RES, which include the specific schedule for the minimum percentage of renewable electricity every year<sup>13</sup>. Based on the RES schedule of each state and the share of 2009 electricity generation among the states ( $I$ ), we generate the region-wide RES as the weighted average of state-level standards. As an example, among twelve states in SERC, only four states have state-level standards: Missouri, Illinois, North Carolina and Virginia. Table S.6 represents the state-level RESs for the aforementioned states. The last row contains the share of electricity generation amounts in SERC. The last column is the load-weighted average of the previous four columns based on the share of electricity generation in SERC; this is the SERC-wide RES. The other five region-wide

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<sup>12</sup> Available at [www.ferc.gov/docs-filing/forms/form-714/elec-subm-soft.asp](http://www.ferc.gov/docs-filing/forms/form-714/elec-subm-soft.asp)

<sup>13</sup> Database of State Incentives for Renewables & Efficiency from United States Department of Energy. Available at [www.dsireusa.org/](http://www.dsireusa.org/)

RESs are calculated in the same way. In addition, based on the share of electricity generation amounts among the regions, we calculate the entire Eastern Interconnection-wide RES, which is 9.6% in 2030. Even though every RES has a different definition of renewable resources, we assume that only biomass, wind, solar, and municipal waste generation may be used to comply with the region-wide RES requirements.

### **13. Wind Power Supply Curves, Potential Production Profiles and Inter-Regional Transmission Cost**

The Eastern Wind Integration and Transmission Study (EWITS) provides the potential capacities and levelized costs for thousands of hypothetical onshore wind generation sites in the eastern and central United States. We develop wind power supply curves for six reliability councils. Fig. S.6 shows the supply curve of onshore wind power for entire Eastern Interconnection.

The CP model uses weighted representative days rather than modeling every day of the year. As an input to the CP, we generate regional potential production profiles for representative days. A potential production profile is an hourly profile of the amount of wind generation achievable in the absence of curtailment. For each region, we aggregate the time-series onshore wind power potential production of the 30 percent of the sites with the lowest cost of energy. EWITS also provides potential capacities for offshore sites but does not provide levelized costs for these sites. Because cost data are not provided for the offshore sites, we include all sites in the aggregate profile for each region.

Based on this time series data, we develop onshore and offshore wind power potential production profiles for high wind, medium wind, and low wind days for each of the three seasons (winter, intermediate, and summer) and for each region. In order to capture the intermittency of the wind power, we take the high wind day to be the day with the highest total potential wind production when aggregating potential production across all candidate sites that could be used to supply a given region. For example, when developing the potential production profile for SERC, we consider wind potential production from SERC onshore sites, SERC offshore sites, MRO onshore sites, and SPP onshore sites. We then pick the day which has the least aggregate potential production assuming 25% of SERC wind demand is supplied from each of the four candidate regions. The CP is able to change the percentage of wind capacity sourced from each of the candidate regions. Correspondingly, we chose the day with the lowest total potential wind production across all candidate regions as the low wind day. In total, we develop 9 one-day wind profiles for each region. Fig. S.7 shows the SERC onshore wind production profiles for each season.

In order to include the wind imports from SPP and MRO, we calculate the cost of transmission between any two regions assuming construction of new HVDC transmission capability between the centroids of the regions. We assume the new transmission is used only to transmit wind energy. If the capability is shared with other resources, wind capacity's cost of transmission will likely fall. A \$/kW cost of transmission is generated using the line (HVDC) cost parameters shown in from Barman and Johnson (19): \$1M/km line cost, \$420M per station, and 3000 MW line capacity. This study ignores the discrete nature of transmission line construction. Based on the centroid-to-centroid distances between regions, a carrying cost of 11%, an average wind plant capacity factor of 42%, and 0% curtailment, the \$/kWh transmission costs are shown in Table S.7. We assume great-circle distances unless a path crosses a large body of water.

Using the wind power supply curves, we develop the step-wise wind supply curves for in-region wind resources. We combine the wind power supply curves with transmission costs to develop step-wise supply curves for imports from SPP and MRO. Fig. S.8 shows the supply curves in each region. While the CP decides how much to import from each region, the surplus wind power capacities in SPP and MRO are assigned to each region proportional to regional generating capacities in 2008. The wind power levelized generation costs range from 6 cents/kWh to 13 cents/kWh, and the supply curve has fourteen levelized generation costs steps, starting from 6.25 cents/kWh and increasing by 0.5 cents/kWh. The supply curves indicate that some wind energy generated in MRO or SPP and shipped to the other four regions (FRCC, NPCC, RFC and SERC) will likely be cheaper than wind energy generated in those four regions. For example, SERC has 1,200 MW of resources under \$80/MWh while SPP has 80,000 MW. At least one utility in SERC imports wind from SPP and new transmission has been proposed to transport wind energy from the SPP and MRO regions to eastern regions. We assume that SPP and MRO regions will export their surplus wind power to other eastern regions in proportion to the demand of the importing regions.

#### **14. Generation of Forecast Wind Potential Production and Actual Wind Potential Production**

The Eastern Wind Integration and Transmission Study (EWITS) provides simulated hourly forecast maximum production and simulated observed maximum production for thousands of onshore and offshore sites within the Eastern Interconnection for three simulated years (2004-2006)<sup>14</sup>. Twenty-four-, six- and four-hour-ahead forecasts are provided. Forecasts provide the expected value of wind production, otherwise known as P50.

P50 forecasts result in observed maximum production values less than the forecasted amount 50% of the time. Based on current operating practices, under prediction is economically

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<sup>14</sup>Eastern Wind Dataset from National Renewable Energy Laboratory. Available at [www.nrel.gov/electricity/transmission/eastern\\_wind\\_methodology.html](http://www.nrel.gov/electricity/transmission/eastern_wind_methodology.html)

disadvantageous but does not challenge security, as wind generators may be curtailed (i.e. operated below their observed maximum production value). However, over prediction can compromise system security since alternative sources of generation, such as thermal units, may not be available in time to compensate for the shortage of wind production. In light of this, operators use a PX forecast, with  $X > 50$ , to ensure that sufficient wind energy is available to maintain security. In a PX forecast, there is an  $X\%$  chance the observed wind maximum production will exceed the forecasted wind production. In some jurisdictions,  $X$  is set dynamically based on risk. However, for this effort, we set  $X$  at a fixed percentage for each case through an iterative process to ensure the system is secure for all time periods.

We converted the EWITS 24-hour-ahead forecasts from P50 to PX using the method described in (20). This method creates a beta distribution of the probability of achieving a given actual maximum potential for each of  $n$  sub-intervals of forecast values. For example, if there are  $J$  evenly spaced sub-intervals, the first sub-interval will span forecast values  $[0, 1/J)$  pu. We determined the number of forecast values assigned to each sub-interval dynamically so that each sub-interval had at least 500 records. The parameters of the beta distribution,  $\alpha$  and  $\beta$ , are solved for each sub-interval  $j$  as seen in equations Eqs. S.28 - S.31

$$\mu_j = \frac{\sum_h \varphi_{actual,h,j}}{Count(j)} \quad \forall i \in \{LL_i < \varphi_{forecast\_P50,h} \leq UL_i\}, \forall h \quad (\text{Eq. S.28.})$$

$$Var_j = \frac{\sum_h (\varphi_{actual,h,j} - \mu_j)^2}{Count(j)} \quad \forall i \in \{LL_i < \varphi_{forecast\_P50,h} \leq UL_i\}, \forall h \quad (\text{Eq. S.29.})$$

$$\alpha_j = \frac{(1 - \mu_j)\mu_j^2}{Var_j} - \mu_j \quad \forall j \quad (\text{Eq. S.30.})$$

$$\beta_j = \frac{(1 - \mu_j)}{\mu_j} - \alpha_j \quad \forall j \quad (\text{Eq. S.31.})$$

Once the beta distribution is estimated for each sub-interval  $j$ , a given P50 forecast is converted to a PX forecast using the inverse beta cumulative distribution function (CDF) as seen in equation Eq. S.32.

$$PX = BETAINV(1 - X, \alpha_j, \beta_j) \quad \forall i \in \{LL_i < \varphi_{forecast\_P50,h} \leq UL_i\}, \forall h \quad (\text{Eq. S.32.})$$

A comparison of the observed potential production, the 24-hour-ahead P50 forecast, and the 24-hour-ahead P99 forecast are shown in Fig. S.9. We compute the forecasted and observed potential production profiles for a fixed number of wind sites per region. This approximates the expected profiles as some cases may use more wind sites from a given region than another case.

## **15. Biomass Supply and Price**

We simplify biomass price and availability from (21) since the impact of biomass electricity is minor in this study. We assume that the cumulative availability up to \$30/dry ton price level is economically feasible, and we use a biomass price of \$30/dry ton. We did not adjust the biomass price to 2009\$. The availabilities of biomass are aggregated by reliability region and converted into the available capacity for biomass plants as shown in Table S.8. Assuming a biomass energy density of 12.8 MJ/kg, the biomass fuel cost is \$2.72/mmBtu (1995\$).

### ***GHG emissions***

## **16. Total system GHG emissions**

By multiplying the amount of electricity from each technology by the GHG emissions factors in Section 9 and 10, the total electricity sector GHG emissions are calculated. We separate the GHG emissions from electricity generation for non-EV and EV loads. In order to calculate the GHG emissions from the LDV sector, we estimate the total gasoline consumption in Section 19 and multiply by GHG emissions factor for tail pipe emissions from gasoline consumption (NETL 2008, 8892 g CO<sub>2</sub>e/gal). For the GHG emissions from LDV manufacturing, we use the GHG emissions for production from (22) of 87 to 95 g CO<sub>2</sub>-eq/km for EVs and 43 g CO<sub>2</sub>-eq/km for CVs, based on the assumption of a 150,000 km vehicle lifetime. To provide conservative results, we use 95 CO<sub>2</sub>-eq/km for EVs, and we calculate the annual GHG emissions for vehicle production over the 13-year vehicle lifetime.

### ***Vehicle and EVSE Total Consumer Expenditure***

## **17. Vehicle Purchase Cost**

We use the 2010 data for the purchase costs of 2010 vehicles as shown in Table S.9.<sup>15</sup> The cost of a future vehicle is calculated based on the vehicle class, type (i.e. CV, BEV, PHEV), and fuel economy standard. The 2010 average cost is augmented by an incremental cost to determine the total cost of a future vehicle. Incremental cost as a function of technology, vehicle class, year and fuel economy are required for our method. While EPA and NHTSA (23), ANL (3), CAR (24), NRC (25), and Electrification Coalition (26), each contain a subset of this information, no study provides enough information to derive the required function from a single reference. The Argonne National Lab study (3) is the most complete. Annexes 2 and 3 of the ANL study present average incremental manufacturing cost and average energy consumption data for five vehicles classes (compact, midsize car, small SUV, midsize SUV, and pickup) at three future time points (2015, 2030, 2045) and for a number of power train types. In addition, Fig. 133 of the ANL report is a scatter plot of incremental cost as a function of year and fuel economy for compact vehicles, and shows that spark-ignition vehicles have the lowest cost. Using Fig. 133,

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<sup>15</sup> Automotive Fleet, Available at [www.automotive-fleet.com/Statistics/Default.aspx?prestitial=1](http://www.automotive-fleet.com/Statistics/Default.aspx?prestitial=1)

two linear relationships are derived for 2010, 2015 and 2030, as shown in Eqs. S.33 and S.34. The first equation relates average incremental cost to the incremental cost of the vehicle with the best-in-class fuel economy. The other relates average fuel economy to best-in-class fuel economy. We apply these relationships to the average values available for the other vehicle classes to estimate the best-in-class fuel consumption and incremental costs as seen in Eqs. S.35 and S.36. Given that the vehicle with the best fuel economy has an incremental cost lower than or equal to the average fuel economy, we assume this technology will dominate the market.

$$\gamma_{fuel\ consumption,t} = \frac{\delta_{average,compact,t} - \delta_{best-in-class,compact,t}}{\delta_{average,compact,t}} * 100\% \quad (\text{Eq. S.33.})$$

$$\gamma_{cost,t} = \frac{C_{average,compact,t} - C_{best-in-class,compact,t}}{C_{average,compact,t}} * 100\% \quad (\text{Eq. S.34.})$$

$$\delta_{best-in-class,i,t} = \delta_{average,i,t} (1 + \gamma_{fuel\ consumption,t}) \quad (\text{Eq. S.35.})$$

$$C_{best-in-class,i,t} = C_{average,i,t} (1 + \gamma_{cost,t}) \quad (\text{Eq. S.36.})$$

where  $\delta_{j,i,t}$  is the fuel consumption of type  $j$  (average or best-in-class) for vehicle type  $i$  in year  $t$ ,  $\gamma_{fuel\ consumption,t}$  is the fuel consumption adjustment factor for year  $t$ ,  $C_{j,i,t}$  is the incremental cost for type  $j$  (average or best-in-class) for vehicle type  $i$  in year  $t$ , and  $\gamma_{cost,t}$  is the incremental cost adjustment factor for year  $t$ . Applying these linear factors to the other vehicle classes, we arrive at the results for CVs, shown in Table S.10 and S.11.

