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Three Essays in Environmental and Transportation Economics

Stephanie Margalit Weber
Yale University Graduate School of Arts and Sciences, stephanie.weber14@gmail.com

Abstract

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The transportation sector contributes around 30% of US greenhouse gas emissions, and reducing these emissions is an important part of any large-scale climate policy. This dissertation examines three questions about policies and programs designed to reduce emissions from heavy-duty trucks and cars, using a range of economic data and methodologies.

The first chapter considers the recent federal fuel efficiency standards for heavy-duty trucks, which mandated that the average fuel efficiency of trucks sold by each manufacturer reach certain levels. To estimate the welfare implications of the policy, I develop a model of supply and demand in the sector using detailed data on vehicle sales and new data sources to observe model-level fuel efficiency. Buyers choose vehicles to maximize their utility based on vehicle characteristics and the industry in which they operate. Manufacturers choose prices and the level of fuel efficiency technology in order to maximize profits while complying with the standards. I find that buyers undervalue fuel efficiency in heavy-duty trucks. Under conservative assumptions about the cost of improving fuel efficiency needed to rationalize the historic non-adoption of certain technologies, the environmental benefits are smaller than the costs to manufacturers and buyers. However, when the uninternalized fuel savings are taken into account, the benefits are 1.1 to 6.8 times larger than the costs of the policy. These findings suggest that the fuel efficiency standards can reduce emissions from trucks while improving economic efficiency in the aggregate, though the costs and benefits are not evenly shared among buyers.

The second and third chapters examine the potential of electric vehicles to replace gasoline vehicles and reduce emissions. In the second chapter, which is coauthored with Kenneth Gillingham and Marten Ovaere, we analyze the interactions between electric vehicle adoption and different levels of a carbon tax. Using historical data on the relative price of coal and natural gas as a proxy for a price on carbon, we show that in several regions of the US, marginal generation becomes more emitting as the implicit carbon price, based on the coal-to-gas price ratio, increases and coal plants are pushed to the margin. We complement this empirical analysis with a detailed simulation of these dynamics over a longer time horizon and with non-marginal changes in electricity demand associated with electric vehicle adoption. Here, too, we find that for moderate carbon prices similar to those in place in parts of the country today, when electric vehicles are adopted in combination with a moderate carbon price, they may increase environmental damages. This adverse interaction is the result

of increased electricity demand from electric vehicles keeping online coal plants that may otherwise have been forced to retire by the carbon tax. Under higher carbon prices, no such interaction occurs. These results may be useful for policymakers who are considering implementing a portfolio of related environmental policies in tandem.

Where the second chapter took as a given that a combination of policies, technology innovation, and changes in preferences could increase electric vehicle adoption, the third chapter evaluates how potential electric vehicle buyers respond to price incentives. With Kenneth Gillingham, I analyze the effects of a short-term incentive program available to Connecticut residents who purchased new Nissan Leafs in 2017. We estimate that the $10,000 incentive increased demand for new Nissan Leafs by at least 240% in the short term, with no observable reductions in other electric vehicle sales and only a small amount of cannibalization of future Leaf sales. However, using data on the other vehicles that buyers were considering, which were disproportionately other fuel efficient cars, we find that the environmental benefits were limited relative to the magnitude of Nissan's incentive or the state and federal subsidies also available to buyers. While these large subsidies may be rationalized by other market failures, this may have implications for how policymakers try to target electric vehicle incentives.

A range of policies may be adopted in coming years to increase the sales of fuel efficient or alternative fuel vehicles. This dissertation aims to provide useful insights about the effectiveness and tradeoffs of different policies.

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Chapter 1

Estimating the Costs and Benefits of Fuel Efficiency Standards in Heavy-Duty Trucks

Abstract

Heavy-duty trucks are major contributors to transportation greenhouse gas emissions, and recent fuel economy legislation was put in place to address these emissions. This paper is the first to measure the effect of the recent policy on consumer welfare, manufacturer profits, and environmental damages, and does so using a structural model of buyers from different industries and manufacturers choosing prices and technology to respond to the policy. Because of the undervaluation of future fuel savings in the commercial vehicle market, which the demand estimates document, there are large gains from heavy-duty vehicle fuel efficiency regulation. In fact, even under relatively high costs of technology that rationalize historical non-adoption of these technologies, the fuel savings and environmental benefits of the 2014 standard exceed the costs to consumers and manufacturers.

1.1 Introduction

Reducing fuel usage and CO_2 emissions from the transportation sector is a key part of overall emissions reduction policies. Heavy-duty trucks, the subset of trucks with the highest weight capacities, are only 1% of vehicles on the road, but they contribute nearly 30% of on-road greenhouse gas emissions. The former statistic may explain in part why historically, few policies have tried to reduce truck emissions. While fuel economy standards for cars have been in place since the 1970s, the first engine standards for trucks were introduced in the late 2000s and fuel economy standards were introduced a few years later. Announced in 2011, the Heavy-Duty (HD) National Program, a set of greenhouse gas emissions standards for heavy-duty vehicles, went into effect in 2014. The standards designate an emissions limit and corresponding average fuel efficiency threshold for the trucks sold by a given company in a given year, with separate standards for different categories of trucks.

This paper analyzes the welfare effects of these heavy-duty truck fuel efficiency standards. This question is important because it sheds additional light on the effect of fuel economy standards in general, which are used in the US, Europe, China, and Japan, and on how these effects may operate in the truck market. The welfare effects of fuel efficiency standards are an empirical question, as the standards impose costs on manufacturers in order to induce the purchase of more fuel efficient new vehicles, and thereby contribute to a reduction in fuel usage and emissions. Fuel efficiency standards for cars and trucks have been rationalized by EPA based on the assertion that vehicle purchasers are undervaluing future fuel savings, but limited research has examined the costs and benefits of such a policy in the heavy-duty truck context.

To answer these questions, I estimate a model of supply and demand for the heavy-duty truck market. Specifically, heterogeneous consumers choose trucks based on preferences that differ depending on their industry (and therefore, their intended use for the vehicle). Manufacturers can comply with the policy in two ways: they can adjust prices so that consumers buy more fuel efficient models, a practice called "mix shifting," or they can adopt technology that improves vehicle fuel efficiency. Manufacturers choose a combination of these strategies that maximizes their profit. A major challenge in analyzing the truck market is data availability and particularly, data on model-specific fuel efficiency. I compile new data on empirical fuel usage and combine this with other, commercially available data on additional truck characteristics in order to estimate policy effects.

I find that despite limited information available outside of firsthand experience[1], truck buyers value fuel efficiency in the trucks that are used for long-haul shipping: conventional tractors with sleeper compartments and, to a lesser extent, conventional tractors without sleepers (called day cabs). Buyers are willing to pay approximately $18-20,000 for a 1 gallon/thousand ton-mile improvement in fuel intensity in a sleeper and $3-$4,000 for the same improvement in day cabs. On average, this would be equivalent to a 32-36% valuation of fuel savings over a sleeper truck's 30-year lifetime, a number slightly larger than previous estimates of approximately 30%, which did not distinguish between sleeper and day cabs (Adenbaum et al. 2015). According to EPA's estimates of technology adoption costs, buyers would be willing to pay for most of the technology required to comply with the policy, raising questions about why profit-maximizing manufacturers would not have adopted this technology even in the absence of policy. One potential explanation is that EPA is underestimating the cost of compliance, so I estimate what the optimal pre-policy technology adoption level would be using firms' first-order condition with respect to technology and shift the marginal technology cost curve for the post-policy period by this amount. This leads to high costs, borne particularly by consumers in industries with strong preferences for conventional tractors. However, these costs, and the costs to manufacturers, are dwarfed by the fuel savings

[1] There is a notable absence of fuel efficiency data made available in truck marketing materials, in online configuration tools, or from the government. This absence of information is discussed in more detail in subsequent sections.

and, to a lesser extent, the environmental benefits of those fuel savings.

While understanding the trucking sector is critical both for the emissions implications and for its importance to the economy as a whole, there are few papers in the economics literature that attempt to do so, and fewer still use recent data, even as the trucking industry has seen major changes in recent years. One key paper that develops a model of truck manufacturer decision-making with endogenous product attributes is Wollmann (2018), which assesses the implications of recent bailouts on the sector. This project builds upon features of Wollmann's model, but incorporates fuel efficiency standards, which were not in place during the period he examines, as well as additional vehicle characteristics relevant to the policy and to prospective truck buyers, such as the presence of a sleeper compartment.

Other papers examine decisions made by truck owners, including the relationship between market structure and adoption of technology affecting truck performance and efficiency (Hubbard 2000, 2001, Baker & Hubbard 2003, Vernon & Meier 2012) and responses to changes in fuel costs. Leard et al. (2016) estimate the rebound effect among trucks in order to predict the savings from truck fuel efficiency standards. By contrast, Cohen & Roth (2016) consider the effect of fuel costs on dispatch decisions. These papers address margins of response to fuel efficiency standards outside of the main purview of this paper, which focuses on production and demand, though these results will inform the ultimate welfare consequences. Adenbaum et al. (2015) estimate the willingness to pay for fuel efficiency in heavy-duty vehicles and find that while there is considerable heterogeneity, fuel efficiency is undervalued. Their paper relies on older survey data and does not model the responses of the supply side to consumer demand, which I incorporate.

Another research area that this paper builds upon is the study of light-duty vehicle regulation. There is a rich literature examining these and related questions in the context of Corporate Average Fuel Economy (CAFE) standards. A large number of papers consider the effect of CAFE by directly modeling the profit maximization problem of manufacturers, but over differing timelines with correspondingly different levers through which to respond to the policy. Virtually all studies include price modifications to incentivize mix shifting, whereby more fuel efficient vehicles are sold at lower prices to improve the average fuel economy, as this paper does (Jacobsen 2013). Goldberg (1998) examined another short-term channel for manufacturers to respond to the standards–switching production between domestic and foreign facilities. More common is research which considers a longer-term response to CAFE: technological changes that improve the efficiency of a given vehicle model (Bento et al. 2009, Kleit 2004, Shiau et al. 2009, Austin & Dinan 2005), and Reynaert (2020) adds gaming to the set of manufacturer responses. Another strand of the literature focuses on the extent to which fuel economy improvements were attained via technological progress versus tradeoffs along the technological frontier (Knittel 2011, Klier & Linn 2012, 2014).[2] This paper contributes to the CAFE literature by examining the extent to which the results apply to a new context and by being the first paper to systematically analyze the heavy-duty truck fuel economy standards, which are a complement to CAFE.

This paper is organized as follows. Section 2 provides background on truck attributes, the fuel efficiency policy this paper examines, available data, and market structure. Section 3 outlines the model, and section 4 provides detail on the estimation approach. Model results are presented in section 5, and section 6 contains the welfare analysis of the policy. Section 7 concludes.

1.2 Background

1.2.1 Product Characteristics

Before examining the truck efficiency standards, this section briefly discusses relevant truck characteristics. Heavy-duty trucks are characterized by a limited set of features: gross vehicle weight rating (GVWR), vehicle type (i.e., whether it is a combination tractor, in which the vehicle pulls a detachable trailer, or a straight truck, in which the cargo-carrying component is permanently attached to the vehicle), cab type, axles, and fuel efficiency. GVWR, the amount of weight the vehicle can carry (including the weight of the vehicle itself), takes a range of values; the Department of Transportation categorizes vehicles into classes 1 through 8 based on their GVWR (see table A.1.1 and figure A.2.1 in the appendix for more detail), and the light- vs. medium- vs. heavy-duty designation is determined by these classes. Heavy-duty vehicles fall into classes 7 (between 26,0001 and 33,000 lbs) and 8 (>33,000 lbs). The weight rating affects the uses of a vehicle (i.e., a truck intended to tow heavy machinery needs to be rated for loads greater than the weight of the machinery) and, in general, price is increasing in GVWR.

The cab, the portion of the vehicle that encloses the driver, any passengers, and potentially a sleeping area, is also important to potential buyers. Cab length affects comfort, safety, and ease of navigation. Shorter cabs, particular cab-over-engine designs, place the seating area directly over the engine and front axle and allow improved visibility but reduced safety. Longer cabs provide greater comfort and safety for the driver. Cabs also differ in roof height, which affects the height of trailer that can most efficiently be attached as well as the ability of the driver to stand up comfortably in the cab. Finally, some class 8 cabs feature

[2] This approach may be less relevant here, because evidence from the trucking sector suggests that the ability to substitute vehicle attributes like horsepower for fuel efficiency is weaker in heavy-duty vehicles compared to those under the purview of CAFE (He 2017).

a sleeper compartment, in which drivers can spend the night. Sleeper cabs are important for long-haul trucks that will be used for multi-day transport, but as they involve additional amenities, sleepers tend to be more expensive than non-sleeper alternatives.

As in cars, axles determine the configuration of wheels and, in the case of drive axles connected to the engine, transmit torque to the wheels. All axles also carry the weight of the attached trailer. As the number of drive axles increase, trucks are able to maintain better traction on poorly maintained or slippery roads, but efficiency tends to decrease. The same make and model can be sold with a number of different axle configurations. Historically, configurations with more drive axles have been more popular due to presumed higher retail value (Cummins 2016).

Finally, fuel economy is an important characteristic for trucks, as it governs one of the main variable costs (i.e., fuel costs) for truck owners. Fuel economy is, for the purpose of this paper and the policy it examines, measured in gallons per thousand ton-mile, as the fuel usage of a given truck differs considerably depending on whether it is empty or towing as much as 26,000 or more pounds. Historically, limited information about truck efficiency was available; manufacturers produce designated energy efficient models, but do not publicize the expected fuel usage in a standardized way.

1.2.2 Policy

Though CAFE standards were first enacted for light-duty vehicles in 1975, the federal government only recently undertook the regulation of heavy-duty vehicle fuel economy. Diesel fuel and engine emission standards were implemented in the 2000s, and in August 2011, the Environmental Protection Agency (EPA) and the National Highway Traffic Safety Administration (NHTSA) issued joint greenhouse gas emissions and fuel economy standards for medium- and heavy-duty trucks (EPA & NHTSA 2011*b*). Phase I of the rule covers model years 2014 through 2018, while Phase II, introduced in 2016, covers model years through 2027. The Heavy-Duty (HD) National Program features separate standards for three categories: combination tractors (see definition above), heavy-duty pickup trucks and vans, and vocational vehicles. This paper focuses on the first category, but includes a subset of heavy-duty vocational vehicles to accurately represent tradeoffs between potential substitutes. Heavy-duty pickups and vans are omitted.

The EPA standards for combination tractors are delineated across cab type and three roof heights for a total of nine categories (class 7 vehicles are only offered as day cabs) and, as is discussed below, compliance with the standards allows averaging across several weight categories (see table 1.2 for the 2017 combination tractor standards). By contrast, heavy-duty pickup trucks and vans (classes 2b and 3) are regulated in a similar manner to light-duty vehicles, subject to adjustments based on vehicle capacity and 4-wheel drive. Finally, vocational vehicles is the catch-all category covering vehicles as varied as cement mixers, school buses, tow trucks, etc., and this wide range of forms and purposes dictates the manner of regulation. Vocational vehicles, which fall into classes 2b-8, are divided into subcategories based on engine size, and though the standards consist of emissions/fuel economy targets, adherence is primarily based on tire choices.

Though fuel economy standards are intended to drive research and development in efficiency measures, the standards target levels of efficiency that are achievable with existing technology. The standards rely upon a subset of technologies included in a 2010 National Research Council (NRC) report on approaches to reduce medium- and heavy-duty truck fuel consumption (EPA & NHTSA 2011*a*). Some of the largest efficiency improvements are available via improvements to engines, aerodynamics, rolling resistance, and drivetrain (NRC 2010).

Compliance is determined using a simulation model, the "Greenhouse gas Emissions Model" (GEM). The model pre-defines a number of inputs including tractor frontal area, tire radius, etc. (EPA 2011). When examining combination tractors, users are able to input the coefficient of aerodynamic drag, steer and drive tire rolling resistance, whether the vehicle has a speed limiter, weight reductions from lighter components, and the use of extended idle reduction technology. Vocational vehicle standards only consider engine fuel intensity and improvement in rolling resistance.

1.2.3 Data

Analyzing the effect of heavy-duty truck fuel efficiency policy requires data on the quantity and characteristics of trucks sold, buyer attributes, and fuel efficiency technologies and their costs. I combine data from a number of sources. First, class 7 and 8 vehicle sales data for 2010-2018 come from IHS Markit (formerly R.L. Polk).[3] The sales are disaggregated by brand, model name or number, GVWR class (7 or 8), cab length, axle configuration, engine size, engine manufacturer and model (where available), and buyer information. The buyers are delineated into 13 broad categories including for-hire, local/state/federal government, private, individual, utilities, multiple lease categories, and dealer or manufacturer. Buyer types are further broken down by industry where possible (e.g., general freight, specialized/heavy hauling, forestry/lumber products, etc.). There are 32 categories in this latter field, though for this paper I often combine vocations.

[3]The IHS Markit data includes all class 7 and 8 trucks. I omit vehicles that are neither tractors nor straight trucks, which are primarily buses, fire trucks, step vans, and motor homes.

To the sales data, I join a panel of vehicle models and their characteristics from Price Digests. The characteristics from Price Digests include brand, model name or number, gross vehicle weight, axle configuration, BBC (a measure of the distance from bumper to back of cab), an indicator variable reflecting whether a vehicle is a tractor, a sleeper type field that includes roof height where available, wheelbase (the distance between front and rear wheels), and manufacturer suggested retail price (MSRP). The attribute data was merged with the sales data based on brand, model name, GVWR category, axle configuration, and the tractor flag. Where no matches were available, I first checked for alternate names (sometimes model numbers were used in one source while model names were used in the other; in other instances, one source combined models under a broader model name while the other distinguished between e.g., "model name 500" and "model name 600") and then relaxed the attributes on which the merge was performed. A feature of the heavy-duty vehicle sector (that also applies to cars and light trucks to a lesser extent) is that multiple configurations may be categorized as falling under the same brand-model within a year. Where multiple models in the Price Digest data mapped to a category in the sales data, I calculated the average price and gross vehicle weight to use in the demand estimation. Of the more than 1.8 million class 7 and 8 vehicle sales in the data, almost 98% can be mapped to price and other attribute data. Price Digests also includes information on retail price, which I use to adjust MSRP.

Table 1.1 contains the summary statistics for vehicles available in model years 2011-2019. There are more class 8 vehicles than class 7, and the largest number of unique vocational vehicle offerings (though this table counts all sleeper roof heights as a single product offering). At the level of disaggregation I consider, there are several hundred product offerings per year, and both within and across time, there is considerable variation in price and other attributes. It is also worth noting that the total market size for the included class 7 and 8 trucks is considerably smaller than the market for cars and light trucks. Market size is responsive to a number of economic conditions, and the minimum annual sales are for the 2011 model year, when the Great Recession was ongoing. The maximum sales occurred for model year 2016.

Importantly, neither the IHS Markit data nor the Price Digests data include empirical measures of fuel efficiency. While fuel efficiency data for cars and light trucks is made available by the EPA[4], no such website exists for heavy-duty vehicles. The lack of reliable, agency-vetted data on performance has been noted by other stakeholders, who have advocated for more public data including a labeling program comparable to that which exists for light-duty vehicles.[5] As a result, I use empirical data on fuel efficiency performance

[4] `www.fueleconomy.gov`

[5] As ACEEE noted in their public comments on the Phase II standards, "The absence of a label or any other publicly available information stating the fuel efficiency of the vehicle at the time of sale means the consumer is in effect cut out of the market for efficiency."

from a website used by truck drivers to track their fuel usage.[6] Drivers are able to register their trucks on the website and for each fuel up, record the gallons of fuel used and the distance travelled. Their trucks are identified by year, make, and model, and drivers are able to record additional details, including average speed, average GVW, modifications they have made to the vehicle, etc. See appendix figure A.2.2 for what the data looks like at the aggregate and individual-truck level. I combined this data to calculate average miles per gallon for each truck model-year, and using known GVWR and assumptions about how full the trucks typically operate, rescaled this into a fuel intensity measure in gallons per thousand ton-mile. This measure is imperfect and selection into using a fuel tracking website is certainly a concern, but I am able to confirm that models designed to be relatively more fuel efficient were determined to have lower fuel intensities than other models.[7] Figure 1.1 shows the sales-weighted average fuel intensity among sleeper cabs over time. There is an observable decline in fuel intensity in the first year of the standards (2014).

Several additional data sources merit discussion. The costs of different fuel efficiency technologies were derived from EPA's Regulatory Impact Analysis. Patterns in annual VMT by class and sleeper are based on the Vehicle Inventory Use Survey with adjustments that bring the data in line with the Regulatory Impact Analysis. State-level manufacturing wages by year, used to construct an instrument for price, come from the Bureau of Labor Statistics, while Canadian province-level manufacturing wages were ascertained via Statistics Canada. Wages were then matched to the assembly plants at which each model is assembled, which in turn was derived from model VINs. The US Census County Business Patterns data provided the numbers of firms and employees in each industry. The variation in this data is the basis for the distribution of truck buyer industry types each year.

1.2.4 Market Structure

The structure of the truck market–in which a small number of manufacturers produce most of the models purchased by commercial buyers–informs the modeling decisions made in the following section.

[6] `www.letstruck.com`

[7] Historically, the census conducted a regular survey of truck owners, the Vehicle Inventory Use Survey (VIUS), that included fuel usage and vehicle payload data that would address selection concerns in my data. The survey was discontinued after 2002, but many papers examining truck-buying behavior (Wollmann 2018) or fuel price responsiveness among truck owners (Adenbaum et al. 2015), relied on this dataset. The census has begun a new iteration of the survey, and results will be available in late 2023.

Manufacturers

The heavy-duty truck market is more concentrated than the light-duty market. There are 19 brands, or makes, of class 7 and 8 vehicles in the sales data, and 14 of these produce models available as conventional tractors (i.e., are affected by the tractor-specific policy). 10 of the brands can be found in the Price Digests data (the remaining four sell less than 1% of vehicles in the sales data). Several of these brands are owned by the same parent company: while Autocar, Caterpillar, Ford, and International brands are all separately owned, Daimler's brands include Freightliner and Western Star; PACCAR owns Kenworth and Peterbilt; and Volvo produces both the brand of the same name and Mack. These ownership structures are accounted for in the supply model. Figure 1.2 shows the market share of each brand over time. Through the entire period, Freightliner's market share is at or above 30%.[8] The only other brand that comes close is International, which gradually loses market share for much of the time period.

In addition to market concentration, the supply side of heavy-duty trucks differs from that of light-duty vehicles in a few key ways. For example, not all components are produced by the manufacturer. Rather, axles, transmissions, and engines are often produced by outside companies. When a customer purchases a new vehicle from a particular brand, the buyer is given a choice of many attributes, and the brand serves as the central contact point to acquire and assemble parts within the main vehicle body. Because of this role, the efficiency standards are enforced at the manufacturer level, though separate engine standards also apply.

Buyers

The majority of trucks are purchased for commercial purposes. In the data, approximately 4% of class 7 and 8 trucks are purchased by local, state, and federal government, while the remainder go to individuals and firms. Among vehicles sold to firms for which data is available, the freight industry purchase nearly half of vehicles (48%), while service industry buyers purchase 13%, the wholesale and retail sector buys 7.2%, and construction firms purchase another 7.1% of vehicles.[9] However, there is also meaningful variation in industry

[8] Freightliner is, as noted above, one of two brands owned by Daimler, but Freightliner's sales are considerably larger than the other Daimler brand, Western Star. Interestingly, the vast majority of Freightliner's sales come from the Cascadia model, which is available in a range of configurations. Between 2010 and 2019, the Freightliner Cascadia's sales were between 13 and 28% of all class 7 and 8 sales included in the data.

[9] This excludes leased vehicles, for which only the nature of the lease (rental, finance, manufacturer sponsored) is available. Unfortunately, the industry of the lessee is unavailable in the data. This might be an issue for my estimation if particularly industries are disproportionately likely to lease vehicles rather than purchase outright.

shares over time.

Buyer industry is important because it determines the distance traveled and weight carried, which in turn shapes preferences for cab characteristics and GVWR. This is evident in table 1.3 which shows that sanitation and construction are much more likely to purchase vocational vehicles than general or specialized freight or other industries, and that while all industry groups are more likely to purchase class 8 vehicles than class 7, sanitation and general freight in particular purchase a large share of class 8 vehicles.

Beyond industry, firm size is an important attribute that affects the appropriate choice of demand model. The size of truck-purchasing firms varies tremendously. At the time of the most recent VIUS, 70% of respondents operated 1-6 tractors, but more than 8% operated more than 50 tractors. The decisions made by large fleet operators may be different from those made by smaller purchasers, but following Wollmann (2018), this paper abstracts from these issues. Future research may consider how decisions made by the managers of smaller or larger fleets differ.[10]

A number of surveys study the decision-making and behavior of truck owners. Large fleets sell or replace tractors more frequently than small fleets do–generally, after three to five years (Schoettle et al. 2016). While both types of fleet operators seem to require payback periods for efficiency-improving technologies considerably shorter than the expected lifespan of a given tractor, Klemick et al. (2015) and Schoettle et al. (2016) found that larger fleets had longer payback periods. Fuel economy was a major consideration in tractor purchase decisions but was a relatively lower priority for operators of short-haul or regional fleets.

1.3 Model

To analyze the effects of the fuel economy policy, I estimate a model of consumer and manufacturer decision-making. The demand model features heterogeneous buyers choosing vehicles to maximize utility based on vehicle attributes and their own industry-specific preferences for truck characteristics. On the supply side, manufacturers choose vehicle prices and technology to improve fuel efficiency. Pre-policy, they face an unconstrained profit maximization, but once the policy is in place, they must make their choices while complying with average fuel economy standards for each vehicle subgroup. This is one advantage of studying fuel economy standards in the heavy truck setting compared to light-duty vehicles: because the policy was adopted more recently, we are able to observe the results from the unconstrained problem and estimate marginal costs without assumptions about relative

[10]Cursory analysis suggests that, as expected, fuel efficiency measured in miles per gallon is higher for vehicles operated as part of larger fleets, conditional on vehicle weight rating.

dealer and manufacturer markups that are common in the CAFE literature.

1.3.1 Demand

Each buyer i considers the set of trucks J and the outside good and makes a purchase decision in order to maximize utility.[11] For each truck j in J, the buyer derives utility from the attributes of the truck, though the utility may vary according to buyer characteristics, and derives disutility from the price. The expression for buyer i's indirect utility from inside good j is

$$U_{ij} = x_j(\beta_x + \beta_x^i) + p_j\beta_p + \xi_j + \varepsilon_{ij} \tag{1.1}$$

and from outside good is $u_{i0} = \varepsilon_{i0}$. x_j is a vector of vehicle j's characteristics, including gross vehicle weight rating, indicators for each cab type (sleeper vs. day vs. vocational) and roof height, indicators for common axle configurations, estimated fuel intensity, and make dummies. Price p_j enters separately. Buyers have heterogeneous preferences for some characteristics that differ at the industry level. The two shocks are ξ_j, representing unobserved attributes of truck j, and $\varepsilon_{r,j}$, representing idiosyncratic preferences for product j. From this specification, the purchase probabilities can be derived. That is, the probability that buyer i chooses product j is given by

$$\Pr(j|x) = \frac{\exp(x_j(\beta_x + \beta_x^i) + p_j\beta_p + \xi_j)}{1 + \sum_{j' \in J} \exp(x_{j'}(\beta_x + \beta_x^i) + p_{j'}\beta_p + \xi_{j'})} \tag{1.2}$$

The aggregate demand s_j can be found by integrating this probability over the distribution of demographics.

This demand specification assumes that each buyer only buys one vehicle at a time, is a price taker, and makes a static decision without regard to other vehicles he or she may own (i.e., buyers do not purchase trucks as a "bundle" or consider complementarity or substitutability across their fleet). In practice, there are some large freight companies that purchase many trucks for their fleet at the same time, but the majority of buyers are small firms that may own multiple vehicles but purchase a limited number of new vehicles each year.

[11] The outside good in this setting includes the decision not to purchase a truck or to purchase a vehicle outside the categories considered in this paper (i.e., medium-duty trucks or certain vocational vehicles).

1.3.2 Supply

In this section, I outline a supply model in which firms respond to a fuel economy standard imposed at the class-sleeper-roof height (henceforth, regulatory-group) level. This is the model used to simulate welfare outcomes below. The initial estimation uses pre-policy data to estimate a standard, unconstrained supply model.

In this model, firms have chosen the set of vehicles and their non-fuel intensity characteristics well in advance, i.e., the product set is exogenous. In order to comply with the policy, firms have two levers: vehicle price and additional technology that improves their fuel efficiency by a given percentage.

Each firm f, offering a set of vehicles J_f, maximizes profits subject to the constraint imposed at the regulatory-group level:

$$\max_{\mathbf{p},\mathbf{t}} \sum_{j \in J_f} \pi_f(p,t) \tag{1.3}$$

subject to

$$\frac{\sum_{j \in J_f^r} q_j e_j}{\sum_{j \in J_f^r} q_j} \leq \bar{e}_r \ \forall \ r \tag{1.4}$$

where J_f^r is the set of firm f's vehicles that are in regulatory group r, e_j is the fuel intensity of vehicle j, and $\bar{e}_r$ is the fuel intensity standard for regulatory group r. Technology adoption t is modeled as a percentage reduction in fuel consumption, where $0 \leq t \leq 1$. I ignore the possibility of permit-trading across firms and do not consider dynamics.

We can write the firm's Lagrangian as follows:

$$\mathcal{L} = \sum_{j \in J_f} (p_j - c_j(t_j)) s_j(p,t) N + \sum_r \mathbb{1}\{j \in J_f^r\} \lambda_f^r s_j(p,t) N L_{j,r} \tag{1.5}$$

where c_j is the marginal cost of producing vehicle j, s_j is vehicle j's share of the total market, N is the market size, λ_f^r is the shadow cost of the regulation per unit of sales specific to firm f and regulatory group r, and L_j is a measure of how far vehicle j is from complying with the standard: $L_{j,r} = (1 - t_j)e_j - \bar{e}_r$. If the standard is not binding, λ_f^r will be 0. For firm-groups for which the standard is binding, at the optimum, λ_f^r should be equal for all vehicles in J_f^r, but because averaging is not allowed across groups, we would not expect λ_fs to be equal for vehicles in different regulatory groups.

The solution to firms' profit maximization problem in the presence of the regulation is pinned down by two first-order conditions and the assumption that firms comply with the standards exactly. The $2J$ first-order conditions with respect to price and technology are:

$$\frac{\partial \mathcal{L}}{\partial p} = \mathbf{s} + \Phi \circ \Delta_p(\mathbf{p} - \mathbf{c} - \lambda \circ \mathbf{L}) \tag{1.6}$$

$$\frac{\partial \mathcal{L}}{\partial t} = (-\mathbf{c_t}' + \lambda \circ \mathbf{e}) \circ \mathbf{s} + \Phi \circ \Delta_t(\mathbf{p} - \mathbf{c} - \lambda \circ \mathbf{L}) \tag{1.7}$$

Bold letters refer to $J \times 1$ vectors of characteristics, Φ is a $J \times J$ ownership matrix where $\Phi_{j,k} = 1$ if product j and product k are produced by the same firm, and λ is a $J \times 1$ vector where the jth element contains the shadow price for product j's firm-regulatory group. Δ_p is a matrix of the derivatives of market shares with respect to price where $\Delta_{j,k} = \frac{\partial s_k}{\partial p_j}$, and Δ_t is the similarly defined matrix of the derivatives of market shares with respect to technology. $\mathbf{c_t}'$ is a vector of the derivative of marginal costs with respect to technology. $\circ$ denotes the Hadamard product. For tractability, in the counterfactual simulation, I impose that t decisions are made at the firm-regulatory group level, which reduces the number of first-order conditions with respect to technology to the number of firm-regulatory group combinations.

1.4 Estimation

1.4.1 Demand Estimation

The set of parameters I estimate are β_x (the common tastes for characteristics), β_x^i (the industry-specific tastes for characteristics), and β_p (the sensitivity to vehicle prices). Demand estimation follows the Berry et al. (1995) approach. That is, the procedure starts with a guess of the linear $\beta_1 = (\beta_x, \beta_p)$ parameters. From this, $\delta(\beta_1)$, the implied mean utility, can be derived using the standard contraction mapping approach. In turn, the non-linear parameters, β_x^i, are estimated via GMM. The GMM problem is:

$$\min_{\beta_2} g(\beta_2)' Z W Z' g(\beta_2) \tag{1.8}$$

where $g(\beta_2)$ is a vector of moments, and in all specifications, it includes the unobserved characteristics, ξ_j. Because product characteristics are chosen before the realization of the consumer demand shocks, $\mathbb{E}[\xi | x, w] = 0$, where x is product characteristics and w is manufacturing wages. W is a weighting matrix and Z is a matrix of instruments.

Instruments are required to address the endogeneity of price and fuel intensity. The excluded instruments for price are things that shift the price of product j without directly affecting utility from purchasing product j: own-firm and other firms' products, which affect price via competitive effects, and wages corresponding to the region in which each tractor is produced, which affect price via marginal cost. While there may, over the long term, be strategic decisions about where to open factories and which vehicles to produce in different locations, these decisions are made well before the product-specific preference shocks are revealed.

Finding excluded instruments for fuel intensity poses a challenge. In other settings, people have used measures of the endogenous characteristics in other markets or the endogenous characteristics on other vehicles that share the same platform (Reynaert 2020, Klier & Linn 2012). Unfortunately, here we lack data on truck efficiency in other markets and there is no clear analogue to platforms. One source of variation is the policy itself: there is a meaningful drop in fuel intensity following the first stage of the policy and a smaller reduction following the second stage. I use indicators for being in the post-standard period interacted with cab type (sleeper vs. day) as instruments for fuel intensity. In this case, identification of the fuel intensity preferences comes from differences in fuel intensity among otherwise similar vehicles across time, rather than the cross sectional variation. However, the excludability of these instruments is something of a question: the technology used to comply with the policy may directly affect utility of the vehicles if, for instance, people have a strong preference for cab shape or single- vs. double-wide tires. Hence, results are shown with and without the use of instruments for fuel intensity. Lagged diesel price was also considered as an instrument for fuel intensity, but had a small and insignificant effect in the first-stage regression.

With the IHS buyer industry data, I also include micro-moments in $g()$ as in Wollmann (2018) or Petrin (2002) in order to estimate industry-specific heterogeneity in preferences. Specifically, I match the probability the buyer of a vocational vehicle belongs to a specific industry (sanitation, construction, general freight, specialized/heavy hauling, and other). Identification of industry-specific preferences comes from differences in vocational share across industries and the variation in this share across years as other attributes of vocational and non-vocational vehicles change. Identification of other preferences for exogenous vehicle characteristics comes from the variation in vehicle market shares as the bundle of other attributes vary both within each market and across time.

1.4.2 Supply Estimation

I obtain marginal costs of vehicles produced in the year before the policy comes into effect from the firm's pre-policy first order condition with respect to price, equation 1.6. s and p come directly from the data, Δ_p is derived from the demand results, and $\lambda = 0$ when the policy is not in place.

In the post-policy period, I need estimates of the cost of technology adoption. For this, I rely on estimates from EPA's regulatory impact analysis, fit to a quadratic function for each regulatory group. However, given the low costs of compliance (less than $9000 in 2018 $ to improve high-roof sleeper cabs by 15-16%), consumers may be willing to pay for these improvements even with incomplete valuation of future fuel savings.

If we observe that these fuel economy-improving technologies are not fully adopted, an explanation for why profit maximizing firms would not have done so is needed. There are several potential explanations, with different implications for the costs and benefits of the policy. First, EPA's marginal cost estimates may be overly optimistic. To address this concern, I use the first order condition with respect to technology, equation 1.7, to calculate the pre-policy slope of the marginal costs of improving fuel efficiency. I can then use the pre-policy value as the intercept of the post-policy cost functions in the counterfactuals. Second, there may be fixed costs of adopting the technology that are not observed, such that adopting the technology is only worthwhile once the costs of non-compliance are added to firms' profit maximization. Third, there may be unobserved costs to buyers of the technologies used to improve fuel intensity. For instance, low rolling resistance tires are one of the technologies that EPA considers for compliance, but this may create challenges for drivers of trucks that traverse more rural roads. Additionally, some buyers may not like the aesthetics of more aerodynamic trucks, as the continued sales of "classic" designs suggests. Finally, the technologies may not be as effective as EPA believes in real-world conditions.

1.5 Results

Table 1.4 contains the estimates of the demand parameters. The discrete cab categories are class 7 day cabs, class 8 day cabs, low-roof sleeper cabs, mid-roof sleeper cabs, and high-roof sleeper cabs; the omitted category is vocational vehicles. The results are shown for a logit model and a model with industry-specific preferences for vocational vehicles, both without the fuel intensity instruments, and a logit model with an instrument.[12] The parameter estimates are quite similar across the two models. As expected, consumers dislike higher prices and prefer vehicles with higher GVW, all else equal. Consumers also prefer all non-vocational vehicles to vocational alternatives, with sleepers preferred to day cabs, class 7 day cabs preferred to class 8 day cabs, and mid-roof sleepers more popular than high-roof sleepers, which are in turn more popular than low-roof sleepers. The industry-specific preferences for vocational vehicles are also consistent with expectations–construction and sanitation, two industries that tend to use special-purpose vehicles, have positive coefficients, while freight and specialized/heavy hauling have negative coefficients.

[12] At present, the demand model is estimated without using any supply moments.

Finally, the coefficients on fuel intensity merit further discussion. The fuel intensity, measured in gallons per thousand ton-mile, is inversely correlated with fuel efficiency, and increases cost for a given distance and payload. Because the omitted category is vocational vehicles, the stand-alone coefficient suggests that there may be omitted variables correlated with fuel intensity. However, for the two categories of non-vocational vehicles, the net coefficient on fuel intensity is negative, as we would expect. Furthermore, the coefficient on fuel intensity in day cabs is smaller than the fuel intensity for sleeper cabs, which makes sense, as sleeper cabs tend to be driven more miles. These results are some of the only estimates of willingness to pay for fuel efficiency in trucks, and the first that do not rely on decades-old VIUS results. The uninstrumented estimates suggest that truck buyers would be indifferent between a 1 gallon/thousand ton-mile improvement in sleeper fuel intensity and an \$18,607-\$20,538 price increase, and similarly, a \$3,071- \$4,615 price increase and the same efficiency improvement in day cabs. The IV estimates suggest a slightly greater willingness to pay for sleeper cab fuel efficiency (\$25,251) and a considerably larger willingness to pay for day cab fuel intensity (\$20,910).

While these willingness to pay values seem high, the expected savings associated with a gallon/thousand ton-mile improvement are also quite large. For ease of understanding, we can calculate the expected future fuel savings from a 1 gallon/thousand ton-mile improvement in a sleeper and day cab. Using a 30-year vehicle lifetime, VMT and payload values based on the VIUS survey (adjusted for growth in VMT in the years since 2002[13]) that differ by sleeper status and vehicle class, a 3% discount rate, and a diesel price of \$2.95 (approximately the average over the time frame covered by the demand data), the uninstrumented estimates translate to an average willingness to pay for 36.1% of savings in sleeper cabs and 17.2% in day cabs. The much lower willingness to pay for fuel savings in day cabs may reflect differences in buyers of day cabs vs. sleepers (different degrees of savviness, different abilities to pass through fuel costs to customers) or vehicle usage (potentially greater variation in miles driven or payload transported). However, the IV estimates have the opposite results: buyers are willing to pay for 44% of sleeper fuel savings and 78% of day cab fuel savings. The sleeper estimates are consistent with other evidence. In a study of fuel efficiency valuation among class 8 truck owners that did not distinguish between sleeper and day cabs (and did not include class 7 day cabs, as this estimate does), Adenbaum et al. (2015) found truck owners were willing to pay for 29.5% of expected future fuel savings using a higher discount rate. Truck buyers have also stated in a number of surveys that they require a 3-4 year payback period for fuel efficiency improvements (Schoettle et al. 2016): the willingness

[13]To do so, I re-scale the VIUS data so that the average VMT for age-0 tractors matches EPA's VMT for the same group, which is derived from EPA's MOVES model.

to pay for the 1 gallon/thousand ton-mile improvement in sleeper cabs is an amount saved after 2-3 years of ownership (that is, the discounted expected fuel savings after 2 years for a sleeper cab are around $17,000, and after 3 years, are about $24,000). In general, this incomplete valuation of fuel savings provides motivation for government intervention in fuel efficiency policy.

Using the demand parameters and observed prices and quantities, I derive marginal costs for each vehicle in each pre-policy policy based on the unconstrained first-order condition, equation 1.6. Because I rely on engineering estimates for the cost of fuel intensity improvements needed to comply with the policy, structural supply parameters are not needed for counterfactual simulations. However, for completeness, they are shown in table 1.5 for the different demand specifications, with and without make fixed effects in the cost function. The costs of producing non-vocational vehicles is higher than vocational vehicle costs, with sleeper production costs increasing with roof height. The costs of increasing gross vehicle weight and reducing fuel intensity (i.e., making vehicles more efficient) are both positive, as well.

1.6 Welfare

I use the estimated demand and supply results to simulate outcomes under the fuel efficiency policy. Future iterations will compare alternative specifications of the policy, including increased flexibility across the different regulatory groups.

1.6.1 Simulation Setup

When the policy is in place, firms choose prices and technologies to maximize profits while complying with the policy, as in equation 1.3. I simplify the problem somewhat by only allowing firms to choose technology improvements at the regulatory group level–thus, rather than J first order conditions with respect to technology, there is one technology first order equation per firm-regulatory group.

Firms start with the set of vehicles they had in the year prior to the policy, 2013. I estimate the marginal costs of the vehicles in the baseline from equation 1.6. I solve for the equilibrium so that each firm complies with the policy exactly. While it is possible that firms may have chosen to not comply and instead pay fines, the regulation was extremely vague about the magnitude of fines, and firms may have chosen compliance rather than risk both the bad publicity and the uncertain costs of non-compliance.

The solution approach is to find the set of technology choices, t and shadow costs, λ, such that equations 1.6 and 1.7 hold. That is, for a given guess of λ and t, I determine the updated marginal cost for each vehicle (baseline marginal cost + the additional cost of improving fuel efficiency by t percent) and the λL cost of adjusting prices. I use these to solve for equilibrium prices and shares in equation 1.6. With these, I define my objective function to be the set of constraints and first order conditions with respect to technology, and use a root finding approach to solve for the t and λ such that these equations hold exactly. In the case of firm-regulatory groups that are already in compliance prior to the policy implementation, and might choose a negative t or λ, I constrain their technology choice and shadow costs to 0.

I compare equilibrium outcomes with and without the policy, including firm profits, consumer welfare, and changes in environmental damages. To estimate the change in CO_2 emissions, I use estimates of the vehicle miles traveled and payload by vehicle type, age, and in some instances, industry from EPA's regulatory impact analysis and VIUS data. With these VMT and payload per vehicle-industry-year, I calculate total diesel consumption and CO_2 generation per gallon. Vehicles have a maximum lifetime of 30 years, but vehicle miles traveled in year 30 fall to less than 5% of their total miles traveled when new. I use the 2014 Social Cost of Carbon from the Obama Administration's estimates, which is around $42 in 2018 dollars, and assume a 3% annual discount rate (IWG 2016).

1.6.2 Welfare Results

Table 1.6 contains the welfare results (in millions of 2018 $). The first column shows the results for a logit model in which preferences for fuel intensity are restricted to be 0, i.e., people do not value fuel economy at all. The second column shows the results under logit demand with preferences for fuel intensity included, and the third column contains results for the logit model where fuel intensity instruments are used and there is a higher preference for fuel intensity in day cabs. The final column features results where demand is modeled using a random coefficients specification with industry-specific preferences.

