Environmental Benefits from Transportation Electrification

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Despite the lack of a comprehensive regulatory framework for addressing externalities, electrification of the transportation sector is proceeding. Much of the innovation (and hype) has occurred with automobiles, and electric cars are increasingly seen as a viable option for personal transportation. However, cars are only one aspect of our transportation infrastructure that could be electrified. Recently, Elon Musk unveiled plans for a Tesla long-haul semi-truck. Some buses and trains have long been electrified, such as with overhead power lines or electrified rails, but advances in battery technology, wireless charging, and autonomous driving may open new possibilities for buses and trains as well as for short-haul delivery, commercial and heavy-duty trucking, and other transportation modes.

If policies were to address market failures like externalities, then market adoption of new technologies would be efficient. In other words, market forces would lead to electrified transportation where it is least costly from both private and social perspectives. However, existing policies do not correct all market failures. For example, environmental externalities are not priced through current or anticipated public policy. This necessitates second-best policies that can improve the efficiency of transportation electrification. Carefully designed second-best policy requires estimates of benefits and costs.

This project aims to assess the environmental benefits of electrification across a variety of modes of transportation. Earlier research argues that an environmental benefit of electrification arises if emissions associated with the electrified vehicle are less than the emissions of the non-electric vehicle. Thus, it is crucial to estimate both the emissions of the electrified vehicle and the non-electric version. This problem is especially complicated for a number of reasons. First, emissions of electrified transportation are difficult to assess. Emissions of a diesel bus occur directly from the tailpipe of the bus. However, an electric bus has no tailpipe, but causes emissions from the power plants which are generating the electricity. Assessing emissions from electric transportation requires assigning emissions at power plants to electricity use at various locations. Second, both electrified and non-electrified transportation cause emissions of a variety of pollutants. A complete assessment must analyze multiple pollutants. Third, transportation emissions occur at different locations. While greenhouse gases have the same effects regardless of their location, the effects of emissions of local pollutants, e.g., particulate matter, depend on where they are emitted. These reasons make assessing the environmental benefits of transportation electrification difficult.

We develop and extend techniques to address these difficulties.[2] First, we econometrically estimate the relationship between electricity load (i.e., the quantity consumed) and power plant emissions to estimate the emissions of electrified transport. Second, we use an integrated assessment model to calculate the damages of emissions from multiple pollutants at different locations. Adding up damages across pollutants and locations allows us to assess and compare the damages of electrified and non-electrified transport. The environmental benefit of electrification is then the difference between the avoided damages of the non-electrified transport and any damages from the electrified transport.

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[2] Prior analyses of externalities from electric vehicles include Archsmith et al. 2015, Graff Zivin et al. 2014, Holland et al. 2016, Holland et al. forthcoming, Li et al. 2017, and Michalek et al. 2011.

Our calculations of environmental benefits will be a useful guide to policy for transportation electrification. For example, Holland et al. 2016 show that the second-best subsidy for electric vehicles is simply the difference in damages between the non-electric and electric vehicles, i.e., the environmental benefit, over the lifetime of the vehicle. Our work will contribute by comparing and contrasting the environmental benefits across a variety of modes of transportation including personal vehicles, buses, short-haul delivery, and commercial and heavy-duty trucking.

Data and Methods

We illustrate the data and methods by focusing on bus electrification. The method will then be extended to analyze the other modes of transportation. To calculate environmental benefits of electric buses, we first estimate the transport emissions from non-electric buses, e.g., diesel buses. Diesel buses emit many pollutants. Emissions per mile of some pollutants, i.e., CO2 and SO2, can be determined directly from the carbon or sulfur content of the fuels and the miles per gallon of the buses. Emissions per mile of other pollutants, e.g., NOx, VOCs, and PM, depend on the vehicle's combustion technology.

The damages from local pollutants will depend on where they are emitted, where they are transported by wind currents, the dose-response relationship between exposures and health effects, and how many susceptible people are affected. We use the AP2 integrated assessment model (updated to include 2014 emissions, population, and vital statistics) to estimate the damages from emissions of each pollutant (Muller and Mendelsohn, 2009; Jaramillo and Muller, 2016). Summing across pollutants yields damages per mile from a diesel bus in each county.

To estimate damages per mile from electric transportation, we first calculate the electricity use per mile. We then determine the emissions per mile by econometrically estimating the relationship between electricity load and emissions at each power plant, i.e., the marginal emissions. A major contribution of our analysis will be to account for spatial heterogeneity in damages caused by electricity consumption by analyzing disaggregated electricity load regions. In particular, for each power plant i and hour t, we model emissions of a given pollutant y_{it} as

$$y_{it} = \sum_{h=1}^{24} \sum_{j=1}^{J(i)} \beta_{ijh} HOUR_h LOAD_{jt} + \sum_{h=1}^{24} \sum_{m=1}^{M} \alpha_{ihm} HOUR_h MONTH_m + \epsilon_{it}$$

where $LOAD_{jt}$ is the electricity load in region j; $J(i)$ indicates the number of load regions in the interconnection; $HOUR_h$ and $MONTH_m$ are indicators for hour of day and month of sample; β_{ijh} and α_{ihm} are estimated coefficients; and ϵ_{it} is the error term. The coefficients of interest are the β_{ijh}, which indicate the change in emissions at power plant i due to an increase in load at region j in hour h conditional on the other covariates, namely: conditional on load in other regions and on the rich set of fixed effects. Importantly, the model can nest different levels of aggregation of load by imposing restrictions on the estimated coefficients.