As described in Section 4, the fuel economy standard applicable to the CV vehicles sold in a given year is determined based on the EV market share and EV energy intensities. However, the ANL incremental cost data are for a fixed fuel economy at each of the 3 data points (2010, 2015, 2030). The results from other studies (24, 27) suggest a linear relationship between incremental cost and fuel economy. We assume this linear relationship applies and calculate the incremental cost of a vehicle of a given fuel economy and model year by linear interpolation between the ANL values, as shown in Eq. S.37.

$$P_{i,t} = P_{i,\underline{t}} + (\delta_{i,t} - \delta_{i,\underline{t}}) \left( \frac{P_{i,\bar{t}} - P_{i,\underline{t}}}{\delta_{i,\bar{t}} - \delta_{i,\underline{t}}} \right) \quad (\text{Eq. S.37.})$$

where  $P_{i,t}$  is the incremental price of vehicle in year  $t$  of type  $i$  (\$),  $P_{i,\underline{t}}$  is the incremental price of ANL vehicle of type  $i$  in the ANL time one or more less than time  $t$  (i.e. 2015 when calculating 2030 cost) (\$),  $P_{i,\bar{t}}$  is the incremental price of ANL vehicle of type  $i$  in the ANL time period less

than or equal to time  $t$  (i.e. 2030 when calculating 2030 cost) (\$),  $\delta_{i,t}$  is the specified fuel economy of vehicle of type  $i$  in year  $t$  (mpg),  $\delta_{i,\underline{t}}$  is the fuel economy of ANL vehicle of type  $i$  in the ANL time period one or more less than time  $t$  (i.e. 2015 when calculating 2030 cost) (mpg), and  $\delta_{i,\bar{t}}$  is the fuel economy of ANL vehicle of type  $i$  in the ANL time period less than or equal to time  $t$  (i.e. 2030 when calculating 2030 cost) (mpg).

To calculate the total cost of EVs, we increment the base 2010 CV cost. The ANL report presents EV incremental cost figures for PHEVs with a 16-64 km range as well as BEVs with a 241 km range. The projected energy intensities for 2030 PHEVs and EVs are as much as 20% below the 2010 values. To provide conservative results, we assume the 2010 energy intensities apply to all years. Also, this study uses EVs with a 161 km (100 mile) range and PHEVs with a 64km (40 mile) range. We adjusted the average ANL results to account for the lower battery size and higher energy intensities using the method of equation Eq. S.38. The resulting incremental costs are shown in Table S.12 and S.13.

$$C_{R,i,t} = C_{r,i,t} - B_{act,i,t} P_{bat,i,t} + R_i \varepsilon_{2010,i} \frac{B_{act,i,t}}{B_{usable,i,t}} P_{bat,i,t} \quad (\text{Eq. S.38.})$$

where  $C_{R,i,t}$  is the estimated EV cost with  $R$  km range of type  $i$  in year  $t$  based on 2010 energy intensities (\$),  $C_{r,i,t}$  is the cost of EV with  $r$  km, range of type  $i$  in year  $t$  per ANL study (\$),  $B_{act,i,t}$  is the actual battery capacity of EV of type  $i$  in year  $t$  (kWh),  $P_{bat,i,t}$  is the price of actual battery capacity in year  $t$  (\$/kWh),  $R_i$  is the range of vehicle of type  $i$  (km),  $\varepsilon_{2010,i}$  is the 2010 EV energy intensity (kWh/km), and  $B_{usable,i,t}$  is the usable battery capacity of EV of type  $i$  in year  $t$  (kWh).

We assume the EVs have the same lifetime as the CV vehicles. In addition, we assume there is no incremental difference in end-of-life value between the EVs and CVs. This simplifies potential tradeoffs between the potential resale value of EV batteries and the potential reduced lifetime of the EVs compared to CVs.

## 18. Charging Infrastructure Cost

Electric vehicle supply equipment (EVSE) connects the EV's onboard charger with the electrical grid. We assume Level 2, 6.6 kW charging. As with EV batteries, EVSE costs are projected to decrease with volume. Electrification Coalition (26) assumes a public charging station cost of \$1875 and a private charging station cost of \$300 in 2030. We use these numbers for our estimation. We assume all vehicles have a dedicated home EVSE. For 2030, Electrification Coalition assumes a minimum of 0.5 public EVSEs per vehicle and a maximum of 1.5 public EVSEs per vehicle. For the uncontrolled charging scheme, we assume the minimum projection of 0.5 public charging stations per vehicle. The public EVSE network is solely for security and

all charging energy is assumed to be derived from home chargers. For the controlled charging schemes, we originally assumed that vehicles charged whenever stopped and we consequentially budgeted an additional 1 public EVSE per vehicle. However, when we compared the load flexibility of assuming the vehicles are plugged in whenever stopped versus plugged in whenever stopped at home, we found the load flexibilities to be nearly equal. Due to the additional cost of public charging stations, we therefore assumed 1 private EVSE and 0.5 public EVSE per vehicle even for the controlled cases. No charging was modeled at the public chargers, as it is expected to be a small amount of total charging. However, the cost of public chargers was included as a public charging network may be necessary to mitigate range anxiety.

Electrification Coalition assumes a charging station lifetime of 10 years. We assume a lifetime of 13 years for the private EVSE, to match the assumed lifetime of the average vehicle. We assumed 75% of the cost of a public EVSE lasts 40 years. This cost includes conduit installation and wiring. The remaining 25% of the cost is assumed to last 13 years. We model EVSE acquisition cost as an upfront purchase of a home EVSE at the time of vehicle purchase and a surcharge on charging costs over the lifetime of the vehicle to recoup the vehicle's portion of the public EVSE network. The NPV of EVSE infrastructure at the time of vehicle purchase is \$932 per vehicle.

## **19. Total Consumer Expenditure**

Total consumer expenditure (TCE) is calculated for the light-duty transit and electricity sectors and normalized on a per vehicle basis. The TCE consists of upfront costs and ongoing costs. The upfront costs are vehicle purchasing costs and installation of the EVSE for EVs. The ongoing expenditures are vehicle electricity and fuel expenditures and non-EV electricity expenditures. Electricity expenditures include capacity costs, fuel costs, and O&M costs. The non-EV electricity expenditures are spread over all light-duty vehicles, including pickup trucks, not just the vehicles which may be converted to EVs. We assume a gasoline price of \$4/gallon (2009\$) which is 8% higher than projected by AEO 2010. We also assume demands for non-EV electricity and LDV transportation are inelastic. We develop lifetime cash flows for each vehicle type and calculate the net present value (NPV) of the cash flows. In the end, we convert the NPV into annuity payments over vehicle's lifetime.

We assume vehicle purchase in 2030, vehicle life of 13 years, no tax advantage of purchasing a EV vs. a CV vehicle (i.e. current EV tax credits have expired), no 'gas tax' applied to electricity used to charge EVs, a discount rate of 4.8%, no vehicle maintenance costs and EVs do not require battery replacement. In every EV adoption case, we calculate the TCE of both MY 2030 EV and CV for each vehicle type (compact car, midsize car, small SUV, large SUV) as in equation Eq. S.39. Then, we subtract the TCE of the reference case (10% RES case with no EVs) from the TCE of the case under consideration, to calculate the difference in TCE,  $\Delta TCE$ , as show in Eq. S.40. In the equations below, the reference case is denoted by  $k=0$ .

$$TCE_{i,j,k} = X + IC_{i,j,k} + CC + FC_{i,j,k} + A_k \quad (\text{Eq. S.39.})$$

$$\Delta TCE_{i,j,k} = (X + IC_{i,j,k} + CC + FC_{i,j,k} + A_k) - (X + IC_{CV,j,0} + FC_{CV,j,0} + A_0) \quad (\text{Eq. S.40.})$$

$$\Delta TCE_{i,k} = \sum p_j \Delta TCE_{i,j,k} \quad (\text{Eq. S.41.})$$

where  $X$  is the purchasing cost of Model Year (MY) 2010 vehicle,  $IC_{i,j,k}$  is the incremental cost of MY 2030  $i$  vehicle (EV or CV) for vehicle type  $j$  in case  $k$ , relative to MY 2010 vehicle,  $FC_{i,j,k}$  is the NPV of total electricity charging costs for the EV (and partial gasoline refueling costs for PHEV) or total gasoline refueling costs for the CV for vehicle type  $j$  during vehicle's lifetime in case  $k$ ,  $IC_{CV,j,R}$  is the incremental cost of MY 2030 CV type  $j$ , relative to MY 2010 vehicle in reference case,  $CC$  is the charging infrastructure costs per EV,  $A_k$  is the total cost per vehicle for non-vehicle electricity,  $p_j$  is the 2010 market share of vehicle type  $j$  (We assume the market share of all vehicle types are the same in 2030 as 2010).

The assumed discount rate of 4.8% is nearly the average of the two discount rates, 3% and 7%, used in (7) to assess impacts of the MY 2017-2025 CAFE standard. The assumed discount rate is lower than some estimates of consumer discount rates (28). In our analysis, increasing the discount rate dramatically reduces the attractiveness of EVs relative to CVs, thereby increasing  $\Delta TCE$ . This is expected as vehicle purchase is modeled as a lump, undiscounted sum in year one but any savings are discounted over the lifetime of the vehicle. If we expand our model to capture the fact that most vehicles are financed, the effect of discount rate diminishes. For example, average EVs in the unlinked case with EV100% and 33% RES have  $\Delta TCE$  of \$41 per vehicle per year using our analysis framework. If we assume the vehicle is financed at market rates by the consumer using a 15% discount rate to calculate the NPV, the  $\Delta TCE$  increases to \$130 per vehicle per year.

## 20. Sensitivity Analysis of Total Costs of Expenditure

We perform a multilevel factorial sensitivity analysis to explore the sensitivity of  $\Delta TCE$  to linked fuel economy standards, charging method, gasoline price, EV price, ratio of battery-EVs (BEVs) to plug-in EVs (PHEVs), and RES level. The multilevel factorial design addresses nonlinearities (29). We tested six parameters: two fuel economy standard policies (linked or not), two charging methods (uncontrolled or controlled), three levels of gasoline price (\$3, \$4, \$5/gallon), three levels of EV prices (125% of ANL values, ANL values, 75% of ANL values), two ratios of BEVs to PHEVs (9:1 and 1:9) and two RES levels (10% and 33%). For each case,  $\Delta TCE$ s for CVs and EVs are calculated. The  $\Delta TCE$  is the TCE of the average-EV or average-CV in an EV adoption case minus the TCE of average-CV in the reference case with no EVs, the currently-legislated RES (10%), and the same gasoline price as the EV case.