The results are shown with and without the marginal cost adjustment that rationalizes the non-adoption of technology that would be welfare improving (no such adjustment is needed for the final column because buyers do not want to pay for any amount of fuel intensity improvement). Without this adjustment, most or all of the technology improvements required to meet the model year 2014 standards appear to be welfare improving, even without accounting for the environmental damages (though, as discussed earlier, this may suggest the existence of hidden costs to either consumers or manufacturers). With the adjustment, the marginal costs of additional technology are much higher, which is also evident in table 1.7, which shows the change in prices (weighted by sales as well as unweighted) under the different assumptions. The adjustment also results in higher pollution benefits, in part because the price increases push consumers to shift from sleeper cabs (which experience the largest price increase) to day cabs and vocational vehicles, which tend to be driven less and with smaller payloads.[14] The change in welfare also includes the additional fuel savings that are not already internalized by the buyers. This is difficult to pin down because of the different degrees to which fuel intensity is valued in different vehicles and the change in the share of each of these vehicles when the policy is implemented. Thus, I show the additional fuel savings as if fuel usage was internalized at the sleeper level, the day cab level, and not at all.

Once lifetime fuel savings are taken into account, even under the most conservative assumption about how much of the fuel savings are already internalized by the buyer, the policy's benefits exceed the costs (with the exception of the final column without a cost adjustment, in which fuel usage actually increases as the day cab share increases). The fuel savings are much larger than the costs to consumers under even the highest cost model (again excluding the final column where fuel usage actually increases).

For the models that account for industry-specific preferences, we can also examine how the costs and benefits for buyers of different industries differ. Appendix table A.1.2 shows the industry-specific change in consumer surplus induced by the policy. Intuitively, the effects are largest for the industries that rely more heavily on tractors rather than vocational vehicles, i.e., freight and specialized/heavy hauling. With the cost adjustment, freight buyers face a 37% larger welfare loss than the generic buyers in the other category, and a 60% higher welfare loss compared to sanitation buyers.

1.7 Conclusion

This paper estimates the effects of the 2014 heavy-duty vehicle fuel economy standards using a structural model of demand and supply of trucks. I find that the costs of the policy on buyers and manufacturers must have been large in order to rationalize historical non-adoption of fuel-saving technology. While the environmental benefits alone are not large enough to outweigh these costs, the un-internalized fuel savings benefits are, as drivers of heavy-duty tractors only internalize up to approximately one third of future fuel savings. This

[14]These damage calculations account for the differences in VMT and payload by industry, so that a freight buyer switching from a class 8 sleeper to a vocational vehicle will drive the vocational vehicle in ways similar to how other freight buyers drive vocational vehicles. However, they do not account for the initial selection into vehicle categories, i.e., the fact that a freight buyer who switches from a sleeper cab to a day cab would potentially drive the day cab more than freight owners who would initially have chosen a day cab.

undervaluation of future fuel savings rationalizes not only continued fuel economy standards, but potentially also the collection and public provision of more information about expected fuel usage for heavy-duty trucks. Such information is available in the light-duty vehicle segment and to owners of large fleets who can observe their own historical performance, but other buyers may struggle to make optimal choices with incomplete information.

These results have a number of caveats. First, the estimates rely on limited data about fuel economy and EPA estimates of technology cost. Future work with improved data may directly estimate the cost of adopting different fuel economy technologies and measure preferences for different characteristics that vary along with fuel economy (e.g., more aerodynamic designs vs. low rolling resistance tires). In doing so, it may be possible to disentangle other potential reasons that technologies EPA believes are cost effective were not adopted prior to the policy. Second, more attention can be paid to switching across different vehicle types via the incorporation of additional heterogeneity in preferences for vehicle characteristics and more accurate categorization of vocational vehicles for configurations that are produced as both vocational and non-vocational. Relatedly, the joint decision of vehicle and how it will be used is more important in the truck context than in the light-duty vehicle setting because of the high variance in truck miles driven and weight of cargo. It may be possible to improve the modeling of these decisions using the next version of the VIUS, which will be administered in 2022 and made available in 2023.

Other caveats may best be addressed in other papers. I did not account for dynamics or the used vehicle market in this analysis. Buyers may have made strategic timing decisions about when to purchase new vehicles or hold onto existing vehicles; such an effect has proven important in the light-duty vehicle context and merits further investigation. Finally, both truck manufacturers and owners have other modes of response to changes in fuel economy standards and corresponding vehicle fuel costs. In the former case, other attributes may be adjusted, and the supply model could be revised to account for the endogeneity of other product features. In the latter cases, truck owners can make changes in individual or fleet-wide driving behavior, vehicle weight, routes, or the adoption of technology like trailer skirts. Understanding how fuel economy standards interact with these other behaviors is an important question for future research.

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Tables

Table 1.1: Summary statistics.

	Min.	Max.	Mean
Panel A. Count of product offerings by type			
Class 7	46	61	55.11
Class 8	104	124	115.78
Vocational vehicles	77	96	88.67
Conventional tractors with sleeper cab	17	25	22.00
Conventional tractors with day cab	50	66	60.22
Panel B. Prices and quantities			
Prices ($1000s)	48.85	213.63	120.91
Quantity	122068	301455	218900.56

Notes: Data include sales of model years 2011-2019. Counts contain the number of unique make-model-sleeper-class combinations that are available in each category (e.g., a make-model available as both a class 7 day cab and a class 8 day cab will count as two distinct products), but a make-model-sleeper-class available in multiple configurations that fall under the same category (e.g., a sleeper with multiple roof heights or two class 7 vocational vehicles with different axle configurations) will only count as a single offering.

Table 1.2: EPA and NHTSA standards for combination tractors.

	EPA Emissions Standards ($g\ CO_2$/ton-mile)			NHTSA Fuel Consumption Standards (gal/1000 ton-mile)		
	Low Roof	Mid Roof	High Roof	Low Roof	Mid Roof	High Roof
Panel A. 2014 Standards						
Day Cab Class 7	107	119	124	10.5	11.7	12.2
Day Cab Class 8	81	88	92	8.0	8.7	9.0
Sleeper Cab Class 8	68	76	75	6.7	7.4	7.3
Panel B. 2017 Standards						
Day Cab Class 7	104	115	120	10.2	11.3	11.8
Day Cab Class 8	80	86	89	7.8	8.4	8.7
Sleeper Cab Class 8	66	73	72	6.5	7.2	7.1

Notes: CO_2 and fuel standards are set separately by EPA and NHTSA but designed to be compatible with one another. The first set of standards applied to model years 2014-2016, and a higher set of standards applied to model years 2017 and 2018. Standards data are from Table 2-34 in the Regulatory Impact Analysis.

Table 1.3: Industry Vehicle Attributes.

	Total Sales	Shr Vocational	Shr Sleeper	Shr Day	Shr Class 7	Shr Class 8	Average GVW
Sanitation	47258	0.93	0.03	0.04	0.08	0.92	5143.37
General Freight	602911	0.08	0.54	0.38	0.12	0.88	5004.91
Construction	85527	0.79	0.10	0.11	0.18	0.82	4717.86
Other	1267693	0.36	0.37	0.27	0.21	0.79	4691.57
Specialized/Heavy Hauling	16497	0.50	0.11	0.39	0.22	0.78	4520.66

Notes: This table contains sales by industry for the full dataset (including some model year 2019 vehicles sold in 2018). The share columns indicate the share of vehicles sold to buyers in each industry that are predicted to fall into one of three cab categories: vocational vehicles, sleepers, or day cabs and one of two weight class categories. The final column contains the average gross vehicle weight of vehicles purchased by each industry buyer type.

Table 1.4: Demand parameter estimates.

	(1) Logit	(2) Random Coefficients	(3) Logit IV
Prices ($1000s)	-0.028***	-0.026***	-0.03***
	(0.005)	(0.005)	(0.006)
GVW (1000 lbs)	1.762***	1.488***	4.486***
	(0.555)	(0.553)	(1.139)
Class 7 Day	3.453***	3.583***	13.009***
	(0.479)	(0.477)	(2.152)
Class 8 Day	1.63***	1.591***	9.064***
	(0.41)	(0.406)	(1.64)
Low-Roof Sleeper	4.658***	4.379***	8.88***
	(0.84)	(0.822)	(2.376)
Mid-Roof Sleeper	5.83***	5.552***	10.289***
	(0.905)	(0.888)	(2.598)
High-Roof Sleeper	5.545***	5.259***	10.047***
	(0.905)	(0.887)	(2.595)
4 × 2 axles	0.403***	0.418***	0.607***
	(0.11)	(0.11)	(0.135)
6 × 4 axles	2.462***	2.511***	2.643***
	(0.107)	(0.105)	(0.12)
8 × x axles	-0.006	0.023	0.112
	(0.152)	(0.15)	(0.176)
Fuel intensity (FI)	0.134***	0.156***	0.528***
	(0.044)	(0.044)	(0.135)
Day × FI	-0.22***	-0.276***	-1.146***
	(0.05)	(0.049)	(0.202)
Sleeper × FI	-0.653***	-0.69***	-1.275***
	(0.12)	(0.118)	(0.345)
Vocational × Construction	–	0.409	–
	–	(0.011)	–
Vocational × General Freight	–	-2.243	–
	–	(0.002)	–
Vocational × Sanitation	–	0.5	–
	–	(0.014)	–
Vocational × Specialized/heavy hauling	–	-0.06	–
	–	(0.021)	–

*p<0.1; **p<0.05; ***p<0.01

Notes: The demand model under different sets of assumptions. The first column is a logit model, the second column allows for industry-specific preferences on vocational vehicles, and the third column is a logit model that adds the use of instrumental variables for the fuel intensity measure. All specifications include brand fixed effects. Class 7 Day, Class 8 Day, Low-Roof Sleeper, and High-Roof Sleeper are all indicator variables indicating that a truck falls into one of these regulatory groups (the omitted category is vocational vehicles). The three axle categories are also indicators for a vehicle having a 4 × 2 axle configuration, a 6 × 4 axle configuration, or one of the configurations with 8 wheels (8 × 4, 8 × 6, or 8 × 8). The omitted category is all 6-wheel configurations. Fuel intensity is measured in gallons per thousand ton-mile.

Table 1.5: Supply parameter estimates.

	Logit		Random Coefficients		Logit-IV	
	(1)	(2)	(3)	(4)	(5)	(6)
Low-Roof Sleeper	0.145***	0.147***	0.16***	0.163***	0.138***	0.139***
	(0.025)	(0.027)	(0.027)	(0.029)	(0.024)	(0.026)
Mid-Roof Sleeper	0.242***	0.164***	0.264***	0.179***	0.231***	0.156***
	(0.028)	(0.029)	(0.03)	(0.031)	(0.027)	(0.027)
High-Roof Sleeper	0.304***	0.296***	0.328***	0.321***	0.291***	0.282***
	(0.022)	(0.022)	(0.023)	(0.024)	(0.021)	(0.021)
Class 7 Day	0.572***	0.49***	0.631***	0.547***	0.543***	0.463***
	(0.046)	(0.048)	(0.05)	(0.053)	(0.043)	(0.046)
Class 8 Day	0.067*	0.055*	0.08**	0.069*	0.063*	0.05
	(0.034)	(0.033)	(0.038)	(0.036)	(0.033)	(0.032)
GVW (1000 lbs)	1.628***	1.358***	1.75***	1.461***	1.558***	1.297***
	(0.161)	(0.169)	(0.175)	(0.183)	(0.153)	(0.16)
Fuel Intensity	-0.076***	-0.07***	-0.084***	-0.079***	-0.071***	-0.066***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)
4 × 2 axles	-0.084***	-0.086***	-0.09***	-0.097***	-0.08***	-0.08***
	(0.03)	(0.031)	(0.032)	(0.034)	(0.029)	(0.029)
6 × 4 axles	0.031	0.026	0.034	0.026	0.029	0.027
	(0.027)	(0.027)	(0.029)	(0.029)	(0.026)	(0.026)
8 × x axles	0.137***	0.083***	0.143***	0.084**	0.134***	0.082***
	(0.034)	(0.034)	(0.036)	(0.036)	(0.033)	(0.033)
log(wages)	0.022	-0.106***	0.025*	-0.113***	0.021	-0.101***
	(0.014)	(0.019)	(0.015)	(0.02)	(0.013)	(0.018)
Canadian production	-0.265***	-0.17***	-0.288***	-0.183***	-0.251***	-0.16***
	(0.042)	(0.046)	(0.046)	(0.051)	(0.04)	(0.044)
Make FEs		×		×		×

*p<0.1; **p<0.05; ***p<0.01

Notes: The supply parameters associated with alternative demand specifications. The first two columns are a logit model, the second two columns allow for industry-specific preferences on vocational vehicles, and the final two columns are a logit model that adds the use of instrumental variables for the fuel intensity measure. Class 7 Day, Class 8 Day, Low-Roof Sleeper, and High-Roof Sleeper are all indicator variables indicating that a truck falls into one of these regulatory groups (the omitted category is vocational vehicles). The three axle categories are also indicators for a vehicle having a 4 × 2 axle configuration, a 6 × 4 axle configuration, or one of the configurations with 8 wheels (8 × 4, 8 × 6, or 8 × 8). The omitted category is all 6-wheel configurations. Fuel intensity is measured in gallons per thousand ton-mile. log(wages) are the log of manufacturing wages in the region in which a vehicle is produced, and Canadian production is an indicator variable for vehicles produced in Canada.

Table 1.6: Welfare costs (millions).

		(1) Logit Demand, No FI Preference	(2) Logit Demand		(3) Logit Demand, FI IV		(4) Industry-Specific Demand	
			Marginal Cost Adj.	No Adj.	Marginal Cost Adj.	No Adj.	Marginal Cost Adj.	No Adj.
	Consumer Surplus	-196.866	-887.863	225.771	-1,929.935	704.576	-1,046.505	286.449
	Profit	-43.499	-206.711	68.431	-474.845	207.655	-251.462	88.399
	CO_2 benefits	398.991	656.238	123.279	1,030.040	-192.778	645.945	142.689
Fuel savings	Total	2,744.326	4,513.714	847.931	7,084.786	-1,325.960	4,442.915	981.436
	Total - Day Valuation		3,995.984	750.672	1,531.227	-286.578	3,675.482	811.911
	Total - Sleeper Valuation		3,039.267	570.946	3,941.943	-737.758	2,837.040	626.700
Combined	With Full Fuel	2,902.951	4,075.379	1,265.412	5,710.047	-606.507	3790.893	1498.973
	With Fuel - Day Valuation	3,557.649	1168.153	156.488	432.875	3,023.460	1,329.447	
	With Fuel - Sleeper Valuation		2,600.932	988.427	2,567.204	-18.305	2,185.018	1,144.236
	With No Fuel Savings	158.626	-438.335	417.481	-1,374.739	719.453	-652.022	517.537

Notes: Components of overall welfare changes under the policy. The consumer surplus is calculated based on compensating variation. The CO_2 benefits are based on fuel usage reduction over the lifetime of the truck, at a 3% discount rate. The "full" fuel savings is the total value of fuel savings over the lifetime of the vehicle, assuming an average price of $2.95 per gallon and a 3% discount rate. Because some fuel savings are already valued by the buyers, the subsequent rows contain the fuel savings that are not already incorporated into the consumer surplus changes under several different assumptions. The "Total - Day Valuation" row assumes that all fuel savings are valued at the level that buyers of day cabs value fuel savings. The "Total - Sleeper Valuation" row assumes that all fuel savings are valued at the level that buyers of sleeper cabs value fuel savings. The "Combined" rows sum welfare from consumer and producer surplus, changes in environmental damages, and un-internalized fuel savings. Thus, it is presented subject to the different degrees of fuel savings assumptions including the final row, in which fuel savings are not included. All values in millions of 2018 $.

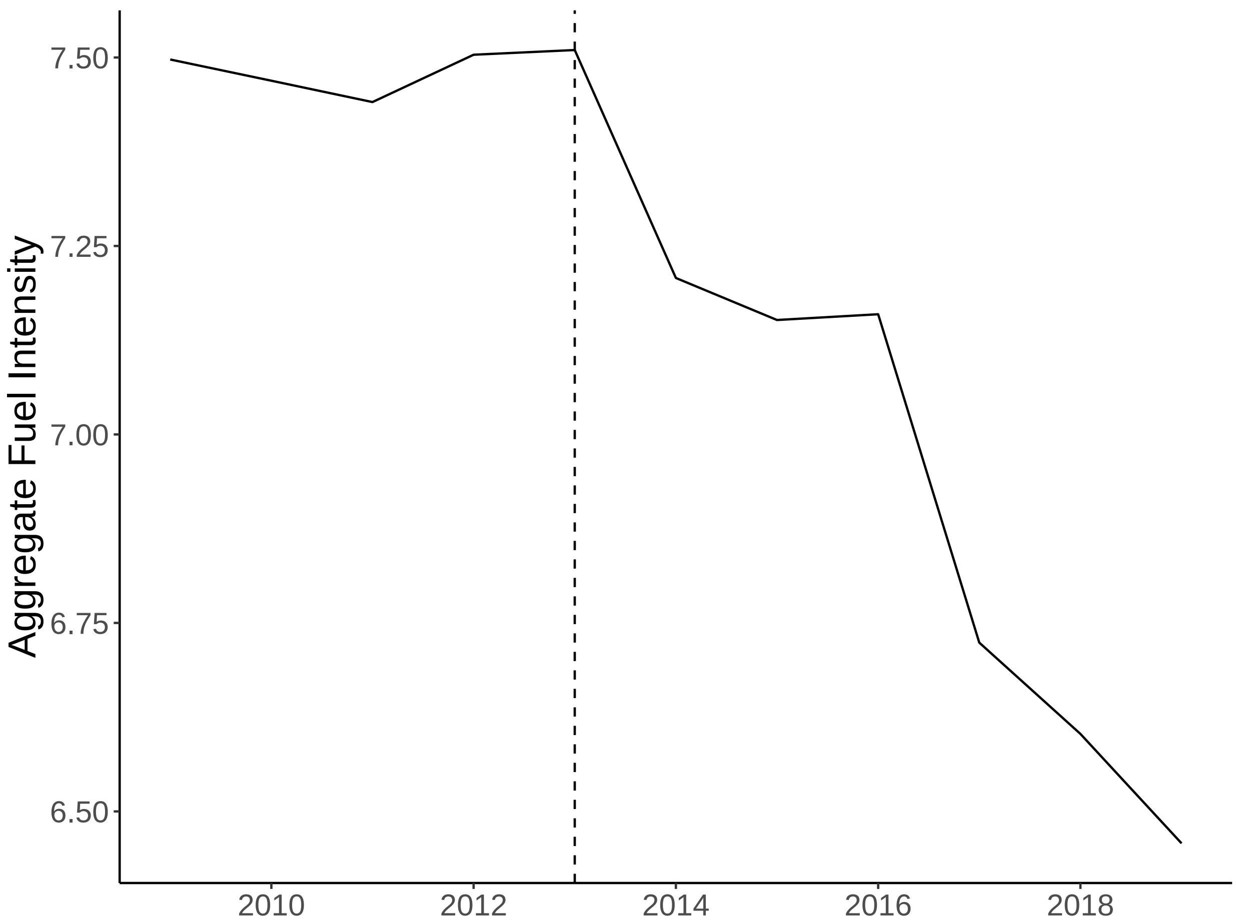
Table 1.7: Changes in prices, quantities

		Δ Price	Unweighted Δ Price	Δ Sales
Ind. Prefs, Base Costs	vocational	0.24	0.20	-3351.23
	sleeper	1.59	1.83	8090.11
	day	1.53	3.77	-3697.84
	combined	2.09	1.62	1041.04
Ind. Prefs, Cost Adj.	vocational	0.24	-0.14	4979.99
	sleeper	17.71	19.96	-14387.61
	day	2.00	5.67	5508.54
	combined	4.48	5.60	-3899.08
Logit No FI Prefs	vocational	0.18	0.06	1659.12
	sleeper	0.75	2.22	-963.82
	day	0.60	4.09	-1639.75
	combined	0.29	1.72	-944.45
Logit Prefs, Base Costs	vocational	0.23	0.20	-3297.06
	sleeper	1.53	1.78	8093.40
	day	1.28	3.94	-3972.58
	combined	1.98	1.66	823.77
Logit Prefs, Cost Adj.	vocational	0.23	-0.13	5299.78
	sleeper	15.13	17.25	-13243.27
	day	1.45	5.10	4529.54
	combined	3.65	4.90	-3413.95
Logit IV, Base Costs	vocational	0.54	0.38	-10599.17
	day	3.26	4.04	4503.90
	sleeper	1.86	2.09	8715.93
	combined	3.69	1.84	2620.66
Logit IV, Cost Adj.	vocational	0.51	-0.44	10565.32
	day	11.11	15.07	483.38
	sleeper	23.90	26.92	-19484.77
	combined	8.30	9.71	-8436.07

Notes: Change in prices and quantities of vehicles sold by category, where changes in price measured in thousands. "Δ Price" is the change in price weighted by vehicle sales, while "Unweighted Δ Price" is the average change in price across vehicle offerings, not weighted by sales. "Δ Sales" is the change in total number of vehicles sold. The first two sets of rows show the results for the demand specification containing industry-specific preferences, with and without the adjustment to marginal cost. The third set of rows is the logit model with no preference for fuel intensity. The fourth and fifth sets of rows contain the logit preferences with and without the cost adjustment, and the final two sets of rows show the logit model with the fuel intensity instrument. The changes are grouped by vehicle type (vocational vehicles, day cabs, and sleeper cabs, and also aggregated in the "combined" category).

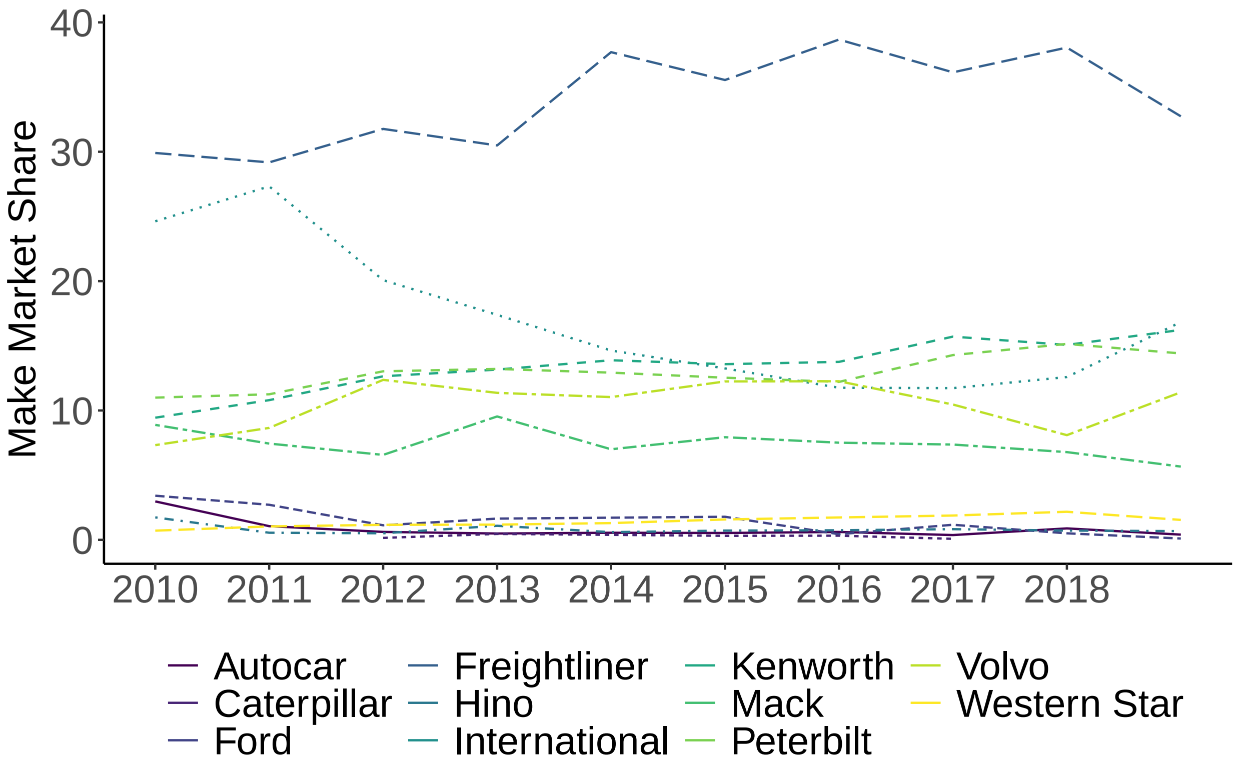
Figures

Figure 1.1: Aggregate Fuel Intensity of Sleeper Cabs



Notes: Sales-weighted average fuel intensity of all sleeper cabs in the data. The dashed line indicates the year before the standards were put in place.

Figure 1.2: Market Share by Brand



Notes: Market share is calculated as the share of vehicles sold among included brands (or makes, used here interchangeably). Line color corresponds to the different brand, and brands owned by the same parent company share the same linetype (e.g., Freightliner and Western Star, both owned by Daimler).

Appendices

Appendix A

A.1 Tables

Table A.1.1: DOT vehicle weight classes

Class	Description/examples	Empty weight range	Gross weight range	Typical fuel intensities	
		Tons	Tons	Gallons per thousand miles	Gallons per thousand ton-miles
1c	Passenger cars	1.2-2.5	<3	30-40	67
1t	Small light-duty trucks (including SUVs and minivans)	1.6-2.2	<3	40-50	58
2a	Standard pickups, large SUVs	2.2-3	3-4.25	50	39
2b	Large pickups, utility vans	2.5-3.2	4.25-5	67-100	39
3	Utility vans, minibuses	3.8-4.4	5-7	77-125	33
4	Delivery vans	3.8-4.4	7-8	83-140	24
5	Large delivery vans, bucket trucks	9.2-10.4	8-9.75	83-166	26
6	School buses, large delivery vans	5.8-7.2	9.75-13	83-200	20
7	City bus, refrigerated truck, fire engine	5.8-7.2	13-16.5	125-250	18
8a	Dump/refuse trucks, city buses, fire engines	10-17	16.5-40	160-400	9
8b	Large tractor trailers, bulk tankers	11.6-17	16.5-40	133-250	7

Source: Harrington & Krupnick (2012)

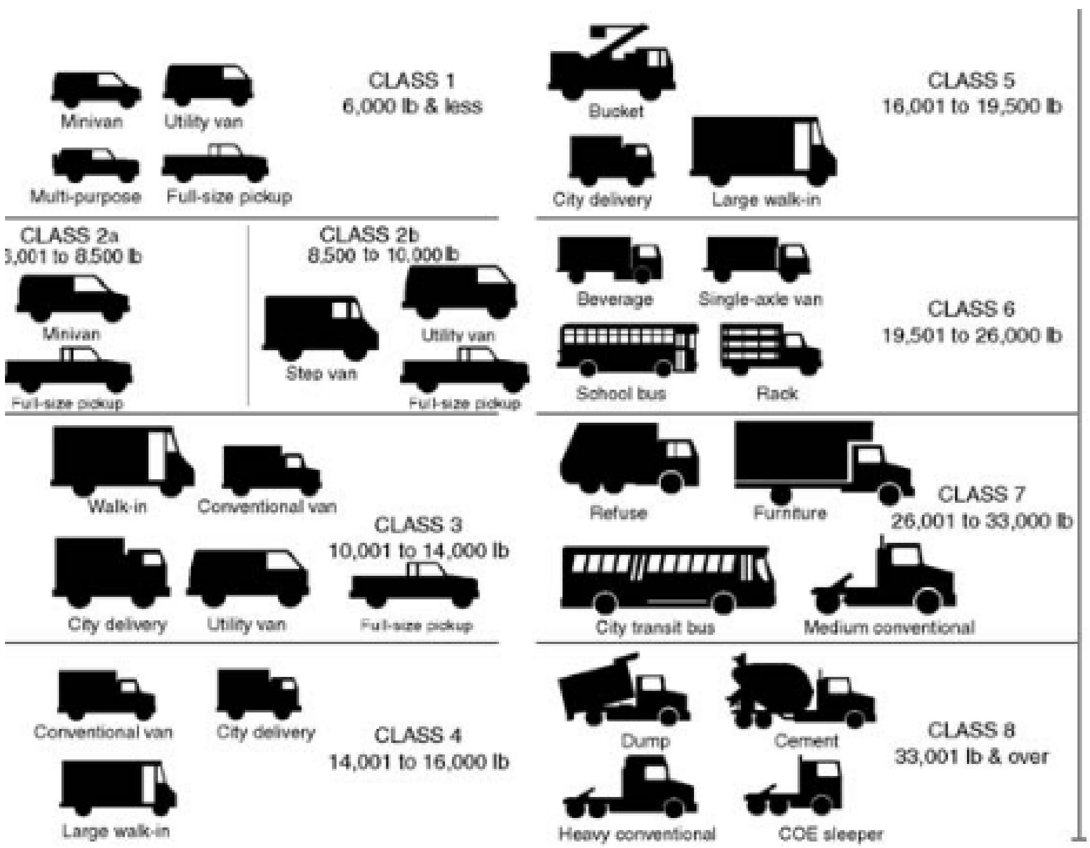
Table A.1.2: Industry Change in Consumer Surplus

	Other	Construction	General Freight	Sanitation	Specialized/Heavy Hauling
With MC Adj.	-3.765	-3.322	-5.155	-3.221	-3.827
Base MC	0.867	0.565	1.778	0.495	.909

Notes: Per-consumer change in consumer surplus by industry. Prices in 1000s of 2018 $. "With MC Adj." contains results from the supply estimation where the costs are adjusted to account for the historical non-adoption of technologies.

A.2 Figures

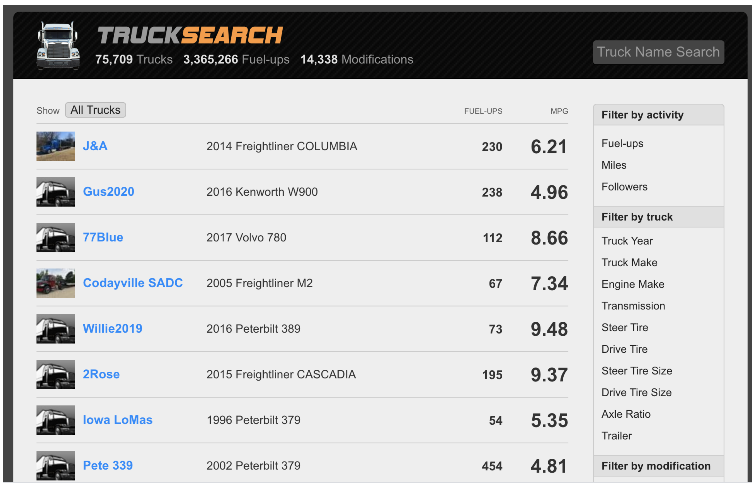
Figure A.2.1: Vehicle weight classes, illustrated



Source: Commercial Carrier Journal http://www.ccjmagazine.com

Figure A.2.2: Screenshots from `letstruck.com` fuel tracking website.

(a) The main page, organized by vehicle. For each vehicle, the year-make-model, number of recorded fuel ups, and average miles per gallon is displayed.



(b) More information is available about each individual truck, including more recent fuel usage, miles tracked, modifications made to the vehicle, etc.

Chapter 2

Carbon Policy and the Emissions Implications of Electric Vehicles

with Kenneth Gillingham and Marten Ovaere

Abstract

Will a carbon tax improve the welfare consequences of policies to promote electric vehicles? This paper explores a possible complementarity between carbon pricing and high electric vehicle adoption. We analyze U.S. electricity generation in recent years to show that in several regions, carbon pricing interacts with electric vehicle adoption. Under moderate carbon prices like those in effect today, additional electric vehicles will be more likely to be charged with coal-fired generation than without carbon pricing. We confirm this finding using a detailed dynamic model that includes the transportation and power sectors. At much higher carbon prices, the effect reverses.

2.1 Introduction

In most countries around the world, environmental policy consists of a patchwork of regulations and incentives. Economists recognize that multiple policy instruments may be needed when there are multiple externalities, such as carbon pricing to internalize damages from greenhouse gases and investments in innovation to address spillovers in the innovation of new green technologies (Jaffe et al. 2005, Popp et al. 2010, Acemoglu et al. 2012, Gillingham & Stock 2018, Stiglitz 2019). However, it is often the case that environmental regulations interact with each other. For example, worries about emissions leaking across borders provide a major argument against the implementation of state-level fuel economy standards at the same time as a federal standard (Goulder et al. 2011) and were also a potential concern in the design of the Obama Administration Clean Power Plan that allowed neighboring states to use different policy instruments (Bushnell et al. 2017).

Interactions between policies may not always be negative though. Consider a policy to promote electric vehicles. Such a policy might be expected to be complementary with carbon pricing, in that it will be more effective at reducing greenhouse gas emissions and improving social welfare if there is also policy in place to decarbonize electricity because the electric vehicles will be charged using cleaner energy (Holland et al. 2021). Indeed, many countries around the world are considering or already implementing policies to promote electric vehicles along with more general carbon pricing policies.[1] In the United States, California has a zero-emission vehicle mandate at the same time as a cap-and-trade system for greenhouse gases. The U.S. Congress currently has proposed bills that allocate funding to electric vehicles and include a Clean Electricity Standard, which would implicitly price carbon in electricity generation. Such a pairing of policy instruments has the potential to improve economic efficiency by helping to address multiple market failures but may lead to consequential interactions between the policies.

This paper demonstrates an important interaction between electric vehicle policies and carbon pricing in both an empirical analysis using data from recent years and a prospective analysis. We show that the two policies may not always be complementary and the emissions benefits of electric vehicle policies may actually be *reduced* in the presence of carbon pricing over a very relevant range of moderate carbon prices. The intuition for this finding is that carbon pricing can change the economics of different types of electricity generation and can push coal generation to the margin more often. Thus, additional demand for electricity due to electric vehicles is more likely to be coal-fired. In the long run, additional electricity demand from electric vehicles can also slow the retirements of coal plants. We empirically document the short-run effect in several large regions of the United States in recent years by exploiting variation in the ratio of coal to natural gas prices, which can be mapped to implicit carbon prices as in Cullen & Mansur (2017). Yet electric vehicles were less than 2% of new vehicle sales in 2020, while many electric vehicle offerings are planned in upcoming years.[2] We thus use a detailed dynamic model including the power and transportation sectors to show how the long-run effect of delayed coal plant retirements could potentially erode the benefits of vehicle electrification.

Our findings provide a cautionary tale for policymakers. They show how electric vehicle policies can be less effective at reducing long-run emissions under moderate carbon pricing than under no carbon pricing or under much higher carbon pricing, and thus would be less likely to be social welfare-improving. To be clear, carbon pricing alone can be highly effective at reducing emissions, regardless of whether or not it is in concert with an electric vehicle policy. And electric vehicles remain a potential long-run pathway to decarbonization. But

[1] For example, China has heavily promoted electric vehicles and has implemented a national carbon cap-and-trade system as of February 1, 2021. Ireland, the Netherlands, Sweden, and Slovenia plan to ban sales of internal combustion engine cars after 2030 at the same time as the European Trading System ratchets down the number of permits available.

[2] See `https://insideevs.com/news/489525/us-electric-car-market-share-record-2020/` for IHS Markit's estimate of the all-electric market share in 2020. For a list of over 45 expected offerings in model years 2021-2023, see `https://www.caranddriver.com/news/g29994375/future-electric-cars-trucks/`.

the combination of the two policies can lead to the same or even lower emission reductions than the carbon price alone. This can happen under realistic conditions, such as carbon prices similar to those implicit in the Obama Administration's Clean Power Plan and some proposed Clean Electricity Standards/Payments in Congress.

We show that the interaction is most likely to happen in regions with coal-fired generation that currently is usually inframarginal but not far from being uneconomic. In such a setting, a moderate carbon price path–in line with many prices in effect or proposed–can push coal-fired generation to the margin more often. It is least likely to happen in regions with minimal coal-fired generation, at extremely low or much higher carbon price paths, or when there are extraordinarily inexpensive renewables. These results provide guidance to policymakers deliberating on where it might be most effective to focus electric vehicle policies and whether to bear the political cost of higher carbon prices, such as those that more closely match recent estimates of the social cost of carbon. Further, the results directly influence calculations of the benefits and costs of electric vehicle policies, by highlighting that a policy interaction is important to consider.

This study contributes to several growing areas in the economic literature. It relates closely to work on interactions between policy instruments. There is a deep literature on interactions in the tax system in second-best settings. For example, environmental taxes can interact with other, distortionary taxes, such as income taxes, leading to optimal environmental taxes below the Pigouvian tax rate (Bovenberg & Goulder 1996). More broadly, economists have emphasized that the combination of quantity and price policy instruments can reduce or eliminate the effectiveness of one of the instruments. For example, a carbon tax can render a renewable portfolio standard for electricity generation non-binding or a royalty surcharge on federal coal leasing (a price instrument) can render the Obama-era proposed Clean Power Plan non-binding in some cases when states choose to use quantity instruments to comply with the plan (Gerarden et al. 2020). Similarly, overlapping jurisdictions can also negatively impact the effectiveness of a policy (Goulder & Stavins 2011). For instance, a state-level fuel economy standard may not reduce emissions on net when there is a binding federal standard (Goulder et al. 2011). In contrast, two policies using price instruments (e.g., a federal carbon tax and a state-level carbon tax) are widely considered to be additive in terms of emission reductions, and indeed desirable to address multiple externalities (Fischer et al. 2017).

Our work shows an important context where two price instruments–such as direct subsidies for electric vehicles and a carbon tax–are not necessarily additive in providing emission reductions, and in fact the effect of the combined policies may be worse than the carbon tax alone.[3] A key feature that leads to this result is that the interaction in our study occurs *across sectors*, rather than across jurisdictional borders. This feature of our study is likely to hold in many other policy-relevant settings as well. There has been a substantial policy effort to switch from fossil fuels to electricity in many sectors. There are bans on natural gas in new homes in over a dozen cities across the United States to encourage all-electric construction.[4] The United Kingdom is currently in the process of banning natural gas boilers for central heat, leaving heat pump and electric options available.[5] Marine ships at berth are in the process of being electrified in many locations (Gillingham & Huang 2020). And there is work underway to shift industrial processes, such as steel-making, to electricity or "green hydrogen" produced with excess electricity from renewables or from nuclear plants.[6] Our findings of an unexpected interaction between policies may become more important over time should these transitions gather speed faster than the electricity is decarbonized.

A transition to electric vehicles also may be underway. Our paper contributes to the economic literature on the emissions implications of electric vehicles. Graff Zivin et al. (2014) find considerable heterogeneity in the carbon dioxide emissions from electric vehicles across regions of the United States, resulting in higher emissions from using an electric vehicle than a gasoline one in many regions. Holland et al. (2016) follow on this line of research by incorporating additional pollutants and find even greater regional variation, but a similar result.[7] Holland et al. (2020) account for the massive decline in emissions from electricity from 2010 to 2017 to find that, as of 2017, electric vehicles became cleaner than gasoline vehicles on average. Holland et al. (2021) use a dynamic model calibrated to the U.S. market to analyze the welfare effects of bans on fossil fuel-powered vehicles. They show that a much higher substitutability between gasoline vehicles and electric vehicles than is observed today would be needed for a gasoline vehicle production ban to be welfare improving. A distinguishing characteristic of our work is the focus on how the marginal emissions from electric vehicles would differ with a carbon pricing policy in both an empirical analysis using data from today's electricity grid and a prospective analysis using a detailed dynamic model

[3]Conceptually, our work also certainly applies to quantity instruments as well, such as a zero-emission vehicle standard and a carbon cap-and-trade. However, there may be differences in how the forces play out. For instance, the combination of incentives for electric vehicles and a binding economy-wide cap-and-trade can never lead to more emissions than the cap, but our results suggest that the incentives for electric vehicles may raise the allowance price and overall cost of the cap-and-trade system.

[4]See `https://www.cbsnews.com/news/cities-are-banning-natural-gas-in-new-homes-because-of-climate-change/`

[5]See `https://www.express.co.uk/news/uk/1372691/gas-boilers-uk-government-energy-savings-install-gas-boiler-climate-change`

[6]See `https://www.forbes.com/sites/scottcarpenter/2020/08/31/swedish-steelmaker-uses-hydrogen-instead-of-coal-to-make-fossil-free-steel/?sh=1a856b2e2c8b`

[7]Archsmith et al. (2015) find that considering regional differences in temperature can further reinforce this result because batteries perform poorly in the cold.

to simulate tomorrow's electricity grid.

Our research also connects to the broader economic literature on electric vehicles. There is a growing literature on electric vehicle charging infrastructure and network effects in the two-sided electric vehicle market (Springel 2021, Li et al. 2017, Zhou & Li 2018, Li 2021). This body of literature suggests the existence of indirect network effects that support policy to build out the charging network and/or increase demand for electric vehicles. Other recent work on electric vehicles examines the effects of electric vehicle policies (Clinton & Steinberg 2019, Muehlegger & Rapson 2021), determining what electric vehicle buyers would have bought otherwise to assess the effects of electric vehicle incentive policies (Xing et al. 2021, Muehlegger & Rapson 2020), and estimating how much electric vehicles are driven to inform analyses of electric vehicle policies (Burlig et al. 2021). Our study examines a key interaction when policies to increase the uptake of electric vehicles are implemented in concert with carbon pricing.

Our quantitative analysis follows a long line of literature in using dynamic simulation models with forward-looking agents to shed light on policy questions. For example, the prospective analysis in our paper has some methodological similarities to Gerarden et al. (2020), although with an entirely different research question and a different dynamic model. For the quantitative estimates in our prospective analysis, we use the National Energy Modeling System run on a Yale server. The National Energy Modeling System is a detailed dynamic structural model developed over many years by the U.S. Energy Information Administration (EIA) for use in policy analysis by the U.S. government. We adopt this model due to its granular detail in both the electricity and transportation sectors. The model has a large team of dedicated personnel continually developing it and projections from the model are widely used by governments and industry. It has also been used in many peer-reviewed publications and other economic analyses over the years (e.g., Goulder 2010, Morrow et al. 2010, Auffhammer & Sanstad 2011, Small 2012, Gillingham & Huang 2019, 2020). By adopting a model commonly used by policymakers, our quantitative estimates have direct relevance to policy discussions in the U.S. government about electric vehicle policy and carbon pricing.

Our short-run analysis focuses very much on analyzing the possibility of a supply-side complementarity between electric vehicle policies and carbon pricing. This is a commonly discussed complementarity in the policy discussions. However, the short-run analysis ignores other possible complementarities between carbon pricing and electric vehicle policies. For example, higher economy-wide carbon prices would also raise the price of gasoline, potentially furthering additions of electric vehicles. Similarly, there could be innovation dynamics, whereby a carbon price may be more effective at encouraging electric vehicle adoption if other policies are already in place to promote technological improvement and bring electric vehicles closer to price parity. Our long-run analysis explicitly models all of these potential complementarities.[8]

The remainder of this paper is organized as follows. Section 2.2 provides a conceptual framework to illustrate how carbon pricing can in certain cases reduce the benefits of electric vehicle policy. Section 2.3 provides empirical evidence showing that these cases are not hypothetical, but are occurring in the current U.S. electricity system. Section 2.4 outlines the research design of our prospective analysis and presents results indicating that our empirical findings are likely to hold over a range of carbon prices over time. Section 2.5 concludes.

2.2 Conceptual Framework

The emission reductions from policies to promote electric vehicles will depend on the carbon intensity of driving the electric vehicle versus the alternative, as well as the number of miles driven by each type of vehicle, as has been explored in the previous literature discussed above. The key insight of this paper is that the carbon intensity of driving an electric vehicle will change when there is carbon pricing.

In this section, we present a simple conceptual framework to fix ideas about how this change might occur. We focus on electric vehicles because of the current policy interest, but this framework would also apply to electrifying many other end-uses. The framework is intentionally stylized to quickly provide intuition. It sets aside a set of complicating issues, including the dynamics of power plant operation (e.g., ramping costs), elastic demand (as might be possible with time-varying pricing or demand response programs), market power, transmission constraints, forward contracts, and unplanned outages and other electricity markets outside of the wholesale market. Adding these features should not affect the basic high-level intuition we are aiming to impart.

