Optimal timing of electric vehicle subsidies

Qingran Li

Abstract

There is geographic variation in the environmental damages from electric vehicles (EVs) relative to gasoline internal combustion engines (ICEs) because power grids have different mixes of generation capacity. On the surface, this cautions against subsidizing EVs before the grid is sufficiently decarbonized. However, in this paper I show that EV subsidies are best introduced *before* the time when EVs become cleaner than gasoline ICEs for two reasons related to the dynamics of decarbonization and technology diffusion. First, because EVs are durable goods, their lifetime damages can be less than those of gasoline ICEs even if the static emission-per-mile comparison disfavors EV adoption at the time of the subsidy. More importantly, policies boosting technology diffusion have positive spillover effects. As marginal emissions of the power grid decline in the long run, more EV adoption produces environmental gains in the process. I simulate an empirically calibrated EV diffusion model, calculate the discounted lifetime damages of EVs versus gasoline ICEs, and examine EV subsidies enacted in different years. Even when EVs are initially more polluting than ICEs, I find that the environmental return from the policy-induced EV diffusion process decreases when governments delay intervention.

Keywords: environmental externalities, technology diffusion, electric vehicle

JEL Codes: D12, D62, H23, L62, O33, Q53, Q54, Q55

1 Introduction

Transportation generated the largest portion (28%) of total U.S. greenhouse gas (GHG) emissions in 2018,[1] and many environmentalists advocate for full electrification of the U.S. vehicle fleet (Fox-Penner et al., 2018). As decarbonization of the grid proceeds, there are indeed significant environmental benefits from electrifying the transportation sector (Zhang and Fujimori, 2020). In U.S. and elsewhere around the world, subsidies to electrify the transportation sector are intended to be second-best policies to abate emissions.[2] However, both internal combustion engines (ICEs) and electric vehicles (EVs) contribute to carbon emissions and local pollution. EVs have zero tailpipe emissions if running just on batteries. But EV demand for electricity means that fuel combustion actually takes place in power plants, and the environmental impact from driving "zero-emission" EVs depends on the generation mix.

Because an EV's emission intensity is grid dependent, the environmental benefits of EVs are not distributed uniformly across geographic regions (Holland et al., 2016). EVs powered by coal fire plants emit more GHGs and local pollutants than ICEs, while those powered by low-carbon power generations are considerably cleaner.[3] The emission-per-mile metric for EVs depends on the marginal generator dispatched, which changes across space as well as across hours within a day. Holland et al. (2020) show that the pace of decarbonization also varies geographically, that is, marginal emissions in different grid regions decline at different rates. Hence, expanding the EV fleet where EVs emit more pollutants than ICE

[1] Fast Facts on Transportation Greenhouse Gas Emissions. `https://www.epa.gov/greenvehicles/fast-facts-transportation-greenhouse-gas-emissions` (accessed September 30, 2020)

[2] The first-best policy is to directly tax emission at the value of its marginal social damage (Pigou, 1920; Newell and Pizer, 2008). Besides the challenge to determine the value of the emission tax, the pre-existing distortions in the economy will change the welfare impacts of a regulatory tax and thus deviating market outcome from the first best. Also due to the fact that many polluting activities are not associated with market transactions and difficult to be taxed, the subsidy for clean alternatives is designed as part of the policy instrument in a second-best world (Fullerton and Wolverton, 2005).

[3] Besides the GHG emission, EVs and gasoline ICEs also differ in emissions of local pollutants which influence social welfare via health co-benefits (Holland et al., 2016, 2018).

cars could contribute to environmental damages, whereas in regions where air pollution from electricity generation is declining rapidly, replacing ICE cars with EVs sooner could lower aggregate emissions from the transportation sector. The findings on geographic variation in EV environmental impacts collectively caution against substantial EV subsidies at the national, state, and local level, especially when driving/charging EVs on a carbon-intensive power grid emits more pollutants than ICE cars.

Despite the fact that EV is expected to be a low-emission technology in the long run as emission intensity of the power sector is declining in the U.S. (Schivley et al., 2018; Holland et al., 2020) and globally (Ang and Su, 2016; Peters et al., 2017),[4] recent studies have identified uncertainties on EV's near-term environmental impact compared with conventional ICE vehicles. First, the spatial variation of EV emissions is found at both the regional level (Graff Zivin et al., 2014; Holland et al., 2016, 2018; Weis et al., 2016) and the national level. Figure 1 presents a ranking of countries by carbon emission rate from driving EVs. The carbon emissions of EVs can be four times greater in countries with coal-based generations than that in those with low-carbon generation profiles and are much higher than tailpipe emission from a typical ICE passenger vehicle.[5] Second, charging behaviors of EV drivers and efficiency of vehicle models can shift an EV's emission footprint calculations (Holland et al., 2018; Tamayao et al., 2015). Third, consumer choices between vehicle models affect the net environmental gains of EV adoption. Studies find that a newly sold EV is more likely to replace a relatively fuel-efficient gasoline ICE (Xing et al., 2019; Muehlegger and Rapson, 2020). This suggests that high-emission cars are less likely to be retired, thus shrinking the net environmental savings from EV adoption. This stream of empirical evidence makes it

[4]The climate uncertainty for 1.5 degrees Celsius warming relative to the pre-industrial level requires ambitious mitigation actions, which involve emission reductions beginning immediately and reaching net zero CO2 emissions by 2055 (Allen et al., 2018). Given the power sector is a major emission contributor (EIA, 2019), it is reasonable to assume a continuous grid decarbonization trend under the ambitious goal on combating climate change. In absence of the decarbonization efforts, electrification and adoption of EVs would unlikely lead to emission abatement in the transportation sector.