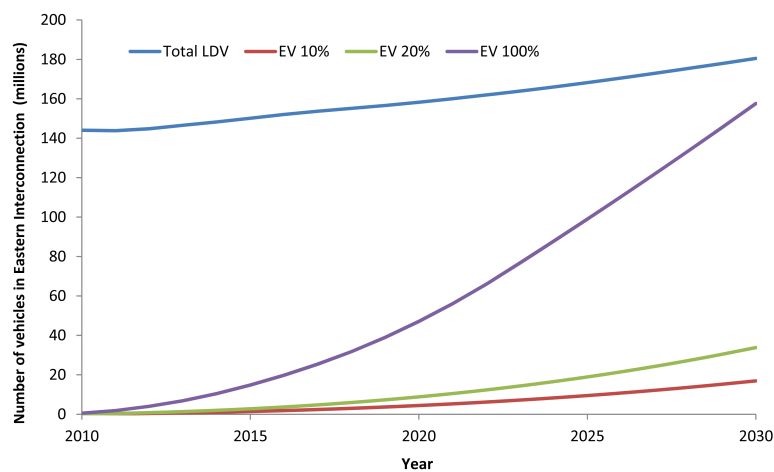
For each sensitivity case, two  $\Delta$ TCEs for both average-CV and average-EV are calculated.  $\Delta$ TCEs range from -\$20 to \$1204/vehicle-year (average \$273/vehicle-year) for CVs and from -\$502 to \$740/vehicle-year (average \$48/vehicle-year) for EVs. For each of the results below, one or more factors are held constant and all combinations of the other factors are evaluated. With linked fuel economy standards,  $\Delta$ TCEs range from \$68 to \$1204/vehicle-year (average \$457/vehicle-year) for CVs and from -\$447 to \$740/vehicle-year (average \$88/vehicle-year) for EVs. With uncontrolled charging,  $\Delta$ TCEs range from \$2 to \$1204/vehicle-year (average \$293/vehicle-year) for CVs and from -\$476 to \$740/vehicle-year (average \$70/vehicle-year) for EVs. With \$3 gas prices,  $\Delta$ TCEs range from -\$20 to \$782/vehicle-year (average \$221/vehicle-year) for CVs and from \$19 to \$740/vehicle-year (average \$298/vehicle-year) for EVs. With EV prices at 125% of ANL values,  $\Delta$ TCEs range from -\$20 to \$1204/vehicle-year (average \$273/vehicle-year) for CVs and from -\$397 to \$740/vehicle-year (average \$135/vehicle-year) for EVs. With unlinked fuel economy standards and controlled charging,  $\Delta$ TCEs range from -\$20 to \$158/vehicle-year (average \$70/vehicle-year) for CVs and from -\$502 to \$541/vehicle-year (average -\$15/vehicle-year) for EVs. With unlinking, controlled charging, and a 33% RES,  $\Delta$ TCEs range from \$148 to \$158/vehicle-year (average \$152/vehicle-year) for CVs and from -\$305 to \$541/vehicle-year (average \$81/vehicle-year) for EVs. With unlinking, controlled charging, a 33% RES, and a BEV to PHEV ratio of 1:9,  $\Delta$ TCEs range from \$148 to \$158/vehicle-year (average \$152/vehicle-year) for CVs and from -\$305 to \$541/vehicle-year (average \$116/vehicle-year) for EVs.

The  $\Delta$ TCEs of CVs do not depend on the levels of EV prices and the ratios of BEVs to PHEVs. Unlinking improves the  $\Delta$ TCEs of the sensitivity cases without exception. Unlinking improves  $\Delta$ TCE by \$74 to \$969/vehicle-year for CVs (average \$367/vehicle-year) and by \$23 to \$190/vehicle-year for EVs (average \$80/vehicle-year). Control charging improves  $\Delta$ TCE of the sensitivity cases without exception. Adding controllability improves  $\Delta$ TCE by \$7 to \$86/vehicle-year for CVs (average \$39/vehicle-year) and by \$8 to \$100/vehicle-year for EVs (average \$46/vehicle-year).

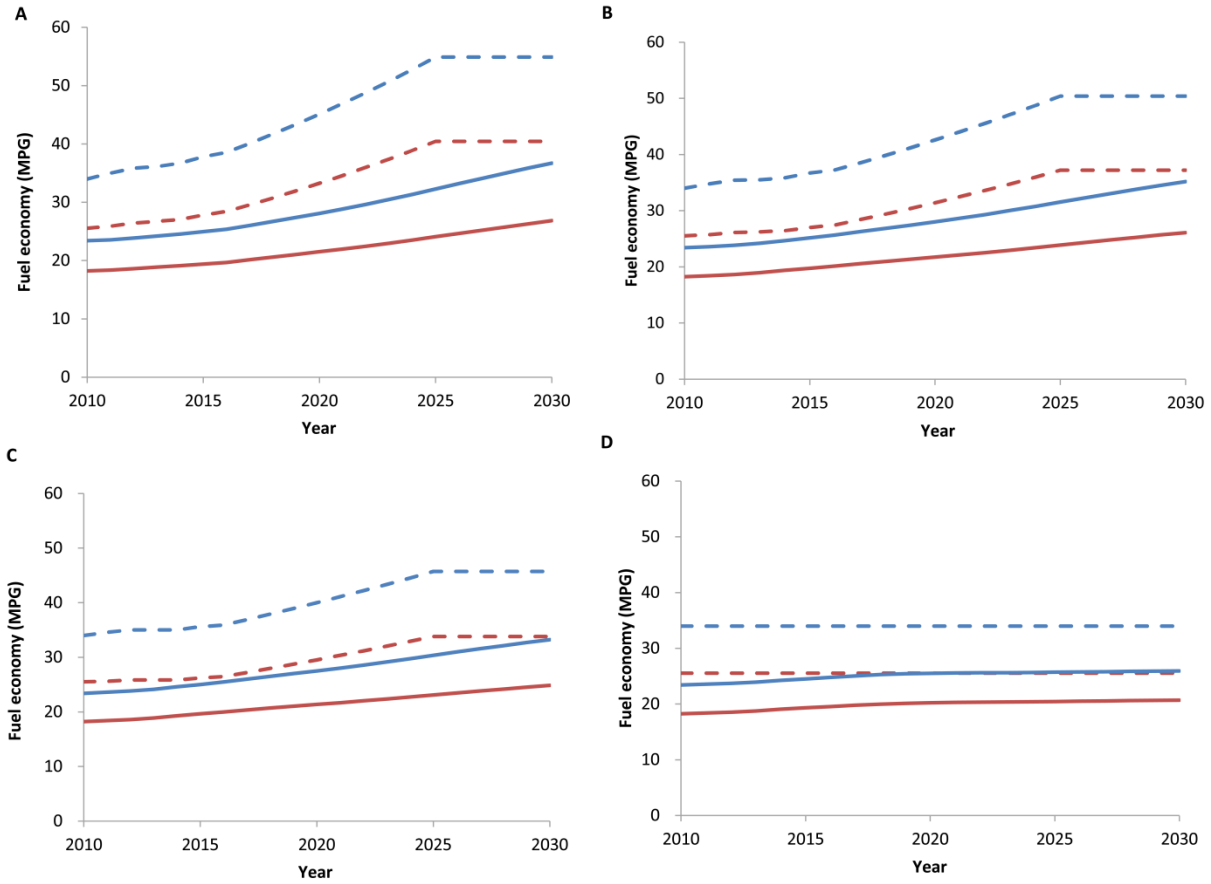
In the sensitivity study, the  $\Delta$ TCE for CVs of the case with the lowest GHG emissions (EV 100%, uncontrolled charging, unlinking, 33% RES) is \$235, but the  $\Delta$ TCE for EVs ranges from -\$140 to \$626/vehicle-year (average \$175/vehicle-year). The  $\Delta$ TCEs of this case under standard assumptions (\$4/gallon gasoline, ANL values for EV prices, 9:1 BEV to PHEV) range from -\$20 to \$993/vehicle-year (average \$273/vehicle-year) for CVs and from -\$156 to \$292/vehicle-year (average \$12/vehicle-year) for EVs. The  $\Delta$ TCE of the controlled version of the above case ranges from \$98 to \$457/vehicle-year (average \$993/vehicle-year) for CVs and from -\$109 to \$292/vehicle-year (average \$53/vehicle-year) for EVs.

We also performed a sensitivity analysis to test the impact of natural gas prices on  $\Delta TCE$ . For 2030, AEO price projections vary by region, from 5.81 to 7.14 \$/mmbtu (2009\$) for the six regions. From January 2002 to August 2012, the highest annual United States-average electric-sector natural gas price was 8.87 \$/mmbtu (2009\$) in 2008. For September 2011 to August 2012, electric-sector natural gas prices averaged 3.35 \$/mmbtu (2009\$). At \$3.43/mmbtu,  $\Delta TCE$  was \$41/vehicle-year lower than the base case natural gas price of \$6.45/mmbtu. Thus, the  $\Delta TCE$  values are largely insensitive to variations in natural gas prices.

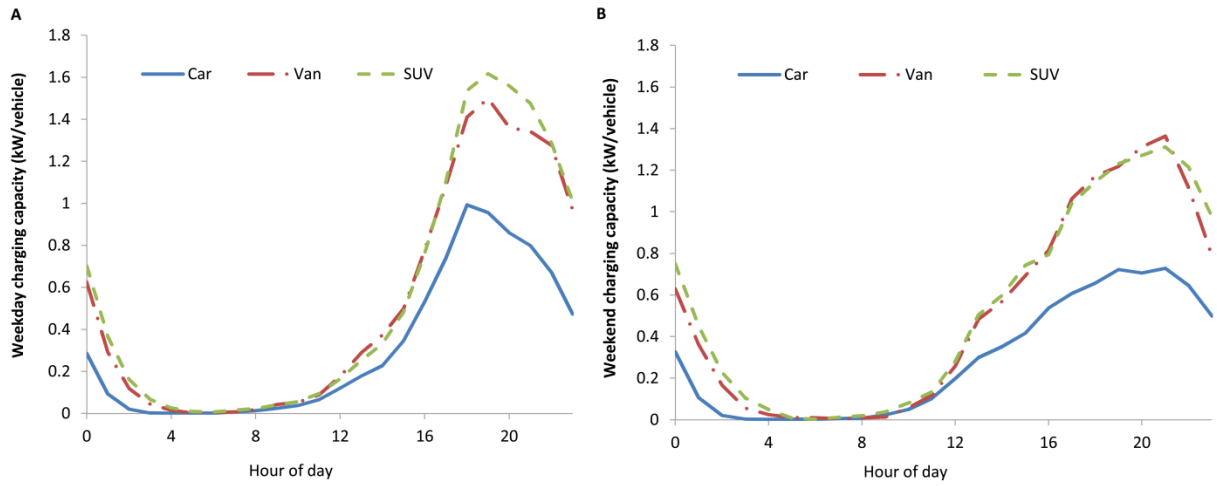
Under all scenarios, it is possible to offset higher efficiencies by driving more, thus eroding some of the benefits we have demonstrated.



