AIR QUALITY IMPACTS OF ELECTRIC VEHICLE ADOPTION IN TEXAS

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ABSTRACT

Widespread adoption of plug-in electric vehicles (PEVs) may substantially reduce emissions of greenhouse gases while improving regional air quality, increasing energy security, and taking advantage of inexpensive solar power. However, outcomes depend heavily on the electricity generation process, power plant locations, and vehicle use decisions. This paper provides a clear methodology for predicting PEV emissions impacts by anticipating battery-charging decisions and power plant energy sources across Texas. Life-cycle impacts of vehicle production and use and Texans' exposure to emissions are also computed and monetized. This study reveals to what extent PEVs are more environmentally friendly, for most pollutant species, than conventional passenger cars in Texas, after recognizing the emissions and energy impacts of battery provision and other manufacturing processes. Results indicate that PEVs on today's grid can reduce GHGs, NO_x, $PM_{10,}$ and CO in urban areas, but generate significantly higher emissions of SO_2 than existing light-duty vehicles. Use of coal for electricity production is a primary concern for PEV growth, but the energy security benefits of electrified vehicle-miles endure.

As conventional vehicle emissions rates improve, it appears that the power grids must follow suit (by improving emissions technologies and/or shifting toward cleaner generation sources) to compete on an emissions-monetized basis with PEVs in many locations. Moreover, while PEV pollution impacts may shift to more remote (power-plant) locations, dense urban populations remain most strongly affected by local power plant emissions in many Texas locations.

BACKGROUND AND INTRODUCTION

Plug-in electric vehicles (PEVs) are becoming more popular in the United States and around the world. As of early 2013, the U.S. held an estimated 70,000 PEVs, nearly 40% of the world's total of over 180,000 (IEA 2013). Since PEVs were reintroduced more strongly into the passenger vehicle market in the early 21st century, researchers and policy makers have been considering the short- and long-term impacts of PEVs on energy, electricity and transportation infrastructure, and the environment. Much of the discussion includes uncertainty regarding consumer adoption and technological development of vehicles and energy infrastructure and whether or not PEVs can reduce the externalities of driving. Despite these uncertainties, many believe that PEV market shares will continue growing in the next few decades (Balducci 2008, Musti and Kockelman 2011, Becker and Sidhu 2009) and that this trend, in most cases, will reduce greenhouse gas (GHG) emissions (Anair and Mahmassani 2012, Stephan and Sullivan 2008, Samaras and Meisterling 2008) and improve air quality (Sioshansi and Denholm 2009, Thompson et al. 2009).

Even as many adopt an optimistic tone towards PEVs, others cite some concerns. Anair and Mahmassani (2012), for instance, note that PEVs can pollute more than some of the cleanest conventional vehicles (CVs) when fueled by "dirtier" electricity grids (powered mostly by coal). They suggest that in such locations (e.g., Colorado and the U.S.'s Midwest) driving an efficient (gasoline-powered) hybrid-electric vehicle will be less harmful (in terms of GHG emissions) than driving a PEV. However, they also note that places like the Pacific Northwest, which sources a large portion of electricity from non-emitting hydroelectric dams, enjoy very low per-mile GHG emissions relative to CVs.

Other concerns with PEVs include the energy demands and pollution involved in battery production and disposal and the greater energy required to produce lighter-weight materials (Hawkins et al. 2012). There is also the potential for driving rebound due to reductions in costs and perceived environmental impacts, causing some owners to increase their energy consumption (Greening et al. 2000).

Furthermore, such limitations are seen in the context of an increasingly clean CV landscape, diminishing PEVs' perceived environmental advantages. Vehicles powered by fossil fuels are producing fewer emissions and becoming more fuel efficient, thanks to increasingly strict standards. Understanding and predicting these trends is crucial to anticipating the transportation sector's energy demands, air quality impacts, and greenhouse gas emissions. While much has been written on this subject, uncertainty remains regarding how electric vehicles impact specific markets and regions.

This work offers a modeling framework to translate electrified driving (and battery charging) to equivalent per-mile emissions of GHGs and pollutants, and their spatial distribution (from tailpipes to power plants). The model is applied to the Texas region, with its mostly isolated power grid (covering most of the state) and many populated (and still growing) urban areas, where air quality is a concern.

Electricity Generation in Texas

As pointed out by Anair and Mahmassani (2012), PEVs' emissions impacts depend on the power grid used to charge the vehicle batteries. Texas's electricity grid covers nearly 90% of the state's population, and serves as an excellent study location, since regional demand can be directly linked to a single grid (as opposed to other, interconnected grids that distribute power across multiple independent system operators, or ISOs). The Electric Reliability Corporation of Texas (ERCOT) is one of the U.S.'s nine ISOs and manages the Texas grid by dispatching power and anticipating short- and long-term electricity demands. 195 of Texas's 254 counties lie within the ERCOT grid, which includes Dallas-Fort Worth, Houston, San Antonio, and Austin, constituting the nation's 4th, 5th, 25th, and 35th most populous metropolitan statistical areas (MSAs) (Census 2010).

Emissions and Air Quality

One criticism of PEVs driving electrified miles is that they are not "zero emissions" vehicles: they produce significant emissions during manufacture, and shift operating emissions from the tailpipe to other locations. Some have argued that PEVs can be worse for the environment, by producing more life-cycle GHG emissions, though the impacts may be obscured by geographical distance and the fact that many impacts occur during upstream production phases (Hawkins et al. 2012, National Research Council 2010, Alonso et al. 2012). Regardless of how overall PEV energy demands compare to those of CVs, it is true that PEVs shift many of their operating emissions (for all miles that are "electrified") from the point of usage (a roadway) to a sometimes very distant point source. PEV users driving off battery power and others in their usage area benefit from zero tailpipe emissions, but populations surrounding the power generator for any electrified miles will generally be subject to more air pollution. The accounting framework is complicated by the inclusion of plug-in *hybrid* electric vehicles (PHEVs), since their drive-cycles (and thus emissions) can (and regularly do) fluctuate between battery and gasoline sources of motive power. The emissions shifting situation, over space, also presents ethical dilemmas and may encourage more driving, by reducing users' perceptions of their environmental impacts (Hertwich 2008). However, reducing exposure of highly populated urban areas (where many more human lungs are present) may be a real benefit of such emissions exporting.

Many U.S. regions are interested in improving air quality to avoid violating the EPA's National Ambient Air Quality Standards (NAAQS). With many Texas regions currently in non-attainment or near-non-attainment for ozone, while experiencing continuing population and VMT growth, PEVs present an opportunity for improved air quality and lower energy demands. This study aims to quantify some of these impacts, and provides a framework for informing local and regional air quality plans.

METHODS

This research translates anticipated PEV demands to emissions over time and space, from tailpipes and power plants across Texas's electricity grid. The emissions impacts are evaluated relative to conventional (gasoline-powered) passenger vehicles (CVs). Several different model components are considered here, including charging behaviors, power production, and emissions from both vehicle manufacture and vehicle operations. The following sections consider how readily PEVs may be adopted, how they will be used and charged, and their power demands over time.