This estimating strategy allows us to estimate effects for disaggregated load regions. Electricity load data are available for electricity regions and sub-regions as defined by the North American Electric Reliability

Corporation (NERC). Our prior analysis (Holland et al. 2016) focused on aggregated NERC regions.[3] This level of aggregation may be appropriate for some questions or some regions. However, the effects of this aggregation have not been tested. Moreover, this aggregation requires the researcher to assume that the effects of charging an electric car are identical throughout the NERC region. For example, Raleigh, NC and Mobile, AL are both in the same NERC region, so aggregation assumes that the damages from charging an electric vehicle are the same in these two locations. This may or may not be appropriate especially given the importance of local effects highlighted in Holland et al. (2016).

Estimating the disaggregated model poses challenges. The first challenge is the sheer number of coefficients that need to be estimated on load data that is both serially correlated over hours and spatially correlated over load regions. Often this challenge can be overcome with additional data, and we have a large number of observations. A more subtle challenge arises due to model overfitting. The best statistical fit of the model may include unrealistically large or negative coefficients, which fit the model well but are not reliable estimates of the true effects. Machine learning techniques, such as LASSO, use purely statistical techniques for variable selection and regularization. For example, variable selection techniques, which punish large positive and negative coefficients, may simply select one of two variables for inclusion in the model. While this may improve the predictive power of the model, variable selection may not be appropriate for estimating marginal emissions because this would effectively assume zero effect for one sub-region but a positive effect for another nearby sub-region.

An alternative approach to the problem of overfitting would reduce the number of coefficients by imposing technological restrictions across the coefficients based on additional information about the functioning of the electricity grid. For example, we might expect that coefficients would not change dramatically from one hour of the day to the next. In this case it might be appropriate to require coefficients to be the same across some hours or to change smoothly across other hours. Similarly, we might expect two load regions which are similarly distant from a power plant to have similar or identical effects. While imposing restrictions on coefficients may seem ad hoc, the approach should generate nested hypotheses that can test the underlying assumptions.

We will explore these two approaches to estimating the disaggregated model as well as a hybrid approach combining the machine learning and technological restrictions approaches. We can compare and contrast the approaches to determine the most appropriate method for estimating the marginal emissions from electrified transport. Combining our updated estimates of marginal emissions with the damage calculations from the AP2 model and summing across pollutants will allow us to assess the marginal damage per mile for electric transportation at each electricity sub-region.

Preliminary findings

Our preliminary results focus on determining the damages from emissions of diesel buses used in urban bus service. These results will be useful for analyzing the environmental benefit of switching to electric buses. Data on miles driven and gallons of diesel fuel used by municipal bus systems were obtain from the 2015 National Transit Database.[4] Data on emissions per mile of VOC, $PM_{2.5}$, and NO_x from diesel buses were obtained from USEPA 2008. Data on emissions per mile of CO_2 and SO_2 from consumption of

[3] Another strand of literature has aggregated the data to the independent system operator (ISO) level, e.g., Callaway et al. Forthcoming. While this approach is desirable is some ways, it is only applicable in regions with ISOs.

[4] Downloaded from "http://www.apta.com/resources/statistics/Pages/NTDDataTables.aspx" on 10/11/17.

diesel fuel were calculated from data in GREET. Combining this information on emissions and miles with marginal damages from emissions as specified by the AP2 model, we determined the yearly damages from the emissions of the fleet of diesel buses in a variety of MSA's.

Table 1 shows preliminary calculations of damages from diesel buses for selected large Metropolitan Statistical Areas with the highest quality data. For the project, we will refine and clean the data for the comprehensive set of MSAs. The preliminary data suggest some intriguing results. First, the results are largely as expected with larger cities having higher total damages. For example, New York has high diesel bus miles which impose large damages. There are also some surprises. For example, Los Angeles has fewer diesel bus miles than comparably sized cities, reflecting perhaps a higher share of non-diesel buses. Second, there is considerable variation in damages per mile across the cities ranging from under $0.20 to over $0.70 per mile. This variation reflects variation in damages from the AP2 model as well as variation in the emissions rates of the various bus fleets. Understanding this variation is crucial for assessing policies fostering electrification of transportation.