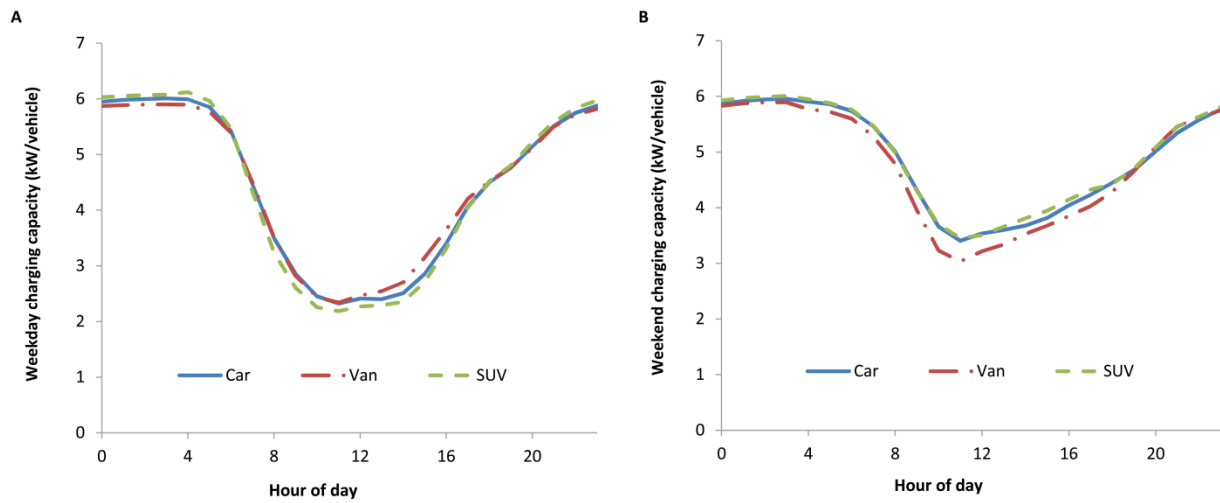
**Fig. S.1.** Projected number of total light-duty vehicles (except pickup trucks) and electric vehicles in the Eastern Interconnection



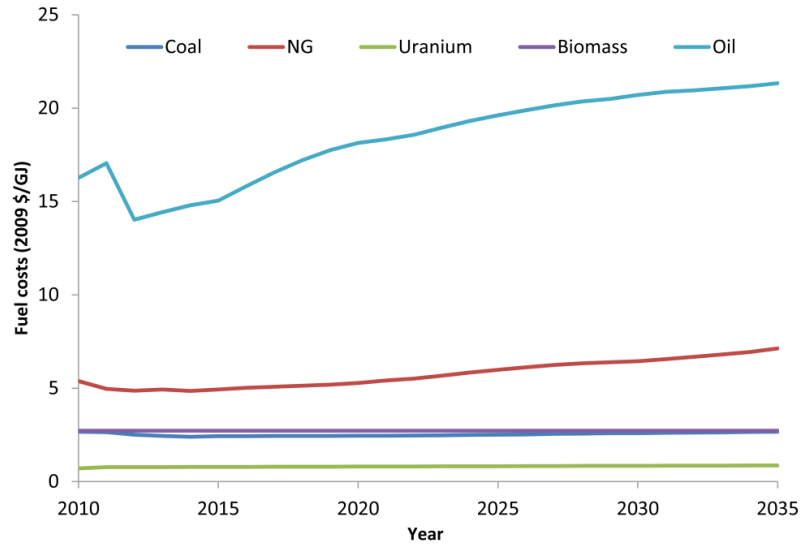
**Fig. S.2.** Projection of the fuel economy of new conventional vehicles and their stock, (A) Reference scenario, (B) EV 10% linked, (C) EV 20% linked, and (D) EV 100% linked. Blue is for light-duty car and red is for light-duty truck. Solid is for vehicle stock and dashed is for new vehicle. All unlinked cases are the same as the reference scenario (A).



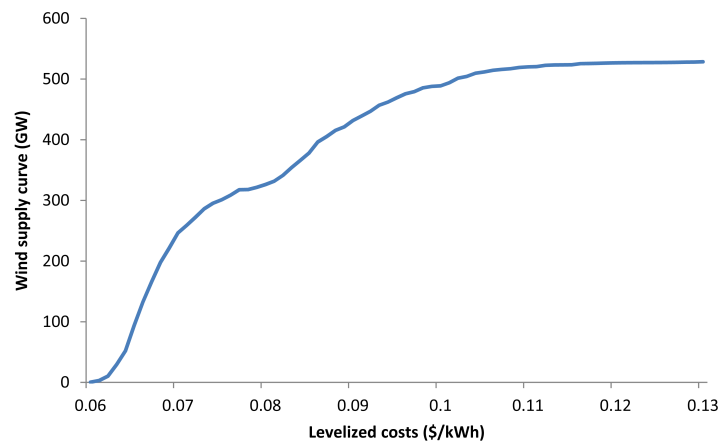
**Fig. S.3.** Average charging profiles per vehicle under uncontrolled charging schemes, for (A) weekdays and (B) weekend days.



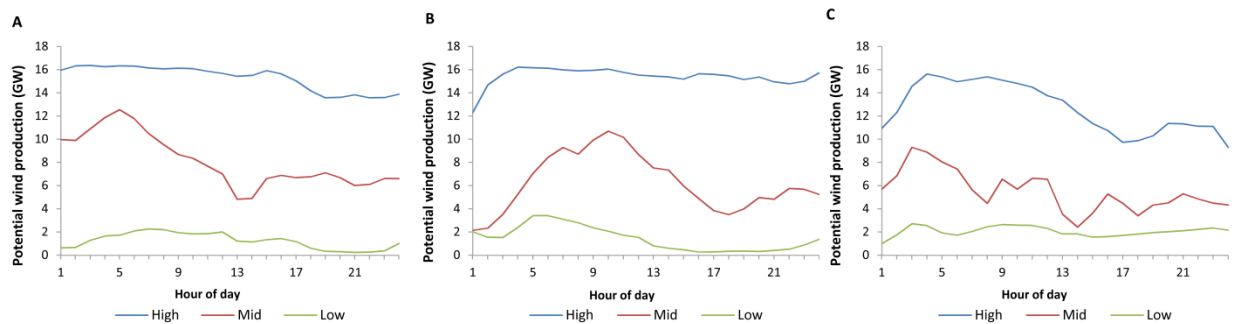
**Fig. S.4.** Average capacity profiles per vehicle under controlled charging for (A) weekday and (B) weekend days, assuming a 6.6 kW charger.



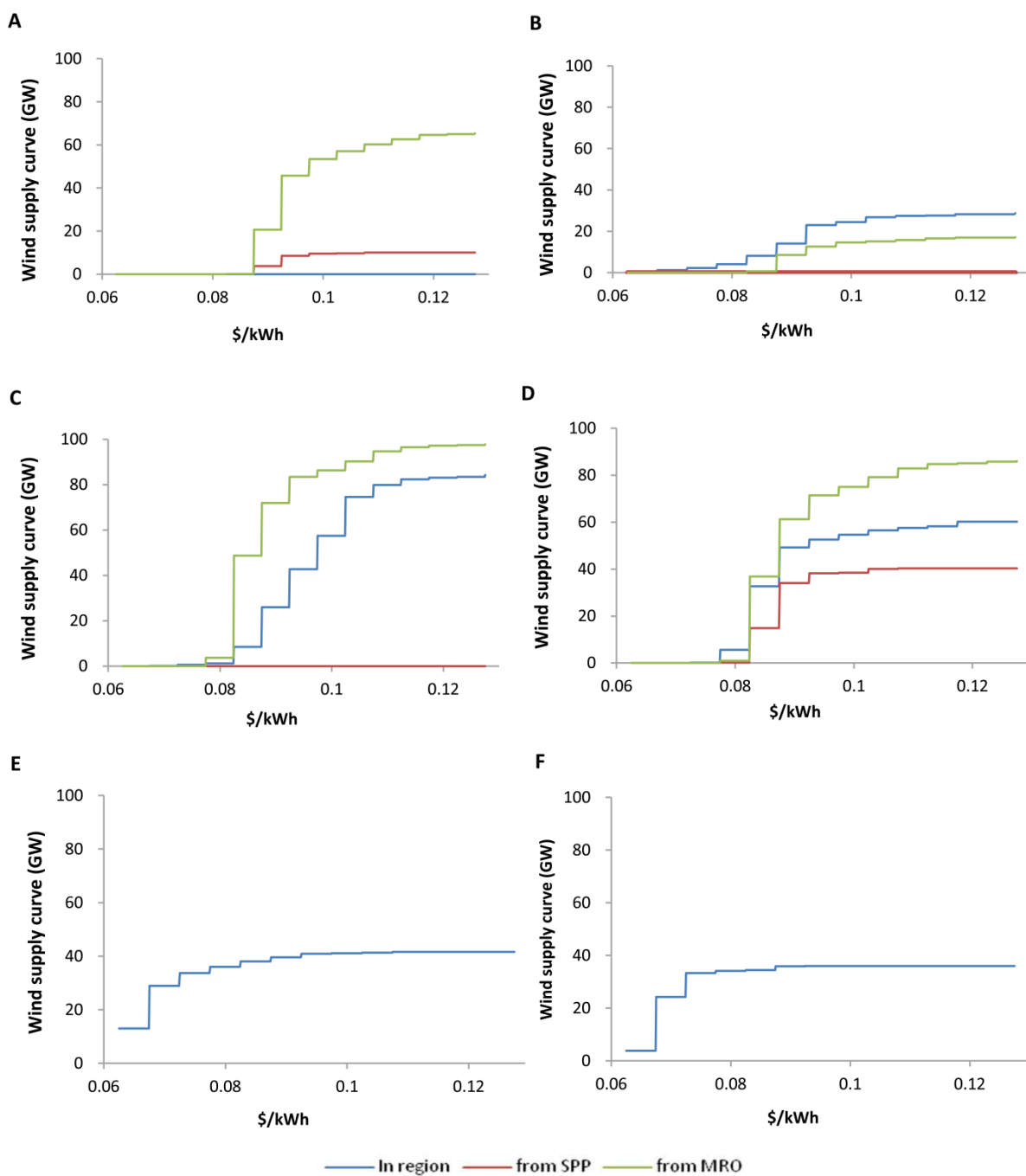
**Fig. S.5.** Assumed fuel costs for CP model in SERC



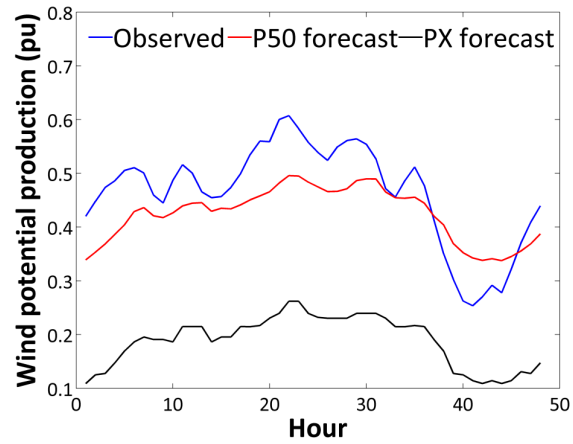
**Fig. S.6.** Wind power supply curve in the Eastern Interconnection



**Fig. S.7.** Onshore wind power production profiles in SERC for (A) winter, (B) intermediate, and (C) summer seasons



**Fig. S.8.** Wind power supply curves in (A) FRCC, (B) NPCC, (C) RFC, (D) SERC, (E) MRO, and (F) SPP, including generation and transmission costs



**Fig. S.9.** Observed, P50 day-ahead forecast, and P99 day-ahead forecast wind potential production for a 2-day period

Energy Intensity (Wh/mi) - Average Values		2010	2015	2030	2045
<b>EV100 Energy Intensity Mapped to NHTS Vehicle Type</b>	<i>Automobile/car/station wagon</i>	242	232	199	191
	<i>Van</i>	368	347	306	291
	<i>Sports Utility Vehicle</i>	401	376	329	315
	<i>Pickup Truck</i>	432	403	353	340
<b>PHEV 40 Energy Intensity Mapped to NHTS Vehicle Type</b>	<i>Automobile/car/station wagon</i>	258	247	226	217
	<i>Van</i>	374	356	330	314
	<i>Sports Utility Vehicle</i>	403	382	351	338
	<i>Pickup Truck</i>	431	408	374	362

**Table S.1.** Energy Intensity of EVs in charge depleting mode for vehicle types in NHTS

	Capital Cost Data (M\$/MW)	Fixed O&M Cost (\$/MW)	Variable O&M Cost (\$/MWh)	Heat rate (Btu/kWh)	Maximum Annual Capacity Factor	Emissions Rate (lb CO <sub>2</sub> /MWh)
Pulverized Coal (PC)	~*	30000	4.5	10200	0.8	2120
Scrubbed Coal (SCPC)	2.753	28910	5.09	9200	0.8	1890
Integrated Coal-Gasification Combined Cycle (IGCC)	3.008	40597	3.07	8765	0.8	1680
IGCC w/ CCS	4.294	48423	4.66	10781	0.8	180
Conventional Gas/Oil Comb Cycle (CC)	1.116	13105	2.17	7196	0.85	1023
Advanced Gas/Oil Comb Cycle	1.069	12283	2.10	6752	0.85	930
Advanced CC w/CCS	2.049	20899	3.09	8613	0.85	100
Conventional Combustion Turbine (CT)	0.778	12714	3.75	10788	0.85	930
Advanced CT	0.735	11061	3.33	9289	0.85	837
Oil	~*	0	0.00	10000	**	3900
Advanced Nuclear	4.994	94525	0.52	7930	0.9	0
Pumped Storage	*	0	0.00	0	**	0
Biomass	4.278	67669	7.05	9451	0.85	0
Hydropower	2.675	14306	2.56	0	**	0
Wind Onshore	2.358	31816	0.0	0	**	0
Wind Offshore	4.483	89267	0.0	0	**	0
Solar Thermal	5.617	59617	0.0	0	**	0
Photovoltaic	6.883	12262	0.0	0.0	**	0
Others (Municipal etc)	~*	0.00	0.00	0.00	**	0

**Table S.2.** Generator parameters by technology for CP model. \*Corresponding technologies are not allowed to expand, so the parameters are not specified. \*\*The capacity factors differ by region.