EV Usage and Driving Behavior

EV use assumptions used here come from extensive GPS-based data of Nissan Leaf vehicle use across the United States, from the EV Project (Ecotality 2013). The EV Project is a joint study between research groups at the U.S. Department of Energy and Idaho National Laboratory, and industry supporters at Nissan, Chevrolet, and Ecotality (an EV Supply Equipment provider), and other various agency and industry partners. The EV Project releases quarterly summary data for vehicle electricity demand and miles traveled, for several locations across the U.S., including two Texas cities: Dallas and Houston. However, sample sizes are rather small for these two cities, especially for the Nissan Leaf. Therefore, U.S. averages for driving distances between charges, and electricity use rates (Wh/mile) are used here, over all quarters of the years in which EV Project data were collected: these range from Quarter 1 (Q1) in 2012 through Quarter 2 (Q2) in 2013.[1] Detailed summaries of these results are compiled by Nichols (2013).

Electric Vehicle Emissions Model

Average daily electricity demand (*D*) is assumed using the average distance traveled (29.7 mi/day) and battery efficiency rate (300 Wh/mi) for Nissan Leaf vehicles, from Ecotality (2013). This provides a baseline for estimating aggregate load on the ERCOT electricity system, but determining generating emissions requires more nuance. For instance, the time-of-day at which a PEV draws power influences the overall emissions profile for that marginal electricity consumption, since demand profiles for electricity change over time as residents, businesses, and industry use electricity for different purposes, and in response to diurnal weather conditions. Similarly, electricity demand is affected by season, as heating and cooling demands vary. Therefore, the time of-day at which EVs are charging is important for anticipating upstream generator emissions.

The EV Project (2013) publishes quarter-hour charging profiles, which were matched to grid generation shares. Quarterly averages of total AC demand in kWh from the EV Project were normalized by the maximum demand during the quarter, to produce standard demand profiles that can applied to any level of electricity demand. For example, if the maximum electricity demanded from PEVs during a 15-minute interval is 0.0475 kWh at 7 PM, all other 15-minute interval demands were divided by this amount to create a maximum value of 1.0 at 7 PM.

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[1] Quarters are defined as follows: Q1 January to March, Q2 April to June, Q3 July to September, Q4 October to December.

162   The EV Project data considers weekday and weekend charging behaviors, so those two empirical
163   charging profiles were considered. Additionally, two theoretical charging behaviors were
164   explored – a concentrated peak demand, and an off-peak demand. The concentrated peak
165   demand is considered a "convenience" charge, in an approach borrowed from Thompson et al.
166   (2011) that represents all EVs starting to charge right after returning home from work (or other
167   activities), at 5pm, when electricity demand is generally peaking (due to households and business
168   being "on" at the same time, and Texas homes cooling down during an especially hot time of day
169   during the summer months). This approach condenses all EV electricity demand into a span of 7
170   hours, from 5 pm to 12 am. Conversely, an off-peak (nighttime) profile was chosen in a way to
171   reduce emissions, by taking advantage of higher renewable (wind) shares, and fewer peak plant
172   emissions in the late night and early morning hours. These profiles are normalized as well, so
173   that total electricity demand is constant across each 15-minute interval, during the charging
174   period.
175
176   The energy E consumed from an EV fleet charging on ERCOT's grid for a 15-minute time
177   interval t is calculated as follows:

$$E_t = D \times \frac{d_t}{\sum_t d_t}$$

178
179   where d_t is the average electricity demand in time-interval t, using EV Project estimates. With
180   this specification, total EV energy demands are spread out across 15-minute intervals concurrent
181   with actual average profiles. EV Project data provide multiple quarterly demand profiles,
182   including maximum and minimum values, as well as inner and outer quartiles. This study simply
183   relies on the median demand value for a weekday. These demand profiles are specific for each
184   quarter, based on the only year for which a complete set of EV Project charging data was
185   available at the time of this research: 2012.
186
187   After determining time-specific total electricity demand across different PEV adoption scenarios,
188   electrified-mile emissions are estimated. Emissions estimation becomes more complex here, with
189   unique electricity generating units (EGUs) entering as model components. Quarter-hour
190   emissions rate tables were matched with interval electricity demands to determine daily and
191   annual PEV emissions. Emissions rate tables for 6 pollutants (NO_x, SO_2, CH_4, N_2O, CO_eeq,
192   PM_{10}, CO, and VOC) were developed at 15-minute intervals for all 4 quarters of 2012 on the
193   ERCOT grid using emissions data from the eGRID database (EPA 2012) and National Emissions
194   Inventory (EPA 2001).[2] These data provide emissions rates for each of the 550 power generators
195   on the ERCOT grid. Weighted average emissions rates for pollutant p are calculated for each fuel
196   type f (coal, natural gas, oil, and biomass) based on annual emissions (A) per power plant z, as
197   follows:

$$w_{pf} = \frac{x_{fpz} \times A_{fz}}{\sum_z A_z}$$

198

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[2] Emissions for NO_x, SO_2, CH_4, N_2O and CO_2eq were taken from actual plant emissions, as found in the eGRID data
set, while PM_{10}, CO, and VOC are based only on grid-wide averages by fuel type, from the National Emissions
Inventory Data set. These average rates were computed by dividing annual emissions from all plants of a given fuel
type by the annual electricity generation. Therefore, these are unweighted estimates, compared to eGRID estimates,
which are weighted by generation of each plant across a given fuel type.

199   where x_{fpz} is the emissions rate for pollutant p of plant z combusting fuel type f. These emissions
200   rates represent the marginal emissions of consuming one MWh of electricity by using a specific
201   fuel type f. Total marginal grid emissions of each pollutant (e), therefore, are a function of fuel
202   type shares (y_f), weighted-average emissions rates, and interval energy demand (E_t) for PEV
203   charging. While weighted emissions rates were assumed constant, fuel type shares change over
204   time and by season. These changes are incorporated based on 15-minute ERCOT generation
205   data, by fuel source, for every day in 2012. Simple averages of total production (per time interval
206   [t]) were calculated for each quarter (k) to produce quarterly average fuel type shares (y_{fkt}).
207   Therefore, quarterly emissions rates can be calculated as follows:
208

$$e_{pkt} = \sum_f y_{fkt} w_{pf} E_t$$

209
210   This approach takes into account the fact that generation fuel type shares change as demand
211   changes over time and season, for any marginal electricity usage. By "marginal" usage, it is
212   assumed that the total PEV demand (D) does not affect the generation fuel type shares. In some
213   cases, where PEV demand is very high, additional EGUs may be required to meet demand. At
214   present, Texas's small PEV population has only a marginal effect on the grid, but if demand
215   increases, perhaps even to 5% of total LDVs, this marginal demand assumption may no longer
216   hold.
217
218   The final result for this approach is a lookup table of quarter-hour emissions rates, by season for
219   8 different pollutants. This is the table multiplied by daily demand to determine average
220   emissions impacts of PEV charging. The result is in terms of aggregate emissions, but results
221   could also be evaluated geographically by considering individual generator locations and
222   proximity to urban areas.