Our stylized framework begins with a common setting in the United States, where the short-run aggregate supply curve for electricity (often called the 'generation stack') in a particular region is as follows. First, there is the must-take generation (nuclear and renewables, R) that produce electricity at zero or very low marginal cost. Then, with low prices of natural gas, comes high-efficiency natural gas combined cycle ($NGCC$) generation. This is followed by coal (C) generation and then by less-efficient natural gas peaker plants (NG), which produce at a high cost.[9] While of course in reality there is going to be some het-

[8] One caveat to our analysis is that we do not model a possible demand-side "charging" complementarity that could occur if a carbon price is more effective at encouraging electric vehicle adoption when there is a robust charging network, but this is an interesting area for future research building on the work of Li et al. (2017) and others.

[9] We assume away imports and oil-fired generation, as including these would add little to the intuition.

erogeneity in each of these categories (e.g., inefficient NGCC that is more expensive than coal generation or natural gas peaker plants that are lower cost than coal generation), this stylized presentation of the supply curve is useful for cleanly presenting how carbon pricing will affect the marginal generator.

Panel (a) in Figure 2.1 shows this illustrative generation stack for an example time period, with the y-axis showing the price in dollars per megawatt (MW) and the x-axis showing the quantity in MW. The dotted line shows a perfectly inelastic demand. One can think of the location of the vertical demand curve in the figure as a fairly typical "average" load on the system and can imagine demand shifting to the left and right throughout the day and over the seasons, depending on the region and types of loads being served.

In Panel (a), additional load due to more electric vehicles being charged on the grid will be powered by natural gas peaker plants in this typical time period. Thus, the emissions implications of electric vehicles are likely to be preferable to gasoline-powered vehicles, due to the much lower emission intensity of natural gas (although line losses and differences in supply chain emissions would have to be taken into account). In Panel (b), we see a shift upwards in the supply curve due to the imposition of a very low carbon price (e.g., a carbon tax close to zero). The shift upwards is greater for coal generation than natural gas generation due to the higher carbon intensity of coal generation. But, the carbon price is so small that there is no substantial change in the order of dispatch. Again, electric vehicles would be powered by natural gas peaker plants in this typical time period.

In Panel (c) of Figure 2.1, a moderate carbon price is imposed. This carbon price is sufficiently high for coal generation to be pushed up the supply curve and become the marginal generation in this typical time period. Operators try hard to avoid ramping coal plants up and down too often due to high ramping costs, so our stylized representation may in practice mean that the length of time that a coal plant is "on" is lengthened due to additional demand from electric vehicles, but it could also mean some modest ramping of already-on coal plants is occurring to meet the marginal demand. The core insight is that adding electric vehicles under a moderate carbon price can lead to more coal generation being used to power the electric vehicles. This erodes the emission reduction benefits from electric vehicles. Of course, the moderate carbon price leads to less coal generation overall–but the key point is that coal generation is more likely to be on the margin in this scenario.

Panel (d) of Figure 2.1 shows a case where the carbon price is much larger. Here the carbon price raises the cost of coal generation so much relative to natural gas generation that coal generation becomes supramarginal and is not turned on at all. In practice, this means that many coal plants will run only rarely, at times of very high load. It also implies that additional electric vehicles will likely be charged by natural gas in most time periods.

This is similar to the situation in Panel (b).

Appendix B.1 develops an analytical model based on the conceptual framework to further explore when carbon pricing is most likely to lead to electric vehicles being charged with coal generation. The modeling indicates that for a given demand, when the carbon price reaches a threshold determined by the relative marginal costs and relative carbon intensities of coal and natural gas peaker plants, coal plants will be pushed to the margin. Similarly, for a given demand, when the carbon price reaches a higher threshold determined by the same factors, coal plants will become supramarginal.

Thus far, this discussion has focused on the short-run implications of adding electric vehicles. However, similar logic might apply in the long run as well. In the long run, the timing of coal plant retirements is crucial. If the carbon price is very low and coal generation remains inframarginal nearly all of the time, then adding electric vehicle load should only minimally affect the timing of coal plant retirements, since the variable operating costs are still below the price. In this case, the coal plants will be less profitable, but the probability of a coal plant exit would only increase if the fixed costs of retaining the coal plant are large relative to the operating costs. If we have a moderate carbon price that is sufficiently high that coal generation is pushed to the margin more often, then there are two forces. The first is that the coal plants will be less profitable, which might increase exits by the coal plants. This occurs regardless of additional load from electric vehicles. However, adding electric vehicle load can raise the wholesale price of electricity and help keep those coal plants economic longer. This would delay coal plant retirements and decrease the economic incentive to build new, cleaner plants relative to a case without the electric vehicle load. If we have a much higher carbon price so that coal generation becomes supramarginal most of the time, the coal plants will already be uneconomic and will be retired anyway. Separately, it is also true that in the long run prices may be passed on to consumers and demand may be more responsive. Carbon pricing may also lead to more renewables being built, making it more likely that coal becomes supramarginal in the long run.

2.3 Empirical Analysis

In this section we use recent historical data to assess whether there have been short-run shifts in electricity dispatch consistent with changes suggested by our conceptual framework.

2.3.1 Research Strategy

Our conceptual framework explains why there might be a range of carbon prices that lead coal generation to be on the margin more often due to changes in the relative prices of coal and natural gas generation. To examine this empirically, we would ideally leverage exogenous variation in carbon prices. However, there is very limited variation in carbon prices in the United States. Moreover, the carbon prices that do exist tend to be in regions that rely little on coal generation, such as California or states in the Northeast under the Regional Greenhouse Gas Initiative. The linchpin of the conceptual framework is that carbon pricing can lead coal plants to replace gas-fired generation on the margin, which could increase the carbon intensity of marginal electricity generation. Without coal plants, carbon prices would not raise the emission intensity on the margin. Thus, our empirical research strategy focuses on variation in the relative prices of natural gas and coal generation, rather than variation in carbon prices, and focuses on regions with sufficient coal generation.

Our research strategy draws from insights in Cullen & Mansur (2017), which is focused on inferring short-run carbon abatement costs in the electricity sector. Cullen & Mansur (2017) rely on exogenous shocks in natural gas prices primarily coming from technological advances in hydraulic fracturing (i.e., 'fracking') to provide variation in the relative prices of natural gas and coal. They then infer how dispatch, and thus emissions, change when natural gas generators become more competitive with coal plants. Our approach also leverages recent variation in natural gas prices from the continued technological advances in fracking and the build out of pipelines in different regions to serve new natural gas drilling. Similar to Cullen & Mansur (2017), we are interested in how the relative prices of natural gas and coal influence dispatch of coal and natural gas generation. However, our focus is on how changes in the relative prices of natural gas and coal affect the likelihood of coal plants being on the margin, rather than inferring carbon abatement costs.

The mapping from the relative prices of natural gas and coal to the carbon price does not hold under all conditions. Cullen & Mansur (2017) provide a detailed discussion of when the price ratio of coal to natural gas can be used as a sufficient statistic for carbon prices in the context of analyzing electricity dispatch and emissions. A first condition is that marginal costs alone determine generation decisions, which should be the case in a competitive market. If marginal costs determine generation decisions, then the ordering of generators by marginal costs will not change regardless of the level of the fuel costs. Another condition is that short-run dynamic considerations do not heavily influence fuel switching between coal and natural gas. For example, coal plants are expensive to ramp up and down, which can lead them to stay on during short windows with low prices to avoid ramping. However, evidence suggests that these considerations are a secondary factor affecting fuel switching (Cullen 2015). A third condition is that firms must also respond to shocks in marginal costs due to fuel inputs in the same way as shocks in marginal costs due to carbon taxation. Fabra & Reguant (2014) provide evidence from the Spanish market that firms respond similarly, suggesting that this condition is likely to hold.

Another condition that is important for the interpretation of any results using this strategy is that demand is perfectly inelastic. This is a standard assumption for analyzing short-run questions in electricity markets, but is not likely to hold in the long run. Responsive demand could lead to lower overall electricity load at higher carbon prices and the marginal generator may not need to be dispatched.

A final condition is that long-run investment decisions have a negligible effect on short-run fuel switching. For instance, carbon prices will likely lead to investment in renewable generation over a longer time horizon. This would shift the entire aggregate supply curve for electricity to the right and lead to an imperfect mapping between carbon prices and the price ratio. Thus, Cullen & Mansur (2017) emphasize that their results are valid for understanding short-run fuel switching between coal and natural gas but not long-run dispatch decisions. Similarly, our research design in this section has only a short-run interpretation.

We focus our research on four regions where there is substantial coal and natural gas generation. These four regions cover much of the middle of the country and are served by four very large independent system operators: Electric Reliability Council of Texas (ERCOT), Midcontinent Independent System Operator (MISO), PJM Interconnection, and Southwest Power Pool (SPP). See Figure 2.2 for a map of the independent system operator regions in the United States. Fuel switching between coal and natural gas is likely to be small or minimal along the West Coast and in the Northeast due to very little reliance on coal, but fuel switching may occur in many other regions, including the four regions we study.

Our research question in this section asks how changes in the relative prices of coal and natural gas influence whether coal or natural gas is being used to serve additional load on the system. To examine this, we segment our sample based on the ratio of coal to natural gas prices. By segmenting the data, we can clearly observe whether the fuel source of the generator that is on the margin adjusts when the ratio exhibits large changes. For example, when the ratio is high, coal is relatively more expensive than natural gas, as might happen with high carbon prices.

Thus, for each subsample based on the coal-gas ratio, each region, and for both coal and natural gas, we estimate the following model of generation of fuel type f at hour-in-the-sample t:

$$q_{ft} = \sum_{p \in \{\text{peak,offpeak}\}} \beta_p \mathbb{1}(t \in p)_t load_t + \gamma_S q_{\text{solar},t} + \gamma_W q_{\text{wind},t} + \delta_{hmy} + \epsilon_{ft}. \tag{2.1}$$

We use q_{ft} to denote the quantity of electricity generated by fuel type f in hour t. $\mathbb{1}(t \in p)_t$ is an indicator variable for the hour t being either a peak or off-peak hour of the day, where the peak period is defined as any hour between 7 am and 10 pm on weekdays. We estimate a separate coefficient for peak and off-peak to shed light on how the results may be different depending on when electric vehicle owners charge their vehicles. $load_t$ refers to the average electricity demand on the system at time t. Our coefficients of greatest interest are β_{peak} and β_{offpeak} for coal generation as they quantify the effect of additional load on coal generation, such as from electric vehicles.[10]

Because intermittent renewable generation can affect the need for conventional generation, we control for hourly solar output $q_{\text{solar},t}$ and hourly wind output $q_{\text{wind},t}$ (Fell & Kaffine 2018). We also include fixed effects δ_{hmy} for each hour-of-the-day interacted with the month-of-the-sample to flexibly account for seasonality and daily patterns in load and fossil generation throughout our sample. ϵ_{ft} is the error term.

When calculating the marginal carbon dioxide emissions rate in each of the four regions, we use the same specification as (2.1) only we replace the dependent variable with emissions. We run this estimation for each subsample and interpret the estimated coefficients β_{peak} and β_{offpeak} as the effect of additional load on emissions.

Our model is similar to the specification in Holland et al. (2016). One difference is the addition of the controls for intermittent renewables to account for greater renewables market share in recent years (the Holland et al. (2016) sample ends in 2012). Another is that we focus on peak versus off-peak hours instead of hour of the day for our primary results. A third difference is that we segment the sample based on the coal-to-natural gas ratio. Identification in both our setting and in Holland et al. (2016) is based on shocks to electricity load after controlling for a rich set of fixed effects. For example, one source of variation is that several more people may happen to be home in a particular hour of a particular month than the average, leading to a positive shock for electricity load. These shocks should be plausibly random with respect to operator decisions at coal and natural gas power plants.

[10]Note that in the presence of congestion in the transmission grid, the marginal plant charging an electric vehicle might differ between locations within the same region.

2.3.2 Data

We bring together a rich data set from several public sources that covers from January 2014 to December 2019. Hourly load and net generation by energy source (e.g., coal, natural gas, nuclear, hydro, solar, wind, import, other) are obtained from the independent system operators. We use EIA Form 923 for plant-level monthly data of coal and natural gas fuel expenditures, electricity generation, and fuel consumption. These also include data on each generation plant's heat rate, which is an inverse measure of fossil fuel power plant efficiency in units of million Btus (MMBtu) burned per megawatt-hour (MWh). Plant-level hourly carbon dioxide emissions come from the Continuous Emissions Monitoring System (CEMS) of the Environmental Protection Agency (EPA). We use EIA data to match plants to the four regions and calculate hourly total carbon emissions for every region.[11]

For every plant, we calculate the variable fuel cost per MWh for every month as the product of the plant's heat rate and fuel cost (in units of \$/MMBtu) for transactions with a maximum contract duration of one year. We then calculate a generation-weighted monthly gas and coal price per MWh for every region.[12]

Table 2.1 reports the mean and standard deviation for the main variables of interest for each region. Panel A shows the summary statistics for the hourly electricity demand in the region and hourly generation by fuel type. PJM is the largest market, with over three times the load in SPP. In MISO and SPP, the coal-fired generation is almost double gas-fired generation, but the two fuel sources generate about the same amount in PJM. In ERCOT, there is less coal generation than natural gas generation. In each of the regions, there is a sizable amount of wind generation, while solar generation is still fairly limited.

Panel B shows the summary statistics for heat rates and emission rates. The heat rates are similar across regions, especially for coal generation. SPP has the highest heat rate for natural gas, indicating it has the least efficient natural gas plants on average.[13] Combining this with hourly generation, the average carbon dioxide emission rate is highest in MISO and SPP. The average rate is lowest in PJM, where nuclear plants produce more than a third of all electricity, and is almost equal to the emission rate of gas-fired generation.

Panel C presents coal and natural gas prices. We observe that the price of coal is relatively stable across the regions, with little variation. In contrast, the price of natural gas has

[11] `https://www.eia.gov/electricity/data/emissions/`

[12] Appendix B.2 provides more detail on the calculation and presents the time series of coal and natural gas prices in all four regions. Our approach largely follows Cullen & Mansur (2017) and we find that additional refinements, such as incorporating the effect of sulfur, ash, and Btu content make little difference to our findings.

[13] Note that the average heat rate of gas-fired plants is going to be the weighted average of natural gas combustion turbines (11.5-12.5 MMBtu/MWh) and combined-cycle natural gas plants (7.4-8.1 MMBtu/MWh).

considerable variation, so we have substantial variation in the coal-to-gas price ratio. Coal prices are on average below natural gas prices, such that the mean coal-to-gas ratio is below one in every region. The ratio is lowest in SPP and highest in PJM.

The substantial variation over time in the coal-to-gas price ratio can be seen in Panel (a) of Figure 2.3.[14] The coal-to-gas price ratio is the lowest early in the sample in 2014. There is a slight trend upwards, as more natural gas drilling occurs and more pipelines open. There are a few shocks due to periods of especially cold weather and/or pipeline constraints. For example, January 2018 included a period of prolonged cold weather that affected much of the eastern United States, leading to much higher natural gas demand for building heating and thus higher prices in the unseasonably coldest areas.[15] Thus, PJM shows a short steep drop in the coal-to-gas ratio, while SPP shows little change.

Panel (b) of Figure 2.3 maps the coal-to-gas price ratios to implicit carbon prices. We refer to these as 'implicit' carbon prices because the mapping holds under the conditions discussed above, and most importantly would be unlikely to hold in the long run.[16] Panels (a) and (b) of Figure 2.3 align in the sense that high values of the coal-to-gas ratio, as in the spring of 2017 or 2019, match high implicit carbon prices. A key observation from Panel (b) is that the variation in the coal-to-gas ratio is sufficiently large that it maps to swings in implicit carbon prices ranging from near zero to as high as \$160/ton CO_2.

2.3.3 Estimation Results

Empirical evidence of coal generation pushed to the margin

Our coefficients of greatest interest are β_{peak} and β_{offpeak}, and we run the regression in (2.1) separately for different levels of coal-to-gas price ratios. Thus, due to the large number of coefficients, we plot the coefficients in figures to show how the share of marginal generation that is powered by coal-fired power plants changes with higher coal-to-gas price ratios. We use five quantiles of evenly sized subsamples, where the quantiles in terms of coal-to-gas price ratios map roughly to implicit carbon prices of around \$8, \$27, \$35, \$40, \$50, and \$120

[14]This figure presents the ratio in terms of the cost of coal-fired and gas-fired generation, which combines the heat rate with the fuel prices to provide the ratio that is relevant for fuel-switching decisions. In Appendix B.2, we show that the figure looks very similar if we plot the ratio of the fuel prices themselves. We ran robustness checks and our findings would not change if we used the fuel prices rather than the generation costs to determine the thresholds to segment our sample.

[15]See `https://www.pjm.com/-/media/library/reports-notices/weather-related/20180226-january-2018-cold-weather-event-report.ashx`.

[16]To perform this mapping, we have to normalize the level of the prices to some value, and we use the average 2014 value throughout the sample to provide a clean illustration of the variation in implicit carbon prices. For expositional purposes, we also added a constant intercept in all four regions sufficient to ensure that the lowest value (PJM in January 2014) is positive.

per ton of CO_2, respectively.

Figure 2.4 presents the results. Each panel represents a different region. We plot the coefficients of each of the five quantiles of implicit carbon prices and connect them with lines. The solid line represents off-peak hours, while the dashed line represents peak hours. For example, in Panel (a), the point on the solid line at the first implicit carbon price quantile indicates that just over 50% of marginal generation during off-peak hours will be powered by coal in MISO when there is a minimal carbon price.[17] The point on the solid line at the fifth implicit carbon price quantile shows that with much higher implicit carbon prices nearly 60% of marginal generation during off-peak hours will be powered by coal in MISO. These results are significantly different from each other.[18]

The findings in Figure 2.4 are striking. For MISO and SPP, the share of marginal generation powered by coal generally increases with the carbon price. In the peak hours the share of marginal generation from coal is much lower than the off-peak hours, but with higher carbon prices, the share for the peak and off-peak begins to converge. This is consistent with coal plants being pushed up the aggregate supply curve as cheaper natural gas becomes inframarginal. The logic for this follows from our conceptual framework: marginal demand during peak periods was previously being mostly met with natural gas, but the higher implicit carbon prices mean that coal generation becomes more expensive and is used to serve marginal demand more often in the peak hours. In short, the upward slope of the curve for MISO and SPP, and the convergence of peak and off-peak, indicate that the carbon price is pushing coal plants to the margin. Recall that MISO and SPP have much more coal generation than natural gas generation during our time frame (Table 2.1). ERCOT shows a similar pattern for peak hours, but in the off-peak hours coal on the margin begins to very slightly decline with higher carbon prices, although the overall trend is upward. This is again consistent with coal plants being pushed up the aggregate supply curve and becoming more marginal during peak hours.

PJM differs from the other three regions. At a low implicit carbon price, the share of marginal generation powered by coal is higher than any of the other regions. But more importantly, we also observe that the share of marginal generation that is powered by coal generally decreases with higher carbon prices, in contrast to all of the other regions (where it is constant or slightly increasing at higher levels of implicit carbon prices). One possible

[17]One question that may arise is whether coal can actually be on the margin, given the cost of ramping. Figure B.3.1 in Appendix B.3 shows that coal generation indeed often serves as the marginal technology. Coal generation follows load in two ways: ramping up and down by changing the capacity factor of individual plants that are running, and starting up and shutting down plants during the course of a day. The latter is likely more costly, but does occur often in the data, consistent with (Cullen 2015), who suggests that ramping costs may be a secondary factor.

[18]In a two-sided t-test for differences in means, we find a p-value of 0.000.

explanation for the inverse relationship between the share of coal-fired marginal generation and implicit carbon prices is that coal is being pushed to the margin and then becoming supramarginal and (eventually) uneconomic. We will explore this possible explanation below.

We also perform the same estimations as those that created Figure 2.4, only focusing on using natural gas generation as the dependent variable. The results are the inverse of those in Figure 2.4 because in all of the regions, coal and natural gas comprise over 90% of marginal generation. In fact, in MISO, SPP, and ERCOT, coal and natural gas generation make up almost 100% of marginal generation. In PJM, marginal demand is also met by imports, dual-fuel generation, and oil generation, at 5%, 3%, and 2%, respectively. Interestingly, none of these show notable changes in response to changing implicit carbon prices. The results showing marginal generation by natural gas in each region over the different carbon prices are included in Appendix Figure B.3.2.

CO_2 emissions from marginal generation

But first we turn to what these findings imply for emissions from marginal generation, which is highly relevant for electric vehicle policy. Figure 2.5 presents the emission rates for marginal generation in each region over the five quantiles of implicit coal-to-gas prices. Due to the increased coal generation on the margin at higher carbon prices for MISO, SPP, and ERCOT, we find that the average emission rate is increasing with the level of the implicit carbon price. The increase in emission rate with the implicit carbon price is even stronger for peak hours, but the emission rate during off-peak hours always remains higher. Importantly, the difference between the emission rate in the peak and the off-peak hours becomes smaller with higher carbon prices, consistent with the convergence we saw for MISO, SPP, and ERCOT in Figure 2.4.

Figure 2.5 also presents the average CO_2 emission rate from marginal generation for two electric vehicle weekday charging profiles from the Electric Power Research Institute (EPRI).[19] The "uncontrolled charging profile" assumes that electric vehicles start charging as soon as they arrive at home, such that the bulk of additional electricity demand is between 4 pm and 11 pm. Thus, most of the electricity for charging will be drawn during peak hours. The "maximum delay" charging profile assumes that electric vehicles start charging at the latest possible time to be fully charged just before being used in the morning, such that the bulk of additional electricity demand is between 4 am and 10 am (mostly off-peak hours). To develop these emission rate estimates, we estimate equation 2.1 for each hour of the day rather than peak and off-peak periods (see Appendix B.3 for details).[20] The emission rate

[19] Appendix Figure B.3.3 shows these charging profiles.

[20] Appendix Figures B.3.4 to B.3.6 present the resulting coefficients of marginal coal, gas, and emissions

results for the two charging profiles for MISO, SPP, and ERCOT mirror the results for the peak and off-peak in each region. The uncontrolled charging profile has a similar emission rate for marginal generation as the rate for the peak hours and the maximum delay charging profile has a similar emission rate as the rate for the off-peak hours. These charging profiles are useful for bringing empirical data to bear on when the marginal electric vehicle owners might actually be charging.

The results in Figure 2.5 for PJM largely match those for PJM in Figure 2.4. In contrast to the other three regions, the emission rate in PJM is slightly decreasing with higher implicit carbon prices. In addition, the gap in the emission rate between the peak and off-peak grows with higher implicit carbon prices because the peak emission rate drops more. Again, this may be because the coal plants that are on the margin during peak hours become supramarginal and uneconomic with higher implicit carbon prices.

These results suggest that for large swaths of the United States, coal plants can be pushed to the margin and be more likely to power new loads with higher implicit carbon prices, implying that higher carbon prices can reduce the emissions benefits of electric vehicles. It is important to note that the *average* share of coal generation is still declining with higher implicit carbon prices (see Appendix Figure B.3.7). So a higher carbon price will still reduce *total* CO_2 emissions, even if it means that in some regions additional electric vehicles may be more likely to be charged with coal.

When is coal likely to be pushed to the margin?

Our empirical results display some heterogeneity across regions, with PJM being quite different from the other three regions. All four regions have sizable market shares of coal generation, which allows for coal-to-gas switching with the imposition of a carbon price. This raises the question of why PJM is different and has *less* of the marginal generation provided by coal when there are higher implicit carbon prices.

Table 2.2 presents a set of statistics that help clarify why PJM is so different from the other regions. The first three columns show the capacity factor for coal at three different quantiles of implicit carbon prices.[21] The capacity factor is defined as the ratio of the average output of a plant to the maximum possible output. The capacity factor provides a sense of how often existing plants are running and how much of their capacity they are using when they are running. In the other three regions, the capacity factor is declining with higher implicit carbon prices. However, in PJM, the capacity factor does not decline.

for every hour of the day and for three quantiles of the implicit carbon price.

[21] We calculate the installed coal and gas generation capacity per region per month using EIA Form 860M. We use the nameplate capacity – which might be 5% to 10% higher than the actual capacity available for generation – including backup plants that do not run very often.

Why would we not see a decline in the the coal capacity factor in PJM when the implicit carbon price is much higher? The main reason is that there was a much larger retirement of coal capacity in PJM than in the other regions during our sample period, as is shown in Column (4) of Table 2.2. This again suggests that coal plants in PJM are becoming supramarginal more often, as some of these plants became entirely uneconomic and end up retiring entirely.

Column (5) of Table 2.2 helps explain why so much coal is being retired. A striking 23 GW of natural gas capacity was added in PJM over our sample period, likely related to the growth of natural gas production in the Marcellus shale in the PJM region. These natural gas additions in PJM far exceed the additions in the other regions. The additional natural gas capacity (which comes in at low cost), provides a force similar to the effect of increasing coal-to-gas ratios and can push coal even further up the aggregate supply curve to be supramarginal more often.

Columns (6) and (7) indicate that the change in the overall average annual load and the growth of renewables during our sample period was not appreciably different in PJM compared to the other regions.[22] These findings paint a picture of the different dynamics that have been occurring in PJM and help explain why PJM is different from the other regions during our sample period in the marginal generation from coal. They also suggest that for coal plants to be pushed to the margin by carbon pricing, there must not only be a sufficient amount of coal capacity that is near the margin, but that the coal plants must be economic enough that they do not become supramarginal and pushed toward retirement.

2.4 Dynamic Simulation

Thus far, we have empirically demonstrated that increases in the ratio of coal to gas prices, as would occur with carbon pricing, can shift coal generation to the margin in the short run. This implies that in the short run, electric vehicle policies may not reduce emissions as much when implemented in concert with carbon pricing because the vehicles will be charged more often using coal-fired power.

In the long run, this effect may not hold. A rapidly increasing market share for electric vehicles may increase electricity demand much beyond the margin. There may be retirements of old coal power plants and builds of new renewable generation. This may be especially important if renewable energy technologies, such as wind and solar, continue to drop in

[22]In the Appendix we have a set of figures to provide more details on how PJM differs from the other regions: Appendix Figure B.3.8 for capacity factors, Appendix Figure B.3.9 showing natural gas capacity over time, and Appendix Figure B.3.10 showing coal capacity over time.

cost. Accordingly, we use a dynamic model to develop projections into the future to provide insight into whether our empirical finding of coal being pushed to the margin in the short run is also relevant in the long run. The National Energy Modeling System is well suited to develop quantitative estimates of the effects of electric vehicle policies with and without carbon pricing.

2.4.1 The National Energy Modeling System

The National Energy Modeling System is a disaggregated dynamic equilibrium model of the U.S. energy system. It includes a detailed representation of all major energy markets, including transportation and the electric power sector. In the electric power sector, retirement, new construction, and retrofit decisions are based on maximizing the net present value with perfect foresight of future prices. The model equilibrates supply and demand in all markets, iterating until convergence to endogenously solve for equilibrium prices in each year.[23] The model includes the full supply chain, beginning from imports and extraction of unprocessed fuels to final end uses. For each primary, intermediate, or final energy market, there are calibrated supply curves based on geologic constraints and engineering data, as well as demand curves based on econometric analysis by the Energy Information Administration.

The model contains 13 modules covering different sectors and produces detailed quantitative estimates of energy consumption and emissions through 2050 at the national and regional level. The regional disaggregation varies depending on the sector, but most sectors, including the transportation sector, are based on the nine Census divisions. The electricity sector is an exception and has 22 regions based on boundaries drawn by the North American Electric Reliability Corporation.[24] The model includes all major environmental and energy regulations that currently exist. Many regulations have an expiration date, and the model assumes these regulations sunset, and thus become non-binding, upon expiration.

The transportation sector covers all primary modes of transportation, including air travel, freight transport, and miscellaneous transportation energy demand (EIA 2016). New light duty vehicle sales are modeled with a nested logit framework, calibrated to match current sales. New sales adjust over time based on projections of future incomes, demand for owning a vehicle, fuel prices, and cost declines of different technologies.[25] The nested logit framework includes fuel economy, price, vehicle range, fuel availability, battery replacement cost,

[23]Oil prices are the one exception; they are exogenously set.

[24]See Figure B.4.1 in Appendix B.4 for maps of the regional disaggregation for the transportation and electricity sectors. Note that the very latest version of the model, as of 2021, has increased the number of electricity sector regions to 25.

[25]New vehicle technologies follow a learning curve calibrated to existing technology costs. Thus, greater adoption of the technology lowers the cost of adding the technology to a vehicle.

performance, home refueling capability, maintenance costs, luggage space, and make and model diversity within vehicle class. The types of vehicles in the model include conventional (gasoline, diesel, flex-fuel ethanol, CNG/LNG and LPG bi-fuels), hybrid-electric, dedicated alternative-fuel (CNG/LNG and LPG), fuel cell (gasoline, methanol, hydrogen), and electric (100- and 200-mile). Cars and light trucks each have six size classes: minicompact, subcompact, compact, midsize, large, and 2-seater for cars, and light trucks are available as commercial or large pickups, vans, and utility vehicles. Existing vehicles are exogenously scrapped as they age using vehicle survival curves. The model uses exogenous charging profiles for electric vehicles.

Automakers add new technologies to vehicles as the technologies become less expensive. They are also subject to the constraints of Corporate Average Fuel Economy standards and state-level zero-emission vehicle standards. The model includes an iterative process to meet the fuel economy standards. If an automaker is in violation of the standards, it can add technologies, change the vehicles they produce, or reduce attributes such as horsepower or weight. Once these decisions are made for all automakers, the vehicle choice model will then provide the new market shares, and compliance will be assessed. This process continues until all automakers are in compliance. The model ensures compliance with zero-emission vehicle (ZEV) standards in a similar way in the relevant regions: solving for the unconstrained ZEV sales and adjusting for compliance. It iterates over both regulations.

The electricity market module makes capacity planning and generating decisions for the 22 regions based on forecasted electricity demand from other sectors, fuel prices, technology costs, emissions policies, and macroeconomic parameters, such as capital costs. The model includes a range of fossil fuel, nuclear, and renewable technologies, including not-currently-economic technologies like advanced nuclear that may become cheaper exogenously over time and through learning-by-doing.[26] Electricity demand is incorporated into representative load curves across seasons, times of day, and regions, and engineering constraints in generation are incorporated. Trading is permitted across markets subject to transmission constraints.

Based on expected demand, the model makes decisions about new construction of generating facilities, possible retirement of existing plants, and the adoption of emissions mitigation technology. These capacity expansion decisions are made to minimize expected costs, where costs include capital, operations and maintenance, and fuel costs, subject to environmental

[26] The full list of electricity generating technologies includes existing coal without flue gas desulfurization (FGD), existing coal with FGD, new pulverized coal with FGD, advanced clean coal technology, advanced clean coal technology with sequestration, gas/oil steam, conventional gas/oil combined cycle, advanced combined cycle, advanced combined cycle (with sequestration), conventional combustion turbine, advanced combustion turbine, fuel cells, distributed generation, conventional nuclear, advanced nuclear, conventional hydropower, geothermal, solar-thermal, solar-photovoltaic, wind, wood, and municipal solid waste.

regulations (i.e., those covering local air pollutants and CO_2 at the state, regional, or federal level). Electricity dispatch is determined simultaneously across regions using a least-cost optimization of plants based on operating and transmission costs, with constraints based on emissions limits, engineering characteristics, and required maintenance. Electricity plants are price takers. The electricity market module ultimately outputs electricity prices, fuel consumption, and emissions.

Our study uses the National Energy Modeling System run on a Yale server, and thus at EIA's request, we refer to it hereafter as "Yale-NEMS." We compile the code given to us by EIA, and make only very minor modifications to the code to allow it to run on our server and to output additional results. We are able to replicate EIA's Annual Energy Outlook reference case results (to a rounding error). Our baseline in this study is the 2017 Annual Energy Outlook, but we run robustness checks with scenarios that more closely align with the results in the 2020 Annual Energy Outlook to ensure that changes over the past few years do not appreciably change our results.[27]

The model we are using is a complex structural model with numerous relationships and parameters. A natural question thus arises as to whether the projections from the model are credible and useful for policy analysis. There are several reasons to believe that the model is capturing relevant policy dynamics. There is an entire team at EIA developing the model for use by the U.S. Congress and executive branch.[28] It is also widely used for analysis by consulting firms such as the Rhodium Group and OnLocation, and the Annual Energy Outlook projections from the model are used for corporate decision-making by numerous companies in the energy industry. The academic literature using the model is also extensive, and includes analyses of policies covering nearly all major energy sectors, including transportation and electricity (Goulder 2010, Morrow et al. 2010, Auffhammer & Sanstad 2011, Cullenward et al. 2016, Mignone et al. 2017, Gillingham & Huang 2019, 2020). The projections from the model have been critiqued as being slow to adjust to changes in the market (O'Neill & Desai 2005, Auffhammer 2007, Wilkerson et al. 2013). Hence, we run sensitivity analysis, including scenarios with much more optimistic renewables costs, to see what happens if the energy transition is more rapid than EIA's analysts expect.

2.4.2 Policy Scenarios

We develop a set of scenarios to illustrate the interactions when electric vehicle policies are implemented along with carbon pricing. These are then compared to the Annual Energy

[27]We use the Annual Energy Outlook reference case without the Clean Power Plan.

[28]The model is extensively documented: see `https://www.eia.gov/outlooks/aeo/nems/documentation/`.

Outlook reference case.

High Electric Vehicle Market Share

There are many possible ways for policymakers to incentivize electric vehicles. Direct subsidies, zero-emission vehicle standards, public funding of charging infrastructure, research and development tax credits, and direct public research into new technologies are among many of the possible approaches that governments could use to foster long-run uptake of electric vehicles. Yet, the fundamental concepts discussed in our conceptual framework should apply regardless of what the exact policy design is, as long as it leads to additional electric vehicles charging on the grid. Thus, we focus on a scenario with a high level of electric vehicles and are agnostic as to the exact policy that leads to this outcome. This approach allows for greater generalizability of our results to many possible policies that could lead to a high market share for electric vehicles.

There are numerous industry projections that show electric vehicles reaching a much higher market share in the upcoming decades. One of the most prominent of these projections is the annual Bloomberg New Energy Finance (BNEF) Electric Vehicle Outlook. In the 2020 BNEF Outlook, electric vehicles are projected to increase from less than 2% market share in 2020 to nearly 60% market share in 2040 in the United States (Bloomberg New Energy Finance 2020). This is a massive transformation of the market, but it is largely consistent with projections by the International Energy Agency (IEA 2020) and others in the industry. BNEF explicitly expects continued policy measures to encourage electric vehicles, including continued subsidies and public funding for charging infrastructure. BNEF also projects battery prices to continue the precipitous decline observed over the past decade.

We develop a scenario intended to roughly match with the BNEF projections for electric vehicle market share over time, which is substantially larger than the market share included in the Annual Energy Outlook reference case. The difference between our scenario and the reference case is more than a marginal change and is useful for allowing us to clearly see the effects of adding many more electric vehicles charging. Appendix Figure B.4.3 shows the share of new light-duty vehicle sales that are electric vehicles by year in this scenario and the reference case. The vehicle stock transitions more slowly. In this scenario, electric vehicles account for approximately 46% of light duty vehicles and 64% of passenger cars on the road in 2050.[29] By 2040, there are 23 million electric vehicles or plug-in hybrid electric light-duty vehicles (20 million cars) in the reference case and 93 million light-duty vehicles (60 million cars) in this scenario.

[29]The more broadly defined category of battery electric and plug-in hybrid electric vehicles account for around 53% of light-duty vehicles and 71% of passenger cars on the road.

We make the following changes to implement this scenario: (1) we assume battery costs decline to roughly reach the price of $40/kWh by 2030, (2) we increase the rate at which the make and model diversity for electric vehicles converges toward that of conventional vehicles, and (3) we adjust the technology-specific constant for all plug-in electric vehicle coefficients in the logit random utility model to ensure that we match the BNEF scenario with the battery cost decline we assume. Appendix B.4 includes the details of each of these changes. After reducing battery costs as discussed above, we allow the model to set overall vehicle prices. Appendix Figure B.4.2 shows the decline of average electric vehicle prices over time in this scenario and the reference case (for compact cars, but the relative price changes are similar for other classes). The vehicle price declines, while perhaps optimistic, are still slower than projections made by Elon Musk, CEO of Tesla, who promised a $25,000 electric vehicle within three years.[30] Volkswagen has also claimed dramatic electric vehicle cost declines.[31]

Carbon Pricing

We model the implementation of a range of carbon pricing policies that gradually increase over time. In practice, these policies could either be carbon taxes or tradeable permit systems with an allowance price equal to the carbon tax. All of the scenarios begin in 2020 with a price of $2/ton CO_2 (2016 dollars) that increases over time until 2040, after which the carbon price remains constant. It is difficult to choose a central case scenario because a wide range of different carbon prices may be politically possible.[32] For the sake of illustration, we choose a central case with a carbon price that increases linearly to reach $30/ton in 2040.[33] We also consider a lower tax that reaches $5.30/ton, a higher tax that reaches around $49/ton, and an even higher tax that reaches $70/ton (all in 2016$). Most of these price paths are well below the path of the social cost of carbon (SCC) in the Obama Administration's estimates, which begins around $49/ton in 2020 (2016$, or approximately $54/ton in 2020$)(IWG 2016), and thus represent a partial internalization of the externality.

In our carbon pricing scenarios, we do not cycle the revenues back into the economy, which could lead to some increased economic activity and emissions. The reason for this is that it is difficult to know how the revenues would be allocated and analyzing the effects

[30] See https://www.nytimes.com/2020/09/22/business/tesla-elon-musk-battery-day.html.

[31] See https://www.theverge.com/2021/3/15/22325813/vw-volkswagen-power-day-battery-electric-car-announcement?mc_cid=982fee4e91&mc_eid=b1fa5041a3.

[32] For example, the allowance price in California's cap-and-trade system is $17.98 in March 2021 (https://www.theice.com/marketdata/reports/142) and the price in the Northeast Regional Greenhouse Gas Initiative was $7.41 in Q4 2020 (https://www.rggi.org/auctions/auction-results/prices-volumes). But there are discussions about substantially tightening these caps, which would lead to higher prices.

[33] $30/ton translates to an increase in the gasoline tax of roughly $0.27/gallon.

of different approaches to revenue allocation is outside the scope of this paper (see Goulder (1995) for one of the early works in a long line of literature on this topic).

We also combine carbon pricing with our high electric vehicle market share scenario to examine the interactions between these policies.

2.4.3 Dynamic Simulation Results

In this section we summarize the results from running the scenarios in Yale-NEMS, focusing on the effects on electricity generation and air pollutant emissions.

Electricity generation

We begin by examining the fuel sources that are used to generate the electricity for the additional electric vehicles in the high electric vehicle scenario. Specifically, we calculate the difference in electricity generation from coal, natural gas, and renewables between the high electric vehicle scenario and the reference case. We calculate this difference both with and without carbon pricing for each year. For the ease of presentation, we sum up the total generation over the full period from 2020 to 2050.

Panel (a) in Figure 2.6 presents these differences in generation between the high electric vehicle scenario and the reference scenario. The first three bars represent the change in total generation for coal, natural gas, and renewables under the reference scenario. The second three represent the change in generation for our central case carbon pricing scenario. The third shows the difference in the additional generation required by the electric vehicle scenario between the carbon pricing and the reference case.

In Panel (a), we observe that under the reference case, the additional generation required by electric vehicles is provided entirely by natural gas and renewables. This is consistent with projected continued low natural gas prices and declining costs of renewables. Despite the additional load, coal generation essentially stays flat and even very slightly decreases. The slight decrease is due to new lower-cost natural gas and renewables capacity coming online leading to older coal plants becoming uneconomic more often.

In contrast, under moderate carbon pricing, all three fuels are used to meet the additional load from electric vehicles. Natural gas and renewables are still used more than coal, but there is a sizable increase in coal generation to power the additional load on the system from electric vehicles. The differences in the third set of bars highlight how much more coal is being used to power electric vehicles under the carbon pricing scenario. These results show an important interaction effect that aligns with the short-run empirical findings.

This interaction effect can also be seen in Panel (b) Figure 2.6, which presents total generation for coal by year out to 2050. The high electric vehicle demand scenario is nearly the same as the reference case (a decline of 14.5 billion kWh/year). The carbon price leads to substantial reductions in coal generation relative to the reference case. However, when the high electric vehicle demand is combined with the carbon pricing, coal generation is used more than without the electric vehicle demand (by 112.4 billion kWh/year).

There are two fundamental reasons for the additional coal generation from electric vehicle charging. The most important is a dynamic effect: the additional demand from the electric vehicles leads to coal plants being retired later. Carbon pricing serves to make many coal plants uneconomic over time, but the additional demand from electric vehicles raises wholesale prices for electricity, rendering some of these coal plants economic for longer. A secondary reason is that in some years coal is dispatched more often to help serve the additional electric vehicle demand (i.e., coal is on the margin). Appendix Figure B.4.4 shows coal generation's capacity factor and total capacity over time, decomposing the interaction effect on coal generation. Without a dynamic model of new plant builds, it would be difficult to develop this insight.

We have focused thus far on coal, but it is worth discussing renewables as well. Our findings for renewables are the inverse of those for coal. The total capacity of renewables is higher whenever there is a carbon price in place. In addition, the total capacity of renewables is higher with many more electric vehicles charging. But the amount of additional renewable capacity brought online to serve the electric vehicles is lower when there is a carbon price (see Appendix Figure B.4.5). An explanation for this finding is that the marginal cost of building renewables is increasing in the amount built both cumulatively and in each year. Thus, with greater capacity of renewables being built anyway under a carbon price, it is less profitable to build more renewables to power the electric vehicles. Instead, more coal plants are kept running longer before retirement to power the electric vehicles.

2.4.4 Emissions

Electric vehicle policies are usually justified based on the emissions savings made possible by switching from gasoline or diesel to electricity (both in the short run and in the long run). A policy leading to a high electric vehicle market share would be expected to reduce emissions from transportation, but increase emissions from electricity unless electricity is fully decarbonized. Thus, we examine emissions from vehicles and the electricity sector.[34] Our emissions analysis assumes a fixed carbon price in each year, but it is important to

[34] We focus on highway vehicles, which would exclude ATVs, agricultural vehicles, construction vehicles, etc. There are modest changes in emissions in other sectors from re-equilibration of prices, but these are second-order effects that do not change the insights presented here.

note that with an economy-wide cap-and-trade system, our results on emissions would be different if the carbon price is allowed to vary to guarantee that the cap is met. Yet the forces at work here would remain.

For each scenario, we examine emissions of CO_2 and several common air pollutants: nitrogen oxides (NO_x), particulate matter with a diameter less than 2.5 micrometers (PM2.5), sulfur dioxide (SO_2), and volatile organic compounds (VOCs). For the electricity sector, Yale-NEMS calculates emissions of CO_2, NO_x, and SO_2. We calculate emissions for the remaining pollutants by estimating implicit emissions factors at the NERC-region level using 2014 National Emissions Inventory Data and then applying those emission factors to power sector fuel consumption outputs.[35] Similarly, Yale-NEMS calculates CO_2 emissions from vehicles, but not the other pollutants. We calculate these emissions using emission factors from the U.S. Environmental Protection Agency, which are delineated by vehicle type, fuel, and vintage and are measured on a gram/mi basis (Lenox et al. 2013).[36]

Figure 2.7 presents the net emissions associated with vehicles and the electricity sector. Several takeaways are apparent in Figure 2.7. First, high electric vehicle demand reduces CO_2 emissions from the reference case, but carbon pricing alone reduces CO_2 emissions just as much as carbon pricing combined with high electric vehicle demand. In other words, when combined with our central case carbon pricing scenario, policies to greatly increase the market share of electric vehicles do not appreciably reduce CO_2 emissions further. This is an important result and we will explore whether this holds with other carbon price paths shortly.