[5]Greenhouse Gas Emissions from a Typical Passenger Vehicle. https://www.epa.gov/greenvehicles/greenhouse-gas-emissions-typical-passenger-vehicle (accessed September 30, 2020).

tempting to conclude that subsidies and other EV incentives should be postponed until EVs are cleaner than ICEs in a static sense, that is, the net environmental gain from replacing an ICE with an EV is positive in the adoption year.

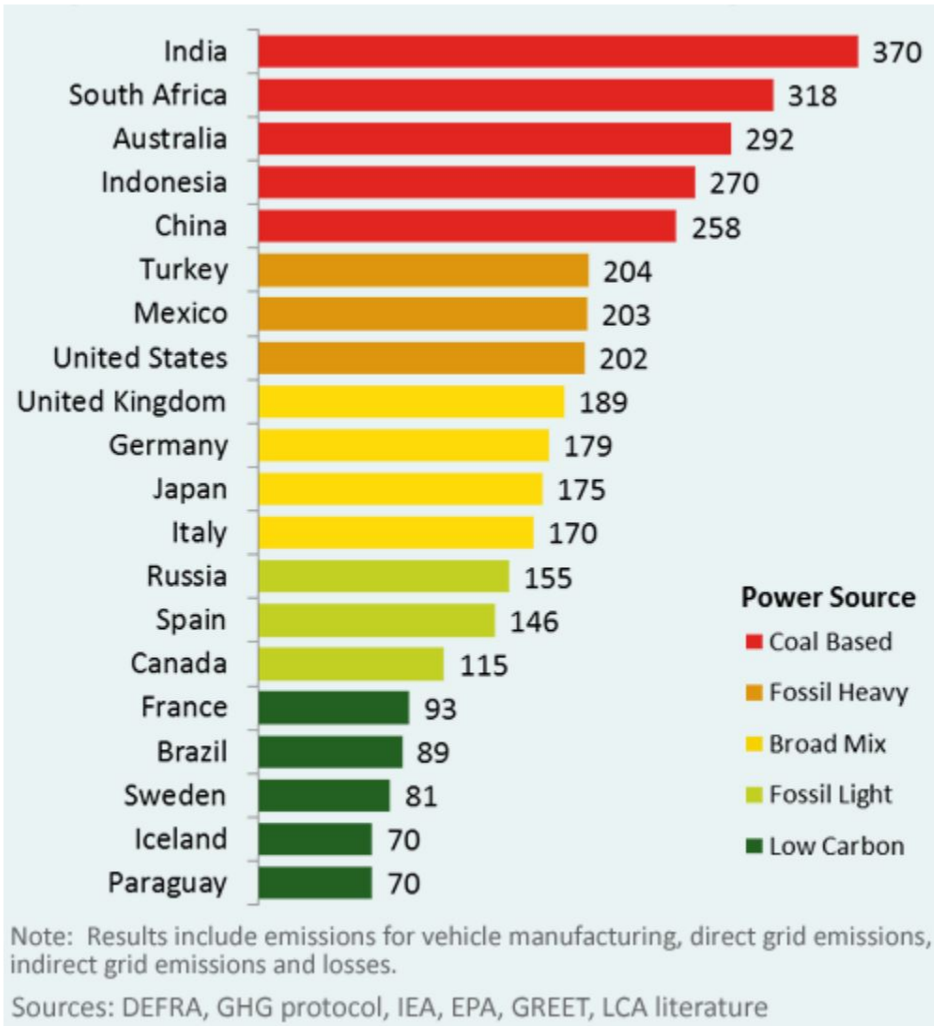

Figure 1: Carbon emissions from electric vehicles by country (in g CO2e/km) depend largely on the generation mix. Estimated by US EPA, tailpipe GHG emission from the average passenger vehicle is about 251 grams CO2 per km (404 grams per mile).

The conclusion to postpone subsidies is based on short-run environmental externalities that ignore EV adoption dynamics. EVs are durable goods with batteries lasting between 10 and 20 years before replacement.[6] Hence, an EV adopted in a period when its emission-

[6] All about electric car batteries. https://www.edfenergy.com/electric-cars/batteries (accessed November 11, 2020).

per-mile metric is higher than that of ICE may yet produce environmental savings over its lifetime as grid emission intensity decreases. The lifetime emissions of an EV is therefore a function of the entry-and-exit schedule of the power plants. In the past, these changes in the power mix tended to reduce average and marginal emissions as natural gas plants substituted for coal plants amidst a decline in natural gas prices and renewable power capacity increased (Holland et al., 2020). How this process is going to proceed in the future determines the time when lifetime damage of an EV will fall below that of an ICE car. In addition to the dynamics of lifetime damages, there are adoption dynamics that can push the optimal timing of the EV subsidy to be before EV constitutes a clean driving technology. I discuss these adoption dynamics in the paragraph below.