223   **Life-Cycle Considerations**
224   For a more complete evaluation of PEV versus CV emissions implications, some attention
225   should be paid to each vehicle's life-cycle emissions, since PEVs generally require more energy
226   (and thereby emissions) to construct, thanks mostly to battery assembly (Hawkins et al. 2012)
227   and use of special materials to lower weights. This analysis uses embodied energy demands
228   directly from Argonne National Laboratory's Greenhouse Gases, Regulated Emissions, and
229   Energy Use in Transportation (GREET) model, which accounts for the upstream emissions and
230   energy inputs required to produce all materials for typical, light-duty vehicles. These components
231   include the various materials used, such as steel, plastic, iron, and rubber; various fluids used
232   (e.g., engine oil, power steering fluid, brake fluid); and batteries (used in CVs and more
233   extensively in PEVs). GREET requires many assumptions regarding vehicle weight, materials,
234   and inputs for upstream energy and emissions from power plants and transportation sources. The
235   analysis here simply assumes all default estimates from GREET 2.1, as originally described by
236   Wang (2001) and revised by Argonne National Laboratory (2013). This estimate of embodied
237   energy across CVs and PEVs provides an additional dimension for a more holistic comparison
238   between the two vehicle types for different electricity fuel mix scenarios.

RESULTS

Average emission rates on the ERCOT grid were computed for 6 pollutant types, with results shown in Table 1. Table 1's emission rates are based on eGRID and ERCOT data that vary by time-of-day and season. Other emissions rates, provided below (for PM, CO, and VOC), are Texas-wide averages, derived from the U.S.'s National Emissions Inventory (NEI) (EPA 2001) for year 2008. NEI data is not available for direct comparison for biomass and "other" electricity combustion sources as defined in eGRID data.

Table 1: Average ERCOT Emissions Rates (lb/MWh) from eGRID 2012 (2009 rates) and NEI (2008 rates).

	NO_x	SO_2	CH_4	N_2O	CO_2eq	$PM_{2.5}$	CO	VOC
Coal	4.04	19.2	284.7	422.3	6,537.5	0.11	2.97	0.03
Natural Gas	0.28	0.006	52.6	5.4	671.8	0.04	0.12	0.02
Other	0.11	1.8	28.1	41.2	641.6	--	--	--
Biomass	2.06E-4	1.41E-5	0.276	0.037	0.004	--	--	--
Renewables, Nuclear	0	0	0	0	0	0		0

Note: SO_2 is a significant precursor of harmful PM2.5 downwind of the EGU.

Comparing different charging profiles indicates little difference between charging scenarios, as shown in Table 2. This result is consistent with Thompson et al.'s (2011) findings of almost no difference between 4 different EV-charging profiles on the Texas grid.

Table 2: Average Electrified-Mile Emissions Rates by Charging Scenario on ERCOT grid (grams/mi)

Charging Scenario	NO_x	SO_2	CH_4	N_2O	CO_2eq
Weekday	0.166	0.721	13.34	16.13	279.41
Weekend	0.165	0.722	13.33	16.16	279.48
Convenience	0.167	0.724	13.39	16.21	280.56
Off-Peak	0.166	0.732	13.02	16.33	276.95

Table 2's differences are rather small, and nearly negligible, with the exception of perhaps CO_2eq. The rate difference from all PEVs charging when convenient (i.e., right when they arrive home) versus off-peak (for power generation) is about 6,730 tons of CO_2eq per year, or just a 1.3% decrease in grams per electrified mile of CO_2eq emissions. Zivin et al. (2012) also studied temporal variations in CO_2 emissions and noted that the ERCOT grid is one of the most stable over times of day, as compared to the eastern and western (WECC) interconnections. Since little difference appears to exist by time of day in Texas, assuming average grid mixes (rather than a special, generator-specific dispatch model), the state's weekday charging emissions profile was assumed, to provide the following results.

Conventional Vehicle Emissions

Average PEV emissions were compared to those of four different CV types, as shown in Table 3, in order to evaluate PEVs' relative emissions profiles. For this evaluation, emissions rates for

270 gasoline- and diesel-powered passenger cars and light-duty trucks (like SUVs, minivans, and
271 pickups) were estimated using EPA's MOVES model, as shown in Table 3 (and developed for
272 use in Kockelman et al.'s [2012] Project Evaluation Toolkit, for Texas applications). Table 3's
273 CV rates correspond to an average of rates estimated for Dallas, Waco, and Houston conditions
274 in the summer of 2010, for vehicles traveling at 30 miles per hour, which is close to the average
275 commute speed of 27 mph reported by the National Household Travel Survey (NHTS 2009).
276

277 **Table 3: CV vs. PEV Operating Emissions Rates (grams/mile)**

	NO_x	SO_2	PM_{10}	CO	VOC	CH_4	N_2O	CO_2eq
Gas Passenger Car	0.3739	0.00769	0.0310	3.3905	0.1518	0.00579	0.00316	393.92
Diesel Passenger Car	1.0104	0.00341	0.0689	0.5373	0.0682	0.00166	0.00057	436.76
Gas Light Passenger Truck	0.8869	0.01055	0.0443	7.0989	0.3387	0.01121	0.00889	540.69
Diesel Light Passenger Truck	3.8152	0.00574	0.2746	4.1980	0.6237	0.01010	0.00221	728.29
PEV 2012 Avg. ERCOT Mix	0.17	0.72	**0.014**	**0.15**	**0.002**	13.34	16.13	**280**
PEV 2012: 100% Coal	0.47	2.23	0.036	**0.43**	**0.005**	33.14	49.15	761
PEV 2012: 100% NG	**0.03**	**0.00**	**0.005**	**0.02**	**0.002**	6.12	0.63	**78**
PEV: 25% Increase in Renewables	**0.12**	0.54	**0.011**	**0.11**	**0.002**	10	12.1	**210**

278 Note: Bold indicates PEV emissions rates that are lower than all CV averages.
279

280 Note that these results do not include CVs' cold start emissions, which are higher (per mile
281 traveled) than standard operating emissions, since emissions-control equipment (like the catalytic
282 converters) have not reached optimal activation temperatures (Frey et al. 2002). However,
283 preliminary analysis suggested that broadly considering cold starts did not appreciably change
284 the overall research findings. Finer-scale models that consider detailed trip behavior should
285 consider cold starts for a more comprehensive analysis.
286

287 Both CVs and PEVs are projected to experience significant improvements in emissions in
288 coming years. The Environmental Protection Agency's Tier 3 Vehicle Emission and Fuel
289 Standards Program will harmonize national regulations with existing California Air Resources
290 Board (CARB) Low Emission Vehicle (LEV III) standards, resulting in an estimated 56%
291 reduction in SO_2 by 2018 (EPA 2014b). SO_2 emissions from coal-fired power plants, already at
292 record lows, are projected to drop by another two-thirds from 2011 to 2016 (EIA 2013).
293 Electricity generation with fuels other than coal will result in even lower pollutant emissions.
294

295 These results highlight some major emissions profile differences between electrified miles and
296 CV driving. The most striking difference is the considerably higher SO_2 emissions from PEVs
297 using the average ERCOT feedstock mix, which is over 70 times higher than that of the average
298 CV. Emissions of two particular greenhouse gases - methane (CH_4) and nitrous oxide (N_2O) - are
299 also much higher for PEV miles in all feedstock mix scenarios, yet overall CO_2 emissions are
300 lower in most cases for PEVs (except when powered solely by coal). A key concern here is that
301 electrified miles relying exclusively on power from Texas's average coal-fired power plants
302 produce more than *twice* the CO_2 of a typical gasoline-powered passenger car, 125% more
303 GHGs than a diesel passenger car, and many more times methane and nitrous oxide than CVs,