A second finding is that the impacts of each scenario on the emissions of other common air pollutants are generally similar to the effects on CO_2 emissions. One difference is that the increase in PM2.5 and SO_2 emissions from electric vehicles is larger under carbon pricing than the reference case, due to greater use of coal plants. Another difference is that electric vehicles reduce VOC emissions even under the carbon pricing scenario, most likely because the VOC emissions from electricity generation are very small. Another observation from Figure 2.7 is that carbon pricing leads to notably lower emissions of all pollutants, as would be expected. Despite the perverse interaction with high electric vehicle demand, carbon pricing still remains an efficient and effective approach to reduce emissions.

We next monetize the changes in pollution between each of the scenarios and the reference case. We use values of marginal damages for each of the air pollutants from the widely-

[35] A caveat of this approach is that these emission factors do not evolve over time, but we could not find suitable projections of emission factors for these pollutants from the power sector.

[36] Vehicle non-CO_2 emissions are calculated by multiplying Yale-NEMS estimates for annual vehicle-miles-traveled by the emission factors, and then summing over all vehicle types and years. These emission factors evolve over time based on the U.S. Environmental Protection Agency's estimates.

used AP3 model,[37] and the central case estimate of the social cost of carbon from the Obama Administration's Interagency Working Group (IWG 2016). We calculate the avoided pollution damages for each year out to 2050 and then present the results by calculating a net present value using a 3% discount rate.

We present the net present value of the avoided pollution damages in Table 2.3.[38] This table includes the full set of our carbon pricing policies, allowing us to examine whether our findings above hold at different levels of carbon pricing. Recall that our central case carbon price reaches $30/ton by 2040 (shown in column (2)). All three scenarios result in avoided pollution damages relative to the reference case. The first row shows that our high electric vehicles demand scenario leads to $3.16 billion/year in avoided pollution damages. The second row shows that this is dwarfed by the avoided pollution damages in all of the carbon pricing scenarios except the lowest path in column (1). The third row combines the high electric vehicle demand scenario with carbon pricing.

When comparing the combined scenario to carbon pricing alone, we observe that high electric vehicle demand does not always lead to additional avoided damages on average. Indeed, in our central case estimate, the combined policy leads to *lower* avoided damages than carbon pricing alone. This is primarily the result of the emissions from the increased coal generation used to power the electric vehicles (as seen in Figure 2.6) dominating the emission reductions from vehicle electrification.

However, at lower or higher carbon pricing paths, the emission reductions from vehicle electrification dominate, so there will be avoided pollution damages. This aligns with the basic intuition in our conceptual framework and empirical results. At low carbon prices, coal generation generally remains inframarginal (and is not being retired), so the additional electric vehicles are powered to a greater degree by natural gas and renewables. At much higher carbon prices, coal plants are pushed to being supramarginal and are retired earlier, leading the additional electric vehicle demand to again be powered to a greater degree by natural gas and renewables.

In the last row of Table 2.3, we calculate what we call 'net complementarity.' This metric compares the avoided damages from the combined policy to the sum of the avoided damages from each policy separately. A positive value suggests a complementarity between the two policies in that the sum is greater than the parts. A negative value suggests the opposite. In the last row, we see that the value is negative for all carbon prices that we simulated. This may be surprising because a common intuition is that electric vehicles will reduce emissions more with a decarbonized electricity system and carbon pricing would facilitate

[37] See `https://public.tepper.cmu.edu/nmuller/APModel.aspx`.

[38] A graphical breakdown of these damages by scenario and pollutant can be found in figure B.4.6.

such a decarbonized electricity system. Our quantitative results indicate that another force dominates: added electric vehicles are powered from generation on the margin and carbon pricing increases the emission intensity of the marginal generation. This effect will eventually dissipate at much higher carbon prices.

Emissions by region

One finding that emerged strongly from our empirical analysis is that there are substantial regional differences. For example, regions that have minimal coal generation are not going to observe an effect in dispatch or retirements of coal plants. Our quantitative simulation results thus far suggest that the regions that do have sufficient coal generation can drive the results for the entire country. We now turn to exploring heterogeneity across regions. Yale-NEMS endogenously chooses where in the United States the electric vehicles are purchased, following existing patterns.[39]

In Figure 2.8 we illustrate how the avoided pollution from adding electric vehicles can be quite different across regions.[40] There are two bars for each of the nine Census regions. The first bar calculates the difference in the discounted avoided pollution damages between the reference case and the high electric vehicle scenario. The second bar calculates the difference in the discounted avoided pollution damages between our central carbon price scenario and the combined high electric vehicle plus carbon pricing scenario. We again use a 3% discount rate for both and include avoided pollution benefits out to 2050.

Figure 2.8 shows that all of the regions benefit from avoided pollution damages due to adding electric vehicles in the reference case. But when there is a moderate carbon price in place, five of the nine regions show increases in pollution damages. Notably, these are all regions with a higher market share of coal generation (see Appendix Figure B.4.1 for a map of the Census regions). Indeed, regions that have minimal coal generation, such as New England and the Pacific region, show avoided pollution damages.

These results align reasonably closely with those that would be expected from the empirical analysis, although they should not be expected to align perfectly because avoided pollution damages are a function of many factors. Appendix Figure B.4.8 shows the addi-

[39] In the reference case, the Pacific region (Alaska, California, Hawaii, Oregon, and Washington) accounts for 28% of all electric vehicles sold, followed by the South Atlantic region (Delaware, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, and West Virginia), which is responsible for 18% of new electric vehicle sales (see Appendix Table B.4.1 for electric vehicle sales by region in 2030 and 2040). Under the increased electric vehicle demand scenario, the regions that gain the most new electric vehicles are the South Atlantic, followed by the Pacific, the West South Central region (Arkansas, Louisiana, Oklahoma, and Texas) and the East North Central region (Illinois, Indiana, Michigan, Ohio, and Wisconsin).

[40] Appendix Figure B.4.7 shows maps of the avoided damages per year by region for each of the scenarios to further illustrate the heterogeneity.

tional generation from coal, natural gas, and renewables used to charge the electric vehicles in the high electric vehicles scenario by region. In all of the regions, coal generation increases more when there is the carbon price in place than when there is not. However, in some regions, the increase in coal generation is small and is offset by larger increases in natural gas or renewables generation, contributing to the overall avoided pollution damages.[41]

2.4.5 Sensitivity Analysis

In Table 2.3 above, we included several carbon price paths, illuminating that our quantitative modeling results accord with our conceptual framework in showing that for a range of moderate carbon prices, electric vehicle policies may reduce emissions less than in the absence of carbon pricing–and may not even reduce emissions at all. With much higher carbon prices or much lower carbon prices, this is not a concern. However, the moderate carbon price path is in the range that may be politically feasible. Here we explore other assumptions that may influence when the negative interaction between carbon pricing and electric vehicle policy is likely to be present.[42] For each we present a representative scenario to help clarify when we would and would not expect our results to hold.

Earlier electric vehicle adoption

A major uncertainty is just how quickly electric vehicles will be adopted. Thus, we adjust the BNEF electric vehicle adoption projection to allow for even faster adoption of electric vehicles. We accomplish this by adjusting the consumer preferences for electric vehicles in the logit model, and leave battery prices consistent with the other scenarios. We show electric vehicle adoption over time in this early adoption scenario in Appendix Figure B.4.3.

Our key finding is that if electric vehicle adoption occurs earlier, then there are more coal plants online, and thus more that can be moved to the margin and retired later. This

[41]In the previous section, the carbon intensity of marginal generation in ERCOT increased with carbon pricing, but here, the West South Central region (which includes ERCOT, along with parts of SERC and SPP) is one of the regions where the carbon tax actually increases avoided pollution benefits from electric vehicles. This difference is due to price effects in the non-ERCOT subregions that are present in the West South Central region. Specifically, in the SERC Reliability Corporation/Delta, electric vehicle charging in the presence of a carbon tax raises prices by 20% more than it does in the absence of the carbon tax (the fourth highest increase of the 22 NERC subregions). This price increase reduces electricity demand and, therefore, generation in the SERC Reliability Corporation/Delta subregion, and in West South Central overall. Thus, in Figure B.4.8, the sum of the bars under 'price' is lower than the sum of the bars under 'reference' (this is particularly apparent in the 'price - reference' bars, where the magnitude of the decrease in natural gas generation is clearly larger than the magnitude of the increase in both coal and renewables).

[42]We also explore a robustness run where the reference case is matched to be somewhat close to AEO2020, and find that the interaction between electric vehicle policy and carbon pricing remains (e.g., see Appendix Figure B.4.9 showing coal generation).

can be seen in Column (2) of Table 2.4. Accordingly, our interaction between electric vehicle policies and carbon pricing is exacerbated. If electric vehicle adoption occurs later, there will be less expensive renewables and more coal plants will have been retired anyway. So the interaction effect tends to be dampened.

Low-cost renewables

One possible circumstance that could affect whether moderate carbon prices negatively affect the emission reductions from electric vehicle policies is a case where the cost of renewables drops very rapidly. Because renewables are must-take generation, massive builds of renewables could push coal generation up the supply curve to be supramarginal and eventually uneconomic. Renewables are also intermittent, so dispatchable natural gas generation is more likely to benefit than coal generation, which is more expensive to ramp up and down. Yale-NEMS accounts for these issues.

We model a low-cost renewables scenario based on AEO 2020's high renewables case. These changes lead to an increase in capacity of more than 300 additional gigawatts by 2050, relative to the reference case in the same year. By 2050, then, renewables make up approximately 39% of total electricity sector generation, compared to 23% in the reference.

Results for this scenario are in column (3) of Table 2.4; we find that electric vehicles now reduce emissions in the presence of a carbon tax, but we still do not observe net complementarity. Even with much lower renewables costs, it is less expensive to keep coal plants online and run existing coal plants slightly more than to build new facilities. Appendix Figure B.4.10 reveals that this outcome is a function of both mechanisms: coal retirements are avoided and coal capacity factors increase in the latter half of the simulated time frame.

With much more optimistic renewables costs–well beyond the historical improvements we have seen–coal plants will eventually be pushed up the aggregate supply curve and electric vehicles will be charged with renewables and natural gas.

2.5 Conclusion

Using both an empirical analysis of historical data from recent years and a detailed dynamic model, we demonstrate an important interaction between electric vehicle policy and carbon pricing policy that plays out over a range of moderate carbon prices that very likely fall within the range of politically feasible prices. The key intuition for our results is that carbon pricing will push coal generation up the aggregate supply curve to the margin and eventually to retirement. Thus, within a range of carbon prices, additional electric vehicles are more likely to be powered by coal, and the additional demand for electricity can slow coal retirements.

These results do not indicate that carbon pricing is ineffective at reducing emissions. In fact, we show that carbon pricing can be quite effective at all levels, and the perverse interaction can be reversed with sufficiently high carbon prices that push coal generation to be uneconomic. Further, our results do not controvert electric vehicles as a pathway to decarbonizing transportation in the long run. But the United States still relies on coal for nearly a quarter of its electricity, and in some regions the coal share is much higher. Thus, this work should be viewed as a cautionary tale about how two policies in different sectors can interact to reduce the effectiveness of the policies combined–even if they are both price policies.

Electric vehicle policy is particularly germane in policy discussions today. Our results highlight that higher carbon prices (or no carbon price) would allow electric vehicle policy to be much more effective at reducing emissions than the carbon prices observed in the recent past in the United States. Holding the cost of electric vehicle policy constant, this also implies that the welfare benefits of such policy will be greater under no carbon price or higher carbon prices. And from an overall social welfare perspective, higher carbon prices closer to the social cost of carbon would provide larger welfare benefits than no carbon price at all. Stepping back, our findings reinforce the simple point that the benefits of electric vehicle policies will be much greater if they are sequenced *after* coal plants are retired, allowing for a complementarity.

Our results show that emissions could even increase by adding electric vehicle policy to a moderate carbon policy. Under an economy-wide cap-and-trade system, total emissions are capped, so they would not increase. However, the coal-fired electricity dispatch and retirement effects we show in this paper with moderate carbon prices could still occur, only they would raise the allowance price, implying that the cost of meeting the cap would be higher. This could possibly lead to less tightening of the cap in the future. In a cap-and-trade system that covers the electricity sector but not the transportation sector, like the Chinese national carbon trading scheme, a shift to electric vehicles would unambiguously decrease total emissions.

There is ample room for further work on this topic. With new technologies and regulations, electric vehicle owners can be encouraged to charge at the most economically efficient times of day, which could change the charging patterns and thus marginal emissions from electric vehicle policies. Further, vehicle-to-grid technology could mean that electric vehicles could be used to dispatch to the grid during peak times, increasing their monetary and emissions benefits. Exploring these in future research could provide additional insight to policymakers on the design of electric vehicle policy in concert with carbon pricing.

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Tables

Table 2.1: Summary Statistics for Empirical Analysis

Variable	Units	MISO	SPP	ERCOT	PJM
Panel A. Hourly electricity generation and load					
Load	MWh	77,421	29,056	41,008	90,327
		(12,047)	(5,558)	(9,509)	(16,629)
Coal generation	MWh	35,129	13,853	11,553	27,296
		(8,740)	(3,853)	(3,654)	(8,359)
Gas generation	MWh	17,557	6,503	18,047	27,161
		(6,714)	(3,202)	(7,876)	(9,635)
Solar generation	MWh	N.R.	38	218	162
			(60)	(199)	(259)
Wind generation	MWh	4,748	5,773	6,443	2,358
		(2,691)	(3,643)	(3,996)	(1,645)
Panel B. Heat rate and emission rate					
Heat rate coal	MMBtu/MWh	10.60	10.46	10.71	10.16
		(0.09)	(0.18)	(0.20)	(0.20)
Heat rate natural gas	MMBtu/MWh	8.33	8.83	7.73	7.73
		(0.58)	(1.19)	(0.25)	(0.56)
Emissions rate coal	tCO_2/MWh	1.01	1.00	1.02	0.97
		(0.01)	(0.02)	(0.02)	(0.02)
Emissions rate natural gas	tCO_2/MWh	0.44	0.47	0.41	0.41
		(0.03)	(0.06)	(0.01)	(0.03)
Average emissions rate	tCO_2/MWh	0.55	0.57	0.46	0.41
		(0.07)	(0.11)	(0.08)	(0.05)
Panel C. Coal and natural gas prices					
Coal price	$/MMBtu	2.19	1.67	1.94	2.42
		(0.14)	(0.06)	(0.18)	(0.14)
	$/MWh	23.46	17.57	20.44	24.76
		(1.91)	(0.63)	(1.77)	(1.35)
Natural gas price	$/MMBtu	3.34	3.22	3.27	3.74
		(0.94)	(1.01)	(0.92)	(2.12)
	$/MWh	28.09	28.49	24.85	28.84
		(9.10)	(9.21)	(6.40)	(13.92)
Coal-gas ratio MWh	/	0.90	0.67	0.87	0.96
		(0.23)	(0.20)	(0.19)	(0.25)

Notes: The electricity generation and load data include 52,584 hourly observations from January 2014 to December 31, 2019. The coal and natural gas transactions data include 69,291 plant-month transactions for 273 plants from January 2014 to December 31, 2019. The heat rate of coal and gas is calculated as the monthly generation-weighted average ratio of energy use and electricity generation. The emissions rate of coal and natural gas is calculated by multiplying the heat rate by the carbon content of coal (210 lbs/MMBtu) and natural gas (117 lbs/MMBtu). The average emission rate is defined as the ratio of total CO_2 emissions to load. The region-level coal and gas price is the monthly generation-weighted average product of plant-level heat rate (MMBtu/MWh) and fuel expenditure data ($/MMBtu). tCO_2 refers to metric tons of carbon dioxide. "N.R." refers to data that is not reported.

Table 2.2: Key Electricity System Metrics of the Four Regions Showing How PJM is Different

ISO	(1) Capacity factor at carbon price: Low	(2) Med.	(3) High	(4) Net coal capacity retirement (GW)	(5) Net gas capacity addition (GW)	(6) Growth of average load (GWh)	(7) Growth of average renewable generation (GWh)
MISO	83%	77%	68%	7.89	-2.49	-0.93	1.37
SPP	68%	65%	54%	2.56	0.60	4.14	5.35
ERCOT	70%	67%	52%	4.87	5.02	4.99	5.10
PJM	58%	54%	58%	16.79	22.77	-1.17	1.05

Notes: The capacity factor is the average value in three equal subsamples with a low, medium, and high implicit carbon price. Net natural gas capacity additions and net coal capacity retirements are between January 2014 and December 2019. The growth of average hourly load and average renewable generation are calculated between the average for 2014 and for 2019 (except for PJM, where renewable generation data is only available as of 2016).

Table 2.3: Discounted Avoided Pollution Damages to 2050

	(1)	(2)	(3)	(4)
		Carbon price in 2040		
	\$5.30/ton	\$30/ton	\$48.70/ton	\$70/ton
Electric Vehicles	3.16	3.16	3.16	3.16
Carbon Price	3.68	30.84	48.86	61.82
Electric Vehicles + Carbon Price	6.76	29.60	50.02	63.01
Benefit Adding EVs to Carbon Price	3.08	-1.24	1.16	1.19
Net Complementarity	-0.08	-4.40	-2.00	-1.96

Notes: Units are billions of 2016 \$/year and all values are changes relative to the reference case. The discount rate is 3%. 'Electric Vehicles' refers to our high electric vehicle demand scenario. 'Benefit Adding EVs to Carbon Price' shows the added discounted avoided damages from adding high electric vehicle demand to an existing carbon pricing policy. 'Net Complementarity' is calculated as the avoided damages from the 'Electric Vehicles + Carbon Price' policy minus the sum of the avoided damages from each of the electric vehicle and carbon pricing policies.

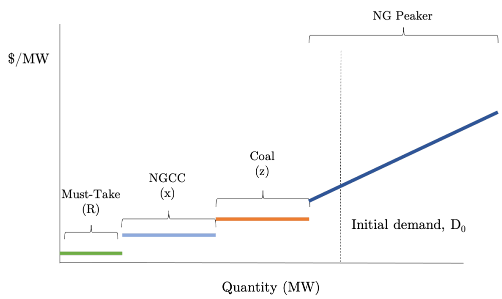
Table 2.4: Discounted Avoided Pollution Damages to 2050 for Sensitivity Cases

	(1)	(2)	(3)
		Sensitivity Case	
	Baseline	EV Timing	High Renewables
Electric Vehicles	3.16	3.14	2.68
Carbon Price	30.84	30.84	36.06
Electric Vehicles + Carbon Price	29.60	28.54	36.46
Benefit Adding EVs to Carbon Price	-1.24	-2.30	0.41
Net Complementarity	-4.40	-5.44	-2.27

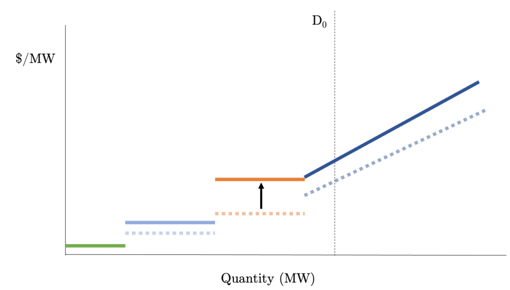
Notes: Units are billions of 2016 $/year and all values are changes relative to the reference case. The discount rate is 3%. 'Electric Vehicles' refers to our high electric vehicle demand scenario. 'Benefit Adding EVs to Carbon Price' shows the added discounted avoided damages from adding high electric vehicle demand to an existing carbon pricing policy. 'Net Complementarity' is calculated as the avoided damages from the 'Electric Vehicles + Carbon Price' policy minus the sum of the avoided damages from each of the electric vehicle and carbon pricing policies.

Figures

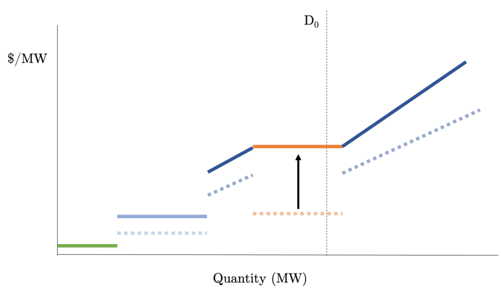
Figure 2.1: Stylized electricity framework.



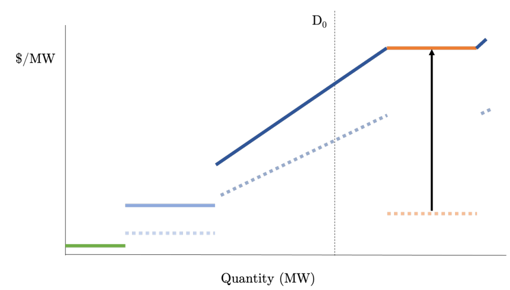
(a) Short-run aggregate supply of electricity.



(b) Reordering with low carbon price.



(c) Reordering with moderate carbon price.



(d) Reordering with high carbon price.

Notes: This stylized framework illustrates how electric vehicles may be powered by coal generation under a moderate carbon price, but not a higher or lower carbon price. Each bar represents one type of plant, in ascending order of marginal cost. In figures (b) - (d), the solid line represents the post-tax marginal cost and the dashed line represents the original marginal cost depicted in (a). The arrow shows how the post-tax marginal cost for coal rises substantially more than the post-tax marginal cost for natural gas.

Figure 2.2: Independent system operators in the United States.

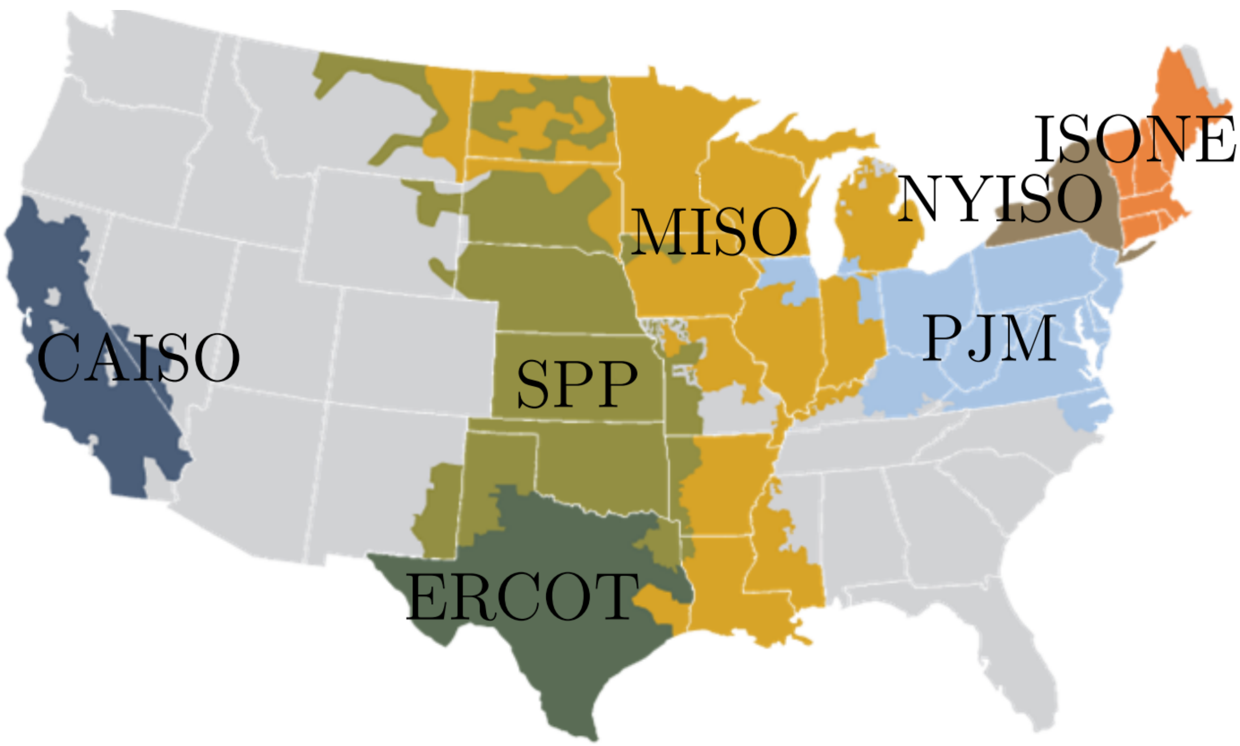
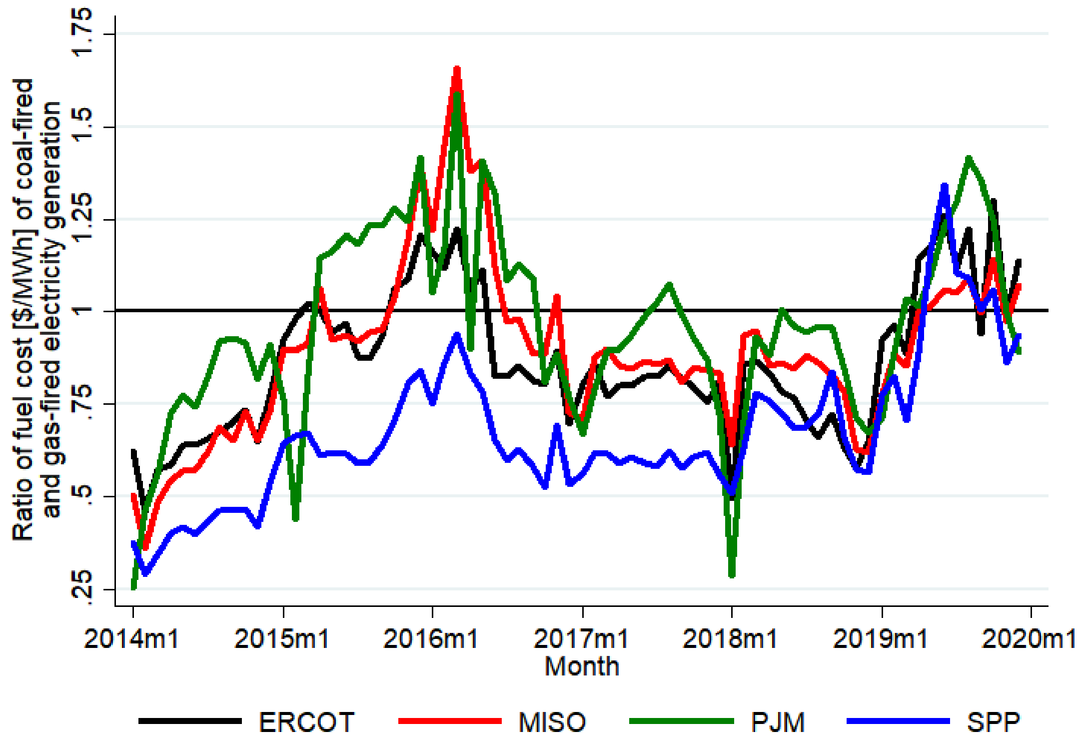


Figure 2.3: Historical coal-to-gas price ratio and implicit carbon price.

(a) Ratio of the variable fuel cost of coal-fired to gas-fired electricity generation by month.



(b) Implicit carbon price corresponding to the coal-to-gas ratio.

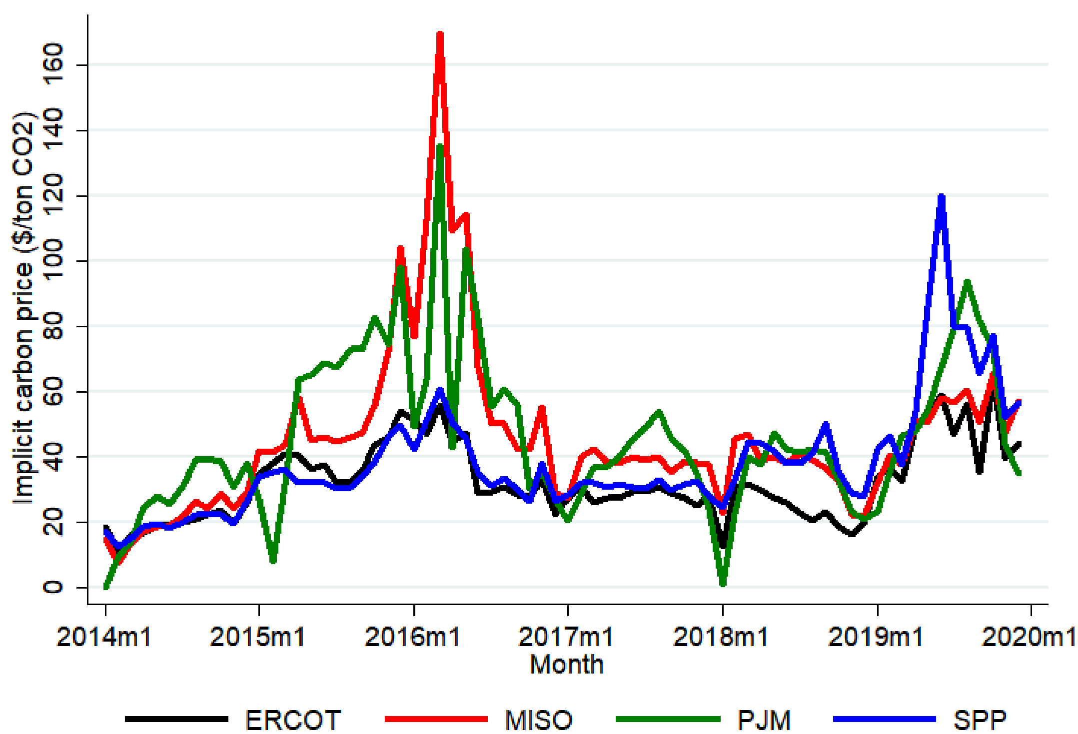
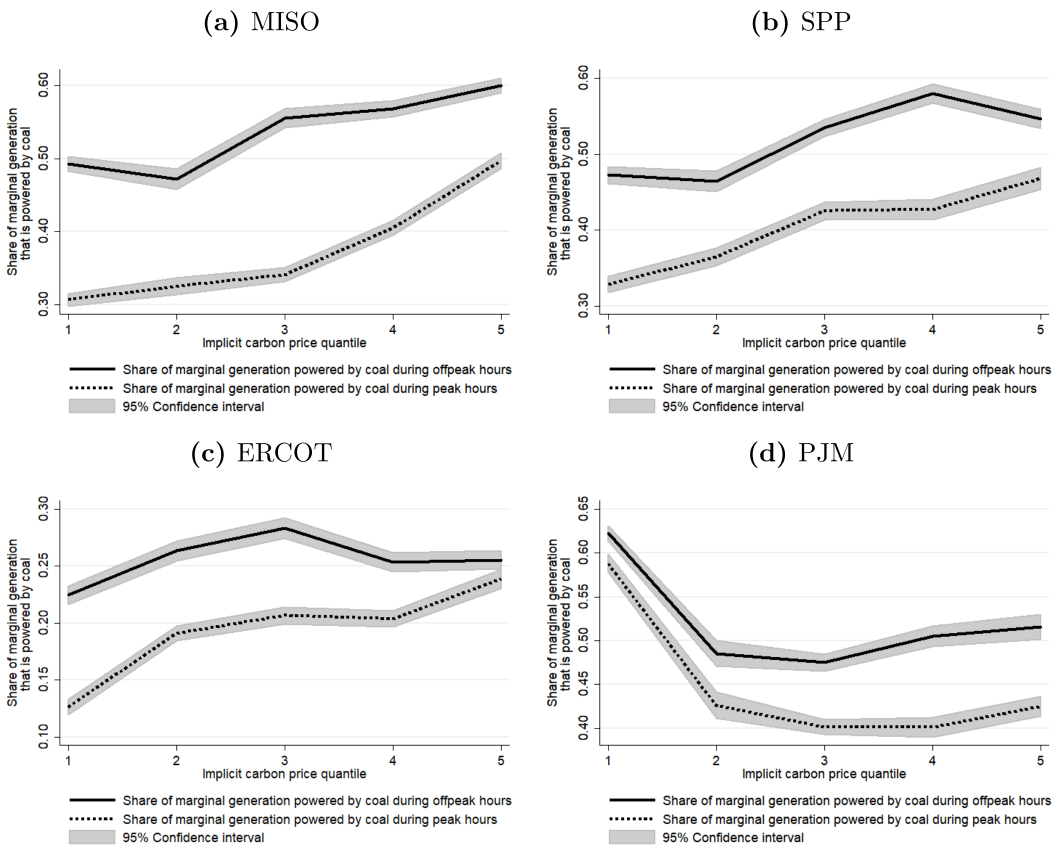


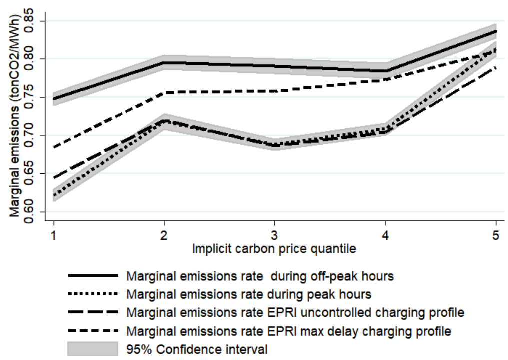
Figure 2.4: Marginal coal share by implicit carbon price.



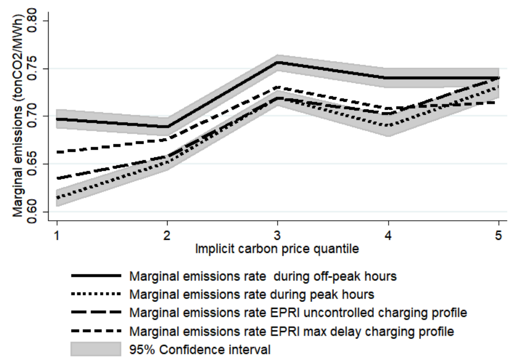
Notes: Share of marginal generation that is coal-fired for different levels of the implicit carbon price in ERCOT, MISO, PJM, and SPP. Error bars represent the 95% confidence interval.

Figure 2.5: Marginal CO_2 emissions rate by implicit carbon price.

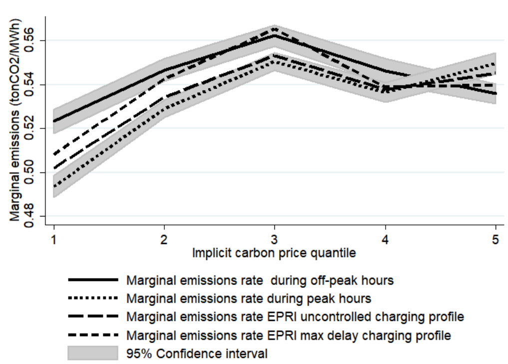
(a) MISO



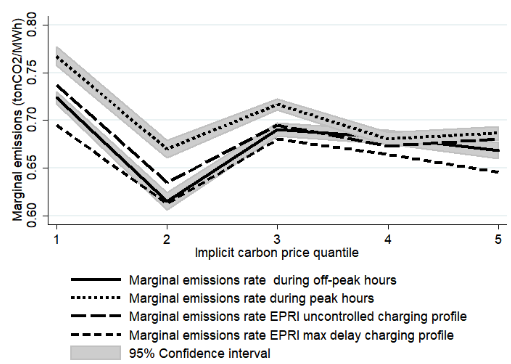
(b) SPP



(c) ERCOT



(d) PJM

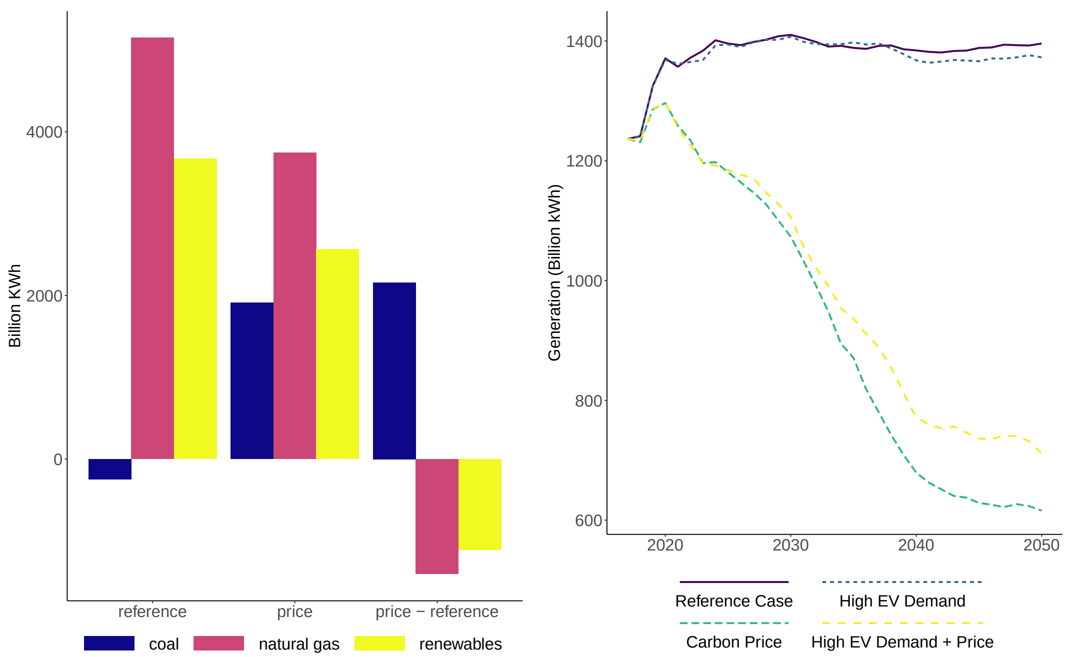


Notes: CO_2 emission rate for marginal generation for different quantiles of the implicit carbon price in ERCOT, MISO, PJM, and SPP. Error bars represent the 95% confidence interval.

Figure 2.6: EV-induced changes in electricity generation.

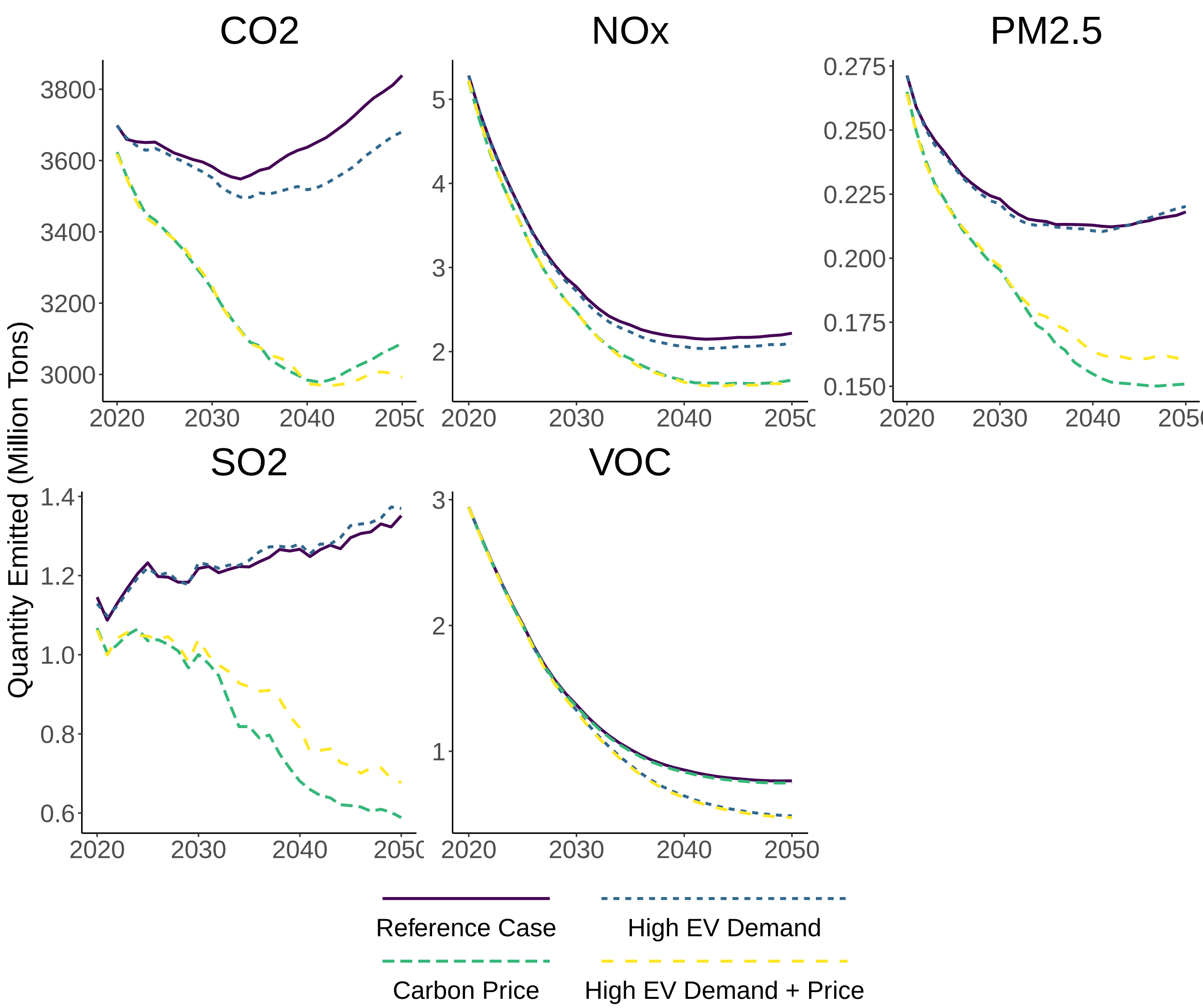
(a) Additional generation from EVs

(b) Coal-fired generation



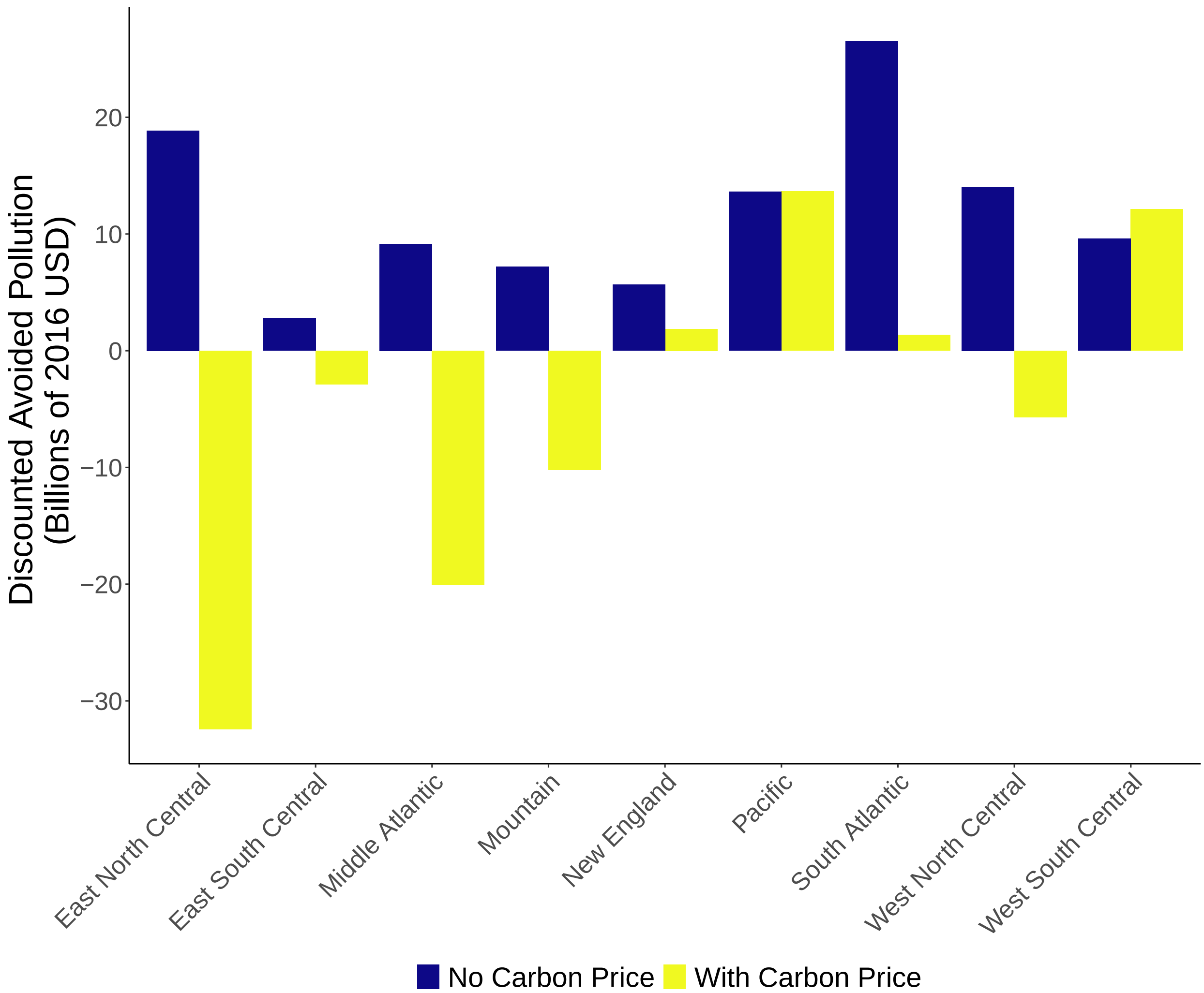
Notes: Panel (a) shows additional generation between 2020 and 2050 associated with the added electric vehicles between the reference and high electric vehicle case. 'Price' refers to our central case carbon price scenario. The rightmost set of three bars shows the difference between the effects with and without the carbon price. Panel (b) shows total coal-fired generation over time under different scenarios.