Low diffusion rates are observed when technologies are characterized by dynamic increasing returns, i.e. users will be better off the more other people adopt the technology. Various reasons can explain the dynamic increasing returns: learning-by-doing that drives costs down (van Benthem et al., 2008), word-of-mouth effects, knowledge spillover, and network dependency (Beck et al., 2008; Sierzchula et al., 2014; Shriver, 2015). The literature on innovation and technology models an S-shaped diffusion path for innovative consumer durable goods, in which the natural rate of technology diffusion starts slow, increases over time, and asymptotes toward complete diffusion (Bass, 1969; Baptista, 1999; Geroski, 2000). In practice, EVs have experienced a slow diffusion process.[7] This is due to higher prices than alternative ICEs and the critical constraints imposed by inadequate and incompatibility of charging facilities (Greaker and Midttømme, 2016; Li et al., 2017; Zhou and Li, 2018; Li, 2019; Springel, 2020). The slow EV diffusion makes it difficult to synchronize electrification of the transportation sector with the decarbonizing transition of the power sector. As a result, regulators should time the subsidy before EVs are cleaner than ICEs.

[7]The sales of electric vehicles were minimal before the Energy Department started to invest in a nationwide charging infrastructure in 2009. With the first commercially available plug-in hybrid (PHEV) for sale in 2010 in the U.S. market, the observed diffusion rate of EV technology is low and EVs are unlikely to be adopted by all potential buyers in a few decades.

Jaffe et al. (2002) argued that the factors discussed above resulting in low adoption of clean technologies are market failures and named them "adoption externalities." The market failure from environmental externalities can interact with the market failures associated with adoption externalities, which reinforces the rationale for policy interventions to target both types of market failures (Jaffe et al., 2002, 2005). Given EVs are grid-dependent technologies, the adoption of EVs will change the environmental benefit/cost calculus with compounding effects over time. EV policies are therefore not only technology policies but also environmental policies. Designing the efficient EV policies requires an integrated analysis of the dynamic interaction between pollution reduction and technology diffusion.

Hence, this paper examines the optimal EV subsidy timing with a framework that integrates the dynamics of two externalities — environmental and adoption. I model a social planner's decision about timing of a one-year subsidy regime with the objective of maximizing environmental return of the policy subject to an exogenous decline in pollution intensity of the power grid. This paper bridges the EV literature on environmental externalities and the literature on technology diffusion. It also has contributes to the policy design literature. Previous studies evaluating policies to incentivize adoption of clean technologies find both positive environmental externalities and positive adoption externalities (Kalish and Lilien, 1983; Jaffe and Stavins, 1994; Kverndokk and Rosendahl, 2007; van Benthem et al., 2008; Langer and Lemoine, 2018). However, policy analyses are sparse for technologies like EVs for which the two types of externalities are likely to have opposite signs initially (when EVs are more polluting than ICEs) while the environmental externality turns positive as the trend of grid decarbonization continues. Instead, discussions on EV policy designs are mostly focused on incentivizing cost-efficient adoptions (Li et al., 2017; Zhou and Li, 2018; Li, 2019; Springel, 2020). Analyses that only account for the static net environmental damages of EVs based on adoption year are likely to bias policy prescriptions towards limiting diffusion before EVs generate positive marginal environmental benefits.

The paper proceeds in Section 2 by presenting the analytical solution to the optimal timing of EV subsidies in a simple model. In Section 3, I calibrate key parameters empirically using estimates in Li et al. (2017), simulate the business-as-usual EV diffusion path assuming no subsidy payments (i.e. the baseline scenario), and simulate policy-induced diffusion paths. I assume that the EV subsidy program has a fixed budget (present value in 2010 dollars), and the regulator chooses a year after 2010 to rebate the subsidies to consumers who purchase EVs in the policy year. Section 4 presents the results of vehicle lifetime damages. The lifetime environmental damages of EVs fall below that of ICEs at different years across regions within the United States. My findings contrast with the SERC Reliability Corporation region[8] in which the net lifetime environmental damage of replacing an ICE car with EV was estimated to be negative until the year 2017. Section 5 presents the policy simulation results, where I show that, by integrating the adoption externalities in EV diffusion, implementing the EV subsidy much earlier than 2017 in Georgia (located in SERC) maximizes the environmental return of this state policy intervention. Although there would be immediate losses from stimulating adoptions of less clean EVs in years before 2017, the future environmental gains amassed along the policy-induced diffusion path largely outweigh the losses. Simulation assuming the average generation mix of the U.S. reiterates the finding that the environmental return associated with EV diffusion decreases as the subsidy is postponed. Section 6 discusses implications of the findings and other potential applications of the model.

