EMISSIONS AND EXPOSURE COSTS OF ELECTRIC VERSUS CONVENTIONAL VEHICLES: A CASE STUDY FOR TEXAS

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ABSTRACT

The emissions and human exposure impacts of electric vehicle (EV) adoption, especially in comparison to conventional gasoline- or diesel-powered engines, depends on numerous factors including geography, electricity generation, and fuel mix. Results of any analysis also vary depending on the nature of data collected and its level of aggregation by time or location. This paper combines several approaches to develop a robust estimate of these impacts specific to the state of Texas by considering marginal emissions by time of day, as well as location of vehicle and power plant emissions. The authors estimate health and other external costs of operating an EV in the state at approximately $62 per year, compared with an average of $136 for a passenger car powered by gasoline.

INTRODUCTION

As electric vehicles (EVs) continue to become more efficient and reliable, EVs have become an increasingly realistic option for individuals in the market for a new car. Battery costs are falling (Nykvist and Nilsson, 2015) and consumers value energy efficiency, especially in times of high fuel prices. Many are motivated by the possibility of reducing their carbon footprint and other emissions. Before rushing to adopt an EV, however, it is important to holistically evaluate all of their costs and benefits.

While pure electric vehicles (or BEVs) are sometimes advertised as “zero-emissions,” this is rarely an accurate characterization, even ignoring the emissions embodied in the vehicle’s production process. Several researchers (Michalek et al., 2011; Anair and Mahmassani, 2012; Tessum et al., 2014; Nichols et al., 2015) have highlighted the variable and often significant emissions resulting from electric power production to charge EV batteries. A fair assessment of EVs’ environmental impacts requires a detailed look at these emissions, their spatial distribution, and their exposure and human health implications.

This paper develops a detailed comparison of EV and conventional vehicle emissions across the state of Texas. Actual emissions data, drawn from state and national databases, are used to characterize the emissions implications of EV charging using the Texas grid, while U.S. Environmental Protection Agency mobile-source emissions software is used to generate the emissions profile of modern light-duty vehicles. Each of these is then monetized using health-cost estimates specific to the emissions location and species. The human health implications of a small dose of sulfur dioxide at ground level, for example, can differ significantly from the large, concentrated plume emanating from a large power plant. Meanwhile, the geographic location of emissions matters a great deal. Even relatively dirty electricity production in a sparsely populated rural area may result in less net human exposure than cleaner generation near a major city.

BACKGROUND

Nichols et al. (2015) investigated the emissions implications of shifting a single travel-mile in a late-model passenger car or light-duty truck to an EV powered by the Electric Reliability Council of Texas (ERCOT) grid, which covers approximately 80% of the state's land area and nearly 90% of its population. Their methodology focused on average plant emissions, and they found that while the EV resulted in generally lower emissions overall, some pollutant species were significantly higher than for the gasoline- or diesel-powered equivalent. Of particular concern was the extremely high monetized cost of sulfur dioxide emissions resulting from coal-fired power plants, even though Texas uses relatively low-sulfur coal from Wyoming (EIA, 2012). In their analysis, this discrepancy actually tilted the final emissions-cost verdict away from EVs because they entailed dramatically higher monetized externalities on average (by a factor of nearly 60%). This outcome assumed all kilowatt-hours of power to be created equally and every ton of emissions to be valued equally, which are not always reasonable assumptions. This situation warrants further consideration.

There are several key points at which the above analysis could be improved. For example, using average emissions estimates for electricity generation can oversimplify the situation. A single dollar-per-ton cost for each pollutant species, uniformly applicable regardless of human exposure, is also misleading. This paper revisits the question of where and when power plant emissions take place, and what that means for population exposure. First, it is important to disaggregate emissions variability throughout the day. Siler-Evans et al.'s (2012) marginal emissions factors for the ERCOT grid are used here to give more accurate estimates of marginal emissions loads by time of day and season of year for EV charging.

This paper also draws on data developed by the U.S. Environmental Protection Agency to quantify aggregate emissions spatially. Muller and Mendelsohn's (2006) Air Pollution Emission Experiments and Policy Analysis Model provides estimates of emissions costs to the environment and human health.