Figure 2.7: Aggregate emissions by scenario.



Notes: Aggregate emissions associated with passenger vehicles and the electricity generation sector.

Figure 2.8: Regional EV damages.



Notes: Change in discounted avoided pollution damages due to the addition of electric vehicles (billions of 2016 $).

Appendices

Appendix B

B.1 Analytical Model

This Appendix section lays out a simple analytical theory model to provide further insight into the concepts discussed in Section 2.2. The purpose of this section is to highlight the main factors that influence when a carbon price is likely to be at a level that pushes coal generation to the margin and reduces the emission reduction benefits of electric vehicles.

The analytical model is explicitly a short-run model, but as discussed in Section 2.2, the implications carry over to power plant retirements in the long run. We make the same assumptions as in Section 2.2: inelastic electricity demand, a typical or average time period, and heterogeneity in efficiencies or heat rates of different generation facilities or differential efficiency investments as a response to carbon pricing. Again, we focus only on the wholesale market for electricity (i.e., the 'energy' market).

Let initial demand be denoted as D_0. This refers to the typical or average load on the electricity grid in a particular region at a particular time. For simplicity, we assume a competitive market for electricity. Power plants produce electricity with different fuels and technologies. As in Section 2.2, we consider must-take generation (nuclear and renewables, R), baseload natural gas combined cycle ($NGCC$), coal (C), and natural gas peakers (NG). For illustrative purposes, we assume that each non-peaker technology faces a technology-specific constant marginal cost and peaking plants face an increasing marginal cost. With the exception of the must-take generation, each technology produces when price reaches or exceeds marginal cost. The supply of must-take generation is constant at the capacity of the technology, and is given by $S_R(P) = Cap_R$. We thus write the supply of electricity from power plants from each of the other fuels as follows:

$$S_{NGCC}(P) = \begin{cases} 0 & P < MC_{NGCC} \\ [0, Cap_{NGCC}] & P = MC_{NGCC} \\ Cap_{NGCC} & \text{otherwise} \end{cases}$$

$$S_C(P) = \begin{cases} 0 & P < MC_C \\ [0, Cap_C] & P = MC_C \\ Cap_C & \text{otherwise} \end{cases}$$

$$S_{NG}(P) = \begin{cases} 0 & P < MC_{NG}(0) \\ y(P) & \text{otherwise} \end{cases}$$

where MC_{NGCC} and MC_C are the marginal costs of generation for natural gas combined cycle and coal plants. $MC_{NG}(0)$ refers to the minimum marginal cost of generation for natural gas peaker plants. Cap_{NGCC} and Cap_C represent the capacity of natural gas combined cycle and coal plants, respectively. $S_{NG}(P)$ is the upward-sloping supply curve of natural gas peakers once the price is sufficiently high that they are dispatched. The aggregate short-run supply curve is thus:

$$S(P) = Cap_R + S_{NGCC}(P) + S_C(P) + S_{NG}(P)$$

Prices are determined by equating electricity demand with supply. That is, the equilibrium price P^* is implicitly defined by the equilibrium condition that supply equal demand, $D_0 = S(P^*)$.

B.1.1 Imposition of a Carbon Price

Now consider the introduction of a carbon price (e.g., a carbon tax or allowance price in a permit trading system). Let the carbon price (in terms of dollars per ton of CO_2) be given by τ. Let β_j denote the emissions intensity of technology j, where $\beta_{NGCC} < \beta_{NG} < \beta_C$. For simplicity, we assume that β_{NG} does not change along the supply curve, but we could easily allow for this without changing the insights from this framework. The carbon tax increases the marginal cost of production by $\tau \times \beta_j$. Under the simplifying assumption that each resource has a constant emissions intensity, $\widehat{S_J}(P, \tau)$ represents the supply function for resource j under a carbon tax of τ. Thus, for each fuel the post-tax supply function is given by:

$$\begin{aligned}\widehat{S_{NGCC}}(P,\tau) &= S_{NGCC}(P-\tau\beta_{NGCC})\\ \widehat{S_C}(P,\tau) &= S_C(P-\tau\beta_C)\\ \widehat{S_{NG}}(P,\tau) &= S_{NG}(P-\tau\beta_{NG}).\end{aligned}$$

Denote the equilibrium electricity price after a carbon price is added by P^{**}. P^{**} is implicitly defined by the following equality:

$$D_0 = Cap_R + S_{NGCC}(P^{**}-\tau\beta_{NGCC}) + S_C(P^{**}-\tau\beta_C) + S_{NG}(P^{**}-\tau\beta_{NG}).$$

Suppose that $P^* > MC_{NG}$, i.e., the natural gas peaker was initially the marginal generator. Then, there are three possible outcomes of the carbon price:

Case 1: The carbon price is low (recall Panel (b) in figure 2.1). In this case, there is minimal reordering of the generation stack and the marginal generator is still the natural gas peaker. This case occurs when $\tau \leq \frac{MC_{NG}(D_0-Cap_R-Cap_{NGCC}-Cap_C)-MC_C}{\beta_C-\beta_{NG}}$.[1]

Case 2: The carbon price is moderate (recall Panel (c) in figure 2.1). In this case, there is more substantial reordering of the generation stack and coal generation is pushed to the margin. This case occurs when $\tau \in \left(\frac{MC_{NG}(D_0-Cap_R-Cap_{NGCC})-MC_C}{\beta_C-\beta_{NG}}, \frac{MC_{NG}(D_0-Cap_R-Cap_{NGCC}-Cap_C)-MC_C}{\beta_C-\beta_{NG}}\right)$.[2]

Case 3: The carbon price is high (recall panel (d) in figure 2.1). In this case, there is even more substantial reordering of the generation stack and coal generation is pushed to being supramarginal and uneconomic. This case occurs when $\tau \geq \frac{MC_{NG}(D_0-Cap_R-Cap_{NGCC})-MC_C}{\beta_C-\beta_{NG}}$.

Note that at both moderate and high carbon prices, the total amount of coal generation will be reduced. But, under a moderate carbon price, the *marginal* generation can be coal-fired.

B.1.2 Adding Electric Vehicle Charging Demand

Given the differences in emission factors between coal and natural gas, the intuition should already be clear about what would happen if we add load from electric vehicles charging.

[1] For no reordering at all to occur, $MC_{NG}(0) + \tau\beta_{NG}(0) \geq MC_C + \tau\beta_C$. This is a subset of case 1. There is an additional case where a small amount of reordering occurs, but the marginal generator is still the natural gas peaker. This occurs when $\tau \in \left(\frac{MC_{NG}(0)-MC_C}{\beta_C-\beta_{NG}}, \frac{MC_{NG}(D_0-Cap_R-Cap_{NGCC}-Cap_C)-MC_C}{\beta_C-\beta_{NG}}\right)$. In terms of the emissions implications, this is identical to the case where no reordering occurs.

[2] In this case, $MC_{NG}(D_0 - Cap_R - Cap_{NGCC} - Cap_C) + \tau\beta_{NG} \leq MC_C + \tau\beta_C$ (the marginal cost of natural gas peakers that dispatch is less than or equal to the marginal cost of coal) as well as $MC_{NG}(D_0 - Cap_R - Cap_{NGCC}) + \tau\beta_{NG} > MC_C + \tau\beta_C$ (it is not cheaper to meet all remaining demand net of renewables and combined cycle electricity with natural gas).

To be precise, we follow through by considering increased demand for electricity. Consider $D_1 = D_0 + D_{EV}$ where $D_{EV} > 0$.

The additional electricity sector emissions from the electric vehicles charging is different depending on the level of the carbon price, in the following way:

Case 1 (Low Carbon Price): $\Delta Emissions = D_{EV} \times \beta_{NG}$

Case 2 (Moderate Carbon Price): There are two possibilities depending on how much load is added by the electric vehicles. Let $\phi = Cap_C - (D_0 - Cap_R - Cap_{NGCC} - NG(P^{**} - \tau\beta_{NG}))$.

Case 2a (New Load Covered By Coal Generation, $D_{EV} \leq \phi$**) :**

$\Delta Emissions = D_{EV} \times \beta_C$

Case 2b (New Load Partly Covered By Coal Generation, $D_{EV} > \phi$**) :**

$\Delta Emissions = \phi \times \beta_C + (D_{EV} - \phi) \times \beta_{NG}$

Case 3 (High Carbon Tax): $\Delta Emissions = D_{EV} \times \beta_{NG}$

The key take-away here is that the change in emissions from the additional load from electric vehicles depends on the level of the carbon price. For moderate carbon prices (where moderate is determined by the marginal costs and emission factors of coal and natural gas), we can find that coal-fired generation is partly or entirely used to power electric vehicles. For a marginal increase in electric vehicle load, case 2b does not apply and a moderate carbon price is covered by case 2a. This is the case even though the moderate carbon pricing can reduce overall emissions itself. It just reduces the emission reductions from policies to promote electric vehicles.

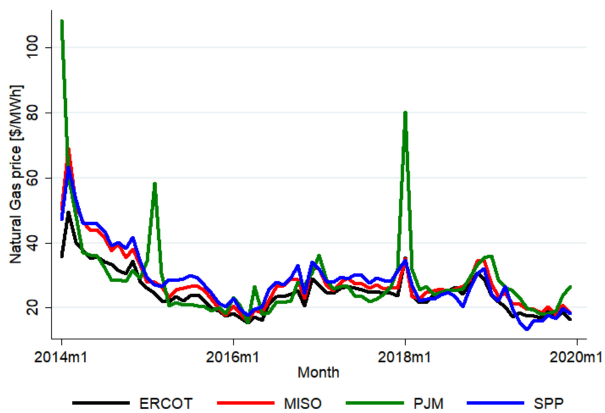
B.2 Commodity prices

This appendix provides additional information on the commodity prices used in the empirical analysis in our study.

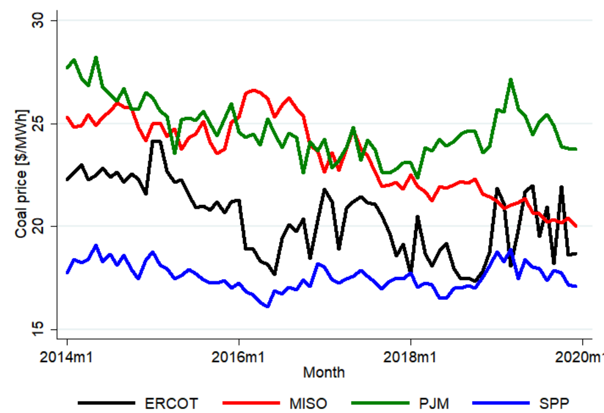
Figure B.2.1 presents the price of natural gas and coal in ERCOT, MISO, PJM, and SPP for every month of our sample, expressed as \$/MMBtu and \$/MWh. The latter is calculated as the plant-specific product of fuel price (in \$/MMBtu) and heat rate (in MMBtu/MWh) in a given month. During 2014-2019, the EIA Form 923 data for ERCOT, MISO, PJM and SPP consists of 71,551 coal and natural gas transactions (plant, month, contract type, fuel type, fuel cost, etc.) with known positive fuel cost, for 276 plants. To calculate the variable fuel cost per MWh, the monthly fuel transactions are matched to monthly heat rates, which are calculated as the ratio of total fuel input for electricity generation and total net electricity generation per month. We can match 69,291 of these transactions for 273 plants[3], of which 26,247 are coal transactions and 43,044 are natural gas transactions. Of these, 58,599 transactions are spot or short-term contracts up to 12 months, of which 17,095 are coal transactions and 41,504 are natural gas transactions.

Figure B.2.1: Historical fossil fuel prices.

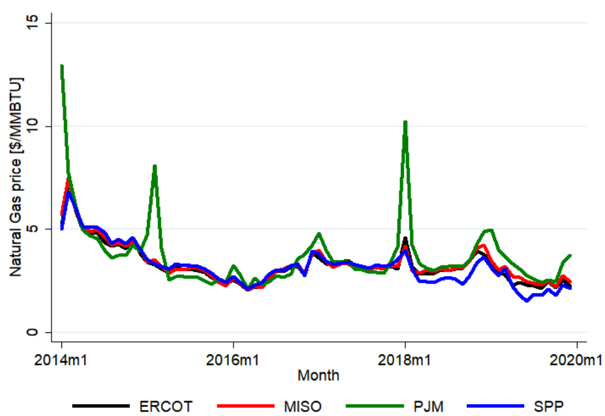
(a) Natural gas price [$/MWh]



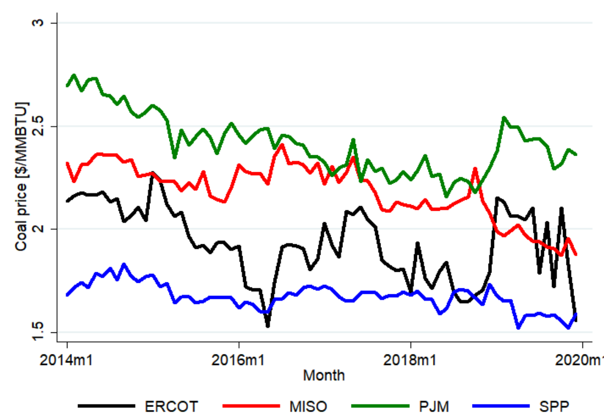
(b) Coal price [$/MWh]



(c) Natural gas price [$/MMBTU]



(d) Coal price [$/MMBTU]



Notes: Price of natural gas and coal in ERCOT, MISO, PJM, and SPP during 2014-2019, using spot prices and long-term contracts up to 12 months, in $/MWh and $/MMBTU.

Figure B.2.2 presents the ratio of variable fuel cost (in $/MWh) of coal-fired and gas-fired electricity generation in ERCOT, MISO, PJM, and SPP for every month in our sample, for different subsamples of the EIA Form 923 transaction data. Panel (a) is the standard case from Figure 2.3 that includes spot prices and contracts up to 12 months. Only focusing on spot prices (panel (b)) does not significantly change the ratio. Similarly, panel (c) shows

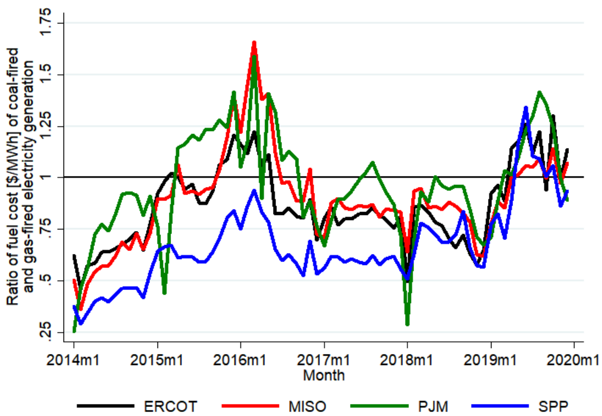
[3]Three plants generate no electricity in our sample: CCT Terminal in IL, BRSC shared storage in MI, and Silver Lake in MN.

that the ratios are not driven by outliers in the heat rate (above 50 MMBtu/MWh) or fuel price (above 200 \$/MMBtu). For example, the peaks in gas prices around February 2015 and January 2018 are robust and arise because of cold spells and congestion in the gas network. Panel (d) shows the coal-to-gas ratio of the fuel cost in \$/MMBtu, ignoring heat rate improvements that are affecting the ratio of the variable generation costs in \$/MWh. As a result, the level of the coal-gas ratio decreases, but not the general trend, because heat rate improvements happened continuously over the duration of our sample and mostly for gas-fired power plants.

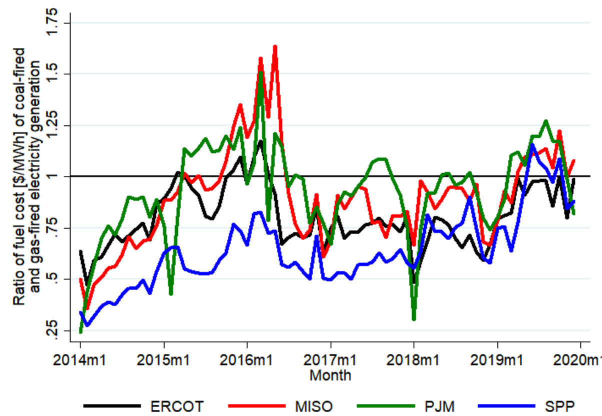
All four panels in B.2.2 are extremely similar and any of these time series could be used for our empirical analysis to give comparable results.

Figure B.2.2: Alternative coal-to-gas price ratios.

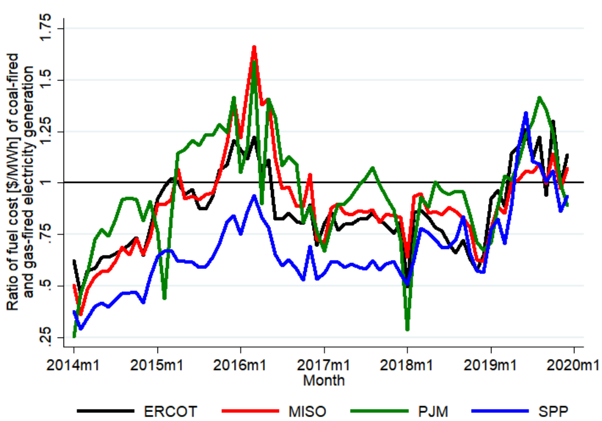
(a) Spot prices and contracts up to 12 months



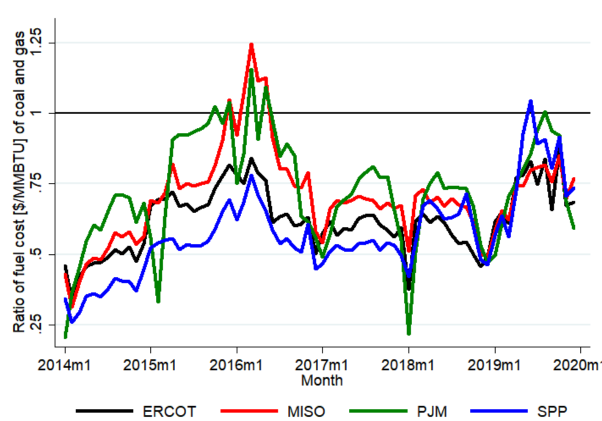
(b) Spot prices only



(c) Spot prices and contracts up to 12 months, with outliers removed



(d) Spot prices and contracts up to 12 months, ignoring heat rate improvements



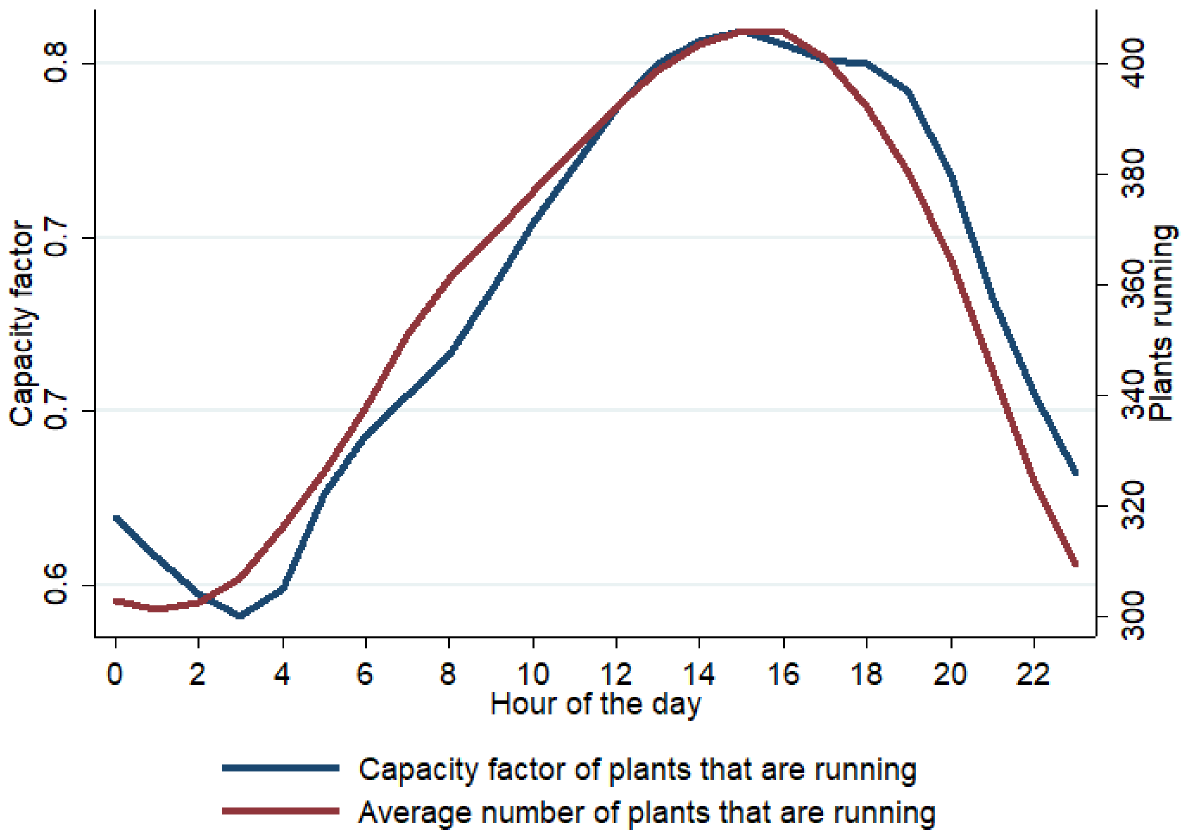
Notes: Ratio of variable fuel costs of gas-fired and coal-fired electricity generation in ERCOT, MISO, PJM, and SPP during 2014-2019, for different subsamples of the EIA Form 923 transaction data. Outliers are defined as having a heat rate above 50 MMBtu/MWh or a fuel price above 200 $/MMBtu. Panel (d) plots the ratio of the fuel cost in $/MMBtu, ignoring the heat rate.

B.3 Additional estimation results

This appendix provides additional estimation results for our empirical analysis to provide further insight into the dynamics at play.

We begin by providing additional evidence that coal can be a marginal technology. Using 2018 Texas data from EPA's Continuous Emissions Monitoring System (CEMS), Figure B.3.1 illustrates that coal plants follow load in two ways. First, coal is ramping up and down during the course of a day, by changing the capacity factor of individual plants that are running, from a minimum below 60% at 3 am to a maximum above 80% at 4 pm. Second, coal plants are starting up and shutting down during the course of a day. Around midnight, approximately 300 plants are running, while more than 400 are running to meet the afternoon peak.

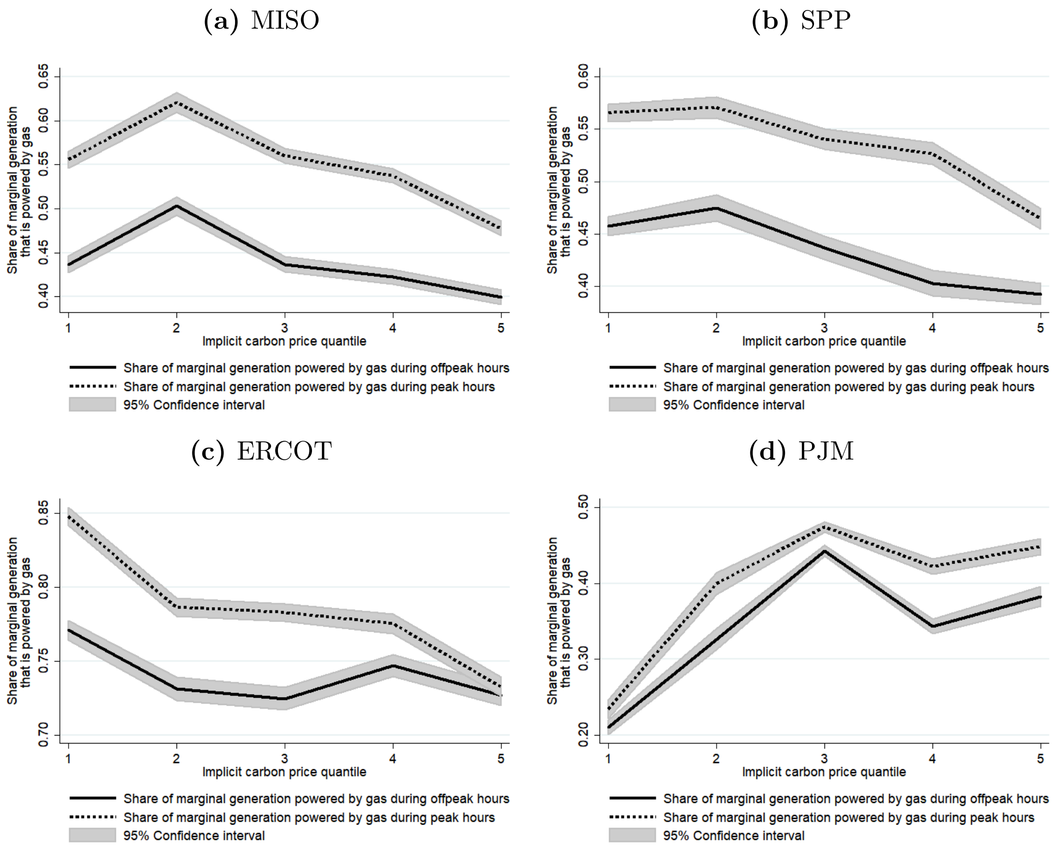
Figure B.3.1: Texas capacity factor and total plant count.



Notes: The average capacity factor and the average number of plants that are running in Texas in 2018.

Figure B.3.2 shows the share of marginal generation that is natural gas-fired over each quantile of the implicit carbon price. This figure is the complement to Figure 2.4, and indeed we find that the relationship flips, with lower natural gas shares at higher implicit carbon prices for MISO, SPP, and ERCOT. PJM shows increasing natural gas shares at higher implicit carbon prices.

Figure B.3.2: Marginal gas share by implicit carbon price.

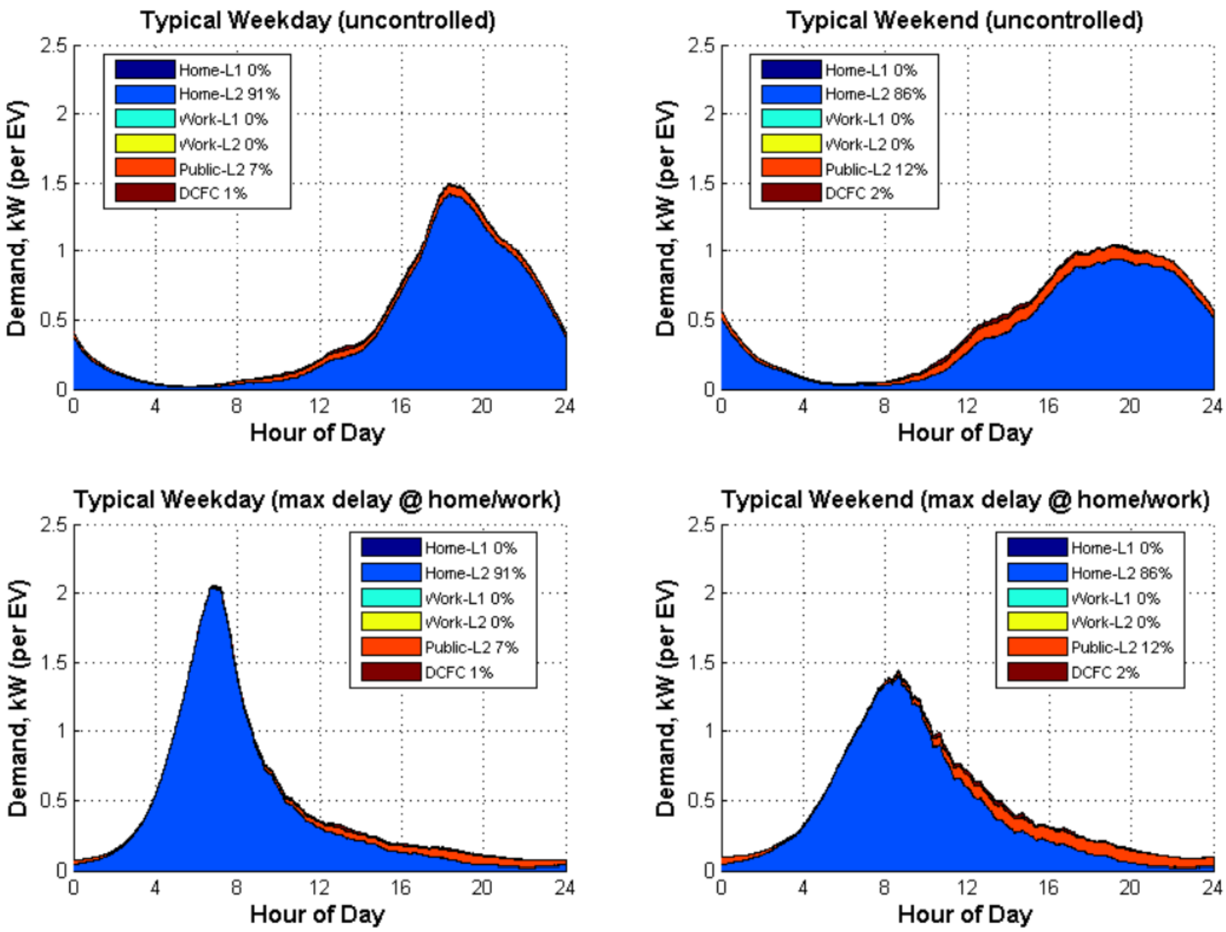


Notes: Share of marginal generation that is gas-fired generation for different levels of the implicit carbon price in ERCOT, MISO, PJM, and SPP. Error bars represent the 95% confidence interval.

We next show the details for the uncontrolled and maximum delay electric vehicle charging profiles from EPRI. As expected, the uncontrolled charging profiles are much higher in the evening hours and into the night, while the maximum delay charging profiles are much higher in the early morning just before individuals leave their home to go to work. These patterns are by design, but are based on some evidence about how consumers charge their electric vehicles that EPRI has collected.

To determine the marginal emissions from charging electric vehicles, we estimate for every ISO region how coal- and gas-fired electricity generation respond to changes in electricity consumption in peak and off-peak hours in our primary specification. Now we allow for a separate coefficient on load for each hour of the day because different charging profiles of electric vehicles would lead to more load at different hours of the day. This approach allows

Figure B.3.3: Electric vehicle charging profiles.



Notes: Uncontrolled and maximum delay electric vehicle charging profiles from EVI-Pro (US Drive n.d.).

for insight into any given pattern of electric vehicle charging that the reader is interested in. The dependent variable in our analysis, q_{ft} is generation technology f hourly generation output at time t.

Similar to Holland et al. (2016) and Graff Zivin et al. (2014), we estimate the following empirical specification:

$$q_{ft} = \sum_{h=1}^{24} \beta_h hour_h load_t + \gamma_S q_{\text{solar},t} + \gamma_W q_{\text{wind},t} + \delta_{hmy} + \epsilon_{ft}. \tag{B.1}$$

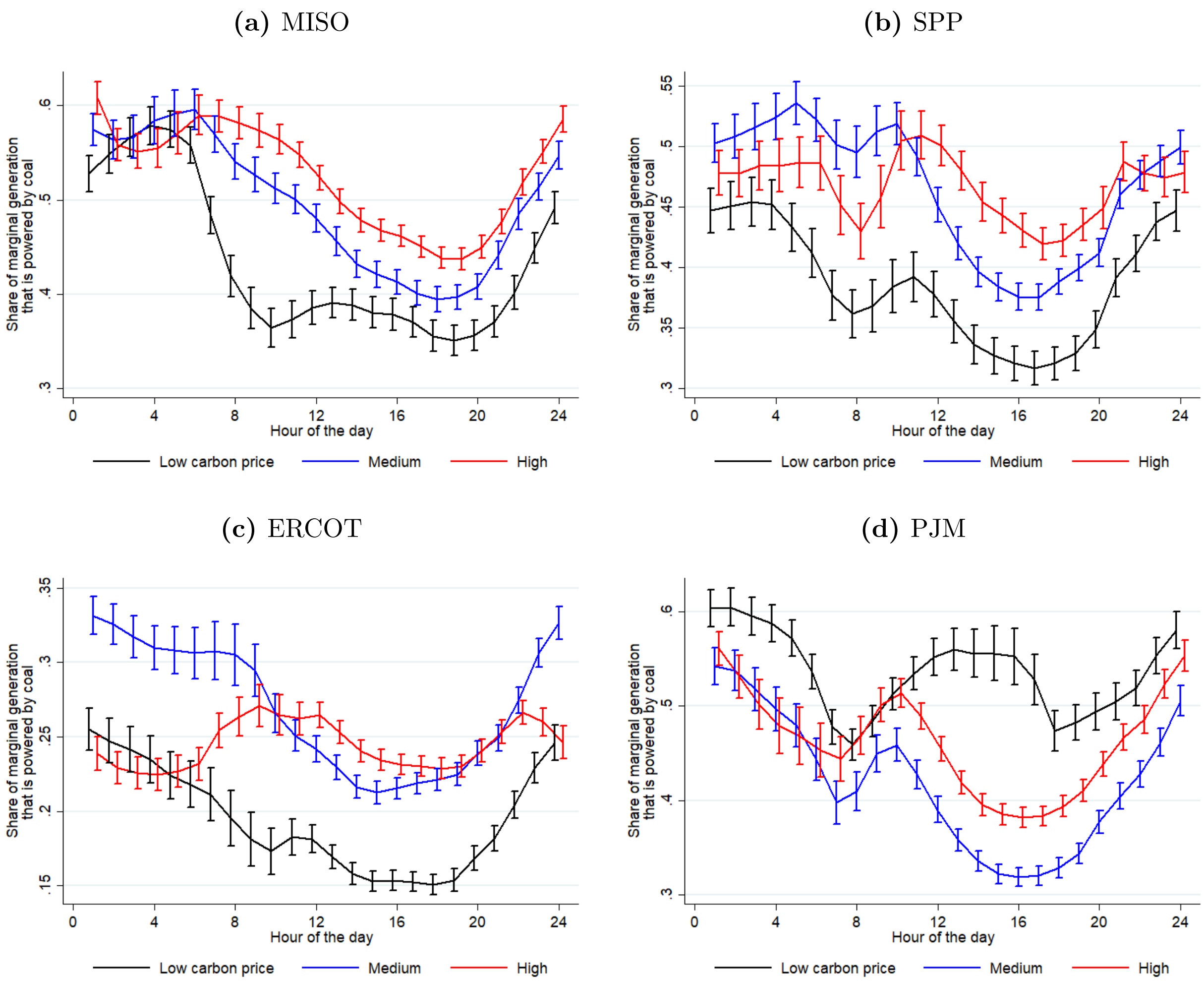
where $hour_h$ is an indicator variable for hour of the day h and $load_t$ is electricity demand at time t. Because intermittent renewable generation can affect the need for conventional generation, we control for hourly solar output $q_{\text{solar},t}$ and hourly wind output $q_{\text{wind},t}$ (Fell & Kaffine 2018). We also include fixed effects δ_{hmy} for each hour-of-the-day interacted with the month-of-the-sample to flexibly account for seasonality and daily patterns in load and fossil generation throughout our sample. ϵ_{ft} is the error term. The coefficients of interest are the marginal emissions factors β_h, which represent the change in coal- and gas-fired electricity generation in response to an increase in electricity consumption in hour of the day h.

To estimate how the marginal generation technologies depend on carbon prices, we run the above specification separately for different implicit carbon prices, just as in our primary specification. For simplicity, in this specification, we use a high, medium, and low implicit carbon price.

Figure B.3.4 presents the β_h coefficients for the regression where the dependent variable is coal generation. These coefficients represent the share of marginal electricity demand that is met using coal-fired power generation for every hour of the day in ERCOT, MISO, PJM, and SPP for three implicit carbon prices. We see that the share of marginal generation that is coal-fired varies throughout the day and is generally higher at night. We find that a carbon price pushes coal to the margin in ERCOT, MISO and SPP, especially during peak hours. This means that at higher carbon prices, a larger share of marginal electricity demand is met by coal-fired power generation. However, in ERCOT we also find that at a high carbon price, this share decreases significantly during nighttime hours. The opposite happens in PJM, where coal is pushed off the margin in almost all hours when the carbon price increases.

Figure B.3.5 presents the share of marginal electricity demand that is met using natural gas-fired power generation for every hour of the day in ERCOT, MISO, PJM, and SPP. In this case, we find the opposite result: in ERCOT and SPP a carbon price pushes gas off the margin and on the margin in PJM. This is the case because in all ISO regions, except PJM, coal and gas comprise almost 100% of marginal generation. In PJM, the share of marginal

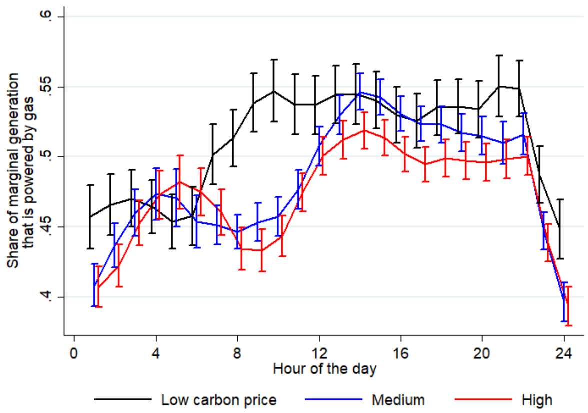
Figure B.3.4: Marginal coal share by hour-of-day.



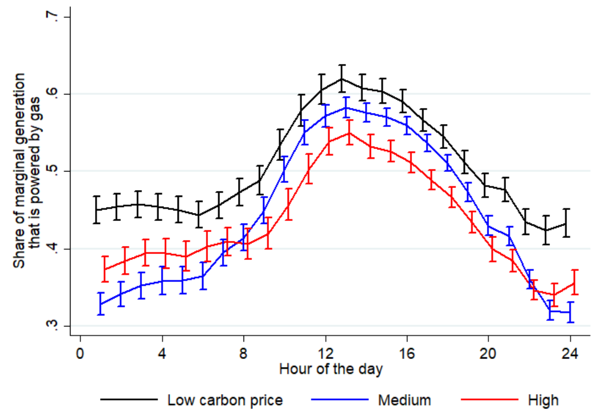
Notes: Share of marginal generation that is coal-fired generation for every hour of the day in ERCOT, MISO, PJM, and SPP. Error bars represent the 95% confidence interval.

Figure B.3.5: Marginal gas share by hour-of-day.

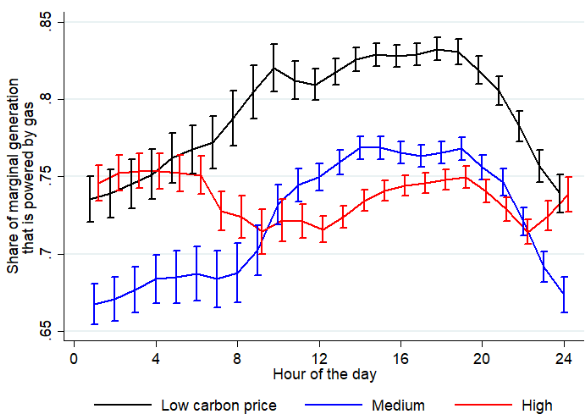
(a) MISO



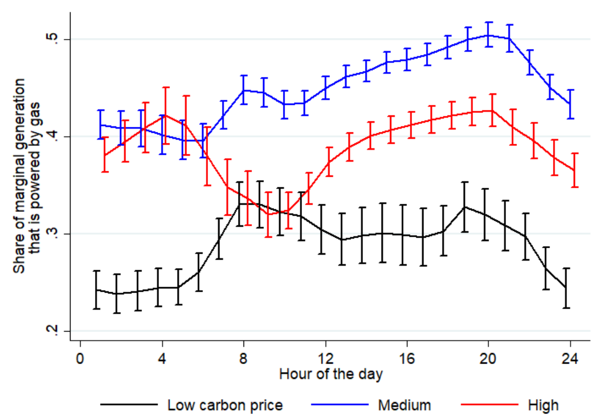
(b) SPP



(c) ERCOT



(d) PJM



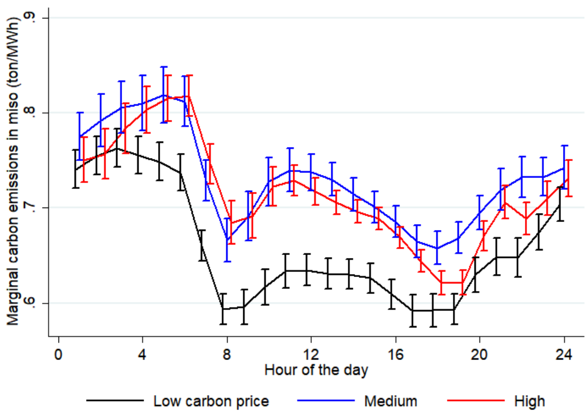
Notes: Share of marginal generation that is gas-fired generation for every hour of the day in ERCOT, MISO, PJM, and SPP. Error bars represent the 95% confidence interval.

demand met by imports, dual-fuel, and oil is, respectively, 5%, 3%, and 2%.

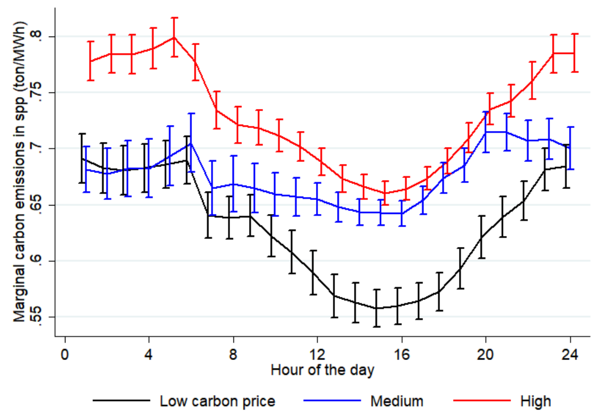
Finally, Figure B.3.6 presents the combined effect of coal- and gas-fired electricity generation on marginal carbon emissions for every hour of the day. Marginal carbon emissions are generally lower in the afternoon peak hours, because of a higher share of gas plants on the margin, but they are increasing with carbon prices, as coal is pushed to the margin. This effect is statistically significant in SPP, MISO, and ERCOT. In PJM, marginal carbon emissions are higher at low carbon prices, especially in the afternoon peak hours.

Figure B.3.6: Marginal carbon emissions by hour-of-day.