304 per mile traveled. The GHG difference between a gasoline-powered SUV (or LDT) and coal-
305 powered PEV passenger car is less pronounced, suggesting about a 20% increase for the PEV
306 car, but still underscores the inherent inefficiency of using a PEV with a dirty fuel source.
307 Fortunately, Texas' average electric-power presently produces about 25% less CO_2 per mile
308 traveled on pure battery power than a typical gasoline-powered car.
309
310 PEVs are expected to produce less NO_x, PM_{10}, VOC, and CO emissions than the average CV
311 under most Texas-power scenarios - except for the case of 100% coal combustion. This shift in
312 emissions offers valuable solutions to various urban air quality concerns. For example, many
313 U.S. regions are in non-attainment or near non-attainment with the national ozone standard (EPA
314 2013), and so will benefit from lower overall NO_x and VOC levels (Farooqui, et al 2013).
315
316 The margin between today's grid emissions and existing CV emissions is only large for CO and
317 VOC, and quite thin for NO_x and PM_{10}. For instance, an average PEV's PM_{10} emissions on the
318 existing grid nearly equal those of the average gasoline car, and PEV's NO_x emissions are about
319 half those of such a car. Though this latter difference is significant, both CV and power plant
320 emissions rates are likely to change. The conventional vehicle fleet is expected to become
321 cleaner, thanks to older, more polluting vehicles being removed from roadways, and better
322 emissions control systems on newer models. The EPA has long been pushing for reduced power
323 plant emissions, especially from coal plants, but the extent of those gains is currently unclear.
324 Changes in the auto industry are expected thanks to the recently-passed Tier 3 emissions
325 standards (EPA 2014b) and CAFE (fuel economy) standards up through 2025. These emissions
326 improvements are expected to be rather significant, as shown below for passenger cars, based on
327 PET's MOVES-based emissions estimates through 2025.
328
329 **Table 4: CV Emissions Changes to 2025 (grams/mile)**
330

	NO_x	SO_2	PM_{10}	CO	VOC	CH_4	N_2O	CO_2eq
2010 Gas Passenger Car	0.3739	0.008	0.0310	3.3905	0.1518	0.00579	0.00316	393.92
2015 Gas Passenger Car	0.1760	0.007	0.0303	2.4759	0.0723	0.00386	0.00174	381.17
2020 Gas Passenger Car	0.0928	0.007	0.0300	2.0677	0.0466	0.00346	0.00144	347.40
2025 Gas Passenger Car	0.0678	0.006	0.0300	1.9627	0.0407	0.00332	0.00136	324.18
PEV 2012 Avg. ERCOT Mix	0.17	0.72	**0.014**	**0.15**	**0.002**	13.34	16.13	**280**
PEV 2012: 100% Coal	0.47	2.23	0.036	**0.43**	**0.005**	33.14	49.15	761
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PEV: 25% Increase in Renewables	**0.12**	0.54	**0.011**	**0.11**	**0.002**	10	12.1	**210**

331
332 If CVs do achieve such emissions reductions, PEVs using today's average ERCOT electricity
333 may no longer provide such clear air quality benefits. For instance, average ERCOT-based NO_x
334 emissions for electrified miles are currently about half those of a 2010 passenger car, but may
335 become *twice* those of such CVs if LDV emissions rates improve and grid emissions stay
336 constant. Though power-grid emissions improvements are expected (EPA 2014a), the turnover
337 rate of older and less efficient power plants is likely lower than that of vehicles. Of course,

338 domestic power provision also offers greater energy security, and EVs can be powered using a
339 variety of "emissions-free" renewable feedstocks, including distributed (household-level) solar
340 panels.

341 **Life-Cycle Analysis Comparison**
342 Though the previous analysis provides some insight into the relative emissions profiles of
343 vehicle use, consideration should be given to differences in emissions from vehicle production
344 phases. This is done by including GREET's embodied emissions results alongside operating
345 emissions, as shown in Figure 1. Another source of such estimates is Michalek et al. (2011), who
346 have estimated high embodied energy implications for EVs.
347
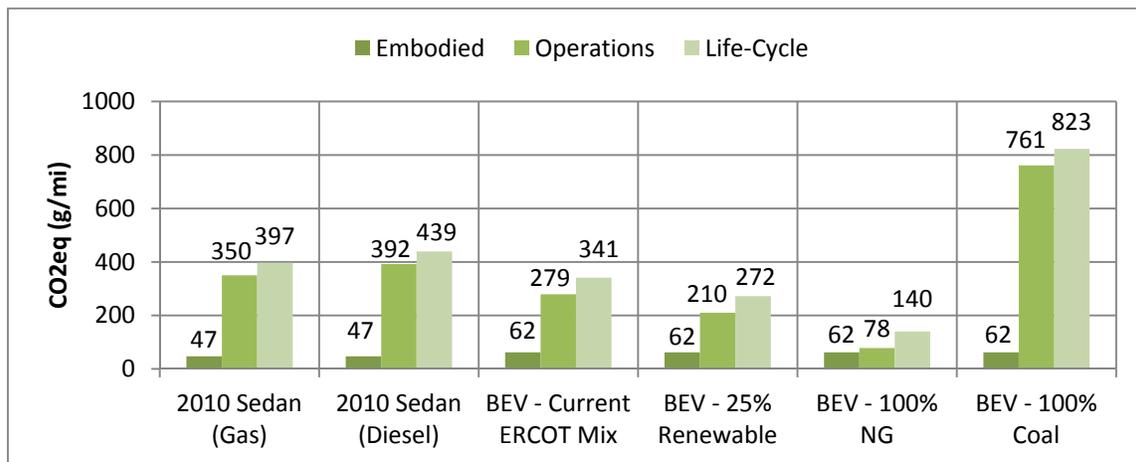
348
349 **Figure 1: Life-Cycle CO$_2$eq Emissions of CVs vs. PEV Scenarios**