2 Solution to a Simple Model

In this section a simple theoretical model is set up in which a social planner optimizes the timing of the policy intervention to EV adoption with the objective of minimizing total emissions. By solving this optimization problem, I focus on answering two questions – "Should

[8]The North American Electric Reliability Corporation divided its territory into eight NERC reliability regions. SERC is one of the NERC regions within the Eastern Interconnection and covers portions of Virginia, Oklahoma, Illinois, Kentucky, Tennessee and Louisiana and the entire areas of Georgia, North Carolina, South Carolina, Mississippi and Alabama (see Figure C.2).

EV be subsidized before it becomes cleaner than a gasoline vehicle?" and "if so, which factor influences the timing of such intervention?". Two dynamic processes are modeled in this framework: the diffusion of electric vehicles in the market and emission factor of a decarbonizing power grid.

Diffusion of EV The transportation sector is assumed to have two type of vehicles – electric vehicles charged by plugging into the grid and gasoline vehicles with internal combustion engines. The market size of automobiles is normalized to be one and fixed overtime. Without any policy intervention, the business-as-usual (BAU) diffusion process of electric vehicle is modeled by an epidemic model (Stoneman, 1983):

$$Y(t) = \frac{1}{1 + \phi e^{-\beta t}}, \quad \phi = \frac{1 - Y_0}{Y_0}, \tag{1}$$

where $Y(t)$ is the installed stock of EV by time t, and Y_0 is the status quo market penetration rate of EV. Parameter β controls the rate of diffusion and $\beta > 0$. Equation (1) generates an S-shaped diffusion curve for EVs. The time point when EV will take 50 percent of the transportation fleet is $ln\phi/\beta$.

The regulator launches a single-period subsidy program to stimulate EV adoption at time x, which is assumed to temporally increase the installed EV base by s. This thus leads to a divergence path $F(t, x)$ from the BAU diffusion process beyond the intervention time point $t \geq x$:

$$F(t, x) = \frac{1}{1 + \phi_x e^{-\beta(t-x)}}, \quad \phi_x = \frac{1 - Y(x) - s}{Y(x) + s}. \tag{2}$$

Figure 2 illustrates a numerical example of the policy-induced diffusion process.

In Appendix A.1, I show that the partial derivative of $F(t, x)$ with respect to the policy timing x is negative, i.e. $\frac{\partial F(t,x)}{\partial x} < 0$, which implies the earlier the policy (if regulators decide to intervene when market share of EV is below 50%), the faster it drives the EV diffusion to a higher penetration level.

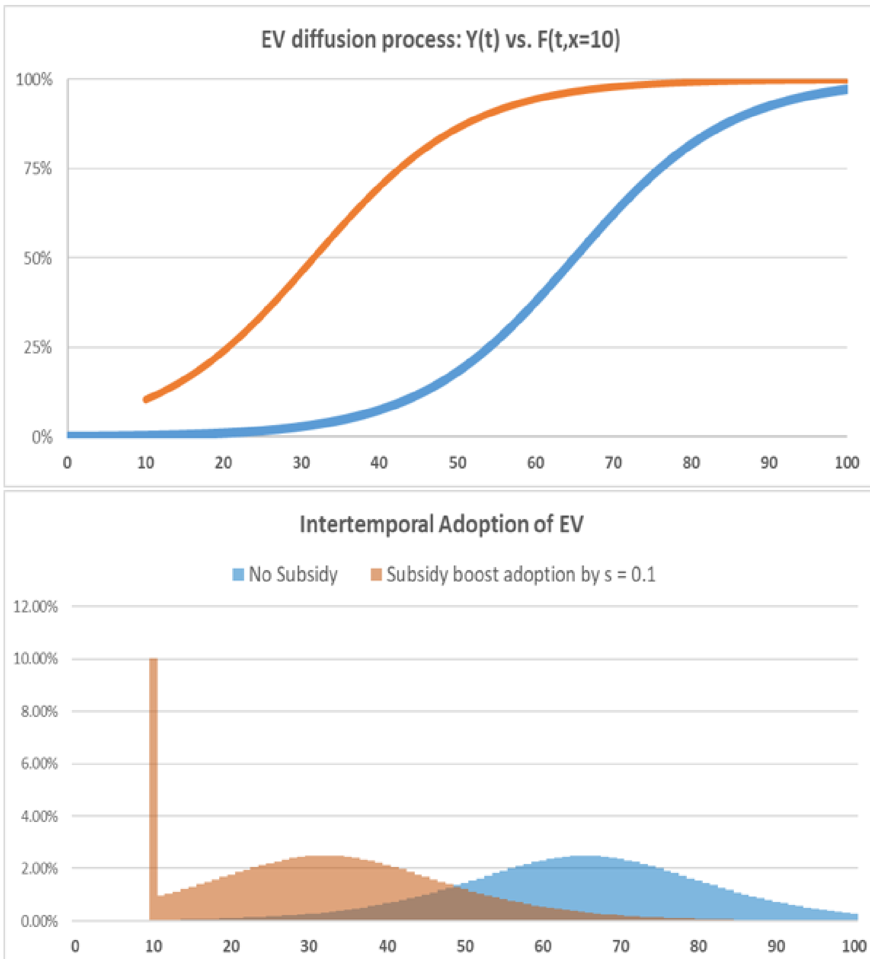

Figure 2: A numerical illustration of business-as-usual diffusion path $Y(t)$ and policy-intervened diffusion $F(t, x)$, where $x = 10$, $s = 10\%$