METHODOLOGY

This paper quantifies the environmental and human exposure costs of emissions from charging of electric vehicles and compares those costs to those of conventional vehicles in Texas. The primary challenge is to map electricity demand to power generation, and then to determine associated emissions and their monetized costs.

Calculations described below rely heavily on the work of Muller and Mendelsohn (2006), who developed externality cost estimates by emissions species, county and source height (for ground level vs. intermediate [250-500 m], vs. tall [over 500 m] plume heights). Their Air Pollution Emissions Experiments and Policy (APEEP) is a reduced-form model that accounts for "adverse effects on human health, reduced yields of agricultural crops and timber, reductions in visibility, enhanced depreciation of man-made materials, and damages due to lost recreation services" (Muller and Mendelsohn, 2006).

The county-level external-cost estimates they have developed based on 2011 data are the most recent available as of this writing. They are applied here to emissions rates from each electric generating unit (EGU) by county of generation, in order to obtain emissions-related externality costs (in dollars) per megawatt-hour specific to each point source in the Texas power grid. The grand total of all of these power-weighted externalities represents the aggregate annual cost of human exposure and monetary damage due to electricity generation within the ERCOT region. Grid totals are then divided by total electricity output to provide average pollution profiles (by species) per megawatt-hour and the associated external costs.

One approach in external-cost estimation is to focus on the *marginal* emissions of the ERCOT grid per kilowatt-hour of demand added. Siler-Evans et al. (2012) estimated marginal emissions factors (MEFs) for each North American Electric Reliability Corporation (NERC) region in the U.S., which offer an emissions profile for each additional kilowatt-hour of electricity usage on the margin, or on top of the grid's base load, for each of the 24 hours of the day and for three seasons of the year. These values represent the marginal emissions from the entire NERC region, in this case ERCOT: nearly all of the state of Texas. Thus, time specificity comes at the expense of spatial specificity. However, this time detail is important: Siler-Evans et al. (2012) report that average emissions factors (AEFs) overstate SO2 emissions by a factor of four for the Texas grid in 2007. Using these marginal rates to estimate exposure costs requires assumptions about how to assign the spatial distribution of this exposure, since it can be quite variable. In this study, Muller and Mendelsohn's (2006) estimates are applied to assess upper bounds for monetized externalities of these marginal emissions, based on worst-case Texas counties for the relevant pollutant species.

For a more nuanced account of spatial variation, it is necessary to forgo such time-of-day detail and rely instead on more comprehensive (but not time-specific) emissions inventories. The U.S. EPA's Emissions and Generation Research Integrated Database (eGRID) database (EPA, 2014a) provides information on the annual emissions associated with every EGU in the ERCOT grid. It thus provides not only an overall accounting of emissions by Texas EGUs, but also a spatial distribution of these emissions. This allows one to match emissions from a given plant to the monetized impact of those emissions. The drawback to this source is that it inventories only two of the pollutant species monetized in Muller and Mendelsohn's (2006) work (oxides of nitrogen and sulfur dioxide), along with carbon dioxide, which was assigned here a value of $20 per short ton in constant year 2000 dollars based on a conservative reading of the Interagency Working Group on the Social Cost of Carbon's (2010, 2013) work.

To remedy this shortcoming, the same analysis was also run with county-level emissions data from the U.S. National Emissions Inventory (EPA, 2014b), which includes all six species covered by Muller and Mendelsohn (2006). The NEI has its own limitations: it does not quantify power generation , and a user inquiry for greenhouse gases produced a system error. The comprehensive nature of this data set's coverage of criteria pollutants, though, makes it a useful reference. Criteria pollutants are the six species regulated by the EPA's National Ambient Air Quality Standards (NAAQS): particulate matter, ground-level ozone, carbon monoxide, sulfur oxides, nitrogen oxides, and lead.

Validation of Combined Model

Together, eGRID and the NEI give quantities of seven airborne species of interest due to electricity generation in Texas. To verify the compatibility of these two different sources, we compared eGRID's and the NEI's, NOx and SO2 estimates of ERCOT totals and found their numbers to differ by 20% for NOx and less than 2% for SO2. We then used an average value for these two species, and drew the other species' estimates from the associated source.