350 This analysis suggests that most life-cycle energy for conventional vehicles, and PEVs fueled by
351 coal, is from daily driving rather than from production phases. Although PEV production might
352 produce around 30% more CO$_2$eq than conventional vehicles, this phase is rather insignificant
353 when compared to operations emissions. In fact, embodied energy comprised only about 11 and
354 7% of GHG emissions of gasoline and diesel vehicles respectively. A critical point to consider
355 here is the life-cycle GHG emissions of conventional vehicles and PEVs using the current mix.
356 These results suggest that PEVs produce around 18% less GHG per mile than CVs, and that this
357 reduction could reach 35% with an increased share of renewables or nearly two-thirds with a
358 100% natural gas source.
359
360 There is one emissions-species case studied here where PEVs, under any fuel mix scenario other
361 than 100% renewables, perform worse than CVs; this is the case of SO$_2$ emissions. Figure 2
362 shows that the average gasoline and diesel sedan produces very little on-road SO$_2$, as compared
363 to SO$_2$ from electricity generation. SO$_2$ causes both respiratory ailments (Chen et al. 2012, Frank
364 et al. 1962) and contributes to acid rain (Park 1987).
365
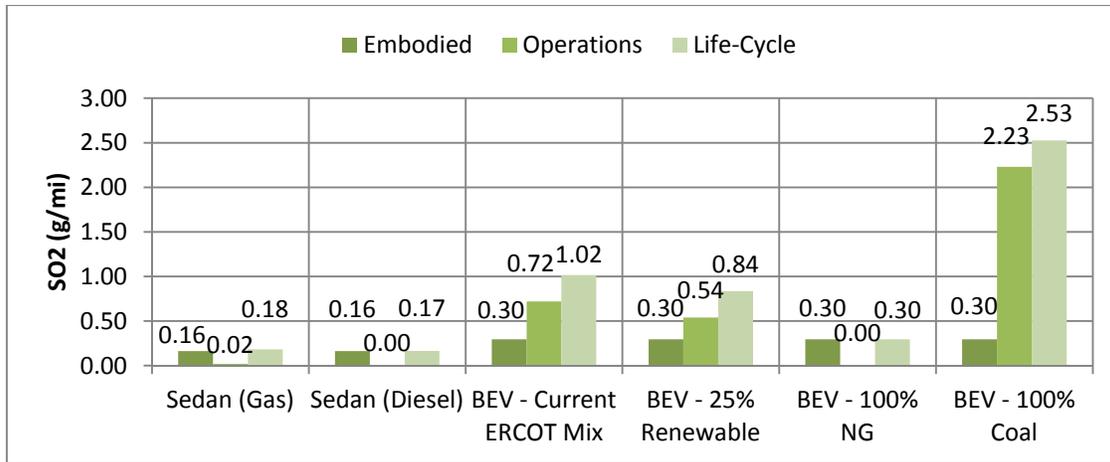
Figure 2: Life-Cycle SO$_2$ Emissions of CVs vs. PEV Scenarios

It should be noted that this life-cycle analysis does not necessarily consider the embodied energy
associated with fuel production or power generation in the operations phase. That is, for
gasoline, diesel, coal, natural gas, nuclear power, and other fuels, the only input is the amount of
fuel consumed in the operations phase. Since the embodied phase of energy or fuel production is
neglected, the magnitude of the operations phase is thereby underestimated for all vehicles. This
may influence the magnitude of operations emissions differently across CVs and PEVs, but is
unlikely to make a noticeable difference, since embodied-energy implications typically average
10 percent of the total energy use and will be overshadowed by the relative differences in
operations. Exploring the embodied phase of operational energy leads to a recursive and
increasingly complicated analysis focused on relatively negligible marginal emissions, so they
are ignored in this case.

PEV Emissions Exposure

Though previous results suggest that PEV emissions rates for air quality pollutants are in most
cases lower than those for CVs (with the exception of SO$_2$), it is important to consider how
emissions may shift over space and exposed populations, when shifting from CV use to PEV use.
Thompson et al. (2009, 2011) performed rather detailed spatial emissions analysis of PEV
emissions at point source locations, and that level of sophistication and expertise in air quality
modeling is not replicated here. Rather, a general "exposure rate" is calculated for each ERCOT
county, as the product of annual power plant emissions (in tons per year) and evenly-distributed
county population. A 25-mile buffer is considered for each power plant to calculate exposure
rates, and overlapping emissions exposures are summed to produce a sense of annual exposure.
Though emissions can affect populations hundreds of miles away, the small buffer size used here
provides more insight to geographic emissions concentrations. This measure provides a sense of
where the largest overall impacts from PEV usage are likely occurring, over the long term (since
at any given time any number of the modeled plants may be operating). This measure is therefore
a sense of the aggregate air quality risks posed by rising PEV use.

Figure 3's results illustrate how Texas' urbanized areas experience some of the greatest total
exposures to power plant emissions, which is unsurprising, given these regions' high population
concentrations. However, there are some less densely-populated counties well away from

Texas's major metropolitan areas (Dallas-Fort Worth, Houston, San Antonio, and Austin) that
show very high exposure rates for all power plant pollutants as shown in Figure 3.
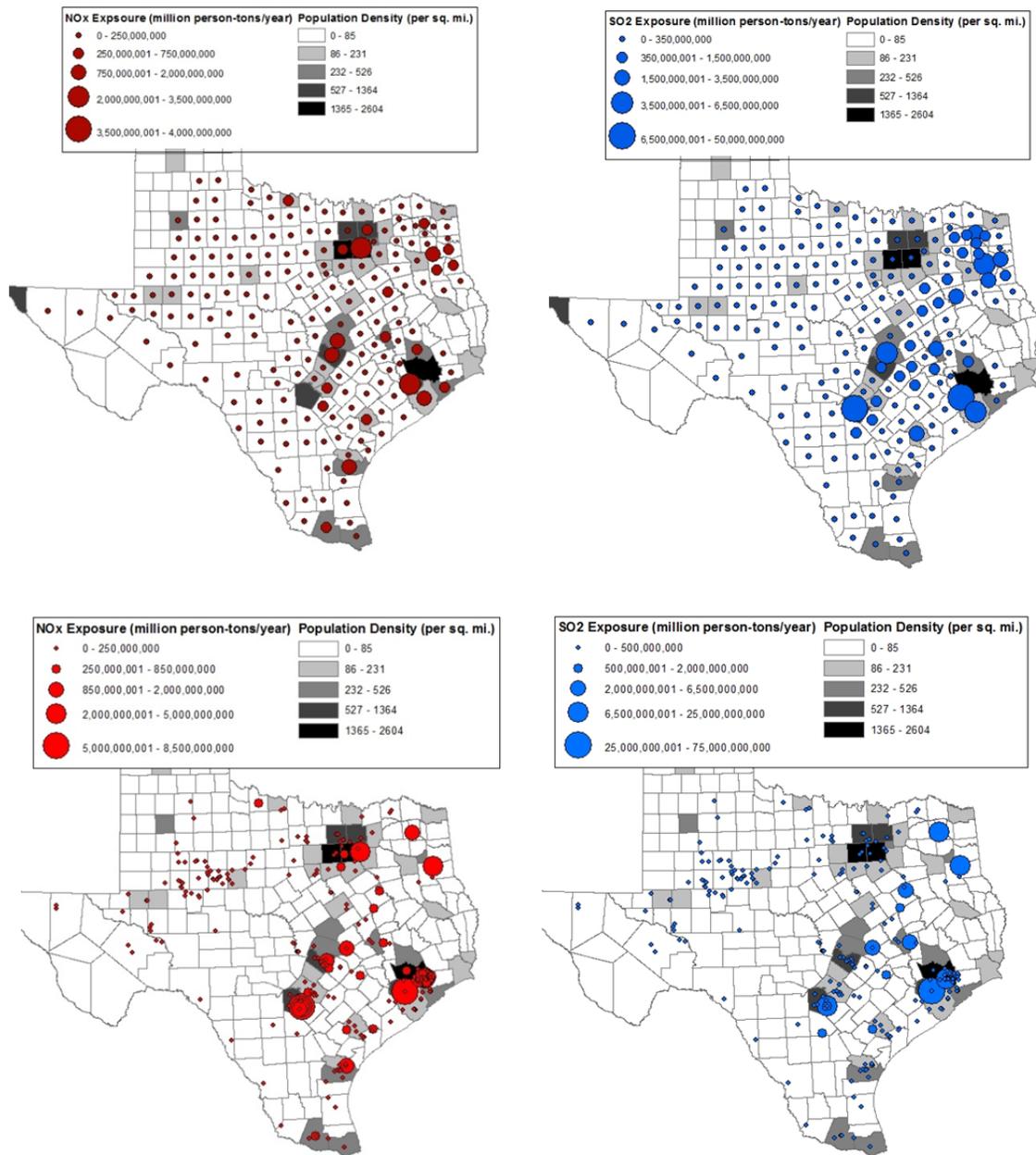
Figure 3: Total Emissions Exposure, by County for NOx, (top left) SO₂, (top right), and by Power Plant for NOx (bottom left) and SO₂ (bottom right), in millions of person-tons per year