Decarbonization of the grid The emission rate of gasoline vehicles is denoted by a constant scalar δ_g. The process of grid decarbonization determines the emission rate of electric vehicles $\delta_e(t)$, which is assumed to be exogenous and independent of EV adoption:

$$\delta_e(t) = \delta_1 + (\delta_0 - \delta_1)e^{-\theta t}. \tag{3}$$

Annual emissions from driving an electric vehicle decreases over time from δ_0 to much lower level δ_1 when the grid decarbonization process completes. The θ controls the speed of this decarbonization process, and $\theta > 0$. Without losing generality of the conclusion, I let $\delta_1 = 0$, which implies that generation mix is carbon neutral in the long run. The emission rate of EV then becomes:

$$\delta_e(t) = \delta_0 e^{-\theta t}. \tag{4}$$

According to the set-up of this model, the current power grid does not make EV a clean product[9], $\delta_e(0) = \delta_0 > \delta_g$. From equation (3) I get that EV becomes cleaner than gasoline vehicles by the time point τ, i.e. $\delta_e(\tau) = \delta_g$, where $\tau = \frac{1}{\theta} \cdot ln\left(\frac{\delta_0}{\delta_g}\right)$.

Social planner's problem With the knowledge of the two processes described above, the social planner determines the optimal timing of EV subsidy x^* that minimizes the total emission over a defined time horizon T:

$$x^* = \underset{0 \le x \le T}{\arg\min}\, E(x), \tag{5}$$

[9]Otherwise, the environmental externality argument would work the same direction as the adoption externality on optimal timing of subsidies.

where $E(x)$ is the sum of emissions from electric vehicles and gasoline vehicles before and after policy intervention.

$$E(x) = \int_0^x [Y(t)\delta_e(t) + (1 - Y(t))\delta_g]dt + \int_x^T [F(t,x)\delta_e(t) + (1 - F(t,x))\delta_g]dt \tag{6}$$

If the regulator subsidizes EV only when it becomes a cleaner good than gasoline vehicle, i.e. $x = \tau$, then the first-order derivative in (7) indicates that optimal timing for minimizing emission should actually be earlier, $x^* < \tau$. Details of this derivation are shown in Appendix A.2.

$$\frac{dE(x)}{dx}|_{x=\tau} = \int_\tau^T \left[(\delta_e(t) - \delta_g) * \frac{\partial F(t,x)}{\partial x}\right] dt > 0 \tag{7}$$

I further consider the influence of EV subsidy to the optimal choice of timing, i.e. how early should regulators start the policy if it works slowly to have impact on diffusion, and vise versa. Examining the sign of the first-order-derivative $dE(x)/dx$ assuming policy starts earliest in (8), I find that timing of the subsidy depends on how effective this policy is. Details of the derivation are shown in Appendix A.2.

$$\frac{dE(x)}{dx}|_{x=0} = \left(\frac{s(2Y_0 + s - 1)}{(1 - Y_0 - s)(Y_0 + s)}\right)\left(\int_{t=0}^{t=T} (\delta_e(t) - \delta_g)dF(t,0)\right) - (\delta_0 - \delta_g)s \tag{8}$$

For the current status quo where adoption of EV is very low, $Y_0 = 0$ is assumed to simplify the express in (8) without losing generality. The above equation then becomes:

$$\frac{dE(x)}{dx}|_{x=0} = -\left(\int_{t=0}^{t=T} (\delta_e(t) - \delta_g)dF(t,0)\right) - (\delta_0 - \delta_g)s. \tag{9}$$

The sign of equation (9) is determined by two components: $\int_{t=0}^{t=T}(\delta_e(t) - \delta_g)dF(t,0)$ represents the emission changes from a diverging diffusion after implementation of the policy, and $(\delta_0 - \delta_g)s$ is the increased emissions due to replacing s more ICE cars with EVs. In our model for T sufficiently large, the EV fleet share $F(t,0)$ increases from s to 1, and the emission rate $\delta_e(t)$ decreases exponentially from δ_0 to a level below δ_g for time periods beyond τ with $\tau << T$. This suggests that in the long run $-\left(\int_{t=0}^{t=T}(\delta_e(t)-\delta_g)dF(t,0)\right) > 0$, implying a net reduction of emissions from the diffusion spillover. By assumption, EV has a higher emission rate than an ICE car, $\delta_0 - \delta_g > 0$. Hence, the sign of (9) is determined by the relative magnitude of the two components:

$$\frac{dE(x)}{dx}|_{x=0} > 0 \text{ for small s, and } \quad \frac{dE(x)}{dx}|_{x=0} < 0 \text{ for large s.} \tag{10}$$

For a policy instrument whose immediate effect is small on EV adoption, regulators should introduce it earlier. Because the environmental gains from a cleaner fleet in the long run will outweigh the immediate loss of subsidizing dirtier EV cars in the beginning. On the other hand, a highly effective EV policy should be postponed so that the negative environmental externalities from replacing cleaner ICE cars with dirtier EVs in earlier years do not trade off too much of the positive adoption externalities.