Network Sub-grids

The interconnectedness of the power grid makes it impossible to know just where the electricity to meet a given load will be generated. However, it is reasonable to surmise that, all things being equal, a given demand will tend to be met by power generated nearby rather than farther away. Accordingly, this paper repeats the above calculations for hypothetical "sub-grids" in the vicinity of Texas' largest cities. A cluster of power plants was identified in the counties surrounding each of Texas' biggest metropolitan areas: Dallas-Fort Worth (population 6.9 million), Houston (6.5 million), San Antonio (2.3 million), and Austin (1.9 million). Average emissions and external costs were then calculated assuming that those cities draw primarily from these clusters of nearby EGUs.

After developing a range of estimates for electric vehicles charging and operating in the state of Texas, it is valuable to compare these results to those that would be obtained in analysis of conventional, gasoline-powered vehicle emissions. While there is no central database akin to eGRID or the NEI to authoritatively document emissions totals for light-duty vehicles, the U.S. EPA's Motor Vehicle Emission Simulator (MOVES) software offers estimates adjusted by county and season. MOVES simulation results were derived for top pollutants in Travis, Dallas, and Harris counties, Texas, in both January and July, as described in Nichols et al. (2015). These results are roughly comparable to the EV estimates described above, as they describe emissions of a typical late-model vehicle in the 2010 fleet. Using the pollutant species for which electricity data were derived earlier, we compared monetized emissions estimates for conventional vehicles to those for electric vehicles. Results are reported below.

EMISSIONS ESTIMATES

Marginal Emissions Factors (MEFs)

Calculating marginal emissions using Siler-Evans et al.'s (2012) MEFs is straightforward because their values are already reported as marginal numbers. The key variable is vehicle efficiency, or how many watt-hours are required to power the vehicle over a given distance. While this figure depends on weather, traffic conditions, vehicle speed, and other factors, an average of 250-300 Wh/mi is common for the most popular electric vehicle models (Nichols et al., 2015). This translates to the range of marginal emissions cost estimates reported in Table 1 for the pollutants they considered. The true upper bound may be higher, since the typical EV is lighter and more energy-efficient than the fleet average, but the values reported below represent the worst hour of generation in the highest external-cost Texas county. Actual damages are likely to be significantly lower than the "high" value derived here.

TABLE 1 Estimated externalities based on marginal emission factors

	kg/ MWh		2010 $/ MWh		2010 $/ 12,000 miles	
	Low	High	Low	High	Low	High
CO2	397.7349	685.0514	7.95	13.70	23.86	49.32
SO2	**	1.658473	**	14.39	**	51.81
NOx	**	0.957945	**	2.64	**	9.51

Note: ** indicates that lowest time-of-day marginal emissions factor is negligible.

The worst-case scenario for each species implies a total external cost of $110 per year considering only the carbon dioxide, sulfur dioxide, and oxides of nitrogen associated with electricity generation in Texas. However, there is considerable variability between low and high marginal emissions factors, especially in the case of sulfur dioxide, since this pollutant is quite time-sensitive. Any four-hour charging window would result in an average emissions intensity at least 12 to 30% lower than these extremes, even if the charging window includes the peak emissions hour. In addition, this worst-case scenario is premised on Muller and Mendelsohn's (2006) work for Fort Bend County, which has by far the highest dollar per ton value in the state. Using the next highest value, for populous Harris County (Houston region), results in a 45% lower estimate in dollars per megawatt-hour.

Statewide Emissions Externalities

As an alternative approach, combining county-based external-cost estimates with emissions inventories from specific EGUs or counties provides a more nuanced way to estimate the actual damages while accounting for spatial variations in human exposure. Table 2 contrasts the statewide external-cost estimates developed by combining eGRID (EPA, 2014a) and NEI (EPA, 2014b) aggregate emissions data with Muller and Mendelsohn's (2006) monetization estimates for NOx and SO2.