For NO_x and SO_2 emissions levels via Texas' power plants, some of the highest exposure
counties host Texas' most populous cities. These include Harris (for City of Houston), Travis
(Austin), Bexar (San Antonio), and Dallas counties. In addition to these urban areas, many rural
counties also emerge with high emissions levels; these include central-Texas counties such as
Anderson and Brazos, as well as most of northeast Texas. These counties have much lower

412   population densities than the metro areas, but show a disproportionate exposure rate than some
413   nearby counties that do not contain a polluting power plant.
414
415   Milam, Fayette, Limestone, Freestone, Grimes, and Rusk counties are all home to major coal
416   plants. While it is not surprising to see such high NO_x and SO_2 exposure rates in these locations,
417   it is interesting to get a sense of the disproportionately higher rates there, versus those in Texas'
418   much more densely populated areas. In other words, smaller populations living near the coal
419   plants are subject to greater power-generation emissions exposure. Even with much higher
420   population numbers in the cities, which have nearby EGUs, aggregate exposure rates are less
421   than those surrounding highly-polluting power plants in Texas' rural areas. Of course, the details
422   of these exposures are much more nuanced, reflecting more than basic proximity. Nevertheless,
423   at this coarse scale of county-level resolution, it seems clear that EV's electricity use (mostly in
424   the major cities) will be outsourcing emissions to more rural populations. This is most apparent
425   with SO_2, while results for other pollutants suggest that urban populations are about as
426   negatively affected as rural populations (in terms of the product of population and emissions
427   tons: the actual epidemiology is much more complex, and holds more hazards for those exposed
428   to higher levels of most pollutants).
429
430   This result supports the idea that some rural areas may be subjected to higher emissions from EV
431   adoption, use, and charging in urban areas, but the regions with more vehicles are more likely to
432   carry the burden of exposure. In other words, enough power plants operate in Texas's most
433   populated regions that EVs are not shifting all or even most of their associated emissions impacts
434   to outlying areas, though there are certainly cases where the shifts may be disproportionate.
435   Figure 3 highlights how EV charging emissions may often affect less populated areas of Texas.
436   Of course, CV users impose emissions externalities on occupants of the cars that follow them,
437   and the pedestrians, cyclists, and school children that travel and play nearby. Without 100-
438   percent clean transport technologies, one cannot avoid the issue of externalities and inequities in
439   emissions impacts.

CONCLUSIONS

441   This analysis confirms an already well-known fact: electricity produced from coal-burning
442   power plants (both newer generation and older generation) is generally much more polluting than
443   that produced by power plants relying on natural gas and renewables. While EVs powered
444   exclusively by the average coal-fired power plant in Texas's ERCOT grid (in year 2012) may
445   produce around 3,200 times more SO_2 (per mile-traveled) than electrified miles powered
446   exclusively by Texas' natural gas plants, their emissions rates of NO_x, CO, and VOCs are still
447   significantly less than those of CVs. Also somewhat surprising are the air quality and GHG
448   savings associated with natural gas plants (with emissions rates based on current ERCOT
449   averages for natural gas plants), and the relatively constant emissions rates (and feedstock mix)
450   of Texas's power plants across different levels of demand on most any day of the year. .
451   Specifically, charging a PEV on the ERCOT grid with only coal plants in the mix results in over
452   14 times as much NO_x emissions, 3,200 times as much SO_2, nearly 10 times as much CO_2 and
453   CO_2eq, 2.5 times as much $PM_{10,}$ and VOCs, and nearly 80 times the N_2O – as compared to a grid
454   powered only by natural gas plants. Of course, including a small share of biomass and
455   renewables (including wind, hydroelectric, and solar power) is even more favorable than the

456   natural gas scenario. This result indicates that coal plants are drastically more polluting than
457   other EV fuel sources, as shown in Table 3.
458
459   Overall, higher PEV shares in urban areas may help improve local air quality and help regions
460   meet NAAQS for CO, N_2O, ozone, and PM (2.5 and 10), specifically. If, however, a region has
461   any nearby coal plants impacting regional air quality, PEVs can create much more of an SO_2
462   (and thereby PM2.5[3]) problem for the region than CVs would. Since SO_2 emissions from coal
463   plants (compared on a per-mile basis to CVs) are so relatively high, one should be cautious when
464   using them to power any PEVs, especially in a place where coal emissions could be affecting
465   large populations. All Texas counties are within NAAQS for SO_2, but several Midwest and East
466   Coast counties are in nonattainment (EPA 2013), presumably from higher concentrations of coal
467   plants, higher sulfur contents of their coal, and heavy industry in these areas. Though SO_2
468   emissions are not necessarily a present concern in Texas, greater PEV demands being met with
469   more coal plants (in populated areas) could be problematic. Essentially, adding an electrified
470   mile to a system that depends on coal power would be equivalent to adding 3,200 CV miles, in
471   terms of SO_2 emissions. This is an interesting result, because even at their relatively small shares,
472   PEVs using coal-based electricity will have very disproportionate SO_2 emissions impacts.
473
474   Pollution carries negative-externality costs, and these have been estimated in recent years. Given
475   the significant difference in associated SO_2 emissions, and the high (estimated) cost of this
476   pollution species, Table 5 calculations suggest that a PEV's emissions benefits may be lost
477   (relative to the 2010 fleetwide average passenger car), if partly powered by coal (ERCOT's
478   feedstock share is 25 percent, very typical of U.S. power production). Table 5's dollar totals
479   assume that each vehicle drives 12,000 miles per year, and damage values (in dollars per ton of
480   species) come from the U.S. NHTSA (2010) for criteria pollutants; social cost of carbon is based
481   on Interagency Working Group estimates (2013). Table 5's costs per ton are somewhat higher
482   than those found elsewhere (see, e.g., Fann et al. 2012), but provide a conservative accounting of
483   the health and environmental impacts attributable to CVs and PEVs.
484
485   **Table 5: Comparing the External Emissions Costs**

	Pollution Costs ($/metric Ton)	Emissions Externalities over 12,000 Annual Miles	
		2010 Avg. Passenger Car (Gasoline)	PEV using 2012 ERCOT Grid
VOC	$1,280	$4.32	$0.03
NO_x	$5,217	$25.75	$10.64
PM_{10} (directly emitted)	$285,469	$116.29	$47.96
SO_2	$30,516	$2.82	$263.66
CO_2	$20	$94.49	$67.20
Subtotal Non-SO_2	--	$240.85	$125.83
Total (per 12,000 mi.)	--	**$243.67**	**$389.49**

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[3] SO_2 condenses to form sulfate particles, an important component of PM2.5, and responsible for tens of thousands of premature deaths each year, just in the U.S. (Fann et al. 2013).