To reiterate the conclusions from analyzing the simple model, I conduct a numerical simulation, the result of which is shown in Figure 3. Parameter values and descriptions of the simulation are documented in Appendix B. Figure 3a presents the aggregated emission of 100 years from all vehicles and shows that though EVs are cleaner than ICE cars after year 30, the optimal timing of this policy stimulus is year 10. Figure 3b illustrates that the optimal timing shifts earlier after tuning down the effect of the EV policy by 8%.

3 Diffusion Model of Electric Vehicles

The empirical framework of the EV diffusion model is borrowed from Li et al. (2017), which specifies the two equations of EV demand and charging station deployment:

$$ln(q_{mt}) = \beta_1 ln(N_{mt}) + \beta_2 ln(p_{mt}) + \beta_3 x_{mt}, \tag{11}$$

$$ln(N_{mt}) = \gamma_1 ln(Q_{mt}) + \gamma_2 z_{mt}. \tag{12}$$

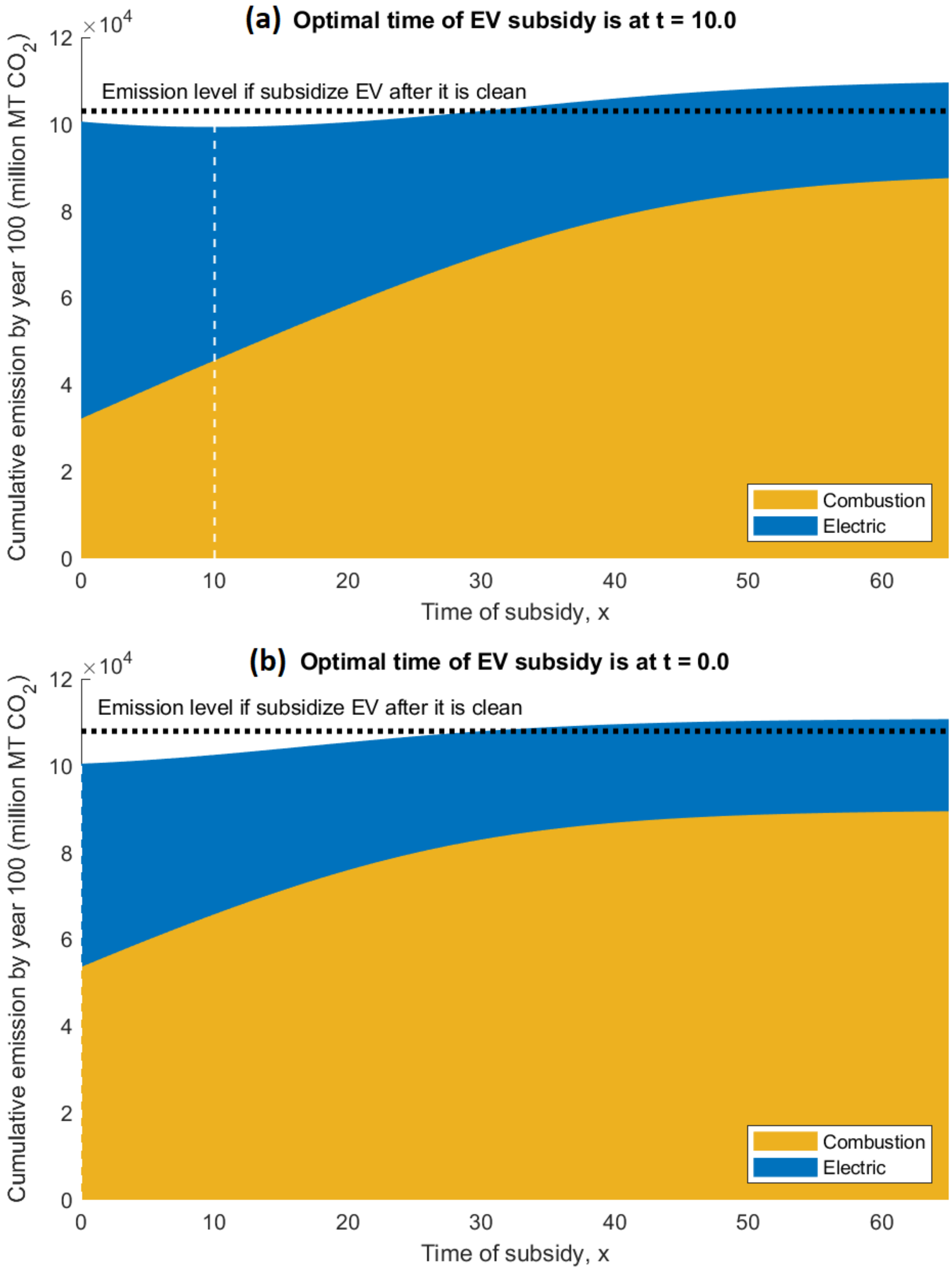

Figure 3: By construction of the grid decarbonization process, EV becomes cleaner than gasoline vehicles by year 30. Varying the start time of subsidy, with the social planner's objective to minimize total emission in the long run, (a) shows that optimal timing of the policy is at year 10 (assuming subsidy boosts adoption by 10%), while (b) shows that optimal timing of the policy is way earlier (assuming subsidy boosts adoption only by 2%).