	Investment Factor
Scrubbed Coal (SCPC)	1.29
Integrated Coal-Gasification Combined Cycle (IGCC) and IGCC w/CCS	1.22
All natural gas technologies	1.16
Advanced Nuclear	1.47
Biomass	1.22
Hydropower, Onshore Wind, Offshore Wind	1.25
Solar Thermal and Photovoltaic	1.14

**Table S.3.** Investment factors by generation technology.

	PC	SCPC	IGCC	IGCC w/ CCS	Conv. CC	Adv. CC	Adv. CC w/ CCS	Conv. CT	Adv. CT
Nameplate Capacity (MW)	1000	1000	1000	1000	500	500	500	250	250
Min power (pu)	0.39	0.39	0.39	0.39	0.43	0.43	0.43	0.34	0.34
O&M Cost (\$/MWh)	4.50	5.02	3.20	4.86	2.26	2.18	3.22	3.91	3.47
Max CF over UC period	1	1	1	1	1	1	1	1	1
Cycling fixed costs - (\$ per nameplate MW)	383	383	383	383	134	134	134	23	23
Cycling fuel burn - (MMBTU per nameplate MW)	0	0	0	0	0	0	0	0	0

**Table S.4.** Generator parameters by technology for the UC and ED models, part I of II

	Oil	Adv. Nuclear	Pumped Storage	Biomass	Hydro	Wind Onshore	Wind Offshore	Solar Thermal	PV	Others *
Nameplate capacity (MW)	500	2000	**	200	**	**	**	**	**	100
Min power (pu)	0.3	0.89	0	0.3	0	0	0	0	0	0.3
Fuel type	5	3	7	4	7	6	6	6	6	7
Max CF over UC period	1	1	0.016	1	0.34	1	1	1	1	1
Cycling fixed costs - (\$ per nameplate MW per cycle)	258.5	1.92	1	258.5	1	1	1	1	1	258.5
Cycling fuel burn - (MMBTU per nameplate MW per cycle)	0	56.98	0	0	0	0	0	0	0	0

**Table S.5.** Generator parameters by technology for the UC and ED models, part II of II.

\*Municipal etc., \*\* Case Specific

	MO	IL	NC	VA	SERC RES
2009	0	2%	0	0	0.32%
2010	0	4%	0	4%	0.87%
2011	0	5%	0	4%	1.03%
2012	4%	6%	3%	4%	1.78%
2013	4%	7%	3%	4%	1.94%
2014	4%	8%	3%	4%	2.10%
2015	8%	9%	6%	7%	3.02%
2016	8%	10%	6%	7%	3.18%
2017	8%	11.5%	6%	7%	3.42%
2018	8%	13%	10%	7%	4.05%
2019	8%	14.5%	10%	7%	4.29%
2020	11%	16.0%	10%	7%	4.75%
2021	11%	18%	12.5%	7%	5.23%
2022	11%	19.0%	12.5%	12%	5.76%
2023	11%	20.5%	12.5%	12%	6.00%
2024	11%	22.0%	12.5%	12%	6.24%
2025	11%	24%	12.5%	15%	6.66%
2026	11%	25.0%	12.5%	15%	6.90%
2027	11%	25.0%	12.5%	15%	6.90%
2028	11%	25.0%	12.5%	15%	6.90%
2029	11%	25.0%	12.5%	15%	6.90%
2030	11%	25.0%	12.5%	15%	6.90%
Share of SERC	7.3%	16.0%	9.8%	5.8%	

**Table S.6.** State-level RES and region-wide RES in SERC

		Source Region	
		SPP	MRO
Destination Region	FRCC	23	25
	SERC	18	19
	RFC	21	18
	NPCC	27	23

**Table S.7.** Inter-regional transmission costs (\$/MWh)

Eastern Interconnection Regions	Available Capacity for Biomass Plants (MW)
FRCC	1447
MRC	1593
NPCC	1461
RFC	1963
SERC	8054
SPP	913
Eastern Interconnection Total	15429

**Table S.8.** Available capacity for biomass plants (MW)

Vehicle Type	MY2010 Vehicle Purchasing Cost
Compact Car	\$15633
Midsized Car	\$18019
Small SUV	\$24229*
Midsized SUV	\$24229*

**Table S.9.** MY2010 vehicle purchasing costs for each class. \*Small and Midsized SUV not separated.

Vehicle Type	Incremental Cost (\$)		
	2010	2015	2030
Compact	-38	750	1100
Midsized	-40	802	1130
Small SUV	99	896	494
Midsized SUV	-108	681	1170
Pickup	-63	697	1047

**Table S.10.** Estimated best-in-class incremental costs of spark ignition vehicles (CV)

Vehicle Type	Fuel Economy (mpg)		
	2010	2015	2030
Compact	40.0	47.6	57.1
Midsized	37.6	41.3	50.4
Small SUV	33.6	39.1	48.8
Midsized SUV	28.9	33.8	40.6
Pickup	24.0	28.3	35.0

**Table S.11.** Estimated fuel economy of best-in-class spark ignition vehicles (CV)

Vehicle Type	Incremental Cost (\$)		
	2010	2015	2030
Compact	24608	13162	6728
Midsized	26877	14276	7205
Small SUV	30883	16123	7839
Midsized SUV	37317	19402	9530
Pickup	45434	23582	11533

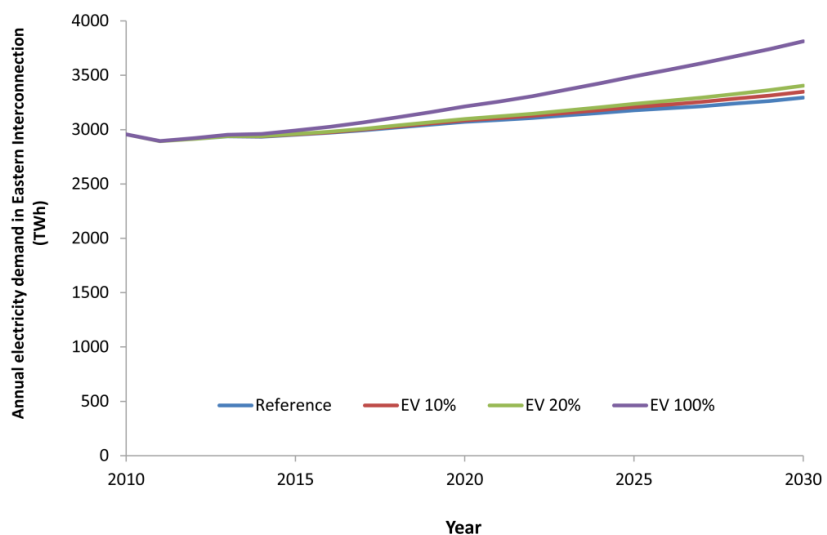
**Table S.12.** Adjusted incremental purchase costs of 100-mile range EV vehicles using 2010 energy intensities

Vehicle Type	Incremental Cost (\$)		
	2010	2015	2030
Compact	16137	9984	6943
Midsized	17673	10802	7369
Small SUV	19106	11301	7414
Midsized SUV	22515	13089	8507
Pickup	26529	15227	9722

**Table S.13.** Adjusted incremental purchase costs of 40-mile-electric-range PHEV vehicles using 2010 energy intensities

## Results

### 21. Electricity and Gasoline Demand



**Fig. S.10.** Effects of EV adoption on electricity demand in the Eastern Interconnection, showing the reference case of no EVs (blue) and 10% (red), 20% (green) and 100% (violet) market share of EVs.

## 22. Changes in electrical generating capacity and electricity sources

### 22.1. Changes in electricity generating capacity

Case	Coal	NG	Hydropower	Biomass	Wind
Reference 33% RES	-19.71	13.68	0.00	3.69	200.67
EV 10% Uncontrolled 10% RES	-1.46	10.19	0.71	0.02	1.63
EV 10% Controlled 10% RES	4.01	-3.92	0.00	0.02	1.63
EV 10% Uncontrolled 33% RES	-20.34	23.94	0.00	3.69	205.34
EV 10% Controlled 33% RES	-14.15	10.88	0.00	3.69	205.52
EV 20% Uncontrolled 10% RES	3.09	14.47	0.71	0.18	2.06
EV 20% Controlled 10% RES	2.67	-4.59	0.00	0.18	2.06
EV 20% Uncontrolled 33% RES	-20.34	23.94	0.00	3.69	205.34
EV 20% Controlled 33% RES	-14.15	10.88	0.00	3.69	205.52
EV 100% Uncontrolled 10% RES	45.44	138.60	0.71	0.24	11.47
EV 100% Controlled 10% RES	16.73	-7.15	0.00	0.24	11.32
EV 100% Uncontrolled 33% RES	-19.02	199.57	0.00	3.69	242.42
EV 100% Controlled 33% RES	-8.35	5.20	0.00	1.79	245.92

**Table S.14.** Change in electricity generating capacities (GW) due to EV charging demand in 2030 relative to

reference case (10% RES and no EVs) in the Eastern Interconnection.

### 22.2. Changes in electricity sources

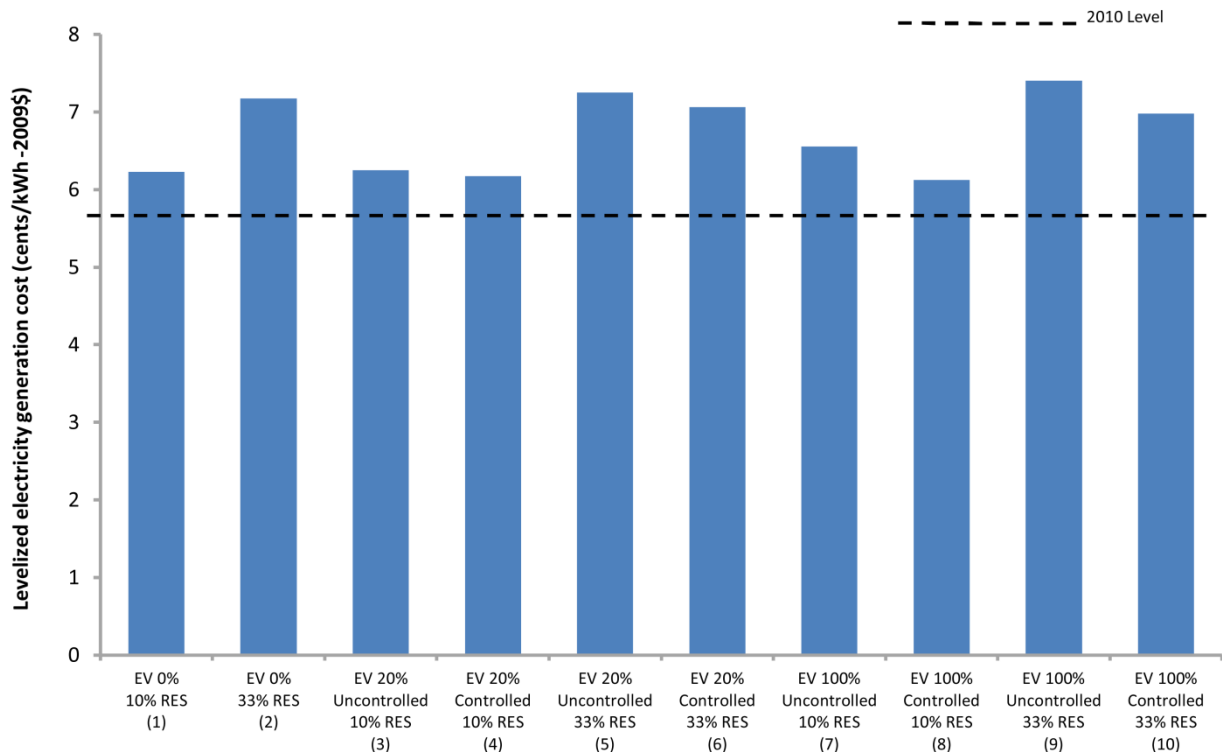
Case	Coal	NG	Hydropower	Biomass	Wind
Reference 33% RES	-402.06	-401.26	0.00	27.45	762.66
EV 10% Uncontrolled 10% RES	-9.73	57.87	2.11	0.16	6.74
EV 10% Controlled 10% RES	28.12	22.42	0.00	0.16	6.74
EV 10% Uncontrolled 33% RES	-398.10	-367.99	0.00	27.45	781.60
EV 10% Controlled 33% RES	-340.13	-411.56	0.00	27.45	781.60
EV 20% Uncontrolled 10% RES	22.17	64.88	2.11	1.37	8.52
EV 20% Controlled 10% RES	18.74	70.58	0.00	1.37	8.52
EV 20% Uncontrolled 33% RES	-390.97	-347.40	0.00	27.24	795.59
EV 20% Controlled 33% RES	-318.07	-405.61	0.00	24.82	798.01
EV 100% Uncontrolled 10% RES	319.36	83.79	2.11	1.81	45.62
EV 100% Controlled 10% RES	128.74	298.55	0.00	1.81	45.99
EV 100% Uncontrolled 33% RES	-359.82	-157.82	0.00	27.45	919.45
EV 100% Controlled 33% RES	-198.98	-273.20	0.00	13.31	933.59

**Table S.15.** Change in electricity sources (TWh) due to EV charging demand in 2030 relative to reference case

(10% RES and no EVs) in the Eastern Interconnection.