486   Note: Pollution costs per ton come from NHTSA (2010) and Interagency Working Group on Social Cost
487   of Carbon (2013). Passenger car emissions rates assume 30 mi/h running speed, and come from MOVES
488   rates, as provided in the Project Evaluation Toolkit (Kockelman et al. 2012).
489
490   It seems clear that an EV's impacts on SO_2 emissions should not be ignored, even if some
491   regions use little coal (notably the U.S. West Coast), actual damage costs are debatable, and
492   shares of renewable feedstocks are rising (roughly a percentage point each year) in many
493   regions. While the non-SO_2 portions of battery-powered EV emissions are less than three-
494   quarters that of a modern gasoline passenger car, including SO_2 increases electrified travel's
495   emissions costs to roughly 1.6 times those of a conventional passenger car. Thus, a grid's power
496   sources, specifically coal-fired plants, are extremely important for EV emissions and benefits (or
497   costs).
498
499   Overall, this study illustrates how a higher share of efficient natural gas and renewables
500   (including nuclear) can reduce electrified-mile emissions, relative to CV use and PEVs powered
501   by coal plants or inefficient natural gas plants. However, a focus on air emissions ignores some
502   other environmental consequences of power production. Simply turning away from coal sources
503   is not without issues. For instance, nuclear power production and waste disposal carries safety
504   and environmental contamination risks, and is a massive freshwater consumer (Gleick 1994).
505   Natural gas may also be responsible for environmental issues, since hydraulic fracturing
506   techniques require much water and may be degrading underground water stores (see, e.g.,
507   Osborn et al. [2011] and Entrekin et al. [2011]), while releasing large amounts of global-
508   warming methane (Howarth et al. 2011). Even wind turbines, solar panels, and hydroelectric
509   power are not immune from environmental damages: generators threaten certain migratory bird
510   populations, solar panels require extensive land area that may disrupt animal habitats, and
511   hydroelectric dams interrupt aquatic ecosystems. Effectively, there is no motorized-transport
512   energy solution that enjoys truly negligible costs, has zero environmental impact, and can move
513   our world's growing population billions of miles per day. However, solutions like electrified
514   transport, with cleaner power sources, vehicles and batteries manufactured with less embodied
515   emissions, greater use of non-motorized travel models, reliance on closer destinations as activity
516   sites (to reduce travel distances), and more efficient power sources and vehicles can help reduce
517   the local, regional, and global costs of our mobility desires, while improving the energy security
518   situation of most nations.
519

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REFERENCES

Anair, D. and A. Mahmassani (2012) State of Charge: Electric Vehicles' Global Warming
Emissions and Fuel-Cost Savings across the United States. Union of Concerned Scientists.
http://www.ucsusa.org/assets/documents/clean_vehicles/electric-car-global-warming-emissions-
report.pdf.

Argonne National Laboratory (2013) GREET Life-Cycle Model. User Guide. Center for
Transportation Research, Energy Systems Division. October 31, 2013.

Balducci, P. J. (2008) Plug-in Hybrid Electric Vehicle Market Penetration Scenarios. Pacific
Northwest National Laboratory. U.S. Department of Energy. Available at
http://www.pnl.gov/main/publications/external/technical_reports/pnnl-17441.pdf.

Becker, T. and I. Sidhu (2009) Electric Vehicles in the United States: A New Model with
Forecasts to 2030. Center for Entrepreneurship & Technology. University of California,
Berkeley.
http://funginstitute.berkeley.edu/sites/default/files/Electric%20Vehicles%20in%20the%20United
%20States%20A%20New%20Model%20with%20Forecasts%20to%202030.pdf.

Chen, R., W. Huang, C. Wong, Z. Wang, T. Thach, B. Chen, and H. Kan (2012) Short-term
exposure to sulfur dioxide and daily mortality in 17 Chinese cities: The China air pollution and
health effects study (CAPES). *Environmental Research* 118: 101-106.

Chester, M. and A. Horvath (2009) Life-cycle Energy and Emissions Inventory for Motorcycles,
Diesel Automobiles, School Buses, Electric Buses, Chicago Rail, and New York City Rail.
Center for Future Urban Transport Working Paper. University of California, Berkeley.
http://trid.trb.org/view.aspx?id=898428.

Dyer, R. A. (2011) The Story of ERCOT: The Grid Operator, Power Market, and Prices Under
Texas Electric Deregulation. A Special Research Project by the Steering Committee of Cities
served by Oncor and the Texas Coalition for Affordable Power. Available at
http://tcaptx.com/downloads/THE-STORY-OF-ERCOT.pdf.

EIA (2012) Annual Energy Outlook 2012 with Projections to 2035. June 2012. U.S. Energy
Information Administration. Office of Integrated and International Energy Analysis.
http://www.eia.gov/forecasts/aeo/pdf/0383(2012).pdf.

EIA (2013) Power Plant Emissions of Sulfur Dioxide and Nitrogen Oxides Continue to Decline
in 2012. U.S. Energy Information Administration. http://www.eia.gov/todayinenergy/

EPA (2012) The Emissions and Generation Resource Integrated Database for 2012 (eGRID
2012) Technical Support Documentation. Prepared for U.S. Environmental Protection Agency,
Office of Atmospheric Programs. Contract No. EP-D-06-001, Work Assignment No. 2-04.

571 EPA (2013) Sulfur Dioxide Designations. U.S. Environmental Protection Agency.
572 http://www.epa.gov/airquality/sulfurdioxide/designations/state.html.

574 EPA (2014a) Cleaner Power Plants. http://www.epa.gov/mats/powerplants.html

576 EPA (2014b) EPA Sets Tier 3 Motor Vehicle Emissions and Fuel Standards.
577 http://www.epa.gov/otaq/documents/tier3/420f14009.pdf

579 ERCOT (2012) Report on the Capacity, Demand, and Reserves in the ERCOT Region.
580 December 2012.
581 http://www.ercot.com/content/news/presentations/2012/CapacityDemandandReservesReport_Wi
582 nter_2012_Final.pdf.

584 ECOtality (2013) The EV Project: Overview. http://www.theevproject.com/overview.php.

586 Fann, N., K. Baker, and C. Fulcher (2012) Characterizing the PM2.5-related health benefits of
587 emission reductions for 17 industrial, area and mobile emission sectors across the U.S.
588 *Environment International* 49: 141-151.

590 Fann, N., C. Fulcher, and K. Baker (2013) The Recent and Future Health Burden of Air Pollution
591 Apportioned Across U.S. Sectors. *Environmental Science and Technology* 47(8): 3580-3589.

593 Farooqui, Z., K. John, J. Biswas, and N. Sule (2013) Modeling analysis of the impact of
594 anthropogenic emission sources on ozone concentration over selected urban areas in Texas.
595 *Atmospheric Pollution Research* 4(1): 33-42.

597 Frank, N. R., M. Amdur, J. Worcester, and J. Whittenberger (1961) Effects of acute controlled
598 exposure to SO_2 on respiratory mechanics in healthy male adults. *Journal of Applied Physiology*
599 17(2): 252-258. http://jap.physiology.org/content/17/2/252.short.