EV sales q_{mt} (region m time t) depends on the scale of charging network (N_{mt}), price (p_{mt}), and other demand-related product characteristics combined (x_{mt}). The number of charging stations built by time t depends on the active EVs on-road (Q_{mt}) and other variables (z_{mt}) that are related to cost of building the stations. The installed base of EVs is computed by equation (13), with δ being the survival rate of EVs from the previous period:[10]

$$Q_{mt} = q_{mt} + \delta Q_{m,t-1}. \tag{13}$$

To simulate the new EV sales, estimates of the key parameters are taken from Li et al. (2017): a 10 percent increase in charging stations leads to 8.4 percent increase in q ($\beta_1 = 0.844$), a 10 percent decrease in vehicle price net of any subsidy leads to 12.9 percent increase in q ($\beta_2 = -1.288$), and a 10 percent increase in on-road EVs leads to about 6.1 percent increase in charging stations ($\gamma_1 = 0.613$). I plug (12) into (11) to get a discrete-time dynamic function for simulation purposes:

$$ln(q_{mt}) = \beta_1(\gamma_1 ln(Q_{m,t-1}) + \gamma_2 z_m) + \beta_2 ln(p_{mt}) + \beta_3 x_m. \tag{14}$$

The x and z variables are assumed to be region-dependent but time-invariant. Hence, they were backed out as constants from (11) and (12) using state-level network status, sales and EV registration data from the year 2017.

The non-subsidized real price of the vehicle is set to be 33,000 dollars assuming no learning, i.e. $p_0 = 33000$. With a per vehicle subsidy of y_{mt} dollars, the purchase price of EV in region m is modeled as $p_{mt} = p_t - y_{mt}$. Learning-by-doing can be added to the diffusion model by specify the form of price function:

$$p_t = p_0 \left(\frac{X_t}{X_0}\right)^b, \tag{15}$$

[10]Assuming an average lifetime of the vehicle to be 17 years, the annual survival rate of δ is estimated to be 94%.

where b is the experience index, $X_t = \sum_{t=0}^{t} q_t$ is the accumulated EV soled/produced from all regions up to period t. The rate of learning is measured by $\rho = (1 - 2^b) \times 100\%$, which is the rate of price declining for each doubling of adoption. In the base model, we set $b = 0$.

To initialize the simulation of EV diffusion in year 2011, I collected EV sales data for 50 states and District of Columbia from the EVHub Market Data Dashboard[11] and locations of charging stations with open dates before the end of 2011 from the Alternative Fuels Data Center[12]. The time horizon for the EV diffusion simulation is set to be from year 2011 to 2100. Figure 4 illustrates the simulated results for the no-policy baseline scenario.

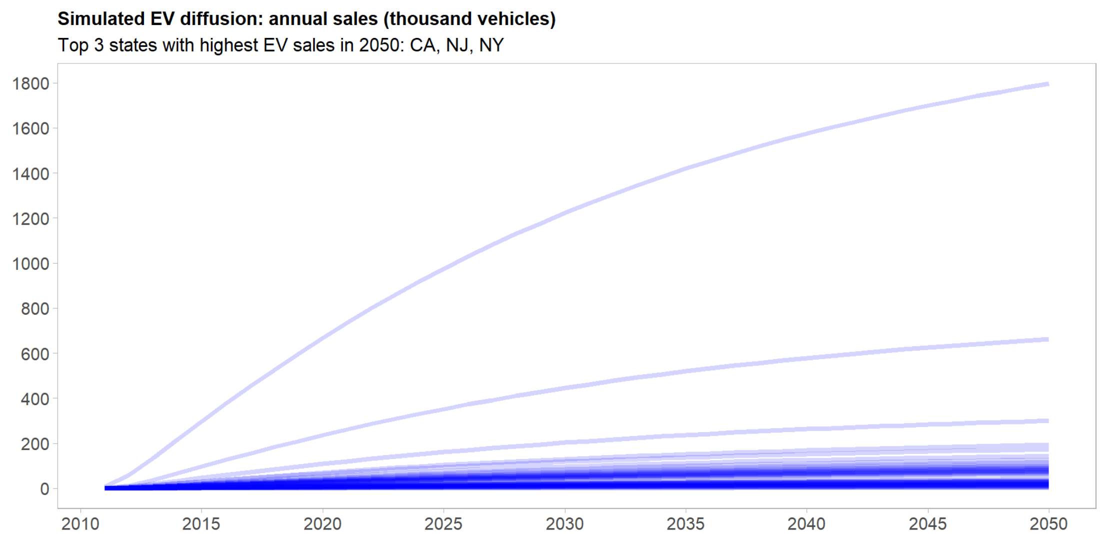

Figure 4: Simulated baseline EV sales from year 2011 to 2050. The top three states with highest EV sales are California, New Jersey and New York.