Conclusion

Advances in electric motors, battery technology, wireless charging, and autonomous driving open new possibilities for electrification of transportation. Whether market forces can result in efficient electrification depends on the extent to which externalities can be adequately regulated. Understanding the benefits and costs of regulation is thus crucial to assessing public policy toward electrification.

Our project will calculate the environmental benefits to electrification of different modes of transportation including personal vehicles, buses, short-haul delivery, and commercial and heavy-duty trucks. Our updated estimates for electric vehicles will assess how the grid and damages have recently changed. Our project will also make a methodological contribution through estimating and testing for greater spatial heterogeneity in damages than allowed for in prior literature. The results will offer guidance as to which modes of transportation offer the best possibilities for amelioration of externalities through electrification.

References

Archsmith, James, Alissa Kendal, and David Rapson. 2015. “From cradle to junkyard: Assessing the life cycle greenhouse benefits of electric vehicles." *Research in Transportation Economics* 52: 72-90.

Callaway, Duncan, Meredith Fowlie, and Gavin McCormick. Forthcoming. "Location, Location, Location: The Variable Value of Renewable Energy and Demand-side Efficiency Resources". *Journal of the Association of Environmental and Resource Economists*.

Graff Zivin, Joshua S., Matthew Kotchen, and Erin T. Mansur. 2014. “Spatial and temporal heterogeneity of marginal emissions: Implications for electric cars and other electricity-shifting policies." *Journal of Economic Behavior and Organization* 107 (A): 248-268.

Holland, Stephen, Erin Mansur, Nicholas Muller, and Andrew Yates. 2016. “Are there environmental benefits from driving electric vehicles? The importance of local factors.” *American Economic Review* 106(12): 3700-3729.

Holland, Stephen, Erin Mansur, Nicholas Muller, and Andrew Yates. Forthcoming. “Distributional Effects of Air Pollution from Electric Vehicle Adoption.” *Journal of the Association of Environmental and Resource Economists*.

Jaramillo, Paulina, and Nicholas Muller. 2016 "Air pollution emissions and damages from energy production in the U.S.: 2002 - 2011." *Energy Policy* 90: 202 - 211.

Li, Shanjun, Lang Tong, Jianwei Xing, and Yiyi Zhou. 2017. “The market for electric vehicles: Indirect network effects and policy design.” *Journal of the Association of Environmental and Resource Economists* 4 (1): 89-133.

Michalek, Jeremey J., Mikhail Chester, Paulina Jaramillo, Constantine Samaras, Ching-Shin Norml Shiau, and Lester B. Lave. 2011. “Valuation of plug-in vehicle life-cycle air emissions and oil displacement benefits.” *Proceedings of the National Academy of Sciences* 108: 16554-16558.

Muller, Nicholas Z. and Robert O. Mendelsohn. 2009. “Efficient pollution regulation: Getting the prices right.” *American Economic Review* 99: 1714-1739.

USEPA 2008, "Average in-use emissions from urban buses and school buses", Office of Transportation and Air Quality, EPA 420-F-08-026.

Table 1. Damages from Diesel Buses in Selected Metropolitan Statistical Areas

Metropolitan Statistical Area	Total Damages ($ millions)	Diesel Bus Miles (millions)	Damages per bus mile
New York, NY	$38.03	164.10	$0.23
Oakland, CA	$23.71	31.99	$0.74
Newark, NJ	$20.67	107.30	$0.19
Denver, CO	$18.49	40.94	$0.45
Milwaukee, WI	$18.10	41.78	$0.43
San Francisco, CA	$15.95	29.29	$0.54
Washington, DC	$13.10	64.36	$0.20
Salt Lake City, UT	$11.82	19.55	$0.60
Seattle, WA	$11.32	71.71	$0.16
Philadelphia, PA	$9.82	43.48	$0.23
Houston, TX	$8.94	47.69	$0.19
Charlotte, NC	$7.38	23.23	$0.32
Los Angeles, CA	$6.40	10.62	$0.60
Austin, TX	$5.82	17.83	$0.33
Kansas City, MO	$5.79	11.56	$0.50
Pittsburgh, PA	$5.36	28.61	$0.19
Phoenix, AZ	$4.57	10.68	$0.43
San Antonio, TX	$4.46	22.25	$0.20
Detroit, MI	$4.32	22.10	$0.20
Louisville, KY	$3.85	8.15	$0.47
Atlanta, GA	$3.80	15.75	$0.24
Tampa, FL	$3.75	9.81	$0.38
Boston, MA	$3.43	20.49	$0.17
Ft Lauderdale, FL	$3.08	19.44	$0.16

Conflict of Interest Statements

Stephen Holland has no financial or other interests that might bear on the proposed work and has no ties to the energy industry.

Erin Mansur has no financial or other interests that might bear on the proposed work and has no ties to the energy industry.

Nicholas Muller has no financial or other interests that might bear on the proposed work and has no ties to the energy industry.

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