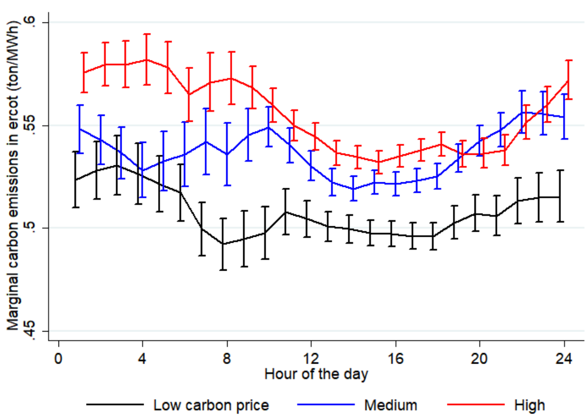
(a) MISO



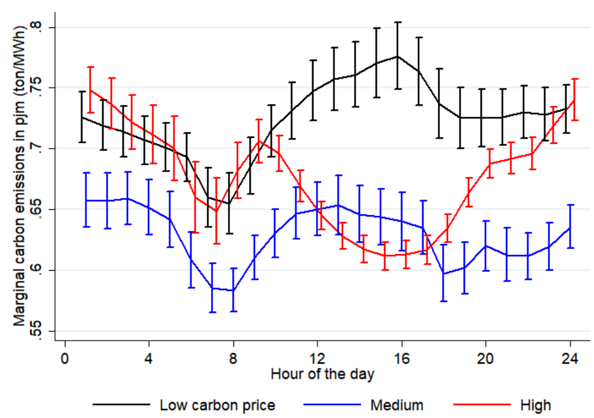
(b) SPP



(c) ERCOT



(d) PJM

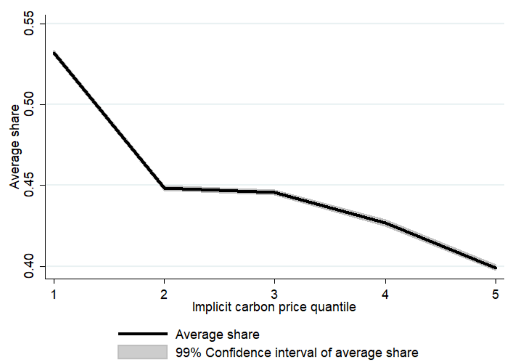


Notes: Marginal carbon emissions (ton/MWh) for every hour of the day in ERCOT, MISO, PJM, and SPP. Error bars represent the 95% confidence interval.

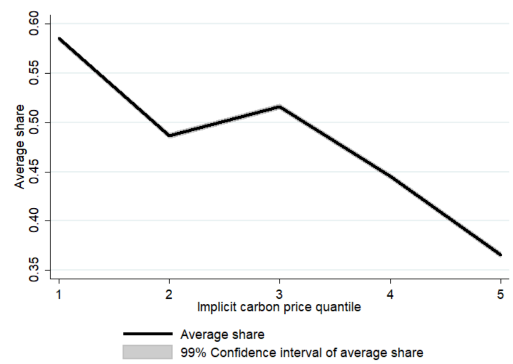
For reference and to provide further context, we also estimate the *average* share of coal generation at different levels of the carbon price in the four regions over the implicit carbon price quantiles (Figure B.3.7). We observe that in all four regions, the average share of coal generation is declining with higher implicit carbon prices.

Figure B.3.7: Average coal share by implicit carbon price.

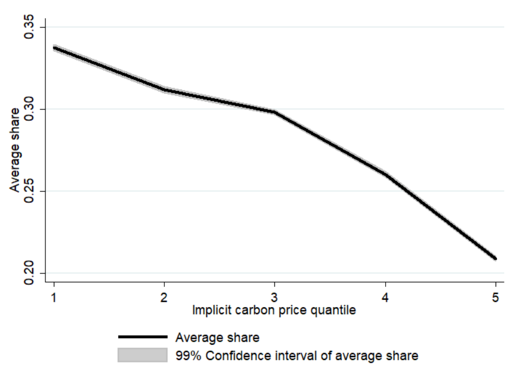
(a) MISO



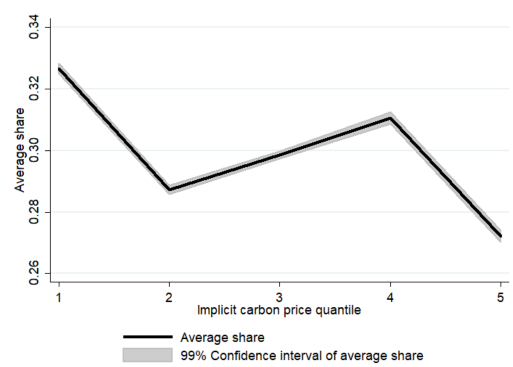
(b) SPP



(c) ERCOT



(d) PJM

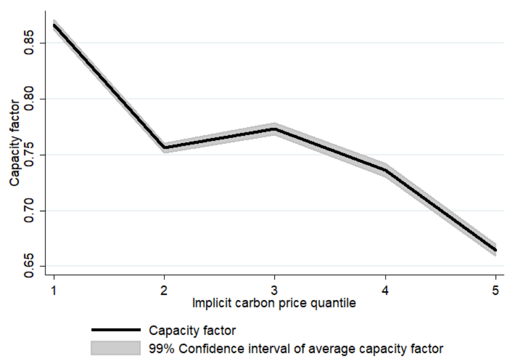


Notes: Average share of coal generation at different levels of the implicit carbon price in ERCOT, MISO, PJM, and SPP.

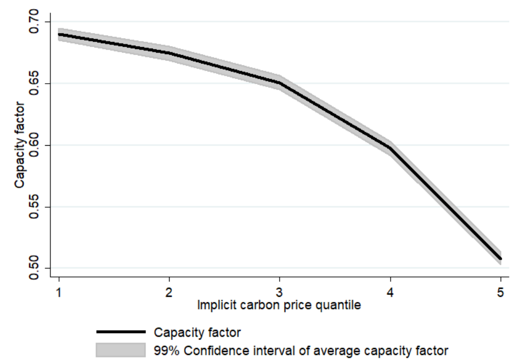
Next, we examine the capacity factors for coal generation for each of the four regions (Figure B.3.8). We observe that in general, the capacity factors decline with higher implicit carbon prices, although the pattern in PJM is not nearly as clear or steady as in the other three regions, as in PJM there is a quick decrease followed by an increase and then another decrease.

Figure B.3.8: Coal capacity factor by implicit carbon price.

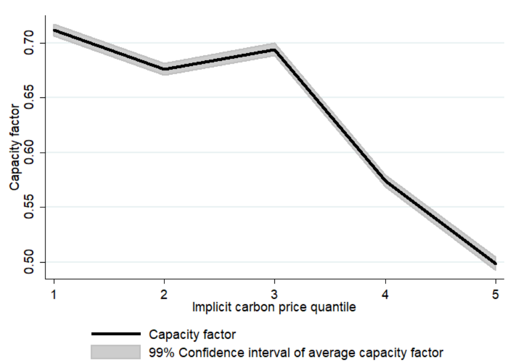
(a) MISO



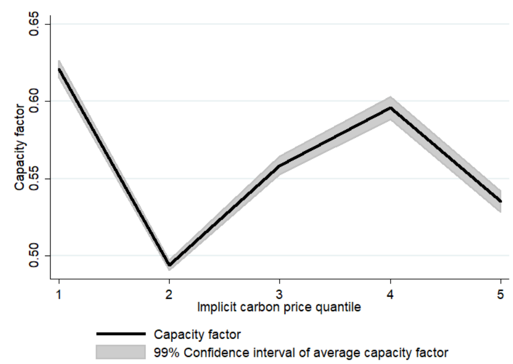
(b) SPP



(c) ERCOT



(d) PJM



Notes: Capacity factor of coal generation at different levels of the implicit carbon price in ERCOT, MISO, PJM, and SPP.

In Figures B.3.9 and B.3.10, we show the net new natural gas-fired capacity over time and the total installed coal capacity over time. These are shown for each of the four regions and highlight that PJM had much more new natural gas-fired capacity come online and many more coal plant retirements than the other three regions.

Figure B.3.9: Net new gas-fired capacity over time in ERCOT, MISO, PJM, and SPP.

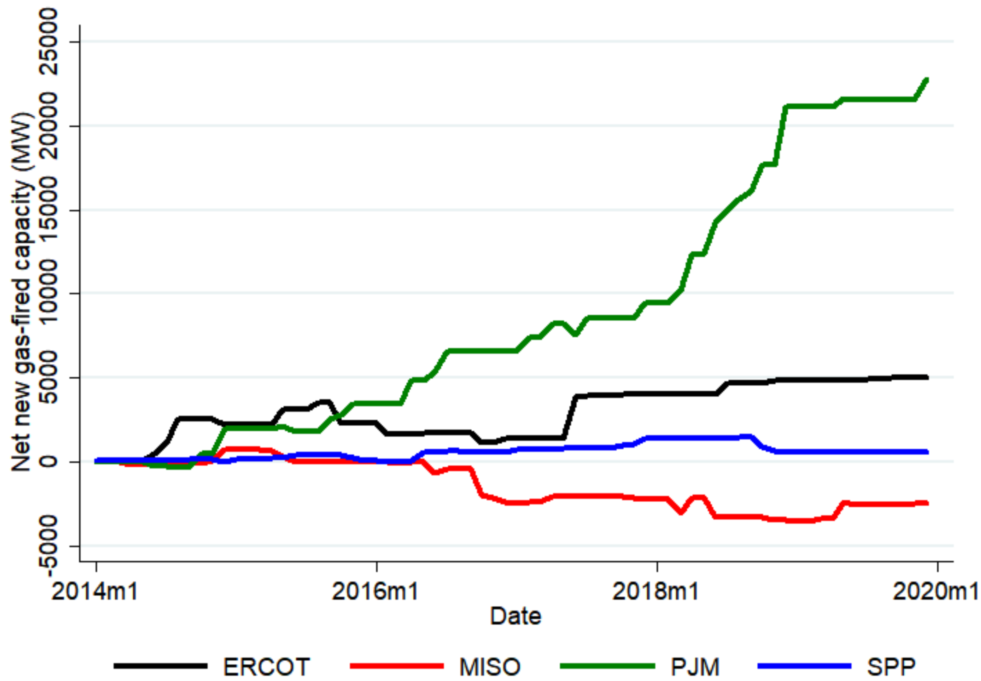
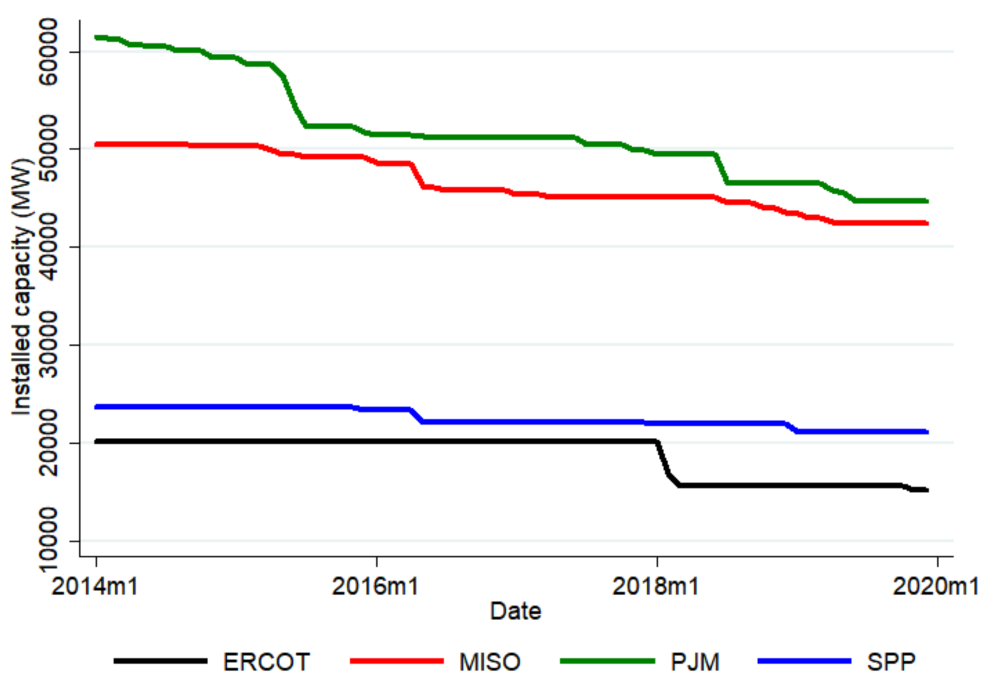


Figure B.3.10: Installed coal capacity over time in ERCOT, MISO, PJM, and SPP.



B.4 Dynamic simulation

B.4.1 Literature Using the National Energy Modeling System

To be more inclusive than there is space to be in the main text, here we discuss several more of the papers and reports that use the same modeling framework we do. Researchers have used versions of the National Energy Modeling System to examine a range of policy-relevant questions: to model proposed federal energy policies such as the Clean Power Plan (EIA 2015, Houser et al. 2015, Larsen et al. 2016) and others (Cullenward et al. 2016), to assess the capacity of broad policy portfolios to reduce emissions (Brown et al. 2001, Bernow & Duckworth 1998, Geller et al. 1999, Palmer et al. 2010), to examine the efficacy of energy efficiency policies (Koomey et al. 2001, Scott et al. 2007, Auffhammer & Sanstad 2011, Brown et al. 2011, Houser & Mohan 2013), to explore dynamics of the natural gas markets (Brown et al. 2009, Brown & Krupnick 2010, Mignone et al. 2017, Bordoff & Houser 2014, Gillingham & Huang 2019), to evaluate transportation policies alone and in combination (Gallagher & Collantes 2008, Morrow et al. 2010, Small 2010, Chandel et al. 2011, Small 2012, Gillingham 2013, Gillingham & Huang 2020), and to consider other changes to residential (Wilkerson et al. 2013), commercial, or industrial emissions (Brown et al. 2013).

B.4.2 Changes to Create Yale-NEMS

In this study, we take a recent version of the National Energy Modeling System, and run it on a server at Yale. We call this "Yale-NEMS" at EIA's request as it may have small differences from the model run at EIA. Our modifications are quite minor and relate simply to outputting additional results and developing scenarios of our own. We can replicate EIA's own Annual Energy Outlook baseline (to a rounding error). In this Appendix section, we discuss the changes we made for this study to the modeling framework.

Electric Vehicle Demand

As discussed in the main text, vehicle adoption is modeled using a nested logit framework. The first stage is a choice of five fuel groups (conventional, hybrid electric, dedicated alternative fuel vehicle, fuel cell vehicles, and electric vehicles); the second stage involves choices between sub-technologies (e.g., 100- and 200-mile electric vehicles within the 'EV' category). Utility in the first stage depends on estimated utility for the sub-technologies in the second stage. Utility in the second stage is a function of vehicle characteristics including fuel economy, price, vehicle range, fuel availability, battery replacement cost, performance, home refueling capability, maintenance costs, luggage space, and make and model diversity within vehicle class. Increasing electric vehicle adoption in Yale-NEMS involves a combination of changes to the characteristics that contribute to this estimated utility: to battery prices (which in turn affect vehicle sales prices), to make and model diversity, and to preferences for different technology types.

Attributes of alternative fuel vehicles, including electric vehicles, are determined endogenously in the model. In particular, electric vehicle prices are based on the cost of comparable conventional vehicles with an additional battery system cost. Lithium ion costs (in dollars per kWh) are modeled as a function of production scale and a learning rate that changes over four production stages. The $/kWh price is scaled by battery size and combined with an additional non-battery system cost before being added back to the base vehicle cost. Yale-NEMS' baseline treatment of battery prices is arguably conservative on a number of fronts. First, the starting price in 2017 is higher than many estimates–100 mile and 200 mile range electric vehicle batteries are assumed to cost $340 and $290 per kWh, respectively, while industry estimates are much lower (note that the newest AEO has lower battery costs). Additionally, the learning curve is rather flat. Under the default assumptions, the price levels off by 2040 at around $190/kWh and $165/kWh for the two types of electric vehicles, which is above more recent estimates (e.g., around $156/kWh in 2019 and even lower today).[4] Several of our scenarios involve directly modifying the price trajectory for batteries to be consistent with much more optimistic industry projections (as low as $20/kWh in 2040 in both the main high EV demand scenario and the high electric vehicle demand scenario with preferences for electric vehicles increased earlier).

Make and model diversity is a straightforward parameter that captures the diversity of offerings of a given technology relative to gasoline vehicles. We gradually increase this parameter to equal gasoline vehicle offerings through the 2020s, but it has only a modest effect on vehicle adoption.

For each technology in the calibrated logit model, there is a constant added to the utility from specific characteristics that captures unobserved preference for different types of vehicles. As electric vehicles become more widespread, people may become more comfortable with the idea of purchasing them and utility from an electric vehicle may change, even controlling for observable improvements in characteristics. To incorporate this dynamic and to match BNEF's electric vehicle adoption trajectory, we increase the constant for all plug-in electric vehicles. This preference adder increases over time, following the logistic shape typical of the adoption of new technologies. Exact details on this trajectory are available

[4] See https://www.theverge.com/2021/3/15/22325813/vw-volkswagen-power-day-battery-electric-car-announcement?mc_cid=982fee4e91&mc_eid=b1fa5041a3.

from the authors upon request.

B.4.3 Additional Figures and Tables from Dynamic Simulation

In this Appendix section, we present a set of additional figures and tables to further highlight different aspects of the results and better explain our scenarios. We begin by showing a map of the electricity market module and the transportation module regions used in this study (Figure B.4.1). We then present the path of prices over time of 100-mile and 200-mile range compact electric vehicles in both the high electric vehicle demand and reference case (Figure B.4.2). The path of prices over time for conventional vehicles is also shown for reference. This figure shows that the price is declining faster in the high electric vehicle demand case than in the reference case. Figure B.4.3 shows the share of new light duty vehicles that are electric vehicles or plug-in hybrid electric vehicles across our scenarios, showing the ambition in our high electric vehicle scenario.

For additional context, in Table B.4.1 we show the number of electric vehicle sales in two example years, 2030 and 2040, along with the number of total light-duty vehicles for reference. This table shows the dramatic increase in electric vehicle sales in the high electric vehicle scenario relative to the reference case, which amounts to an additional 2.47 million sales in 2030 and an additional 8.84 million sales in 2040.

On the left side of Figure B.4.4, we show the capacity factor for coal-fired power plants in each of our scenarios. On the right side of Figure B.4.4, we present the total capacity of coal-fired power plants. These figures show that the dominant force in the Yale-NEMS results is the retirement of coal plants (and delayed retirements due to electric vehicles when there is carbon pricing that would have been retiring the coal plants anyway). Figure B.4.5 shows the total net installed capacity of renewable energy in each of the scenarios. The high electric vehicle demand combined with carbon pricing leads to the most renewables installed, and this is followed by the carbon pricing scenario, the high electric vehicle demand scenario, and the reference case.

Figure B.4.6 shows the net present value of avoided pollution damages by pollutant for each of the scenarios relative to the reference case. Again a 3% discount rate is used. The greatest avoided pollution damages are from avoided CO_2, followed by SO_2, NO_x, PM2.5,, and VOCs. Figure B.4.7 presents a map of the United States, with lighter colors showing higher net avoided damages (summed over all sectors and all pollutants) relative to the reference case by Census region. The greatest benefits accrue to the Southeast in the high electric vehicle scenario and to the upper Midwest in the other scenarios. These results are a function of the existing vehicle stock, existing electricity generation mix, and what

Table B.4.1: Sales of electric vehicles and total vehicles by region and scenario

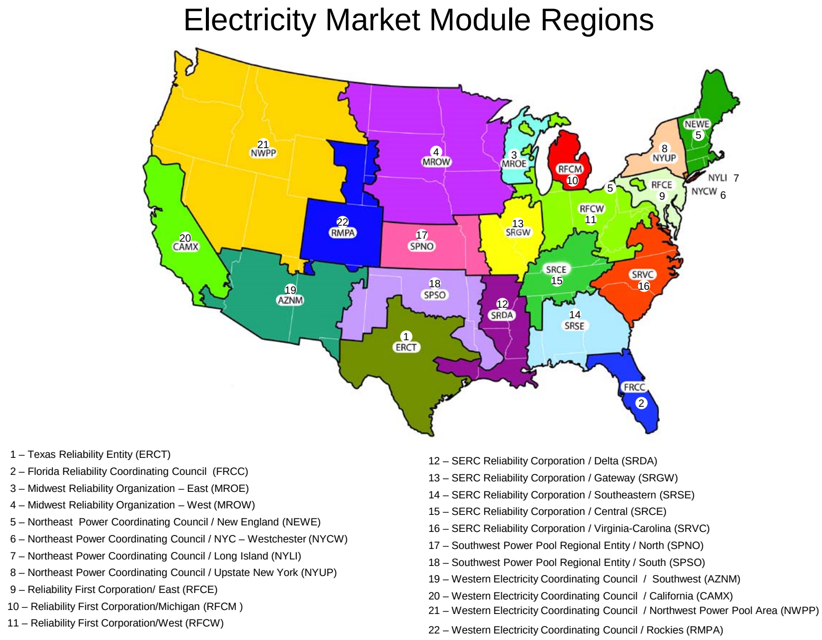
		Reference Case		High EV Demand	
		EV Sales	Total LDV Sales	EV Sales	Total LDV Sales
East North Central	2030	0.17	2.58	0.57	2.59
	2040	0.21	2.61	1.56	2.63
East South Central	2030	0.06	0.79	0.18	0.79
	2040	0.07	0.81	0.46	0.81
Middle Atlantic	2030	0.20	2.25	0.52	2.25
	2040	0.19	2.27	1.37	2.27
Mountain	2030	0.09	1.23	0.27	1.24
	2040	0.12	1.39	0.80	1.40
New England	2030	0.06	0.71	0.15	0.72
	2040	0.06	0.72	0.40	0.72
Pacific	2030	0.46	2.38	0.69	2.37
	2040	0.46	2.51	1.56	2.47
South Atlantic	2030	0.25	3.36	0.83	3.35
	2040	0.33	3.63	2.17	3.61
West North Central	2030	0.06	1.04	0.20	1.04
	2040	0.08	1.08	0.62	1.10
West South Central	2030	0.17	2.45	0.58	2.45
	2040	0.23	2.65	1.65	2.67
United States	2030	1.52	16.80	3.99	16.80
	2040	1.76	17.67	10.60	17.67

Notes: Sales are in millions of vehicles. The 'Reference Case' and 'High EV Demand' columns contain sales of electric vehicles ('EV Sales') and of all light-duty vehicles ('LDV Sales') in those scenarios in both 2030 and 2040.

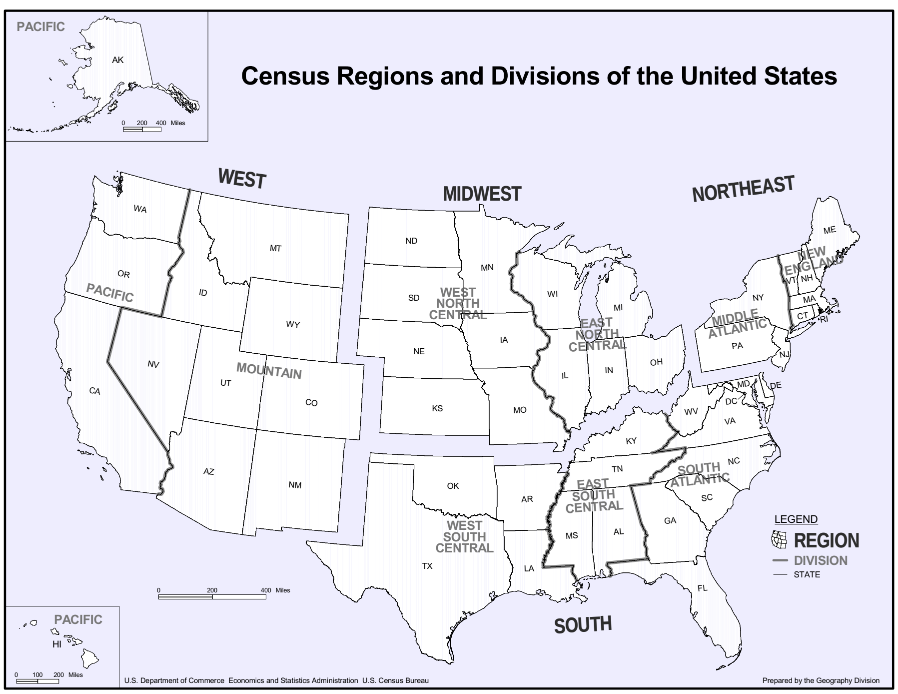
generation will be used to charge the electric vehicles. Figure B.4.8 shows a breakdown of Panel (a) of Figure 2.6 by region. The top panel (Panel (a)) shows two regions where electric vehicles reduce more emissions under a carbon price than in a world without the carbon price: Pacific and West South Central. The bottom panel (Panel (b)) shows that in five regions there is an increase in emissions due to added electric vehicles under a carbon price policy.

Figure B.4.9 shows that the interaction between electric vehicles and carbon pricing can still occur when the model is adjusted to run a reference case similar to AEO2020. Our last figure, Figure B.4.10, shows the capacity factor for coal and the total capacity under the sensitivity run with low-cost renewables and the sensitivity run with earlier electric vehicle adoption. We see that our main finding–that higher electric vehicle demand can slow coal retirements–can still hold under lower-cost renewables and are even stronger with faster adoption of electric vehicles. Of course, we should caution that low-enough costs of renewables would eventually push coal supramarginal and would flip our main finding.

Figure B.4.1: Regions used in different parts of Yale-NEMS.

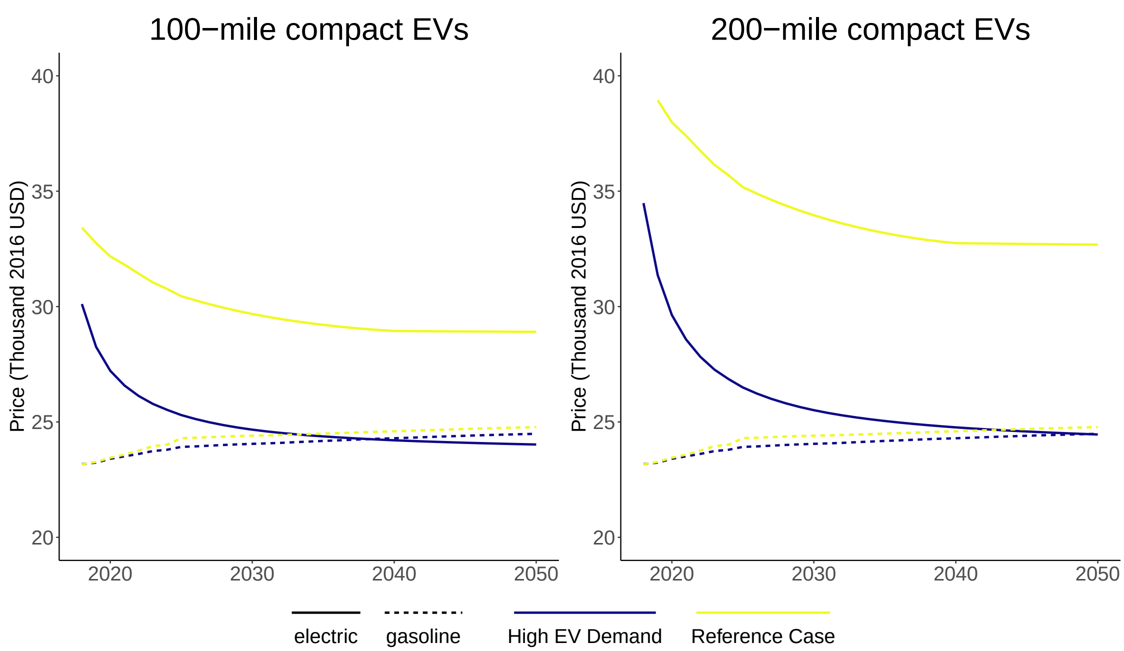


(a) Yale-NEMS electricity market module calculations are done at the NERC region level. Source: EIA



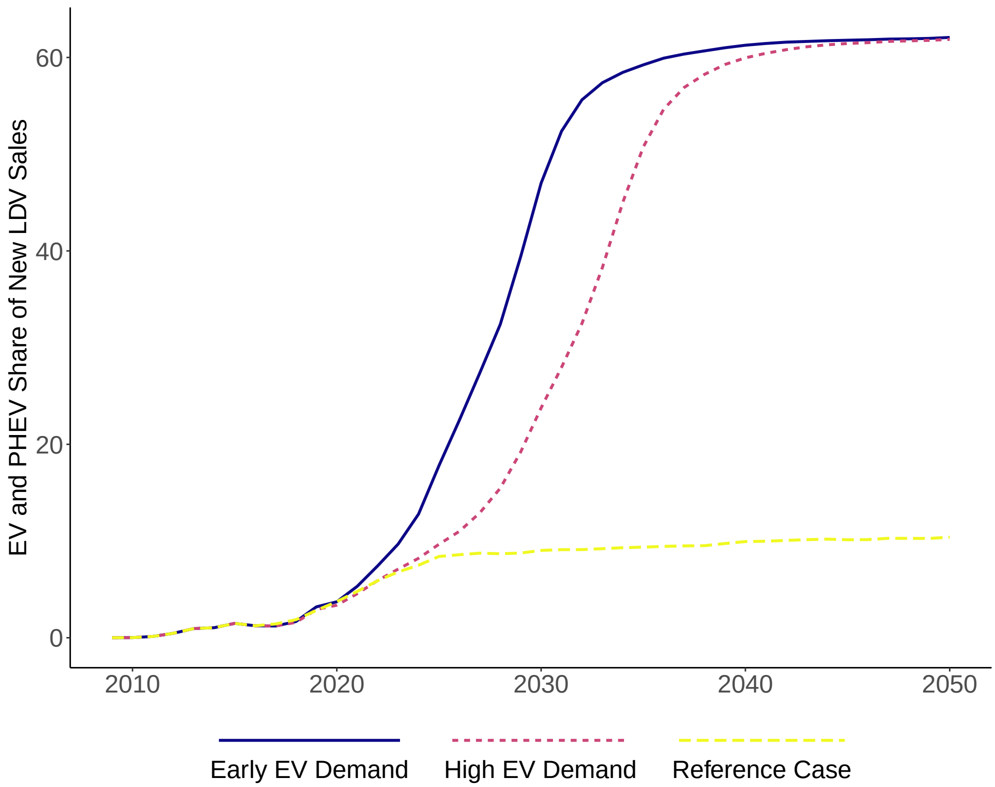
(b) Many submodule calculations are done at the census region level, including the transportation calculations. Source: US Census Bureau

Figure B.4.2: Compact EV prices.



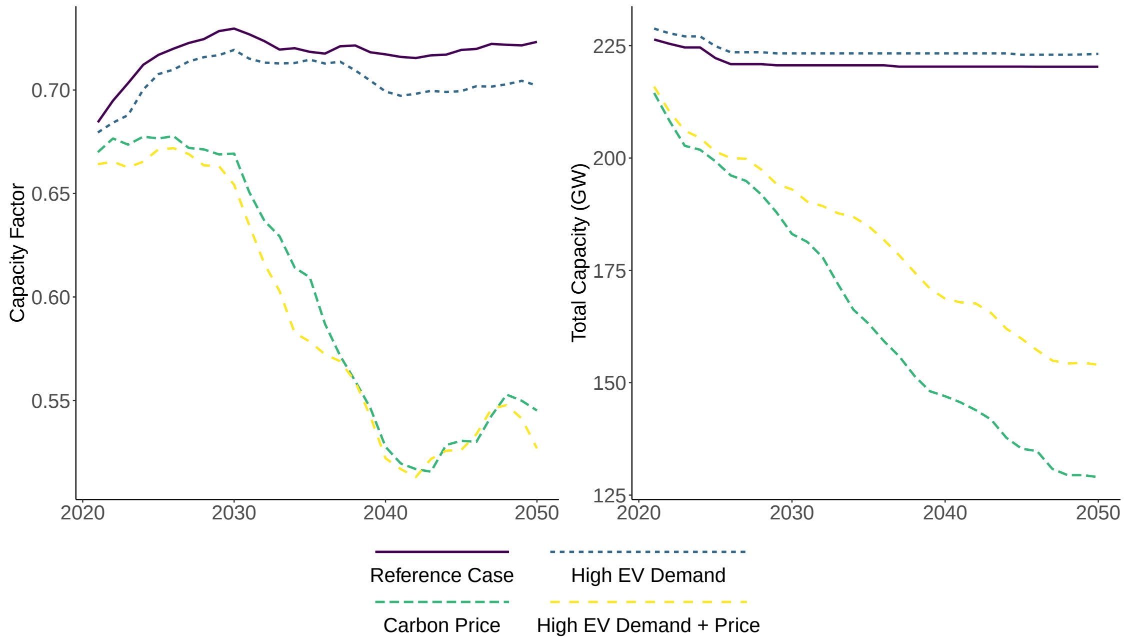
Notes: Price of 100-mile and 200-mile compact EVs for the reference scenario and the high EV demand scenario compared to gasoline vehicle prices.

Figure B.4.3: EV sales share.



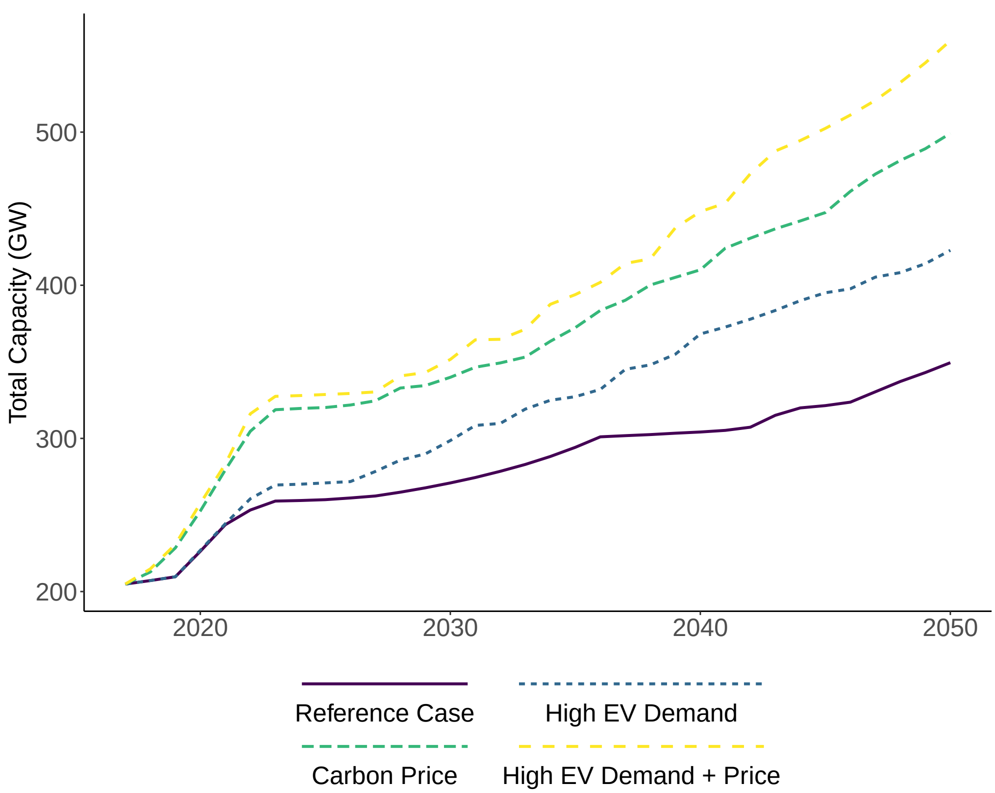
Notes: Share of new light-duty vehicle sales that are EVs or plug-in hybrid EVs (PHEVs) in the high EV demand case compared to the reference case and a sensitivity case.

Figure B.4.4: Coal capacity factor and total capacity.



Notes: Coal capacity factor (left) and total capacity (right) under the central four scenarios.

Figure B.4.5: Renewables capacity.



Notes: Capacity of renewables facilities for the central four scenarios.

Figure B.4.6: Total avoided damages by pollutant relative to the reference case.

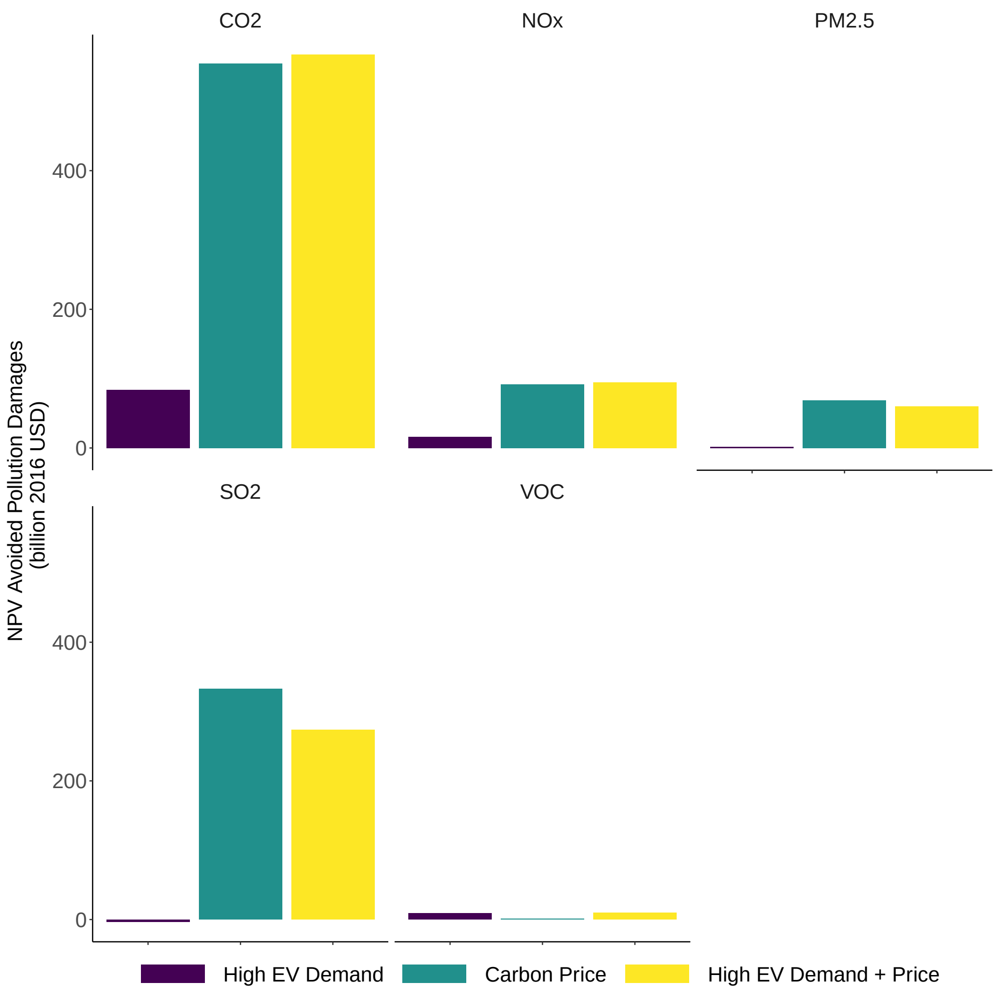
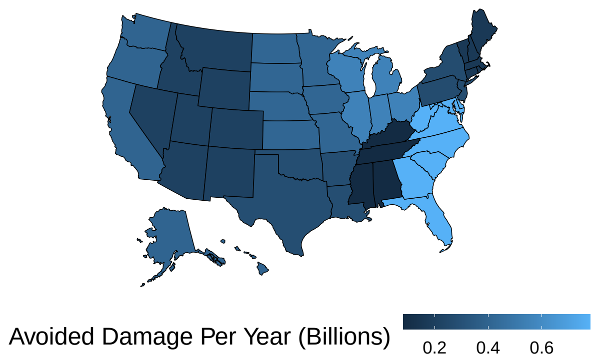
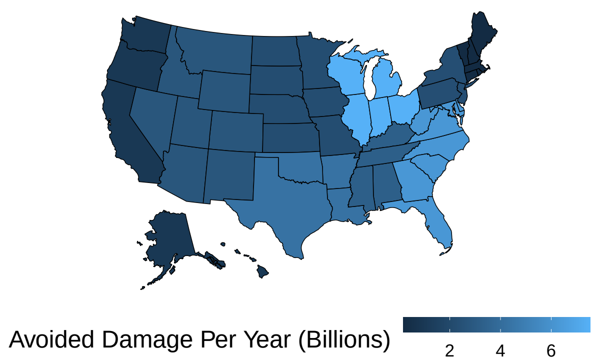


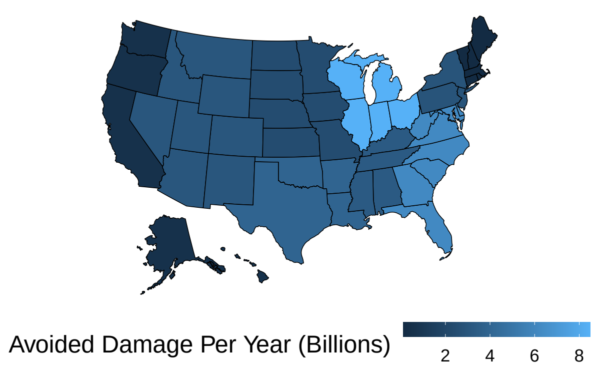
Figure B.4.7: Regional damages by scenario.



(a) Avoided damages (billions) per year in the high EV scenario.

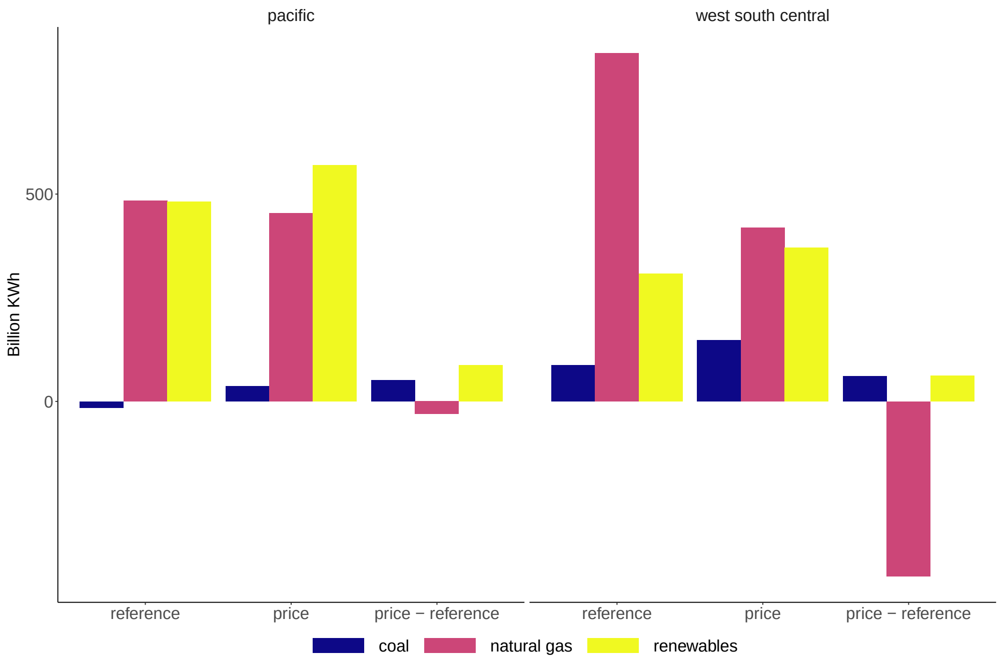


(b) Avoided damages (billions) per year in the combined high EV + carbon price scenario.