### 23. Levelized electricity generation cost

Fig. S.11 shows the levelized wholesale electricity costs under the 0%, 20% and 100% EV scenarios, and Table S.16 is corresponding table. In all cases with EVs, controllability (bars 4, 6, 8, and 10) reduces the cost of electricity relative to an uncontrolled case with the same EV adoption and RES level (bars 3, 5, 7, and 9). Under the 10% RES, the costs of electricity with controlled charging of EVs (bars 4 and 8) are lower than without EVs (bar 1). However, the costs of electricity with EVs and uncontrolled charging are higher than without EVs (bars 3, 5, 7, and 9 vs. bar 1). Controlled charging enables the system operator to moderate peak demand and increase the utilization of wind energy and lower-cost baseload power plants. The benefits increase with more renewable adoption, so realizing a 33% RES with controlled EVs at 100% market share results in a cost of electricity 2.7% lower than a 33% RES with no EVs (bar 10 vs bar 2).



**Fig. S.11.** Levelized electricity generation cost in the Eastern Interconnection in 2030, for 0%, 20% and 100% EV adoption scenarios.

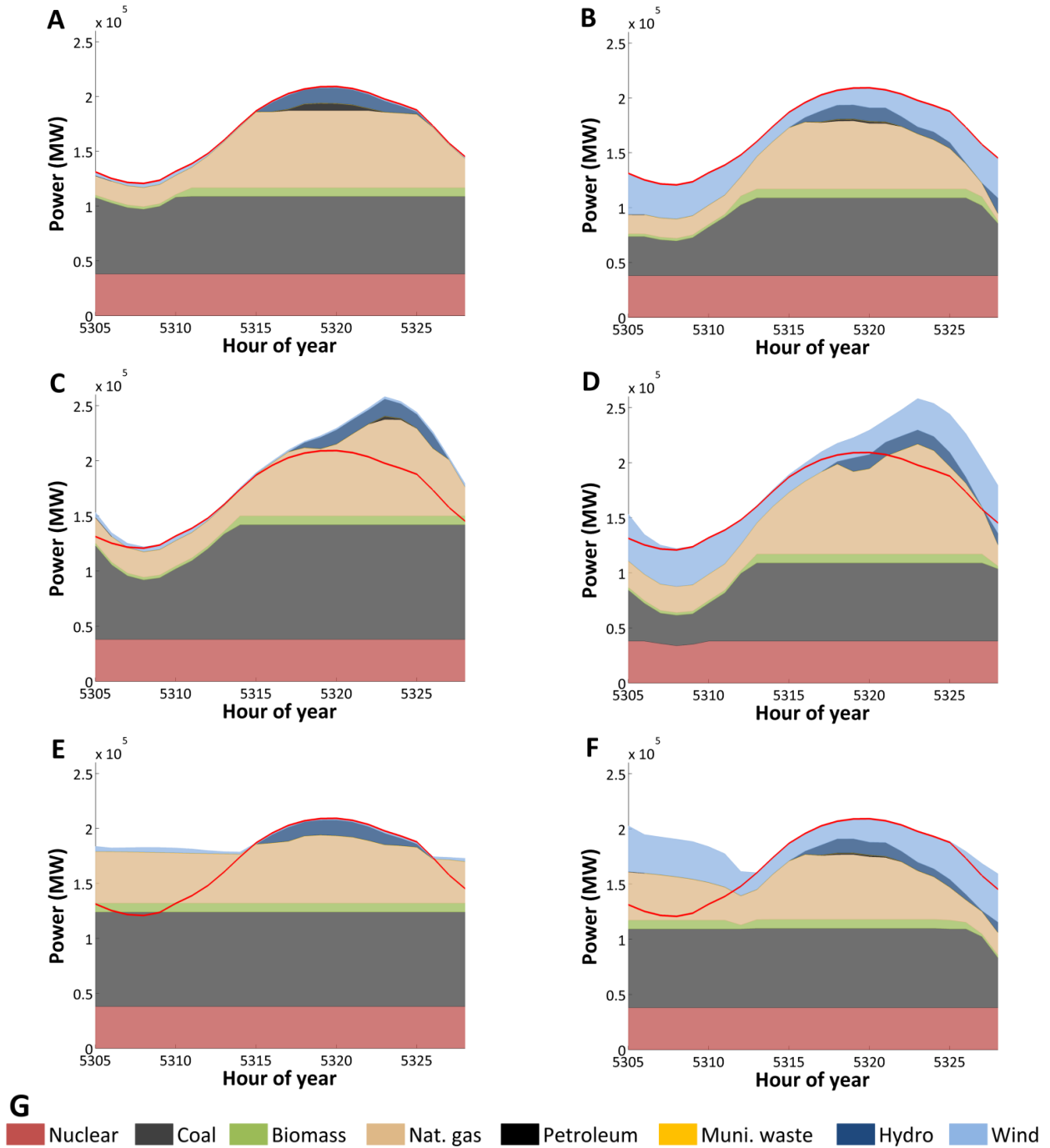
RES Level	Reference		EV 10%	EV 20%	EV 100%
10% RES	6.23	EV Uncontrolled	6.24	6.25	6.56
		EV Controlled	6.19	6.17	6.12
33% RES	7.17	EV Uncontrolled	7.17	7.25	7.40
		EV Controlled	7.13	7.06	6.98

**Table S.16.** Levelized electricity generation cost (cents/kWh) in the Eastern Interconnection in 2030

The costs above do not include the electric system savings from improved wind energy management and reduced demand volatility. The system operation impacts of controlled charging are quantified by simulating the 2030 capacities in a day-ahead unit-commitment model and an hourly economic dispatch model. For the case with 100% EVs and 33% RES, wind curtailment is 7% of potential production under the uncontrolled case and 1% under the controlled case. The average cycling costs are 0.07 cents/kWh for the uncontrolled case and 0.03 cents per kWh for the controlled case. These cost savings slightly increase the cost benefits of controlled charging relative to uncontrolled charging shown in Fig. S.11.

#### **24. Sample simulation results of electric power systems**

The electric power systems for six reliability regions have been simulated in the CP, UC, and ED models. Fig. S.12 shows the final generation dispatch, as calculated by the ED model, for the day containing the SERC peak hourly load.



**Fig. S.12.** Effect of different EV charging schemes and renewable electricity standard levels on electricity generation with 100% EV adoption, for the SERC region. The red line shows the non-EV load; the EV load is above the red line. (A) Reference with 10% RES. (B) Reference with 33% RES. (C) EV 100% Uncontrolled charging scheme with 10% RES. (D) EV 100% Uncontrolled charging scheme with 33% RES. (E). EV 100% Controlled charging scheme with 10% RES. (F) EV 100% Controlled charging scheme with 33% RES.

## 25. Greenhouse gas emissions

### 25.1. Total system GHG emissions

Table S.17 shows total GHG emissions from electricity generation, light-duty fleet gasoline consumption, with and without CAFE linkage, and light-duty fleet manufacturing.

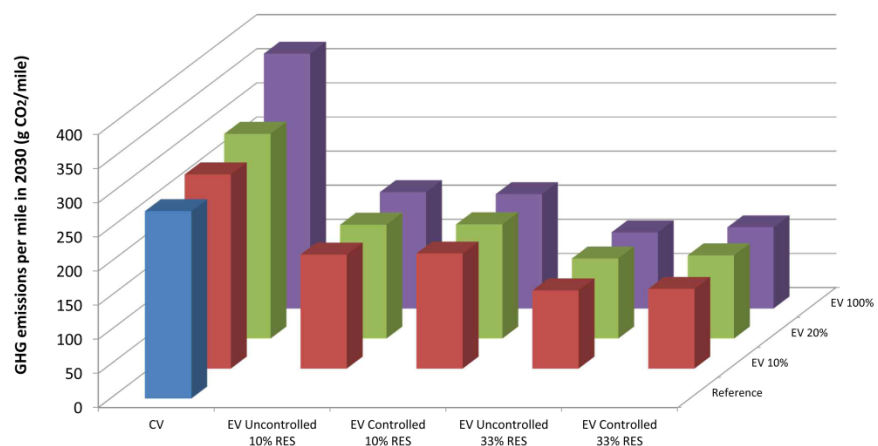
Case	Electricity (non-EV)	Electricity (EV)	Gasoline	Gasoline from CAFE linkage	Vehicle Production	Total
Reference 10% RES	1870	0	848	0	98	2816
Reference 33% RES	1265	0	848	0	98	2212
EV 10% Uncontrolled 10% RES	1846	31	797	27	108	2809
EV 10% Controlled 10% RES	1864	31	797	27	108	2827
EV 10% Uncontrolled 33% RES	1265	21	797	27	108	2218
EV 10% Controlled 33% RES	1290	22	797	27	108	2244
EV 20% Uncontrolled 10% RES	1845	62	745	65	118	2836
EV 20% Controlled 10% RES	1850	62	745	65	118	2841
EV 20% Uncontrolled 33% RES	1298	43	745	65	118	2271
EV 20% Controlled 33% RES	1349	45	745	65	118	2323
EV 100% Uncontrolled 10% RES	1885	297	349	118	195	2844
EV 100% Controlled 10% RES	1855	293	349	118	195	2809
EV 100% Uncontrolled 33% RES	1236	195	349	118	195	2092
EV 100% Controlled 33% RES	1316	208	349	118	195	2185

**Table S.17.** Total GHG emissions from electricity generation, vehicle gasoline consumption, and vehicle production in the United States Eastern Interconnection in 2030 (Million ton CO<sub>2</sub><sup>16</sup>)

### 25.2. Vehicle GHG emissions

The greenhouse gas (GHG) emissions per mile of EV travel in the charge-depleting mode can be calculated on an average basis. Average GHG emissions are the total greenhouse gas emissions emitted by the regional electricity system, divided by the total electricity produced by the regional electricity system, times the electricity consumed per mile. Fig. S.13 shows the greenhouse gas emissions per mile for CVs and EVs, for the four EV adoption levels, the two RES levels, and the two charging methods considered. The GHG emissions from EVs are less than from CVs in every case.

<sup>16</sup> We use CO<sub>2</sub> emissions factor for electricity generation sector as shown in Table S.2. However, CO<sub>2</sub>-eq emission factors are used for the GHG emissions for gasoline consumption and vehicle production as described in section 16.