TABLE 2 External-cost estimates for NOx and SO2 emissions from ERCOT grid ($2010)

	eGRID	NEI	Average
NOx	103,205,482	124,385,378	113,795,430
SO2	886,214,493	897,066,020	891,640,257

For a comprehensive look at emissions costs, these average values for NOx and SO2 were combined with similar results for other species, which are shown in Table 3. Results were then divided by total ERCOT generation, as provided in eGRID, and translated into an average cost per mile traveled by an electric vehicle powered by the ERCOT grid. This estimate is automatically weighted by fuel type because it accounts for production levels at individual plants, and population exposure because the external-cost factors are county-specific. The cost per mile is then scaled up to an estimate per 12,000 miles because this represents a typical year of driving for the average vehicle. Overall external costs are reported in Table 4.

TABLE 3 Total external costs for 7 species (2010$)

Species	Data Source	External Cost
NOx	average	113,795,430
PM10	NEI	6,552,757

PM2.5	NEI	51,164,433
VOC	NEI	1,683,775
SO2	average	891,640,257
NH3	NEI	4,041,106
CO2	eGRID	5,328,681,043
total		6,397,558,801

TABLE 4 Average external-cost estimates based on eGRID and NEI data

Total ERCOT Generation (MWh)	342,146,877
Total Externalities for 7 Species (2010 $)	6,397,558,800
Grid Average (2010 $/ MWh)	18.70
Vehicle Average (2010 $/ mile)	0.0051
Yearly Average (2010 $/ 12,000 miles)	61.70

Sub-grid Analysis

Thus far we have maintained our assumption that electricity used at a given location may be generated anywhere in the grid, so one cannot assign a specific power plant based on vehicle charging location. The picture can change if we restricted our focus to some subset of the ERCOT's power plants. Siler-Evans et al.'s (2012) MEFs are not available at the EGU level, but the spatial calculation matching eGRID and NEI emissions to Muller and Mendelsohn's (2006) external-cost estimates proceeds exactly as before, this time restricted only to the plants identified as "nearest" to each city. Table 5 shows those cost estimates derived for Texas' biggest metro regions using this process.

TABLE 5 External-cost estimates for Texas sub-grids based on eGRID and NEI data

	Dallas/ Fort Worth	Houston	San Antonio	Austin
Total Generation (MWh)/yr	46,843,328	98,239,680	23,683,685	27,227,779
Total Externalities (2010 $)/yr	306,595,935	1,522,900,370	589,854,395	694,427,887
Average External Costs (2010$/MWh)	6.55	15.50	24.91	25.50
Driving Cost (2010 $/ mi)	0.0018	0.0043	0.0068	0.0070
Yearly Cost (2010 $/ 12k mi)	21.60	51.16	82.19	84.16

Finally, Muller and Mendelsohn's (2006) cost-per-ton values were applied to several MOVES-based estimates of emissions rates from gasoline vehicles. Table 6 reports external-cost values per vehicle-mile based on an average annual travel distance of 12,000 miles. While MOVES accounts for many additional species, Table 6 reflects only those species (2010$) which appear in eGRID and the NEI and have been monetized by Muller and Mendelsohn, to enable a more direct comparison.

TABLE 6 External-cost estimates of conventional vehicles in Texas

	2010$/ mi	2010$/ 12,000 mi
Dallas	0.0106	127.70

Houston	0.0105	126.42
Austin	0.0128	153.79
Average	0.0113	135.97

Note: Austin values do not include ammonia.

OTHER CONSIDERATIONS

The results presented here suggest a strong benefit to adopting EVs in Texas in order to significantly reduce the harmful effects of motor vehicle operation. The grid-wide external costs in Table 4 are less than half the equivalent costs of operating a conventional vehicle in any of the state's largest metro areas. While worst-case calculations based on marginal emissions factors are much higher, the best marginal scenario often involves no extra air pollution. Assuming that externalities are properly priced, then, smart charging technologies that take only the lowest-emissions power during the day could potentially result in minimal harmful air quality impacts to power the fleet of the future.

While we have been careful to compare similar vehicle types in this analysis, several differences exist. Our hypothetical electric vehicle is mostly powered by the entire Texas grid and thus draws on both emissions and external-cost estimates from approximately 200 Texas counties. The conventional vehicle values used for comparison, on the other hand, are based only on numbers from three large counties (Dallas, Harris, and Travis). Much of the difference in external costs may come from geographic differences: by exporting emissions from urban tailpipes to distant power plant stacks.