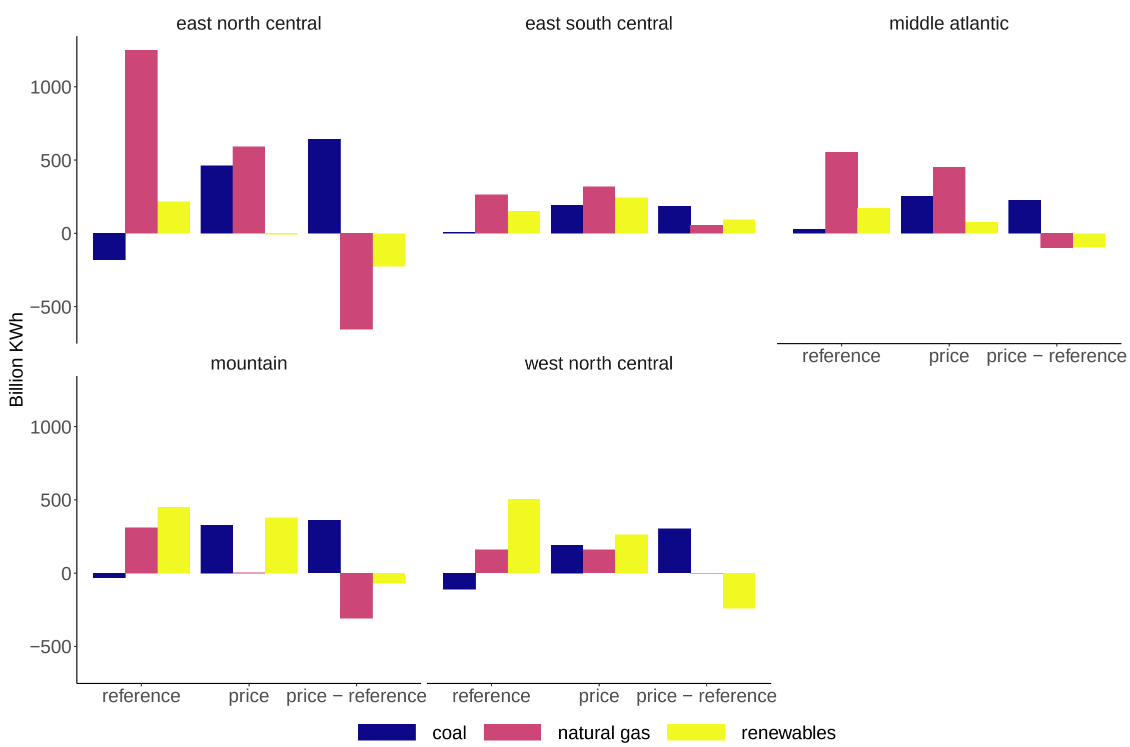


(c) Avoided damages (billions) per year in the pricing-only scenario.

Figure B.4.8: Regional EV-induced changes in electricity generation.



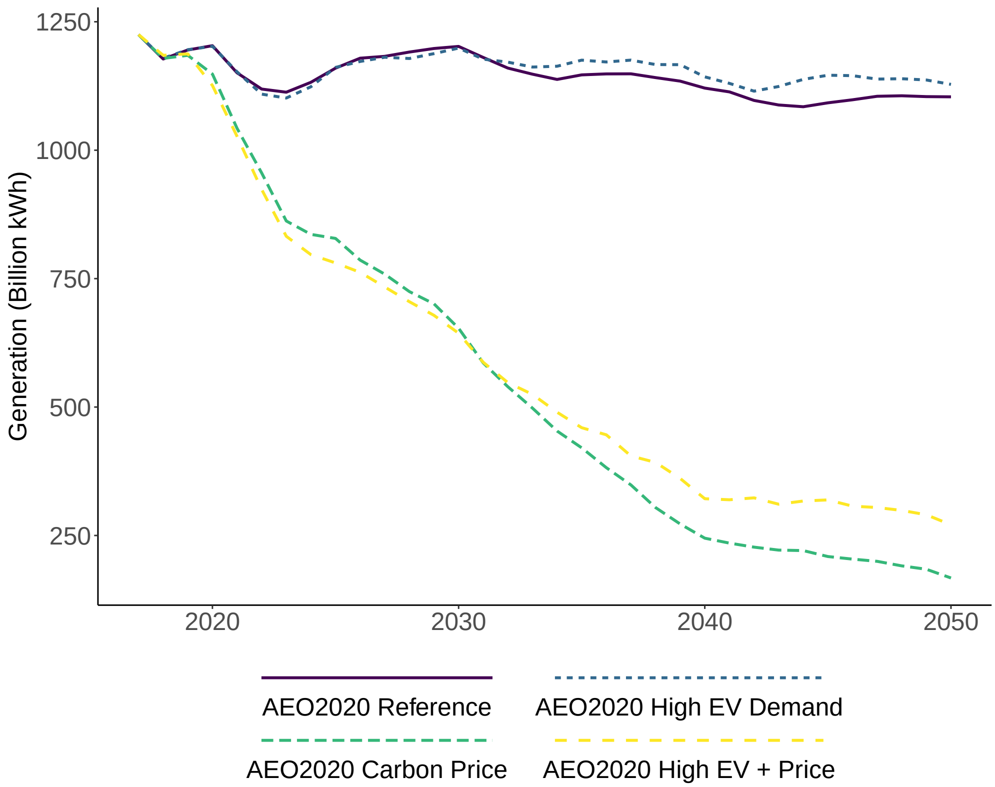
(a) In two regions, EVs are more emissions reducing under a carbon price than in a world without it.



(b) Five regions see an increase in emissions associated with EVs under a carbon price.

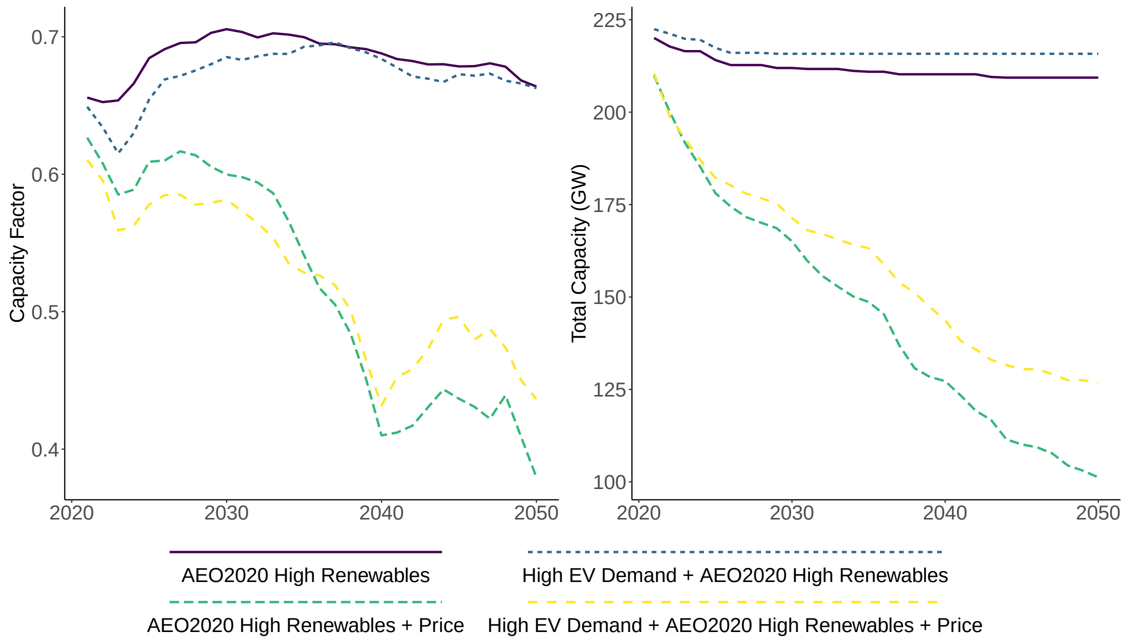
Notes: Regional changes in generation from coal, natural gas, and renewables associated with adding EVs in the presence and absence of a carbon price. Part (a) shows regions where EVs reduce emissions more in the presence of a carbon price (i.e., regions where EVs and carbon pricing policy are complementary), and part (b) shows regions where EVs increase pollution damages in the presence of a carbon price.

Figure B.4.9: Coal generation under alternate scenarios.

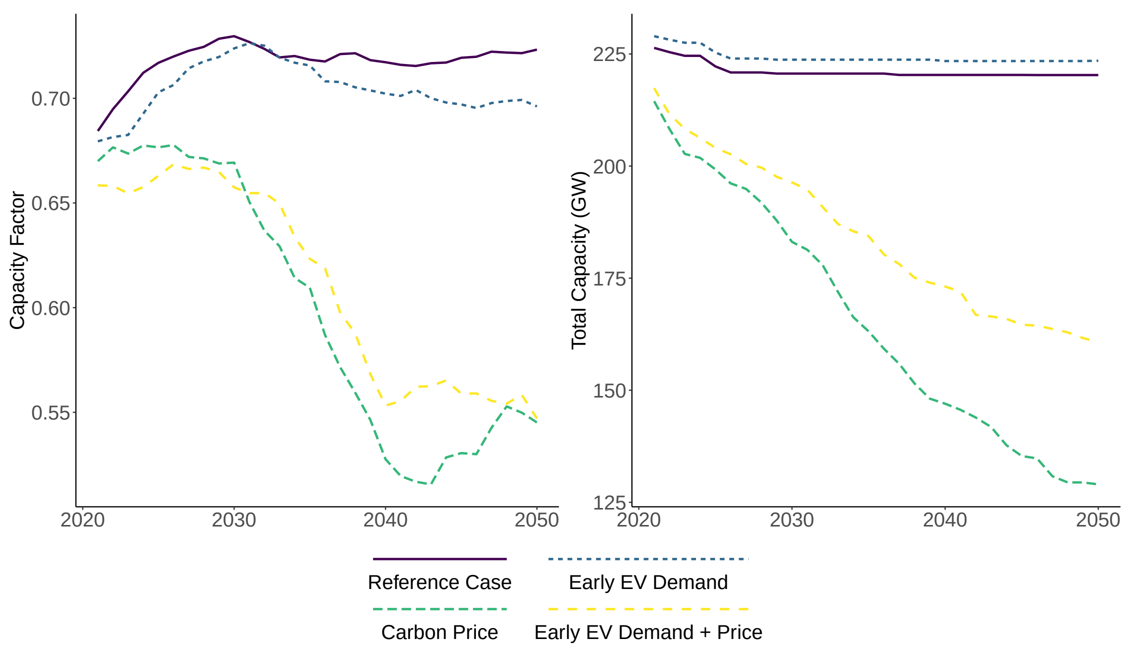


Notes: Coal-fired generation over time under scenarios that replicate AEO 2020 natural gas and renewable assumptions.

Figure B.4.10: Coal capacity factor and total capacity for sensitivity cases.



(a) Coal capacity factor (left) and total capacity (right) under the low-cost renewables assumption.



(b) Coal capacity factor (left) and total capacity (right) under the early EV adoption trajectory.

Chapter 3

Turning Over a New Leaf: The Impact of Electric Vehicle Subsidies

with Kenneth Gillingham

Abstract

Direct subsidies are one of the most widely used policy tools to promote electric vehicle adoption. In this paper, we examine the effect of a short-term discount program for Nissan Leafs to quantify the consumer response. We find that the program, which reduced Leaf costs by $10,000, increased adoption by at least 240% in the immediate term. We also observe limited effects on other electric vehicles and fairly small effects on Leaf sales over the following 7 months (at most 20-40% of the additional sales observed during the incentive program represent cannibalized future Leaf sales). With these results, we document, with quasi-experimental data, the elasticity of demand for Nissan Leafs, with estimates of at least -2.7 and larger estimates specifically for solar households. Based on stated second choice vehicles, program participants were likely considering other electric vehicles or particularly fuel efficient conventional vehicles, and thus the environmental benefits of these additional electric vehicle sales were limited.

3.1 Introduction

Electric vehicles are an increasingly important part of plans to decarbonize the transportation sector. Around the world, governments have adopted a range of policies to promote the adoption of electric vehicles, with financial incentives among the most popular. In the United States, the federal government offers a $7,500 tax credit for the purchase of a new electric vehicle, and recent legislation in the Senate proposed increasing the amount to $12,500 and phasing out the credit more gradually.[1] Under the current credit regime, several automakers have already sold enough electric vehicles that they no longer qualify for the tax credit. Understanding how individuals respond to direct subsidies, particularly when they are applied differentially to different electric vehicles, is thus of the utmost importance in gauging the effects of policy.

[1] https://www.reuters.com/world/us/us-senate-panel-advances-ev-tax-credit-up-12500-2021-05-27/

In this paper, we examine a short-term vehicle-specific incentive program to examine both the direct effect on vehicle sales and, ultimately, the environmental benefits of encouraging electric vehicle adoption. The program, offered by Nissan North America, introduced a $10,000 discount on the Nissan Leaf to large groups of prospective customers in Connecticut, including households with solar panels and state and local government employees. The discount was only available for a brief window, and we are able to examine both the short and longer term impacts of a large, targeted reduction in price on purchases of both Nissan Leafs and other electric vehicles.

Quantifying the effects of this short-term electric vehicle subsidy is of interest to policymakers and automakers alike, and these stakeholders may also differ in their understanding of success for this specific program or others like it. If the program merely subsidizes inframarginal Leaf purchasers, it would be of limited value both from the perspective of Nissan and the perspective of an environmental policymaker. If it draws inframarginal electric or fuel efficient vehicle buyers, it may still be of value to Nissan, while providing limited environmental benefits. To estimate how many new Leafs were purchased and what, if anything, they replaced, we use a combination of vehicle registration data from the DMV and the state electric vehicle incentive program as well as direct survey evidence from program participants. Households interested in the incentive were required to take a survey before they could make the purchase using the discount, and so we are able to look at stated second-choice vehicles in calculating the environmental effect of the program. Unlike other settings with selection into survey completion, we have survey responses for 100% of households who took up the incentive.

We find that the incentive had a large and statistically significant effect on Leaf sales, increasing purchases by at least 240% for the months the incentive was available. Comparing the estimated additional purchases to the documented number of purchases made with the discount code, over 80% of the Leaf purchases were additional during this period. We do not see evidence that these Leaf sales were merely the capture of other brands' electric vehicle sales that would have happened otherwise. However, we do document that over approximately 7 months following the conclusion of the program, there was a reduction in Leaf sales; as much as 40% of sales during the program were harvested future Leaf sales. We cannot show conclusively whether there was a long-term effect on the sales of other electric vehicles. Using these estimates in aggregate, we find fairly large elasticities of demand for the Nissan Leaf, with a lowerbound of -2.7 to -9 for the full program population, when long-term spillovers are accounted for, and even larger elasticities of at least -4.6 for the solar households specifically. These estimates are larger than others in the literature, which have generally been estimated based on price variation that was not as vehicle-specific or time-limited.

Using the survey evidence, we find that households who buy electric vehicles through the program were already considering efficient vehicles. Even among those households who were not already considering an electric vehicle, the average fuel efficiency of the cars they were considering was 32 mpg. Holland et al. (2016) also used stated preference results as a robustness check for their central gasoline vs. electric vehicle comparisons and found that the majority of respondents were considering electric vehicles. As electric vehicles have become more mainstream, electric vehicle buyers may be less committed to purchasing an electric vehicle, and thus, we might expect the second choice vehicles to change. In fact, while we observe a disproportionate number of survey households whose second choice was an electric vehicle, it was less than half (37%). Other studies have also found that electric vehicles replace relatively fuel efficient cars based on empirical purchases among comparable populations (Xing et al. 2019, Muehlegger & Rapson 2020). Perhaps also notable is the fact that the different subpopulations who received the incentive did not appear to be considering vehicles with significantly different fuel efficiencies. Ultimately, we find that the environmental benefits of the additional electric vehicles is positive but small (less than $250), even though the marginal damages of air pollution in Connecticut are high (due to relative population density and existing air quality) and the marginal emissions of electricity generation are relatively low compared to other parts of the Eastern Interconnect. Though Nissan likely had other incentives at play, the program was certainly not cost effective from an environmental standpoint.

This paper contributes to a burgeoning literature on electric vehicle adoption. A number of papers look at the effects of different policies, particularly price policies, on electric vehicle purchases. Li et al. (2017) and Springel (2020) examined the relative importance of up-front purchase incentives compared to charging infrastructure, based on long-term electric vehicle incentive policies. Likewise, Clinton & Steinberg (2019) looked at different forms of financial incentives, whether direct subsidies or tax credits available after a delay. Our high elasticities may provide further evidence that consumers are more responsive to rebates than to tax credits. Xing et al. (2019) estimated a demand model for vehicles and find that a majority of electric vehicle buyers are inframarginal. All of these papers examined adoption in the early 2010s; as electric vehicle prices have fallen and familiarity has increased, the landscape of behavior around and preferences for the vehicles has changed dramatically. This paper looks at a slightly later time period in which electric vehicle adoption was already much higher. Muehlegger & Rapson (2020) considered a subsidy program targeting low- and middle-income households in California and found that electric vehicle buyers would have otherwise purchased very fuel efficient vehicles. Our paper examines a different population, and unlike other research, considers a vehicle-specific subsidy, which may be expected to drive different behavior.

The rest of the paper proceeds as follows. Section 2 describes the setting of the program and the data available to analyze it. Section 3 lays out the estimation strategy and then presents the results for our estimates of direct and longer-term effects of the incentive program. In section 4, we calculate the environmental benefits of the program. Finally, section 5 concludes.

3.2 Setting

3.2.1 Nissan Leaf

The Nissan Leaf was one of the first electric vehicles introduced in the US market and was, as of year-end 2017, the third highest selling electric vehicle in the country (after the Chevrolet Volt, a plug-in hybrid electric vehicle, and the Tesla Model S).[2] The vehicle was seemingly slightly less popular in Connecticut, where as of the same period, the Nissan Leaf was the fifth most common electric vehicle (based on applications to receive state incentives, which notably exclude the Tesla Model S).

The Nissan Leaf was introduced in 2010, with a second generation introduced in late 2017. The Manufacturer Suggested Retail Price (MSRP) for the base 2016 and 2017 models was approximately $30,000 (2017 $), making it one of the more affordable electric vehicle models. The 2016 Leaf was available with a battery of 24-30 kWh, while all 2017 trims offered the 30 kWh battery; these translated to vehicle ranges of 84-107 miles. Other electric vehicles available at the same time, including the Chevrolet Bolt, which was available for $36,000+, offered ranges more than twice as large.

3.2.2 Discount Program

In 2017, the Connecticut Green Bank partnered with Nissan North America to offer a $10,000 manufacturer's discount off the MSRP for model year 2016 and 2017 Nissan Leafs.[3] With the incentive, the federal tax credit ($7,500), and the state tax credit ($2,000-$3,000), the

[2]The Tesla Model 3 has since surpassed the Nissan Leaf sales totals, but production only began in July 2017. Source: `https://afdc.energy.gov/data/10567`

[3]From the Connecticut Green Bank's website: "A green bank is an entity that accelerates the deployment of clean energy using limited public dollars to attract private capital investment in clean energy projects. In doing so, it makes clean energy more affordable and accessible to consumers." The Connecticut Green Bank's goals are to support the adoption of clean technology and promote local economic development in the state.

vehicles were available for around $10,000. The discount was offered to Connecticut residential solar PV customers, Connecticut state employees, employees of The Hartford Financial Services Group, employees of the City of Hartford, and employees of member towns of the Lower Connecticut River Valley Council of Governments (RiverCOG). Table 3.1 contains information about the approximate number of members in each group, details of the marketing campaign for each group, and ultimate observed sales by group.

Interested individuals were directed to a page on the Green Bank website with information about the offer, Nissan's advertising spec sheet, testimonials, and a link to register for the offer. As part of that registration, prospective purchasers had to complete a 10-minute survey about basic demographics and EV-related preferences and behaviors. It was not possible to receive a discount code without survey completion, but individuals could complete the survey without following through on their purchase. Ultimately, 301 people filled out the survey, while 103 bought a Nissan Leaf through the program. As shown in table 3.1, 88% of purchases were made by solar PV customers or state employees.[4]

At the same time that Nissan offered the Leaf discount in Connecticut, the automaker was coordinating similar programs with utilities in other states, for instance, in neighboring Massachusetts[5]. These programs unfortunately foreclose the possibility of difference-in-differences or triple difference designs across state lines to measure the effect of the incentives in Connecticut.

3.2.3 Data

As noted above, individuals were required to complete a survey in order to access the discount code. In the survey, individuals were asked whether they were already planning to purchase a new vehicle; whether they were already planning to purchase a new *electric* vehicle; and if they were planning a purchase, what vehicle(s) they were considering. They also answered questions about driving behaviors and household demographics. The full set of survey questions is included in appendix C.3.

In addition, we acquired data on electric and non-electric vehicle sales in Connecticut. These include (1) anonymized vehicle registration data from the DMV at the zip-code level covering the years 2012-2018, obtained via a FOIA request; (2) Connecticut Hydrogen and Electric Automobile Purchase Rebate (CHEAPR) Program statistics (Center for Sustainable Energy 2021), a list of applications submitted to receive the state electric vehicle incentive

[4]We are not currently able to distinguish between the non-solar individuals, so in subsequent analysis, individuals are sometimes categorized as solar and "other."

[5]`https://www.telegram.com/news/20170728/sterling-residents-eligible-for-electric-car-incentives`

at the zip-code level; and (3) vehicle registrations at the individual level as of 2019 for approximately two thirds of Connecticut municipalities.

The DMV data has a number of advantages: it theoretically contains all vehicle registrations in the state of Connecticut, including conventional vehicles, and because of the ways leased vehicles are registered, it allows us to distinguish between leases and outright purchases. However, the DMV data ends in 2017, limiting the ability to do post-program comparisons, and it appears that there is a registration lag such that thousands of vehicles are only listed in the following year's data. Without the 2018 DMV data, this poses challenges for analyzing a program that occurred in mid-2017, so we rely primarily on the CHEAPR data. The CHEAPR data includes all electric vehicles eligible for the rebate (among battery and plug-in hybrid electric vehicles, this means those with prices below a certain threshold[6]) for which the owners applied for the CHEAPR incentive. The CHEAPR data extends through 2020, allowing the analysis of longer-term effects. Finally, the 2019 DMV data has the advantage of being non-anonymous, allowing direct matching of individuals who completed the survey to their vehicles. However, it does not cover the full state and it covers a period more than a year after the program, which means not all households are in the data nor are all vehicles owned or purchased in 2017.

Nissan tracked which group buyers belonged to (individuals were required to provide documentation of their membership in their respective customer group), but did not share individual data (i.e., the names of buyers). For some analyses, we attempt to merge survey completers with the vehicle registration data to determine who followed through on a Nissan Leaf purchase. A detailed description of this matching process is available in appendix C.4.

3.3 Vehicle Sales Effects

Key to understanding the effects of the discount program is disentangling where it drew buyers from: would they have otherwise bought a Leaf, another electric vehicle, or another fuel efficient vehicle in the same period or shortly thereafter? To answer these questions, we use observed sales and registrations as well as direct survey evidence. Using the registration data, we are able to also consider the dynamic nature of vehicle purchase decisions, by testing both the effects on vehicle purchases over the duration of the incentive program and whether there are longer-term spillovers on the purchase of Nissan Leafs and other electric vehicles in the months that follow.

[6] For instance, Tesla Model S vehicles were too expensive to qualify for CHEAPR.

3.3.1 Direct Program Effect

In this section, we quantify the additional Leaf sales. The program increased Leaf sales by 90-100 vehicles over the course of the program (240+%), with limited effects on the sales of other electric vehicles.

Empirical Approach

To estimate the direct effect of the program on monthly sales outcomes, we use several approaches. First, we estimate a treatment effect on Nissan Leafs using a Poisson model to account for the presence of zero-sales months:

$$sales_m = \exp(\alpha + \beta \mathbb{1}\{\text{Program}\}_m + \delta_m + \varepsilon_m) \tag{3.1}$$

where $sales_m$ is the total Leaf sales in month m, $\mathbb{1}\{\text{Program}\}_m$ is an indicator for whether month m is during the program period (June-September 2017), and δ contains month-of-year or quarter-of-year and year-of-sample fixed effects. The coefficient of interest is β, the direct effect of the program on monthly sales. We expect the sign of β to be positive.

This simple event study framework relies on several assumptions. First, that the treatment timing was random or as good as random. While the timing was not random from the perspective of Nissan, it is likely that it was random from the perspective of Connecticut residents, who did not know that the incentive was going to be available in advance. This allows us to compare purchase behavior before the program to purchase behavior during the program without concerns about strategic behavior. Second, with only the pre-period as a "control," we must assume that no other factors were changing during the treatment period. That is, that all increases in Leaf sales are attributable to the program and not to an increase in the perceived attractiveness of electric vehicles due to more public charging infrastructure or increased familiarity. This may be less plausible, which is the motivation for the second specification.

Next, we estimate a series of difference-in-differences equations, as follows:

$$\begin{aligned} sales_{m,v} = \exp(&\alpha + \beta_1 \mathbb{1}\{\text{Program}\}_m + \beta_2 \mathbb{1}\{\text{Leaf}\}_v + \\ &\beta_3 \mathbb{1}\{\text{Program in effect}\}_m \times \mathbb{1}\{\text{Leaf}\}_v + \delta_m + \varepsilon_{m,v}) \end{aligned} \tag{3.2}$$

where $\mathbb{1}\{\text{Leaf}\}_v$ is an indicator for whether v is Nissan Leaf or another vehicle model (or group of models). Here the variable of interest is β_3.

In this case, we still rely on the as-good-as-randomness of the timing with respect to the customers. However, now, rather than assuming that all changes in sales during this period are attributable to the program, we rely on assumptions that other groups of electric vehicles are plausible controls for Nissan Leafs. Among other implicit assumptions, this entails SUTVA, or the belief that the Leaf subsidy did not affect demand for other electric vehicles. If we believe that in fact some of the Leaf buyers would otherwise have purchased other electric vehicles or that the program actually increased awareness of electric vehicles in general, this assumption would not hold. In the former case, β_3 would be an overestimate, while in the latter case β_3 would be an underestimate.

Descriptive Evidence

Figure 3.1 shows electric vehicle sales at the monthly level, based on applications to the CHEAPR state incentive program. Figure 3.1a contains Leaf sales, while figure 3.1b contains all other electric vehicles that received the rebate. It is clear that Nissan Leaf sales during the program exceeded the level of all prior months and most subsequent months. By contrast, June-September 2017 non-Leaf electric vehicle sales were slightly lower than sales in the months immediately before and after the program.

Results

Tables 3.3 and 3.4 contain the estimated effects of the program on sales. Columns (1) and (2) are estimated from equation 3.1, where column (1) uses the CHEAPR state incentive data while column (2) uses the DMV vehicle registration data, which extends back much further. The coefficient on the program indicator is between 1.82 and 1.93 and statistically significant. These imply a 517-589% increase in Leaf sales during the program.[7] In other words, during the four months the program was operational, the results suggest that sales of Nissan Leafs increased by 103-105. These results are strikingly similar to the number of vehicles purchased using discounts through the program, suggesting that virtually all Nissan Leaf purchases in the program came from people who otherwise would not have bought a Nissan Leaf during that time frame.

We also estimate the differential treatment effect on Leafs compared to other electric vehicles, based on equation 3.2, in columns (3) through (5). The comparison in column (3) contains all other electric vehicles sold during this time period, column (4) contains all of the top-selling electric vehicles, and column (5) contains the Chevrolet Bolt and Volt, two of the vehicles listed most frequently in the survey as the car an individual was considering. The effects are slightly smaller, reflecting the general increase in electric vehicle demand over this time period, but remain statistically significant, ranging from 1.227 to 1.382, which translate

[7]Percent change estimates are calculated from $e^{\beta} - 1$.

to increases of 241-298%. In these cases, we estimate that there were 87-91 new Leaf sales due to the program, still reflecting a large share of non-marginal purchasers.

3.3.2 Lease vs. Buy

The Nissan incentive, unlike state and federal tax credits, was not available for new leases. Thus, if the uptick in Leaf sales is indeed a function of the program rather than an overall increase in electric vehicle interest or a general change in preferences for the Leaf, we would expect to see an increase in the share of new Nissan Leafs that are purchased outright rather than leased. We would not expect to see a similar increase in the share of other electric vehicles purchased vs. leased, as no other incentives were changing at the time. We can test this using DMV data, where the registration zip code for leased vehicles is not the local zip code for the registrant but the zip code of the lease financing company. Specifically, we estimate a variant of equation 3.1 separately for sales and leases as well as variants of equation 3.2, where the outcome is share of vehicles leased.

Table 3.5 shows the results of equation 3.1 separately estimated on sales and leases. The effect is concentrated in sales, rather than leases, though there is a small but insignificant increase in leases, as well, potentially due to the informational effect of the incentive program.

The corresponding shift in proportion of vehicles leased vs. sold for Leafs is apparent in table 3.6. Columns (1) through (5) differ by the comparison group–column (1) uses all electric vehicles, (2) uses the top-selling electric vehicles, (3) uses Chevrolet Bolts and Volts, (4) uses non-electric Nissan vehicles, and (5) uses all Priuses (plug-in hybrid and gasoline hybrid). While the lease share of each comparison group experiences a non-significant increase during the program period, Nissan Leafs in the data are 37-52 percentage points less likely to be leased during the program. It is also interesting to note that compared to other electric vehicles and other non-electric Nissan cars, Leafs are 9-12 percentage points more likely to be leased (and the difference is even larger compared to Priuses: Leafs are nearly 40 percentage points more likely to be leased than Toyota Priuses).

3.3.3 Survey Evidence

Table 3.2 shows the results for survey questions about vehicle purchase plans, broken out for solar and non-solar customers and specifically for those who followed through on their vehicle purchase. Nearly 39% of solar customers who followed through on the purchase stated that they were already planning an electric vehicle purchase (2% explicitly stated that they were already planning to purchase a Nissan Leaf), while 41% of other individuals who followed through were already planning to buy an electric vehicle (4% were planning to buy a Leaf). In aggregate, then, according to the survey, about 40% of Leaf purchases were from inframarginal prospective electric vehicle buyers (though from Nissan's perspective, more than 96% of program participants were new buyers).

There are, however, some reasons not to take these survey results too literally. Respondents may have overstated or understated their intention to buy an electric vehicle out of a desire to appeal to the survey administrators, or they may have been incorrect about their own likelihood of buying an electric vehicle (the gap between stated intentions and actual behavior is highlighted by the fact that around two thirds of survey respondents did not end up buying a Leaf through the program).

3.3.4 Post-Program Harvesting and Spillovers

The previous section makes clear that there was a measurable increase in Nissan Leaf sales for the duration of the incentive's availability without a corresponding decrease in the sales of other electric vehicles. However, some of the new Leaf buyers may have merely shifted future purchases into the incentive period. The survey evidence in table 3.2 documents that 41% of the individuals who followed through on their purchases were planning to buy an electric vehicle. In the 12 months prior to the introduction of the incentive, an average of 70 electric vehicles appeared in the CHEAPR data per month, of which around 4 were Nissan Leafs. If the program participants were future Nissan Leaf buyers brought forward in time, these harvesting effects are likely to be observable; if they are future buyers of other vehicles, the effects may be harder to measure. The dynamic effects may also be offset by positive behavioral spillovers: people may have seen their friends and neighbors buy a new Nissan Leaf through the program and been motivated to buy a new electric vehicle of their own. This could counteract an expected decrease in future sales.

Empirical Approach

The first question, whether Nissan cannibalized future Leaf sales, is more straightforward to estimate. We can estimate variants of equations 3.1 and 3.2 with the addition of an indicator for being in the post-policy spillover period.

To examine whether participation in the program represented redirected future non-Leaf electric vehicle sales, we can compare electric vehicle uptake in zip codes where Leaf purchases were made during the program ("treated" zip codes) to other zip codes in the state of Connecticut. We can estimate the following regression:

$$\begin{aligned} sales_{z,q} = \exp(\alpha + \beta_1 \mathbb{1}\{\text{treatment}\}_q + \beta_2 \mathbb{1}\{\text{treated}\}_z + \beta_3 \mathbb{1}\{\text{treatment}\}_q \mathbb{1}\{\text{treated}\}_z + \\ \beta_4 \mathbb{1}\{\text{post}\}_q + \beta_5 \mathbb{1}\{\text{post}\}_q \mathbb{1}\{\text{treated}\}_z + \gamma_q + \varepsilon_{z,q}) \end{aligned} \tag{3.3}$$

where $sales_{z,q}$ is the sales of all electric vehicles in zip code z during quarter q. Sales are now aggregated to the quarterly level because of the large number of zip code-months when no electric vehicles are sold. β_3 captures the longer-term effects of the program, and consists of two opposing forces. On the one hand, households who participate in the program may have otherwise bought electric vehicles (either a Nissan Leaf or another model) in the months and years following the program. If this effect dominates, we expect that β_3 will be negative. On the other hand, if the presence of new electric vehicles in the neighborhood incentivized others to adopt electric vehicles, we expect that β_3 will be positive.

For this estimate to be causal, we would have to believe that treatment–purchasing a Nissan Leaf while the incentive program was active–is randomly assigned (or that the number of people in a zip code who were given access to the incentive program was plausibly random). An ideal experiment might randomly select geographic units in which the incentive was made available, but no such design was possible here. Thus, we cannot assert that the estimated coefficients are causal effects of program purchases. However, the estimates may still be informative, particularly because Leafs are not the only or most popular electric vehicle.

Leaf Harvesting Results

It is challenging to determine ex ante over what period harvesting effects are likely to be important. Thus, figure 3.2 depicts estimated harvesting effects where the harvesting period is determined to end in each month of 2018 based on a Poisson model. The first approach includes all available CHEAPR data, including several years post treatment. The second approach drops year fixed effects. And the third approach drops all months after the harvesting period is determined to end (and, in order to estimate the spillover into 2018, treats 2018 as a continuation of 2017). For harvesting end dates in the second half of 2018, few estimates are statistically significant and many point estimates are positive. Hence, we estimate that the harvesting persisted until May 2018, for a total of 7 months (October 2017 is omitted due to ambiguity in when the program ended), and ranged from less than 1 vehicle to 21 vehicles. The largest reduction in Leaf sales is likely observed in the final months of 2017 and early 2018, when the supply of 2016 and 2017 Nissan Leafs was exhausted.

Table 3.7 shows the results for the difference-in-differences estimation with an indicator for the harvesting period, which is assumed to persist until May 2018. The three columns use all electric vehicles, only Chevrolet Bolts and Volts, and all non-Tesla electric vehicles as the comparison group. The harvesting effect from these specifications is estimated to be larger: the implied Leaf-specific spillover effect from each of these estimates is a reduction of 25 vehicles (vs. 99 new sales due to the program), 33 vehicles (vs. 85 new sales), and 30 vehicles (vs. 93 new sales), respectively. The higher values compared to the single-difference estimates reflect that while Leaf sales recovered to pre-program levels in early 2018, other electric vehicles experienced larger increases in sales following the program.

Spillovers Affecting Other Electric Vehicles

The 123 Nissan Leaf sales that occurred between June and September 2017 were made in 81 distinct zip codes, according to the CHEAPR data. As might be expected, the "treated" zip codes had a higher propensity to buy electric vehicles prior to the program: in the 12 months leading up to the incentive program (June 2016 to May 2017), the "treated" zip codes had an average of 0.41 electric vehicles sales/month compared to 0.21 in the "untreated" zip codes (in the 4 quarters leading up to the program in the treated and un-treated zipcodes, there were 1.12 and 0.55 sales/quarter, respectively). Figure 3.3 shows total sales in treated and untreated zip codes over time. Appendix figures C.2.2 - C.2.4 show this data normalized to the pre-program level and on a per zip code basis. Appendix table C.1.3 shows basic characteristics of treated and untreated zip codes, including the number of zip codes in each category, the historical electric vehicle sales, and the average number of solar households in each.

Table 3.8 shows the results from estimating equation 3.3. Columns (1) and (2) look at the entirety of the post-period, while columns (3) and (4) split the post-period into the two quarters following the program (Q1 and Q2 2018, called "short-term post") vs. all subsequent periods ("long-term post"). The coefficients are negative, but not statistically significant. That is, there is suggestive evidence of a reduction in electric vehicle sales in the zip codes where households participated in the program, and the effect seems to be larger in the immediate quarters following the program. The overall effect in column (1) suggests an 8% reduction in electric vehicle sales per month in the "treated" zip codes relative to the untreated zip codes, and column (3) suggests that for the first two quarters, that effect may have been on the order of 20%. The estimates for post-policy effects on non-Leafs only (even numbered columns) are generally similar.

There are two main challenges in clearly estimating these long-term effects. The first is that electric vehicle sales adoption has tended to increase non-linearly, which may drown out any harvesting effects from the program. Additionally, the fact that treatment was assigned non-randomly makes distinguishing a program effect from differential preferences for electric vehicles more difficult. Fully understanding the dynamic effects of a subsidy program potentially requires a larger sample and more plausibly random variation in access to the subsidy or subsidy amount.

3.3.5 Demand Elasticities

We can use the estimates from the previous sections to examine what this program reveals about elasticities of demand for Nissan Leafs. This parameter is of interest not only to Nissan, as they choose prices for their vehicles, but for governments that are interested in using price incentives to drive electric vehicle adoption.

In practice, the incentive was not offered to every household in Connecticut and it was not advertised to every sub-group over the full treatment period (see Table 3.1). This makes it challenging to estimate how quantity of Leafs changed for the set of households who had access to the price change. However, we can roughly calculate the elasticity using two different approaches to estimate the increase in vehicles sold during the program: the first assumes that the discount was available to everyone, and the second estimates the elasticity among only solar households, for whom we have more detailed data.

We first calculate the elasticity by estimating the parameter as though the incentive was available to everyone (or, equivalently, that the population of solar households and state and municipal government employees were responsible for all previous Leaf sales). This will lead to an underestimate of the elasticity, by calculating a percent increase relative to a baseline that includes ineligible households. In other words, the counterfactual sales among the targeted population is likely lower than the counterfactual sales for the entire state of Connecticut, and thus the percent increase in sales due to the program is larger than we estimate. We provide a range of elasticity estimates based on the models in tables 3.3, 3.4, and 3.7, where the extent of future sales cannibalization is either estimated separately based on 3.2 or from the same regression (for the specifications in table 3.7). For the elasticities that account for cannibalization, we conservatively use the largest estimate of cannibalization over a 7-month time period.

Next, we use data on Leaf ownership in solar households to roughly estimate an elasticity specific to that group by adjusting both the treated Leaf sales and counterfactual Leaf sales to include only solar households. For treated Leaf sales, we know the share of program purchases made by solar customers–47.6%–and adjust the program sales accordingly.[8] To

[8]For the versions of the elasticity estimates that account for harvesting, we must assume that the share of solar households who were harvested from the future months is the same as the share of non-solar households

get the share of counterfactual Leaf purchases made by solar households, we use the 2019 individual-level DMV data to match Leaf registrations to the full set of solar households (i.e., not just those who filled out the survey) and find the proportion of Leafs owned by solar customers, excluding the model years for which the discount was available. We use this proportion to adjust the counterfactual sales in the absence of the subsidy, using both the share of model year 2015 and 2018 vehicles as well as the share of 2018 Leafs only.[9]

Elasticity estimates are in table 3.9. Our preferred specifications are those based on the difference-in-differences models and accounting for short-term Leaf cannibalization, which range from -2.67 to -9.42. While the results are sensitive to the assumptions, they are quite large, with all but the smallest estimate exceeding the Xing et al. (2019) estimate of -2.83 for Leafs, and slightly higher than Muehlegger & Rapson (2020)'s estimates of -3.2 to -3.4 for all electric vehicles among middle- and low-income households. One reason we might expect the elasticities estimated here to exceed those in other settings is that the program consisted of an informational campaign in addition to an incentive–some of the increase in demand may in fact be attributable to greater awareness of electric vehicles in general and Leafs in particular.

The parameter we estimate is specifically an elasticity of demand for Nissan Leafs. We might expect it to be reflective of elasticities of demand for other electric vehicles at similar price points and with similar characteristics (in particular, range and prestige). However, electric vehicles that are considered closer substitutes to conventional vehicles likely have less elastic demand. Likewise, electric vehicles that appeal to different sets of consumers may be more or less elastic.

There may also be some external validity concerns with this elasticity estimate. First, the demand and price sensitivity for electric vehicles in Connecticut may not be reflective of demand elsewhere in the U.S. Connecticut is a relatively small state, with a high density of charging stations along major transportation corridors, making electric vehicles more appealing.[10] On the other hand, Connecticut also has some of the highest electricity prices in the country, reducing the cost savings from electric vehicle ownership. Even within Connecticut, the population with access to the incentive may not have been representative of the population more generally: while Connecticut state and municipal government employees may be reflective of statewide demographics, households with solar are wealthier and more likely to

who were harvested from future months.

[9]One might be concerned that the 2018 value would be biased downward due to the fact that solar households who might have bought 2018 Leafs were induced to make earlier purchases by the incentive program, but the 2018 solar share is actually higher than in previous years (perhaps due to differences in the amount of time that households hold on to their vehicles).

[10]Connecticut residents' annual VMT is close to the national average, according to the NHTS.

adopt environmentally friendly technology with high up front costs than people who have not adopted solar.

Finally, the incentive program was run in 2017. Since that time, familiarity with electric vehicles has increased across the board and the Tesla Model 3, which dramatically altered the landscape of electric vehicle purchases in Connecticut and elsewhere, was introduced.

3.4 Environmental Effects

The effect of additional electric vehicles depends on the vehicles whose miles they replace. Having quantified the additional electric vehicles, we now turn our attention to the second half of that question–what vehicles did they replace? For this, we rely on evidence from the survey that prospective buyers had to complete.

The survey asked if people were already considering the purchase of a new car, and if so, what car they were considering. We used this data to calculate the expected environmental damages from the set of alternative cars vs. a new Nissan Leaf. To do so, we used estimates of VMT by vehicle age from the 2017 NHTS and vehicle scrappage rates from Jacobsen & van Benthem (2015) to calculate annual VMT, combined with CO_2 produced per gallon of gasoline and forward-looking local air pollution emissions per mile from the EPA MOVES model.[11] These pollution volumes were converted to local damages using Connecticut county-level damages from ground-level sources from AP3 and the 2017 Social Cost of Carbon of $45 in year 2017 dollars (IWG 2016). For the damages from electricity used to charge electric vehicles, we relied on the New England-specific estimates from Holland et al. (2020). We calculated the change in emissions for all listed second-choice vehicles in the survey (and took the average of the results, weighted by the frequency with which a choice was mentioned), because there was not a statistically significant difference in second choice vehicle characteristics among different types of households (solar households vs. government employees) or between households who did or did not follow through on their Leaf purchase.

Using a discount rate of 3%, we find that over 19 years, each additional Nissan Leaf provided $224 (2017 $) of additional environmental benefits, on average. However, this figure masks considerable heterogeneity–nearly half of households' second-choice vehicles would have provided greater environmental benefits. These include electric vehicles that are more efficient on a kWh/mile basis and several hybrid vehicles including, most commonly, the Toyota Prius. Among the subset of second choice vehicles that generate more damages than the Leaf, the average benefits of a Leaf per year were approximately $545. Even this

[11] These included NO_x, SO_2, and PM2.5 to be consistent with the damage estimates in Holland et al. (2020).

is considerably smaller than the $10,000 per vehicle offered by Nissan (who may have been motivated by a desire to clear out old Leaf stock before introducing their redesigned 2018 model and/or compliance with Corporate Average Fuel Economy Standards) and the $2,000 per vehicle from the state of Connecticut, which suggests that the innovation market failures must be extremely large to justify a subsidy of this magnitude. Additionally, given the variation in damages associated with second choice vehicles, it is worth considering whether and how electric vehicle incentives can be targeted to individuals who might otherwise have bought relatively worse vehicles.

3.5 Conclusion

In this paper, we examined the effect of a short-term $10,000 subsidy for Nissan Leafs offered to a subset of households in Connecticut. Unlike state and federal incentives, which are deliberated by lawmakers in advance of their implementation, the subsidy was introduced without warning to consumers, which provides a quasi-experimental setting in which to examine how buyers respond to large price increases. Because of the brief duration of the program, we are able to explore both the immediate and longer-term impacts of the price change on adoption of Leafs and other electric vehicles.