**Fig. S.13.** GHG emissions per mile in 2030 under different charging methods, RES levels, and EV adoption levels (g CO<sub>2</sub>/mile).

	Reference	EV 10%	EV 20%	EV 100%
CV	275	284*	300*	374*
EV Uncontrolled 10% RES		167	167	170
EV Controlled 10% RES		168	167	168
EV Uncontrolled 33% RES		114	117	112
EV Controlled 33% RES		117	122	119

**Table S.18.** GHG emissions per mile in 2030 under different charging methods, RES levels, and EV adoption levels (g CO<sub>2</sub>/mile). \*The values for CV are in CAFE linked cases. In CAFE unlinked cases, the values are the same as the reference case.

## 26. Total consumer expenditure

	CV Linked	EV Linked	Linked Average	CV Unlinked	EV Unlinked	Unlinked Average
EV 10% uncontrolled 10% RES	137	-126	102	2	-165	-21
EV 10% controlled 10% RES	129	-136	94	-6	-175	-29
EV 10% uncontrolled 33% RES	301	67	270	165	28	147
EV 10% controlled 33% RES	294	59	263	158	20	140
EV 20% uncontrolled 10% RES	313	-91	205	4	-162	-40
EV 20% controlled 10% RES	299	-108	191	-10	-179	-55
EV 20% uncontrolled 33% RES	491	119	392	182	48	147
EV 20% controlled 33% RES	457	79	356	148	7	111
EV 100% uncontrolled 10% RES	-	100	100	-	-91	-91
EV 100% controlled 10% RES	-	0	0	-	-191	-191
EV 100% uncontrolled 33% RES	-	295	295	-	105	105
EV 100% controlled 33% RES	-	196	196	-	6	6

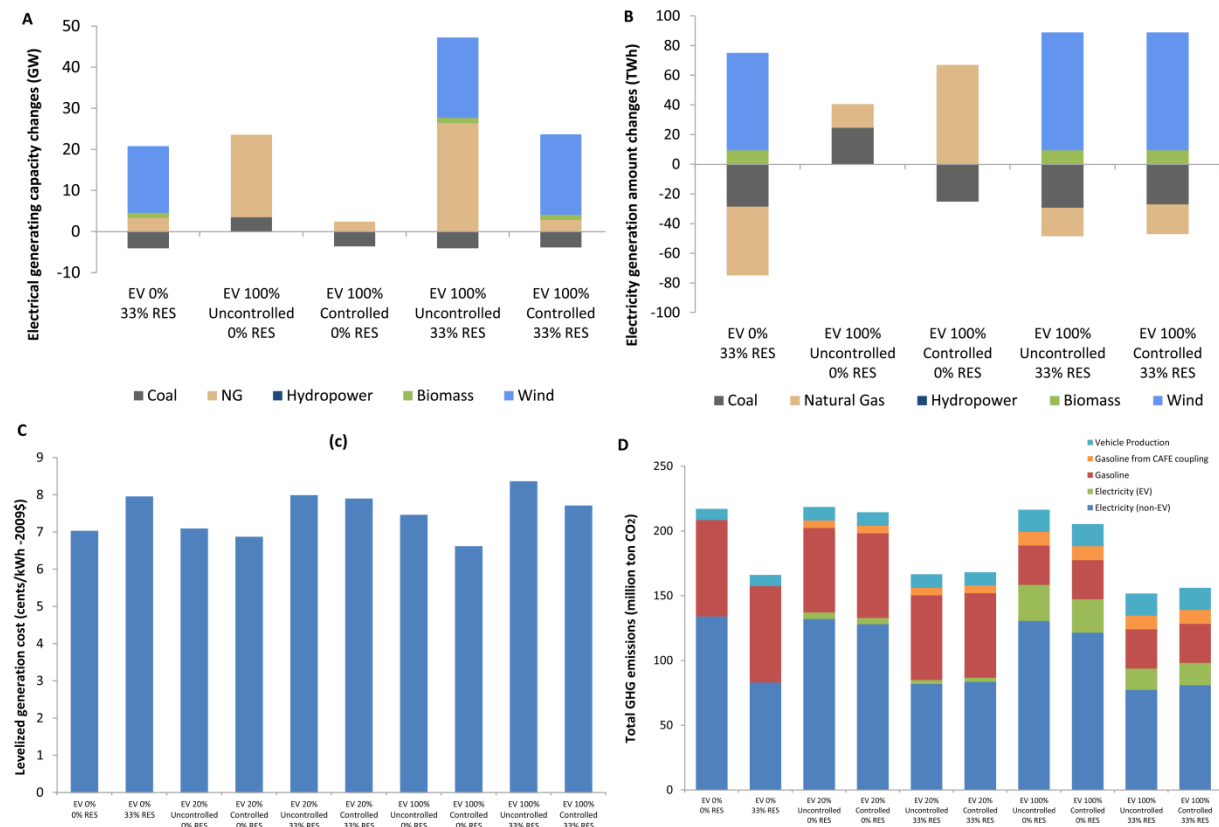
**Table S.19.**  $\Delta$  TCE in total consumer expenditure in 2030 over a 13-year vehicle life. A negative value means the vehicle in EV scenario has a lower TCE than CV in the reference case with no EVs (\$/vehicle-year).

## 27. Summary of regional results

The electricity generation system, the costs of electricity generation, and the renewable electricity standards differ among the regions. In the NPCC region, comprised of Maine, Vermont, New Hampshire, Massachusetts, New York, Connecticut and Rhode Island, natural gas is the primary source of electricity and the weighted-average RES will reach 25% by 2030, with the result that GHG emissions from electricity are less than those from light-duty vehicles. In the RFC region, comprised of Pennsylvania, New Jersey, Delaware, Maryland, West Virginia, Ohio, Indiana, Michigan, and the District of Columbia, the controlled case always produces more GHG emissions than the otherwise identical uncontrolled case.

## 28. Figures for regional results

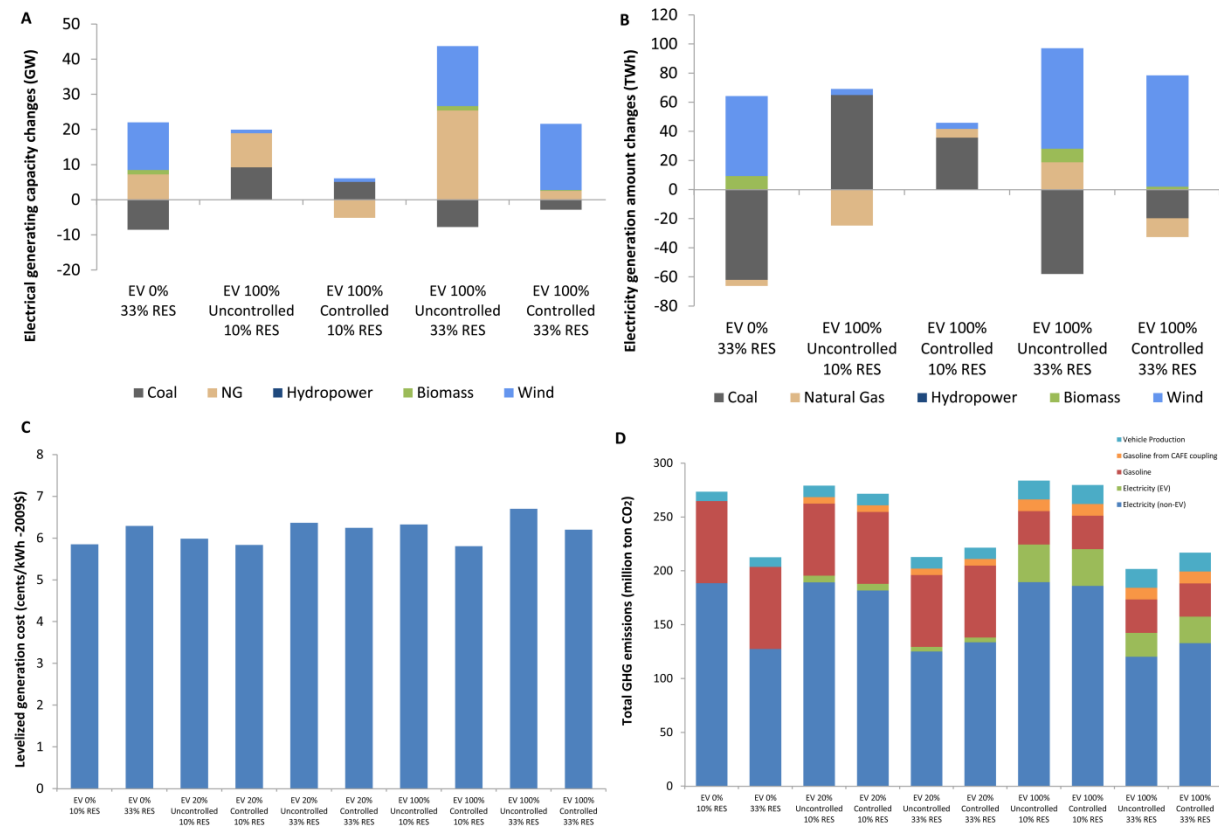
### 28.1. FRCC (Florida Reliability Coordinating Council)



**Fig. S.14.** Changes in (A) electrical generating capacity (B) generating sources, (C) electricity cost and (D)

greenhouse gas emissions in the FRCC region in 2030 due to EV charging demand for 100% EV market share by 2030. The baseline comparison is with 0% RES, as Florida currently has no RES.

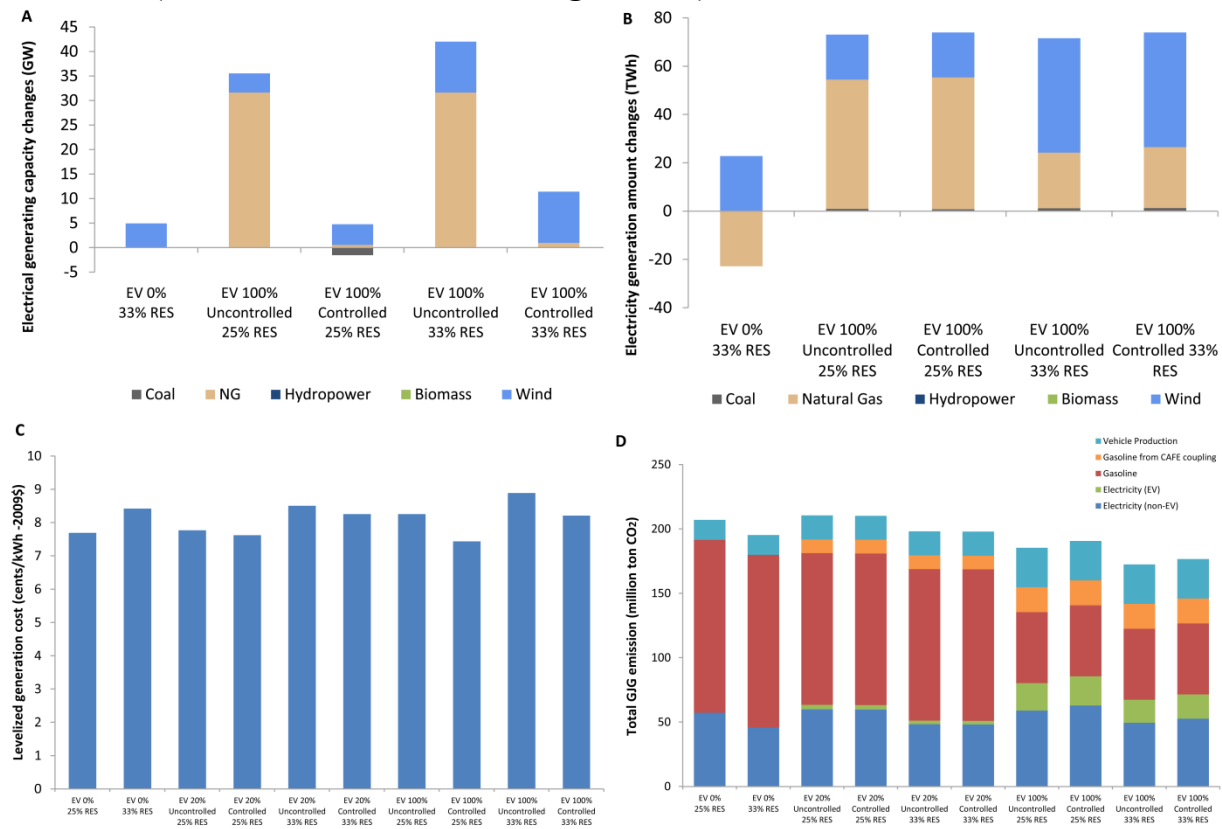
## 28.2. MRO (Midwest Reliability Organization)