On the other hand, the typical Texas vehicle, as in many states, is urban: 70% of the state's population is concentrated in the "Texas Triangle" bounded by Houston, San Antonio, and the Dallas-Fort Worth metroplex. Thus, the comparison given above is a realistic representation of a potential shift from gasoline to electric power: the emissions associated with ground-level combustion in one of Texas' biggest cities would be traded for dispersed ERCOT electricity generation in a typical case of electric vehicle adoption.

There are a number of other differences between electric and conventional vehicles. For example, the performance of EV batteries is susceptible to greater variations with ambient temperature than a combustion engine. This may account for increased annual energy consumption of 15% when compared to a conventional vehicle (Yuksel and Michalek, 2015). In addition, in cold conditions, the waste heat of an internal combustion engine can serve as climate control for the passenger cabin without requiring additional energy. An electric vehicle requires battery charge to provide this heat.

Any fuel source entails additional upstream emissions due to recovery, refining, and transportation to the point of use (Delucchi, 2008). These emissions result in added external costs, which can affect the results above. The nature of the fuel recovery process is tremendously important to this analysis, both for electric and for conventional vehicles. An increased use of natural gas for power generation, for example, holds the promise of reducing both carbon and sulfur dioxide emissions. However, some analysis has suggested that the escaped methane from fracking may more than cancel that benefit (Howarth, 2014).

The best way to resolve this difficulty may be to further develop renewable energy sources such as wind and solar energy. EVs are inherently better suited to promote such technologies, as an electric battery depends on the electricity generation technologies available at the time of use. This stands in sharp contrast with internal combustion engines, which are more or less fixed. It is possible, at substantial cost, to retrofit a gasoline vehicle to run on propane, for example. If the electric grid continues to shift toward cleaner fuels, it will be easy to recharge an EV with solar power instead of coal- or natural gas-generated electricity. Unlike a conventional vehicle, an EV purchased today might be associated with lower per-mile emissions in the future.

CONCLUSION

This paper has deepened our understanding of the health and environmental costs associated with EV charging, at least on grids like those found in Texas. Depending on methods and data sources used, one can derive a wide range of reasonable estimates, but they tend to confirm that emissions costs vary significantly over space/locations and across power feedstocks.

When we examined hypothetical sub-grids around Texas' largest cities, we found substantial variation by city, as well as by data source. The clear winner in each case was EVs charging in the Dallas/ Fort Worth region, which had half the monetized damages of the gridwide average when calculated using eGRID values, and far less using the NEI's values. The other cities were harder to characterize: Houston was near average in the eGRID scenario, with San Antonio and Austin performing quite poorly. Using NEI data, however, Austin fared well, while Houston and San Antonio endured above-average costs. It is worth noting in this case that Dallas estimates were an order of magnitude lower than for other regions, which is a suspicious result.

Another dramatic difference was apparent between the electricity estimates developed here and the conventional vehicles described by MOVES. This difference, while striking, is in some respects not surprising. Even as stringent emissions regulations have cleaned up the vehicle fleet significantly, power plants, especially those fueled by coal, still emit significant quantities of NOx and SO2. In addition, it is important to be mindful of the limitations of these data sources. The National Emissions Inventory, while comprehensive, cannot physically track every gram of air pollution emitted in the country. Individual vehicles, both more numerous and more geographically dispersed, are even harder to track with certainty. MOVES makes no claim to represent precise emissions events; it offers reasonable estimates based on lab tests and simulation.

The nature of electricity transmission makes it impossible to know with certainty what plants are meeting a given demand, but this may be a positive thing. Everyone using electricity in Texas has an interest in, and the power to influence, the emissions of a distant power plant, and those closest to population centers. It is reasonable to place a policy priority on reducing emissions from Texas' dirtiest plants, or replacing those units with cleaner alternatives. Such improvements at one location in the state improve the emissions profiles, and the associated externalities, of EV charging everywhere on the grid.

Finally, it is important not to lose sight of the big picture. Life-cycle analysis, value for money, and social equity considerations must all play a role in determining the place for EV and other emerging technologies in our society. This paper has shown the degree to which operational emissions may be improved by adopting popular models of electric vehicles. A social commitment to improvements in the electricity generation process, in gasoline refinement, in provision of high-quality mass transit, or other creative energy solutions should improve the future situation.

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