The incentive had a large and immediate effect on sales of Nissan Leafs, increasing sales by at least 240% relative to other comparable vehicles. We document that this effect was driven by the subsidy rather than pre-existing trends in electric vehicle popularity by comparing new Leaf leases, which were not eligible for the incentive, to new sales, and comparing the lease ratio for Leafs to that of other electric vehicles during this time period. The majority of sales to which the incentive applied were to truly marginal Leaf buyers–over 80% of Leaf sales during this period would not have occurred during this time period, and at most a further 40% represented cannibalized future sales. There is limited evidence of a long-term effect on the sales of other brands of electric vehicles. Ultimately, we are able to estimate the elasticity of demand for Leafs, with a lower bound of -2.7 for the full set of program participants, and an elasticity of roughly -5.9 for the solar customers specifically.

Finally, we can use unique survey data on the planned second-choice vehicle of individuals who participated in the program. In contrast to other settings which may suffer from selection into survey completion, all individuals interested in the subsidy were required to complete a survey about driving behaviors and purchase plans including, importantly, what other car they might have bought if they did not buy a Leaf. We use this data to measure the environmental benefits of the program, and find that households were already considering extremely fuel efficient vehicles and even a large number of alternative electric vehicles. This limits the environmental benefits of each Leaf sold to approximately $224 over its lifetime, though there is considerable variation in the benefits, and future programs may consider how to target households that would otherwise buy less efficient vehicles.

These results are useful for policymakers considering additional electric vehicle incentives of similar magnitudes at the federal level. Such programs could have large effects on total electric vehicle sales, but the direct environmental benefits will be limited (though these results are specific to the population density and electricity generating mix of the Northeast). Furthermore, these results shed light on the efficacy of particular kinds of public-private partnerships. This setting, wherein Nissan partnered with the Connecticut Green Bank, was distinct from either a direct discount from Nissan or a program offered exclusively by the state government (in terms of targeted population, content of the messaging campaign, and potentially the credibility of the information provided, as well as the underlying objectives, which were discussed in the paper). Future work can more directly explore how the program outcomes would have differed under other possible structures.

The results may also be illuminating for those considering how electric vehicle adoption will change as battery prices continue to fall. According to Bloomberg New Energy Finance, battery pack prices are less than $150/kWh.[12] The largest battery packs on the market are 100 kWh, while Nissan Leafs in 2017 had 30 kWh batteries and 2021 Leafs have 40 or 62 kWh battery packs. Even for the Leafs with larger batteries, battery prices would have to fall to zero in order for the price change in Nissan Leafs to come close to the price change induced by this program. Such a change would not be enough to drive a transition from conventional vehicles to electric vehicles–additional mechanisms, like additional price subsidies or investment in charging infrastructure, would be necessary.

[12]https://about.bnef.com/blog/battery-pack-prices-cited-below-100-kwh-for-the-first-time-in-2020-while-market-average-sits-at-137-kwh/

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Tables

Table 3.1: Green Bank Campaign Summary

	Approx. Group Size	Marketing Methods	Campaign Start	Vehicles Sold
Solar PV customers	21,600	Emails, targeted ads	Late May	49
State employees	40,000	Emails, paystub inserts	Late June	42
The Hartford Group	8,050	In-person event, internal communications	Late June	8
City of Hartford employees	4,500	Internal communications	Early July	3
River COG employees	7,500	In-person presentation and direct distribution to mayors	Early July	1

Table 3.2: Stated Purchase Intent

		Total	Total Planning Vehicle Purchase	Total Planning EV Purchase	Share Planning EV Purchase	Share Planning EV Purchase | Planning Purchase
Solar	All	150	100	64	.427	.64
	Follow Through	49	33	19	.388	.576
Other	All	151	93	47	.311	.505
	Follow Through	49	34	20	.408	.588

Notes: Responses to survey question "Were you considering purchasing a new car or an EV prior to hearing about this program?" Solar households are survey responders matched to the list of households included in the original messaging campaign. "Follow through" refers to the set of households that are determined to have followed through on their purchase as discussed in appendix C.4. "Total planning vehicle purchase" includes all individuals who answered "already considering a new car" or "already considering an EV." Note that some survey respondents selected "was not thinking of buying a new car" and still answered the next question about the make and model they would buy if they were considering a different vehicle. These individuals were not counted as considering a vehicle.

Table 3.3: Poisson Results, Direct Effect on Sales, Monthly FEs

	New Vehicles Purchased Per Month				
	(1)	(2)	(3)	(4)	(5)
Program	1.904**	1.927***	0.042	0.009	0.097
	(0.815)	(0.467)	(0.148)	(0.171)	(0.321)
Program × Leaf			1.376***	1.382***	1.227***
			(0.319)	(0.320)	(0.329)
Observations	29	33	58	58	58

*p<0.1; **p<0.05; ***p<0.01

Notes: Dependent variable is new vehicles purchased/registered by month in a Poisson regression. Columns (1) and (2) estimate equation 3.1 on only Leafs, where column (1) uses CHEAPR data and column (2) uses the DMV registration data. Columns (3) through (5) estimate the difference-in-differences equation 3.2, where Leaf sales are compared to other comparable vehicles. In column (3), the comparison group is all electric vehicles in the data. In column (4), the comparison group is a subset of the top-selling electric vehicles in the data, and in column (5), the comparison group is Chevrolet Bolts and Volts. Columns (3) through (5) use CHEAPR application data. All specifications have yearly and monthly fixed effects.

Table 3.4: Poisson Results, Direct Effect on Sales, Quarterly FEs

	New Vehicles Purchased Per Month				
	(1)	(2)	(3)	(4)	(5)
Program	1.820**	1.868***	0.109	0.083	0.112
	(0.904)	(0.503)	(0.147)	(0.171)	(0.361)
Program × Leaf			1.376***	1.382***	1.227***
			(0.335)	(0.334)	(0.395)
Observations	29	33	58	58	58

*p<0.1; **p<0.05; ***p<0.01

Notes: Dependent variable is new vehicles purchased/registered by month in a Poisson regression. Columns (1) and (2) estimate equation 3.1 on only Leafs, where column (1) uses CHEAPR data and column (2) uses the DMV registration data. Columns (3) through (5) estimate the difference-in-differences equation 3.2, where Leaf sales are compared to other comparable vehicles. In column (3), the comparison group is all electric vehicles in the data. In column (4), the comparison group is a subset of the top-selling electric vehicles in the data, and in column (5), the comparison group is Chevrolet Bolts and Volts. Columns (3) through (5) use CHEAPR application data. All specifications have yearly and quarterly fixed effects.

Table 3.5: Program Effect by Vehicle Purchase Status

	New Vehicles Registered Per Month	
	Leaf Sales	Leaf Leases
	(1)	(2)
Program	3.060***	0.426
	(0.725)	(0.580)
Observations	33	33

*p<0.1; **p<0.05; ***p<0.01

Notes: Dependent variable is new Leafs sold or leased by month. Leases are identified by registrations to out-of-state zip codes in the DMV data.

Table 3.6: Change in Share of Vehicles Leased

	Leased Share of Registered Vehicles				
	(1)	(2)	(3)	(4)	(5)
Program	2.528	0.809	5.152	6.803	0.899
	(10.419)	(10.487)	(12.116)	(9.908)	(10.184)
Leaf	9.535*	10.529**	12.441**	10.745**	39.531***
	(5.120)	(5.210)	(5.793)	(4.997)	(5.183)
Program × Leaf	−40.513***	−38.692***	−52.993***	−48.583***	−37.301***
	(6.793)	(6.589)	(8.792)	(6.193)	(6.604)
Observations	65	65	65	65	65

*p<0.1; **p<0.05; ***p<0.01

Notes: Dependent variable is the share of new vehicle registrations that are leased, where leases are identified by registrations to out-of-state zip codes. Each column contains a different comparison group: column (1) uses all electric vehicles, (2) uses the top-selling electric vehicles, (3) uses Chevrolet Bolts and Volts, (4) uses non-electric Nissan vehicles, and (5) uses all Priuses (plug-in hybrid and gasoline hybrid).

Table 3.7: Difference-in-differences Harvesting Effect.

	New Vehicles Purchased Per Month		
	(1)	(2)	(3)
Program	-0.179	0.241	0.098
	(0.178)	(0.302)	(0.140)
Post-Program	-0.169	0.198	0.044
	(0.150)	(0.152)	(0.087)
Program × Leaf	1.639^{***}	0.920^{**}	1.248^{***}
	(0.296)	(0.365)	(0.299)
Post-Program × Leaf	-0.838^{**}	-1.281^{**}	-1.130^{***}
	(0.395)	(0.508)	(0.431)
Observations	110	110	110

*p<0.1; **p<0.05; ***p<0.01

Notes: Dependent variable is new vehicles sold per month. Quarter and year fixed effects are included. Data includes observations between May 2015 and December 2019, where the program period is June 2017-September 2017, October 2017 is omitted, and the spillover period covers November 2017 through May 2018. Column 1 compares Leaf sales to all other electric vehicles in the CHEAPR data, column 2 compares to only Chevrolet Bolts and Volts, and column 3 compares to all non-Tesla vehicles in the CHEAPR data, as the Tesla Model 3 became widely available in 2018 (after its introduction in 2017).

Table 3.8: Quarterly Electric Vehicle Sales by Zip Code Participation in Incentive Program

	Zip-Code Electric Vehicle Sales			
	(1)	(2)	(3)	(4)
Treated × Post	−0.084	−0.092		
	(0.092)	(0.094)		
Treated × Short-Term Post			−0.226	−0.222
			(0.142)	(0.144)
Treated × Long-Term Post			−0.062	−0.071
			(0.095)	(0.097)
Exclude Leafs	*No*	*Yes*	*No*	*Yes*
Observations	6,072	6,072	6,072	6,072

*p<0.1; **p<0.05; ***p<0.01

Notes: Dependent variable is the sales of new vehicles by zip code-quarter. "Treated" refers to zip codes in which a Leaf was purchased during the program. "Short-term post" is an indicator for the first two quarters of 2018, while all subsequent periods are identified as "long-term post." Columns (1) and (3) include all electric vehicle sales in the dependent variable, while columns (3) and (4) only include non-Leaf electric vehicles. Data is from CHEAPR applications.

Table 3.9: Estimated Demand Elasticities

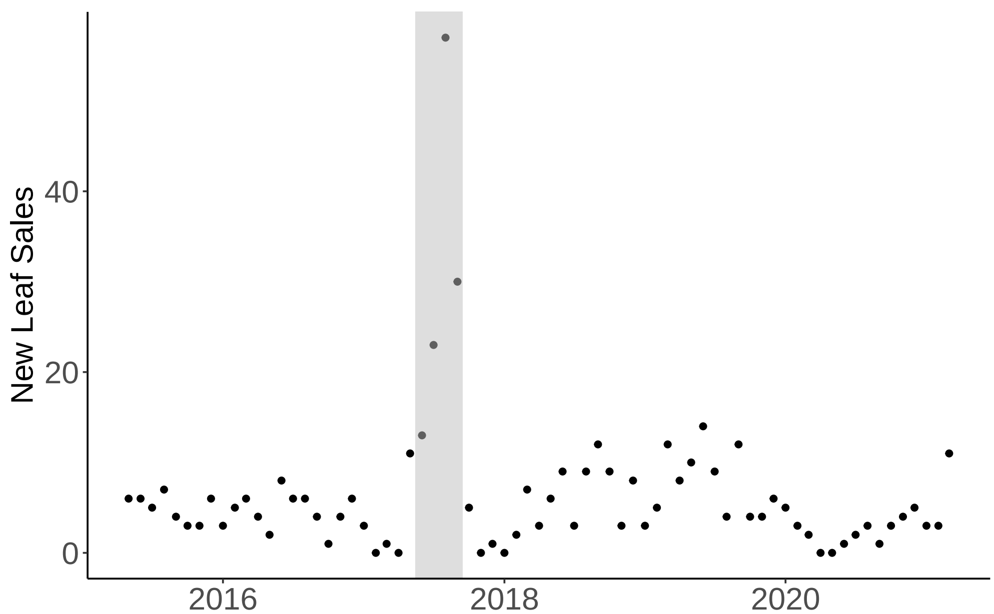
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Lower Bound Elasticity								
With Cannibalization	-8.91	-8.03	-4.45	-4.49	-3.56	-6.02	-2.67	-4.20
Without Cannibalization	-11.14	-10.08	-5.77	-5.82	-4.70	–	–	–
Panel B. Solar-only elasticity (solar share assumption 1)								
With Cannibalization	-23.01	-21.00	-12.77	-12.86	-10.73	-16.37	-8.66	-12.18
Without Cannibalization	-28.15	-25.72	-15.80	-15.91	-13.34	–	–	–
Panel C. Solar-only elasticity (solar share assumption 2)								
With Cannibalization	-13.54	-12.29	-7.19	-7.24	-5.92	-9.42	-4.64	-6.82
Without Cannibalization	-16.73	-15.22	-9.07	-9.14	-7.54	–	–	–

Notes: Elasticities calculated using different measures of the change in quantity. "Lower bound elasticity" assumes that all pre-program sales were made by households that were eligible for the incentive. "Solar-only elasticity" calculates the change in quantity specifically for solar households, by separating out sales to that group. "Solar share assumption 1" calculates the counterfactual sales in the absence of the program by assuming that the share of Leafs purchased by solar households is the share registered to solar households over the 2015 and 2018 model years in the non-anonymous 2019 DMV data. "Solar share proportion 2" uses the share of Leafs registered to solar households for the 2018 model year only. The "with cannibalization" rows adjust program sales based on estimated cannibalization of future Leaf sales in figure 3.2, while the "without cannibalization" columns make no such adjustment. Each column uses a different model from tables 3.3, 3.4, and 3.7 to estimate counterfactual sales without the incentive program: columns (1) and (2) are based on the direct effect with monthly and quarterly fixed effects, respectively; columns (3) through (5) are based on the difference-in-differences specifications that omit the post-treatment period with comparison groups of all non-Leaf EVs, top-selling non-Leaf EVs, and Chevrolet Bolts and Volts; and columns (6) through (8) are based on the difference-in-differences specifications that directly estimate post-treatment cannibalization effects, with comparison groups of all non-Leaf EVs, Chevrolet Bolts and Volts, and non-Tesla EVs.

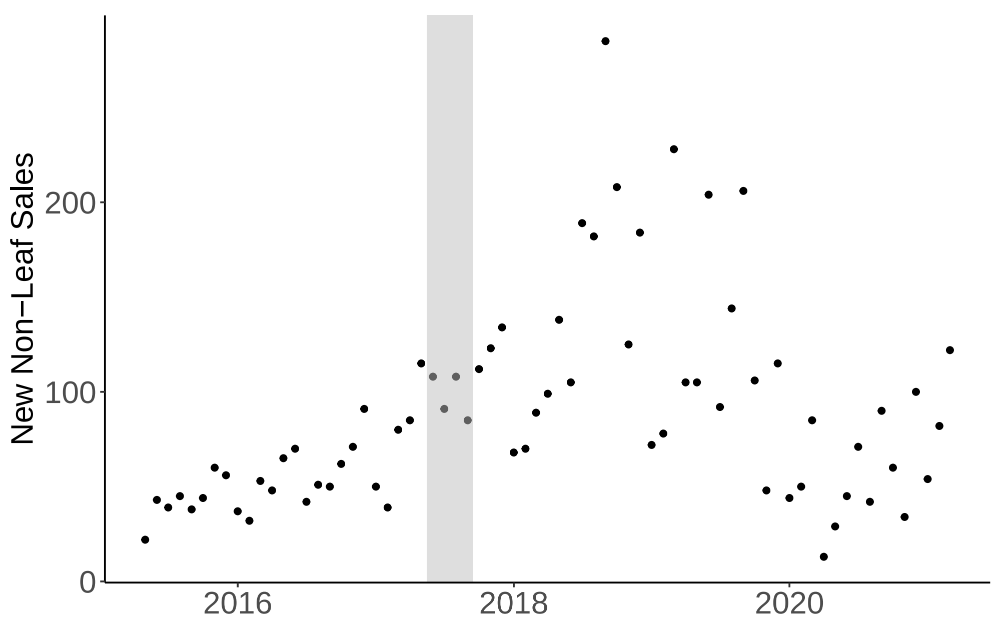
Figures

Figure 3.1: Leaf and non-Leaf sales by month.

(a) Leaf Sales

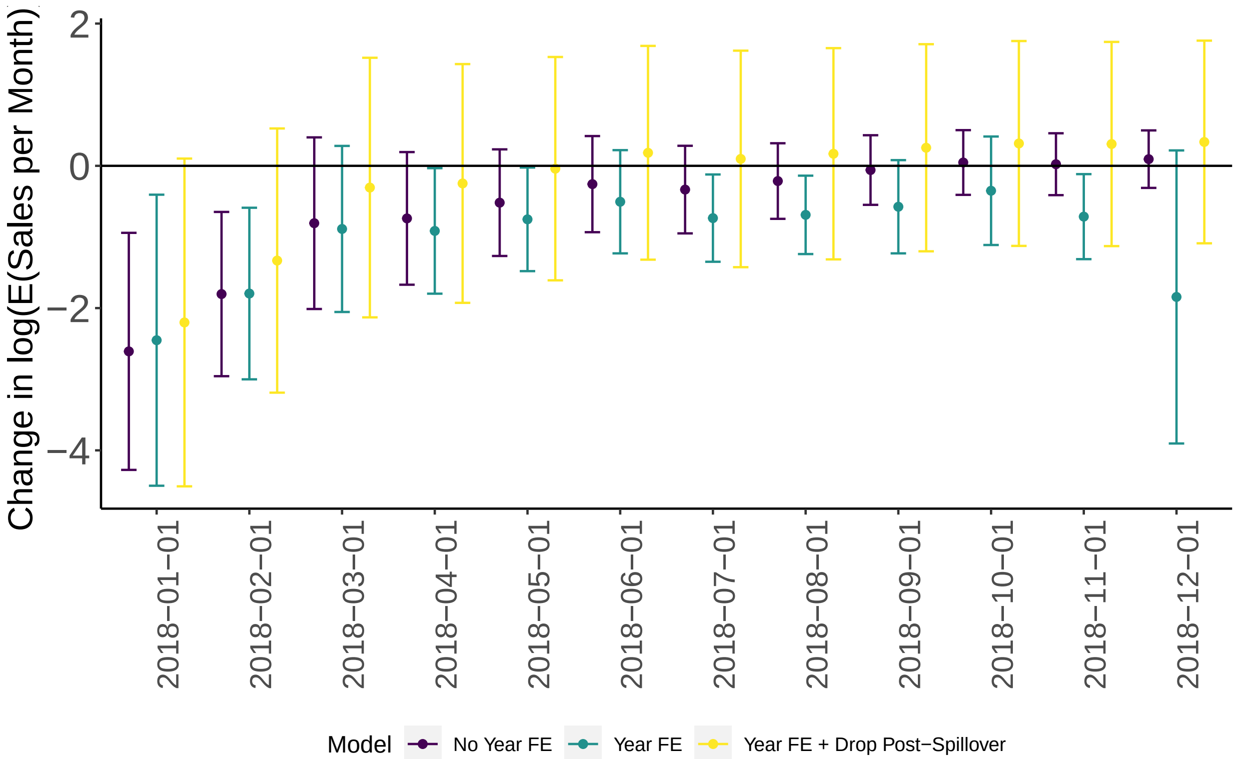


(b) All non-Leaf EV Sales



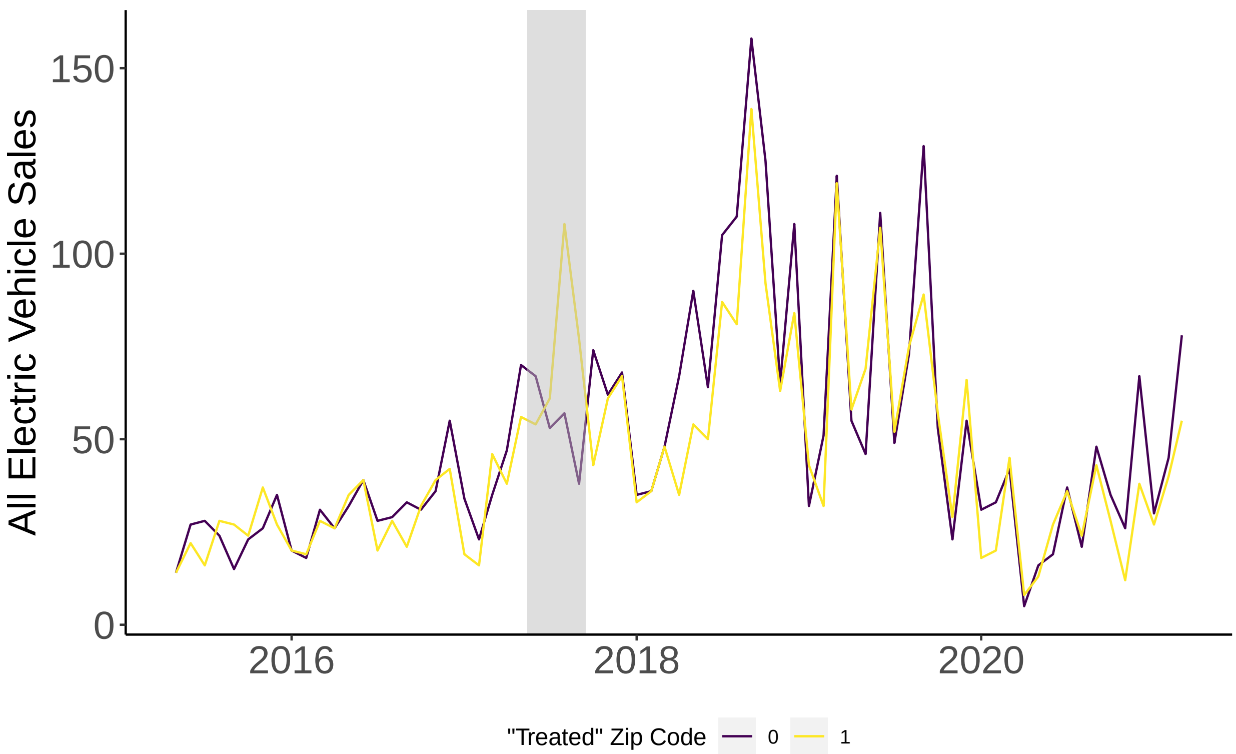
Notes: Figure (a) contains a time series of all Leaf sales in the CHEAPR data, aggregated to the monthly level. Figure (b) contains all non-Leaf electric vehicle sales (including plug-in hybrid electric vehicles). The grey bar indicates the months that the program was active.

Figure 3.2: Post-treatment harvesting effects on Leaf sales



Notes: Each point is the coefficient estimate for a post-program indicator added to equation 3.1 with the 95% confidence interval included. The estimates for each month correspond to a model in which the "post-treatment" effect continues through that month (i.e., the coefficients for 2018-01-01 estimate that the harvesting effects persist from November 2017 until January 2018, and the coefficients capture the effect per month). Model 1 includes all available CHEAPR data, including several years post treatment. Model 2 includes the same data but drops year fixed effects. Model 3 drops all months after the harvesting period is determined to end (and, in order to estimate the spillover into 2018, treats 2018 as a continuation of 2017)

Figure 3.3: Sales of EVs in "treated" and "untreated" zip codes.



Notes: Total EV sales grouped by "treated" and "untreated" zip codes. "Treated" zip codes here refer to those zip codes in which a Leaf purchase was made during the incentive program. There were 81 treated zip codes compared to 183 untreated zip codes.

Appendices

Appendix C

C.1 Tables

Table C.1.1: Direct Effects on Sales, Linear Model

	New Vehicles Purchased Per Month				
	(1)	(2)	(3)	(4)	(5)
Program	25.773***	28.317***	8.932	5.955	4.057
	(8.800)	(7.678)	(12.163)	(12.239)	(13.318)
Program × Leaf			16.841	19.818	21.716
			(15.012)	(15.074)	(15.963)
Observations	29	81	58	58	58

*p<0.1; **p<0.05; ***p<0.01

Notes: This table is analogous to table 3.3, but using OLS instead of a Poisson regression. The dependent variable is new vehicles purchased/registered by month in a Poisson regression, and coefficients can thus be interpreted as the number of new vehicles per month. Columns (1) and (2) estimate equation 3.1 on only Leafs, where column (1) uses CHEAPR data and column (2) uses the DMV registration data. Columns (3) through (5) estimate the difference-in-differences equation 3.2, where Leaf sales are compared to other comparable vehicles. In column (3), the comparison group is all electric vehicles in the data. In column (4), the comparison group is a subset of the top-selling electric vehicles in the data, and in column (5), the comparison group is Chevrolet Bolts and Volts. Columns (3) through (5) use CHEAPR application data. All specifications have yearly and monthly fixed effects, and in columns (3) through (5), the time fixed effects are interacted with Leaf indicators.

Table C.1.2: Direct Effects on Sales, Quarterly FEs

	New Vehicles Purchased Per Month				
	(1)	(2)	(3)	(4)	(5)
Program	24.216***	27.325***	13.937	10.932	6.703
	(9.336)	(8.480)	(11.507)	(11.918)	(13.119)
Program × Leaf			10.279	13.284	17.512
			(14.818)	(15.139)	(16.102)
Observations	29	81	58	58	58

*p<0.1; **p<0.05; ***p<0.01

Notes: This table is analogous to table 3.4, but using OLS instead of a Poisson regression. The dependent variable is new vehicles purchased/registered by month in a Poisson regression, and coefficients can thus be interpreted as the number of new vehicles per month. Columns (1) and (2) estimate equation 3.1 on only Leafs, where column (1) uses CHEAPR data and column (2) uses the DMV registration data. Columns (3) through (5) estimate the difference-in-differences equation 3.2, where Leaf sales are compared to other comparable vehicles. In column (3), the comparison group is all electric vehicles in the data. In column (4), the comparison group is a subset of the top-selling electric vehicles in the data, and in column (5), the comparison group is Chevrolet Bolts and Volts. Columns (3) through (5) use CHEAPR application data. All specifications have yearly and quarterly fixed effects, and in columns (3) through (5), the time fixed effects are interacted with Leaf indicators.

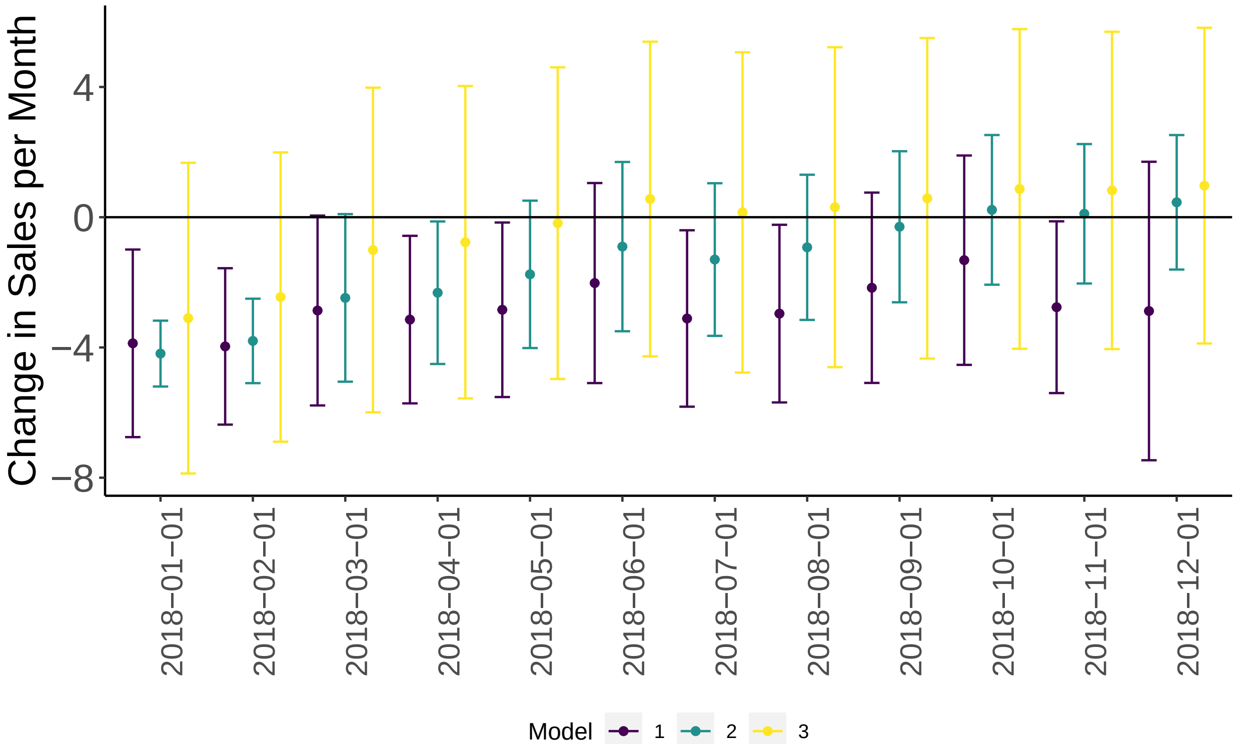
Table C.1.3: Zip Code Characteristics

		"Treated" Zip Codes	"Untreated" Zip Codes
Count		81	183
Average EV Sales	2015	2.407	1.049
	2016	4.309	2.066
Average Leaf Sales	2015	0.025	0.016
	2016	0.031	0.011
Average Solar Households		151.203	79

Notes: Characteristics of "treated" and "untreated" zip codes, where "treated" zip codes here refer to those zip codes in which a Leaf purchase was made during the incentive program. Average EV sales and Leaf sales come from the CHEAPR data, and the average solar households includes all households with solar, including those that were not part of the initial email campaign.

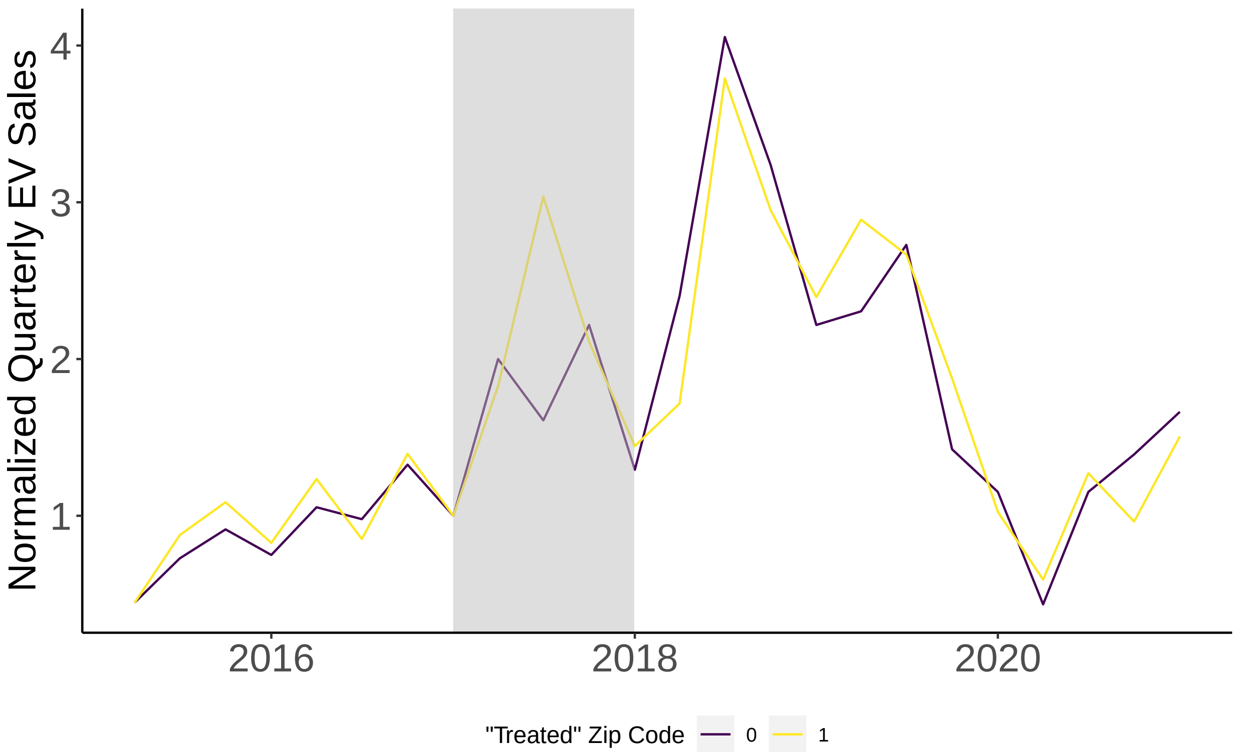
C.2 Figures

Figure C.2.1: Spillover effects from linear model.



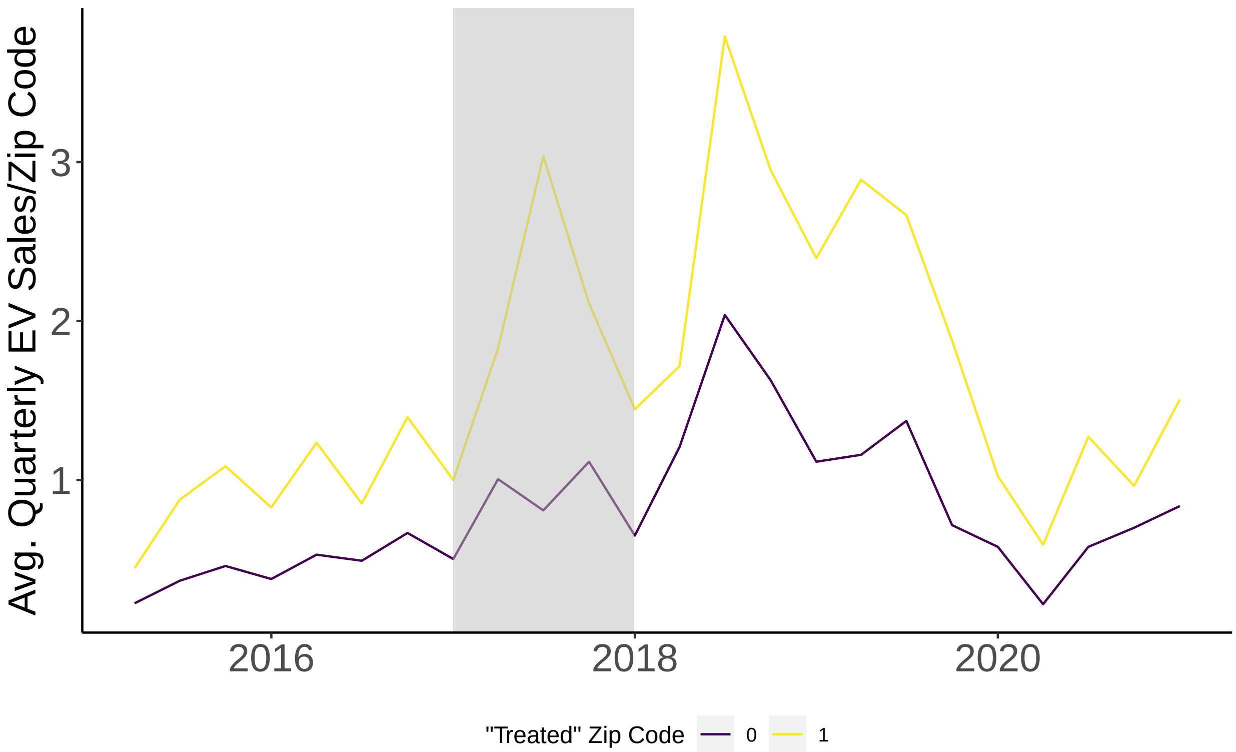
Notes: This figure is analogous to figure 3.2 but estimated with OLS. Each point is the coefficient estimate for a post-program indicator added to equation 3.1 with the 95% confidence interval included and in the OLS case, can be interpreted as the reduction in Leaf sales/month from harvesting effects. The estimates for each month correspond to a model in which the "post-treatment" effect continues through that month (i.e., the coefficients for 2018-01-01 estimate that the harvesting effects persist from November 2017 until January 2018, and the coefficients capture the effect per month). Model 1 includes all available CHEAPR data, including several years post treatment. Model 2 includes the same data but drops year fixed effects. Model 3 drops all months after the harvesting period is determined to end (and, in order to estimate the spillover into 2018, treats 2018 as a continuation of 2017)

Figure C.2.2: Normalized quarterly EV sales in "treated" and "untreated" zip codes.



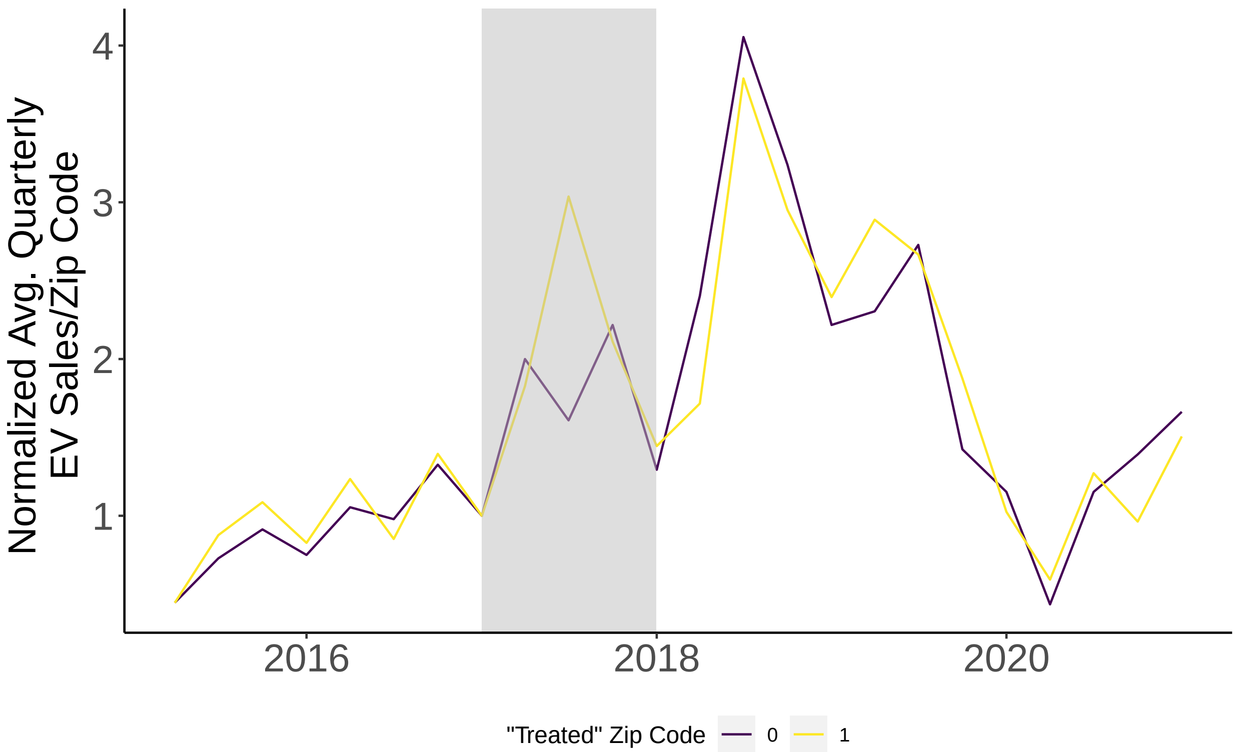
Notes: Leaf sales grouped by "treated" and "untreated" zip codes relative to sales in Q1 of 2017 before the incentive program was available. "Treated" zip codes here refer to those zip codes in which a Leaf purchase was made during the incentive program. There were 81 treated zip codes compared to 183 untreated zip codes.

Figure C.2.3: Average quarterly EV sales in "treated" and "untreated" zip codes.



Notes: Average quarterly Leaf sales per zip code, grouped by "treated" and "untreated" zip codes. "Treated" zip codes here refer to those zip codes in which a Leaf purchase was made during the incentive program. There were 81 treated zip codes compared to 183 untreated zip codes.

Figure C.2.4: Normalized average quarterly EV sales in "treated" and "untreated" zip codes.



Notes: Average quarterly Leaf sales per zip code, grouped by "treated" and "untreated" zip codes relative to sales in Q1 of 2017 before the incentive program was available. "Treated" zip codes here refer to those zip codes in which a Leaf purchase was made during the incentive program. There were 81 treated zip codes compared to 183 untreated zip codes.

C.3 Survey

This section contains a list of the questions included in the survey administered by the Connecticut Green Bank. Everyone who wanted to receive the subsidy was required to complete the survey.

1. Name
2. Address (Street; City; State/Province; ZIP/Postal Code; Country)
3. Email
4. Phone
5. Number of vehicles in household
6. How many miles is your daily commute (one way)?
   (a) 0-5
   (b) 6-10
   (c) 11-15
   (d) 16-20
   (e) 21-30
   (f) 31-40
   (g) 40+
7. Do you live in...
   (a) Single-family housing
   (b) Multi-family housing
   (c) Other
8. Were you considering purchasing a new car or an EV prior to hearing about this program?
   (a) Already considering a new car
   (b) Already considering an EV
   (c) Was not thinking of buying a new car

9. If you already were considering getting a different vehicle, what would the make and model have been?
10. Will you be using the Leaf to replace another vehicle?
11. If yes above, please enter make, model, and year
12. Will this be your first plug-in electric vehicle?
13. How many members of your family will be driving this vehicle?
14. Are you combining this deal with an existing offer from a solar installer?
15. Do you have solar power at home?
16. If not, are you interested in getting solar power at home?
17. Do you plan to purchase or finance a home EV charging station?
18. Please rank which of the following types of EV charging are most important to you.
    (a) Ability to charge at home
    (b) Charging at your workplace
    (c) Charging at major recreational destinations
    (d) Fast charging along major highways
19. Is electric vehicle charging available at your workplace?
20. How many times during a calendar year do you make a trip of 100 miles or more?
21. Household annual income
    (a) $0 - $50,000
    (b) $50,001 - $75,000
    (c) $75,001 - $100,000
    (d) $100,001 - $150,000
    (e) $150,001+
22. How much do you trust car dealerships as a source of information on EVs? (1-5)
23. How much do you trust local government as a source of information on EVs? (1-5)

24. How much do you trust state government as a source of information on EVs? (1-5)

25. How much do you trust electric utilities (Eversource, UI/Avangrid, etc.) as a source of information on EVs? (1-5)

26. How much do you trust environmental organizations as a source of information on EVs? (1-5)

C.4 Matching Individual Purchases

Because Nissan did not share final identified purchase data, we use the data available from the DMV to predict which individuals who completed the survey ultimately followed through on their purchases. This is done in several stages. First, survey data is merged with the DMV vehicle registration data at the zip code level. If no purchases of a 2016 or 2017 Nissan Leaf were made during the program period in an individual's zip code, the individual is determined to not have followed through. Of the 301 survey completers, 124 live in zip codes where no Leafs were purchased. For the 177 remaining survey completers, the timing of the vehicle registration was compared with the timing of survey completion: if there were no 2016 or 2017 Leafs registered in an individual's zip code *after* they completed the survey, the individual is determined to not have followed through. A further 33 individuals are removed on this basis, leaving 144 possible purchases through the program (called "maybes"). Finally, we compare survey completers with the non-anonymous but incomplete vehicle registrations from 2019. Survey completers are matched with Nissan Leaf registrations by name and address. Twenty-five survey completers definitively had a 2016 or 2017 Nissan Leaf registered to their name in 2019, 6 of whom were identified as not following through (all 6 of these were fairly late survey completers). A further 112 survey households were matched to other vehicles in the registration data, suggesting that they either did not make a purchase or that they had gotten rid of their new Leaf by 2019. For most analyses, households are considered to have followed through on their purchase if they were

1. In the initial set of "maybes" and not in the set of households registered to a non-Leaf vehicle in the 2019 data (92 individuals)

2. Registered to a 2016 or 2017 Leaf in the 2019 data (6 individuals)

That is, we identify 98 households as following through on their purchase, though 103 purchases were made using the program discount. The gap is due to the fact that the anonymous DMV data is missing some registrations (i.e., false negatives in the initial "maybe" households) and/or false positives in matching the initial "maybe" households with non-Leaf vehicles in the 2019 non-anonymous DMV data.