**Fig. S.15.** Changes in (A) electrical generating capacity (B) generating sources, (C) electricity cost and (D)

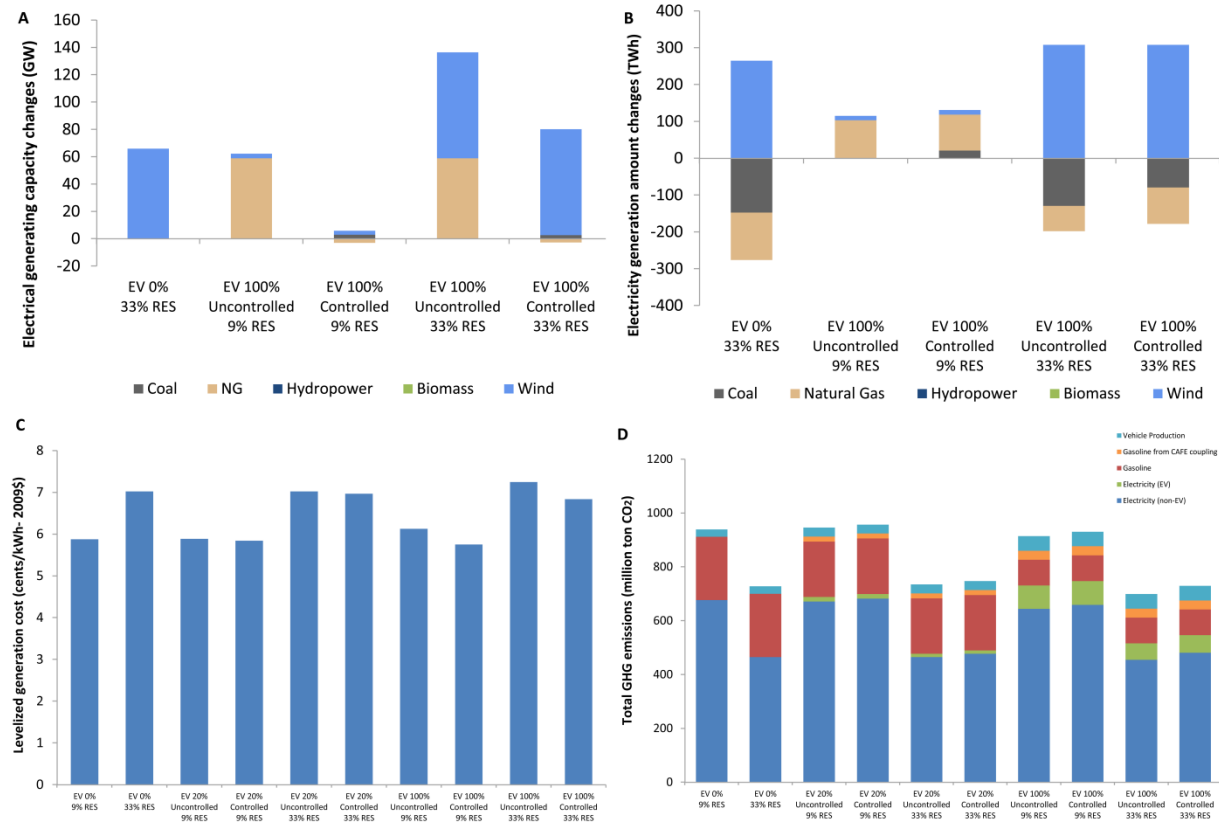
greenhouse gas emissions in the MRO region (MN, ND, NE, MT, SD, IA, and WI) in 2030 due to EV charging demand for 100% EV market share by 2030. The baseline 10% RES is the 2030 weighted average for the MRO region.

### 8.3. NPCC (Northeast Power Coordinating Council)



**Fig. S.16.** Changes in (A) electrical generating capacity (B) generating sources, (C) electricity cost and (D) greenhouse gas emissions in the NPCC region (ME, VT, NH, MA, NY, CT and RI) in 2030 due to EV charging demand for 100% EV market share by 2030. The baseline 2030 average RES is 25%.

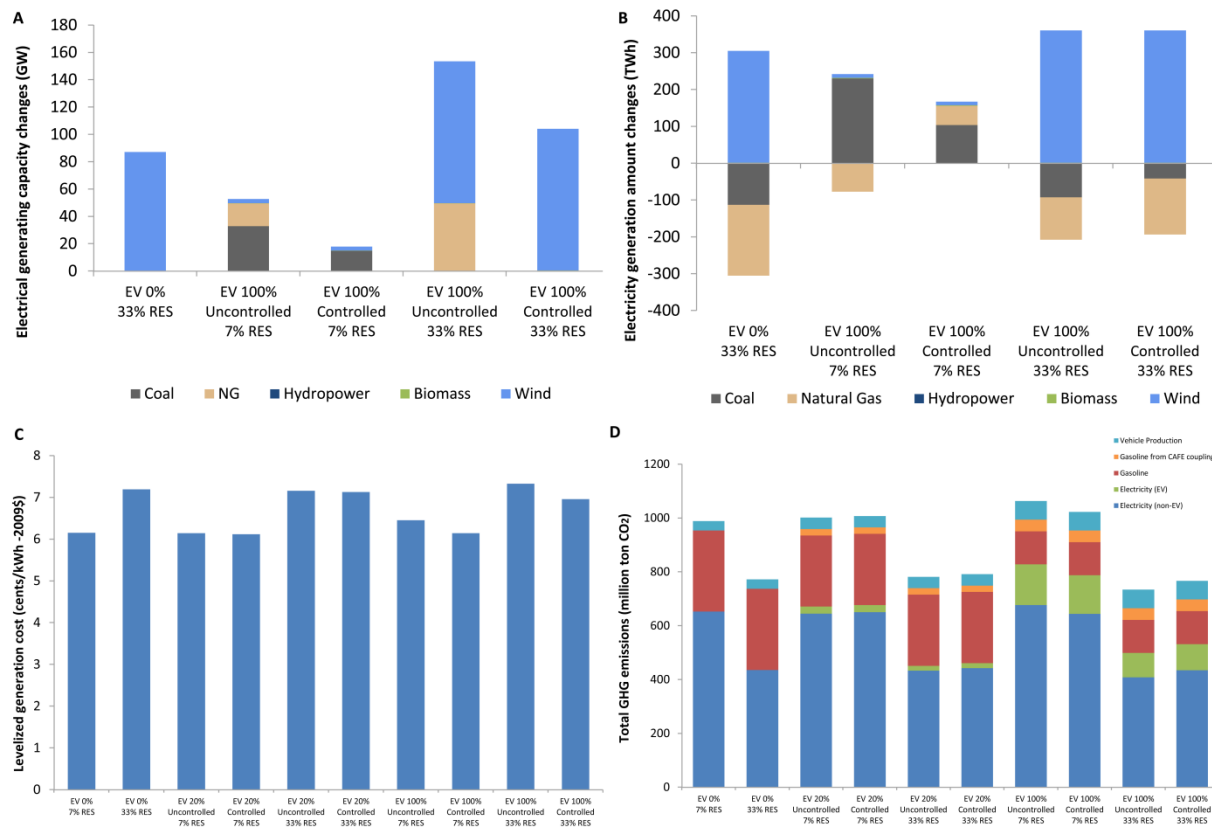
## 28.4. RFC (Reliability First Corporation)



**Fig. S.17.** Changes in (A) electrical generating capacity (B) generating sources, (C) electricity cost and (D)

greenhouse gas emissions in the RFC region (PA, NJ, DE, MD, WV, OH, IN, MI, DC) in 2030 due to EV charging demand for 100% EV market share by 2030. The 2030 baseline average RES is 9%.

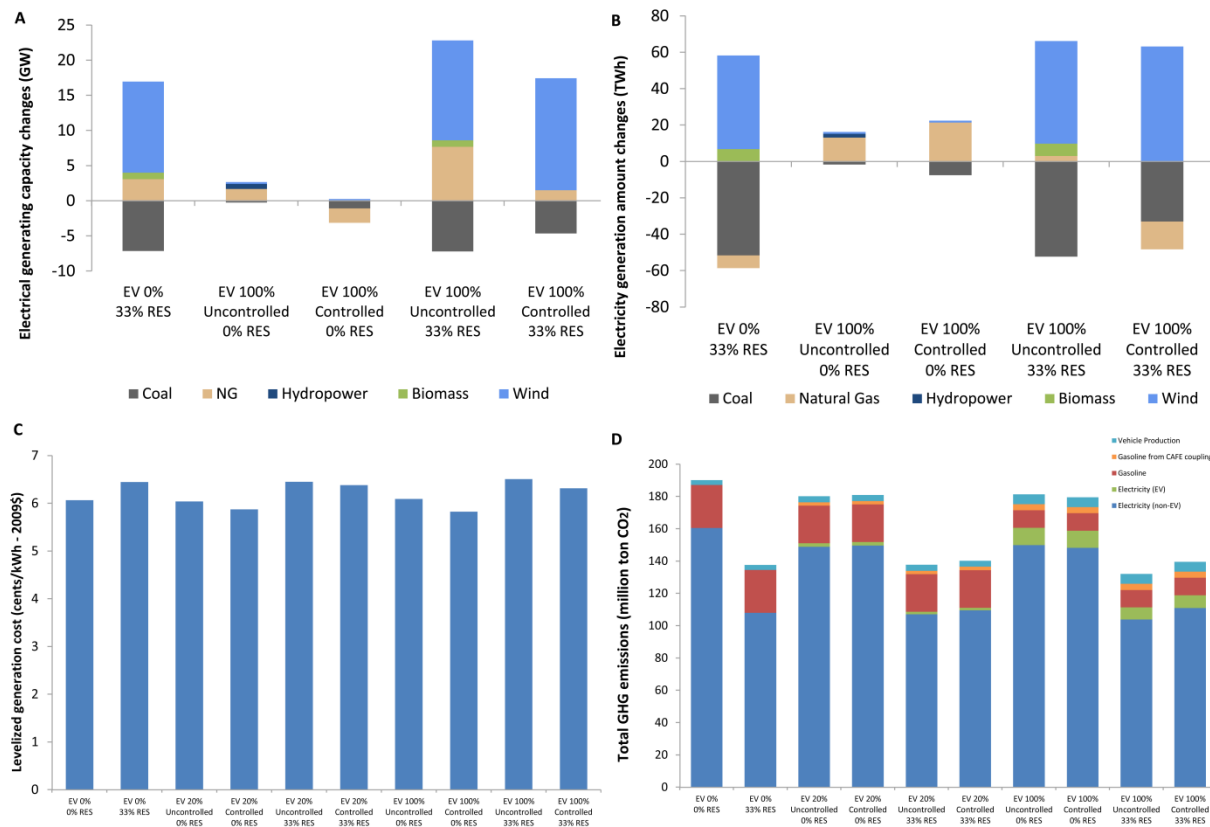
## 28.5. SERC (SERC Reliability Corporation)



**Fig. S.18.** Changes in (A) electrical generating capacity (B) generating sources, (C) electricity cost and (D)

greenhouse gas emissions in the SERC region (MO, IL, NC, VA, AL, TN, GA, SC, MS, KY, AR, LA, and western FL) in 2030 due to EV charging demand for 100% EV market share by 2030. The 2030 weighted average RES is 7%.

## 28.6. SPP (Southwest Power Pool)



**Fig. S.19.** Changes in (A) electrical generating capacity (B) generating sources, (C) electricity cost and (D)

greenhouse gas emissions in the SPP region (KS, OK, and portions of NM, TS, AK, LA, MI and NE) in 2030 due to

EV charging demand for 100% EV market share by 2030. The baseline RES is 0%.

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