601 Frey, H. C., A. Unal, J. Chen (2002) Recommended Strategy for On-Board Emission Data
602 Analysis and Collection for the New Generation Model. North Carolina State University,
603 prepared for U.S. Environmental Protection Agency.

605 Gleick, P. (1994) Water and Energy. *Annual Review Energy Environ.* 19: 267-99.
606 Greening, L., D. Greene, C. Difiglio (2000) Energy efficiency and consumption – the rebound
607 effect – survey. *Energy Policy* 28 (6-7): 389-401.

609 Hawkins, T., B. Singh, G. Majeau-Bettez, A. H. Stromman (2012) Comparative Environmental
610 Life Cycle Assessment of Conventional and Electric Vehicles. *Industrial Ecology* 17(1): 54-64.
611 http://onlinelibrary.wiley.com/doi/10.1111/j.1530-9290.2012.00532.x/abstract.

613 Hertwich, E. (2008) Consumption and the Rebound Effect: An Industrial Ecology Perspective.
614 *Journal of Industrial Ecology* 9(1-2): 85-98.
615 Howarth, R., R. Santoro, and A. Ingraffea (2011) Methane and the greenhouse-gas footprint of
616 natural gas from shale formations. *Climatic Change* 106: 679-690.

617
618 Interagency Working Group on Social Cost of Carbon (2013). Technical Support Document: -
619 Technical Update of the Social Cost of Carbon for Regulatory Impact Analysis -
620 Under Executive Order 12866.
621 http://www.whitehouse.gov/sites/default/files/omb/assets/inforeg/technical-update-social-cost-
622 of-carbon-for-regulator-impact-analysis.pdf
623
624 IEA (2013) Global EV Outlook: Understanding the Electric Vehicle Landscape to 2020.
625 International Energy Agency, Clean Energy Ministerial, Electric Vehicles Initiative.
626 http://www.iea.org/publications/globalevoutlook_2013.pdf.
627
628 Kang, J. and W. W. Recker (2009) An activity-based assessment of the potential impacts of
629 plug-in hybrid electric vehicles on energy and emissions using 1-day travel data. *Transportation*
630 *Research Part D* 14(8).
631
632 Karabasoglu, O. and J. Michalek (2012) Influence of driving patterns on life cycle cost and
633 emissions of hybrid and plug-in electric vehicle powertrains. *Energy Policy* 60: 445-461.
634
635 Khan, M. and K. Kockelman (2012) Predicting the Market Potential of Plug-In Electric Vehicles
636 Using Multiday GPS Data. *Energy Policy* 46: 225-233.
637 Kockelman, K., Fagnant, D., Nichols, B., and S. Boyles (2012) A Project Evaluation Toolkit
638 (PET) for Abstracted Networks: Final Report. FHWA/TX-2013/0-6487-1. Center for
639 Transportation Research, University of Texas at Austin.
640
641 Michalek, J., M. Chester, P. Jaramilloc, C. Samaras, C-S. Shiaue, L. Lave (2011) Valuation of
642 plug-in vehicle life-cycle air emissions and oil displacement benefits. PNAS 108 (40): 16554-
643 16558.
644
645 Musti, S. and K. Kockelman (2011) Evolution of the Household Vehicle Fleet: Anticipating
646 Fleet Composition, PHEV Adoption and GHG Emissions in Austin, Texas. *Transportation*
647 *Research Part A* 45(8): 707-720.
648
649 NHTS (2009) Public Use Codebook, Version 2.1. National Household Travel Survey, Oak Ridge
650 National Laboratory, U.S. Department of Transportation. Available at
651 http://nhts.ornl.gov/2009/pub/Codebook.pdf.
652
653 National Highway Traffic Safety Administration (2010) Corporate Average Fuel Economy for
654 MY2012-MY2016 Passenger Cars and Light Trucks. Available at
655 http://www.nhtsa.gov/staticfiles/rulemaking/pdf/cafe/CAFE_2012-2016_FRIA_04012010.pdf.
656
657 Nichols, B. (2013) Energy and environmental contexts of cities, transportation systems, and
658 emerging vehicle technologies : how plug-in electric vehicles and urban design influence energy
659 consumption and emissions. Master's Thesis, University of Texas at Austin. December 2013.
660
661

662 Osborn, S., A. Vengosh, N. Warner, R. Jackson (2011) Methane contamination of drinking water
663 accompanying gas-well drilling and hydraulic fracturing. PNAS 2011 108(20): 8176-8176.
664
665 Park, C. C. (1987) Acid rain: rhetoric and reality. *Environ. Sci. Technol.,* 22(12): 1402-1402.
666 http://pubs.acs.org/doi/abs/10.1021/es00177a603.
667
668 Rosenberg, D. M., F. Berkes, R. A. Bodaly, R. E. Hecky, C. A. Kelly, J. Rudd (1997) Large-
669 scale impacts of hydroelectric development. *Environmental Reviews* 5(1): 27-54.
670
671 Samaras, C. and K. Meisterling (2008) Life Cycle Assessment of Greenhouse Gas Emissions
672 from Plug-in Hybrid Vehicles: Implications for Policy. *Environ Sci. Technol.* 42(9): 3170-3176.
673
674 Sioshani, R. and P. Denholm (2009) Emissions Impacts and Benefits of Plug-In Hybrid Electric
675 Vehicles and Vehicle-to-Grid Services. *Environ. Sci. Technol.* 43(3): 1199-1204.
676 http://pubs.acs.org/doi/abs/10.1021/es802324j.
677
678 Stephan, C. and J. Sullivan (2008) Environmental and Energy Implications of plug-in hybrid-
679 electric vehicles. *Environ. Sci. Technol.* 42: 1185-1190.
680
681 TDSHS (2009) Texas Population (2009) Texas Department of State Health Services.
682 http://www.dshs.state.tx.us/chs/popdat/ST2009.shtm.
683
684 Thompson, T., M. Webber, D. Allen (2009) Air quality impacts of using overnight electricity
685 generation to charge plug-in hybrid electric vehicles for daytime use. *Environmental Research*
686 *Letters* 4(1). http://iopscience.iop.org/1748-9326/4/1/014002/fulltext/#erl292513bib19.
687
688 Thompson, T., C. King, D. Allen, and M. Webber (2011) Air quality impacts of plug-in hybrid
689 electric vehicles in Texas: evaluating three battery charging scenarios. *Environmental Research*
690 *Letters* 6(2). http://iopscience.iop.org/1748-9326/6/2/024004.
691
692 Tsoutsos, T., N. Frantzeskaki, V. Gekas (2005) Environmental impacts from the solar energy
693 technologies. *Energy Policy* 33(3): 289-296.
694 http://www.sciencedirect.com/science/article/pii/S0301421503002416.
695
696 Wang, M. W. (2001) Development and Use of GREET 1.6 Fuel-Cycle Model for Transportation
697 Fuels and Vehicle Technologies. Center for Transportation Research, Energy Systems Division,
698 Argonne National Laboratory. http://www.transportation.anl.gov/pdfs/TA/153.pdf.
699
700 Zivin, J., M. Kotchen and E. Mansur (2012) Spatial and Temporal Heterogeneity of Marginal
701 Emissions: Implications for Electric Cars and Other Electricity-Shifting Policies. NBER
702 Working Paper No. 18462. http://www.nber.org/papers/w18462.
703
705
706