For a subsidy program implemented in period x that pays y_m dollars per vehicle in region m[13], the policy-induced diffusion path diverges from (14) for $t \geq x$. The sales in period x is

[11] https://www.atlasevhub.com/materials/state-ev-sales-and-model-availability/ state BEV and PHEV sales (accessed May 1, 2020).

[12] https://afdc.energy.gov/stations (accessed January 30, 2020).

[13] The present value of the subsidy program cost is fixed at $\bar{Y} = \frac{1}{(1+\sigma)^x} * \sum_m (y_m q_{mx})$. The discount rate is set at $\sigma = 3\%$.

increased to q_{mx}:

$$ln(q_{mx}) = \beta_1(\gamma_1 ln(Q_{m,x-1}) + \gamma_2 z_m) + \beta_2 ln(p_{m,x} - y_m) + \beta_3 x_m. \quad (16)$$

This has both an immediate uplift and a compounding effect on sales, installed EV base, and number of charging stations in the succeeding years (Figure C.1). Therefore, for analysing the environmental returns of various policy timings, we need to account for the spillovers from the adoption externality as well as the immediate gains/losses from the environmental externality. In the next section, I calculated a projection of lifetime damages of EVs and gasoline ICE cars depending on their model year (i.e. year of sales).

4 Lifetime Damages of Vehicles

This section calculates the lifetime damages of a battery EV versus a gasoline ICE car. The general procedures is to first determine emissions per mile of different car model years and driving years, and then map the emissions to dollar damages of a vehicle's driving lifetime before discounting those damages to the year of sales.

Following Holland et al. (2016), I consider damages from five pollutants: CO_2, SO_2, NO_x, $PM2.5$ and $VOCs$, which account for the majority of global and local air pollution damages. The spatial scale for measuring emissions per kWh follows the North American Electric Reliability Corporation (NERC) and divides the grid interconnections into 9 distinct regions (Figure C.2). As EVs are grid-dependent technologies, the emission factor of these pollutants varies geographically across the electricity regions.

Pollution specific emission rates are simulated by the Argonne Greenhouse gases, Regulated Emissions, and Energy use in Technologies (GREET) model[14] by car model year based on the static status of the regional grid in that year. The projected time series of marginal

[14] https://greet.es.anl.gov/ (accessed May 10, 2020).

emissions per kWh was calculated by netting out the estimates of fuel economy estimates of battery EVs and conventional gasoline ICE cars[15]. Figure C.5 depicts the emission per kWh values of the regional grids and US average. The emission per mile estimates for gasoline ICE cars depend only on the car model year (i.e. year of sales), while the estimates for EVs are determined by both the assumption of vehicle technology advancement as well as the evolving grid generation mix (Fig C.4). Given a fixed number of years in use after vehicle purchase, emission per mile from driving an EV is calculated by dividing its fuel economy[16] projection (a function of model year) by the grid-dependent emission per kWh value. The paths of emission rate conditional on car model years are presented in Figure C.6 (US average) and Figure C.7 (SERC region) for gasoline ICEs and battery EVs.

The emissions are then mapped into environmental damages. For the global pollutant GHGs, we use the EPA social cost of carbon of \$40 per metric ton of CO_2[17]. The Air Pollution Emission Experiments and Policy analysis (APEEP) model[18] is used to get damages dollars per metric ton of the four local pollutants – SO_2, NO_x, $PM2.5$, $VOCs$, which are aggregated for the nine electricity regions (see Figure C.3).

The annual damages from driving a car are calculated by assuming 23000 miles per year for a gasoline vehicle and 15500 miles for an EV[19]. To get the lifetime damages from an incremental vehicle sold, the corresponding annual damages are then discounted to the car sales year using a 3-percent discount rate. Consider the U.S. average generation porfile, if we only look at damages generated in the first year of car sale, i.e. lifetime = 1 year, EV is not cleaner than gasoline ICE until 2015 (Figure 5 left panel). The math changes when multi-year lifetime damages are compared. Figure 5 (right panel) shows that the

[15] The fuel economy (mile per gallon) estimates in the GREET model depend on car model year.

[16] Fuel economy of battery EVs (mpg equivalent) is converted to kWh per mile using the conversion factor of 1 gallon = 33.7kWh.

[17] See "The Social Cost of Carbon", EPA, https://19january2017snapshot.epa.gov/climatechange/social-cost-carbon (accessed Auguest 2, 2020).

[18] https://public.tepper.cmu.edu/nmuller/APModel.aspx

[19] Vehicle mileage is estimated by taking the average annual mileage from EIA's 2020 Annual Energy Outlook.

longer lifetime of EV, the earlier it becomes cleaner than gasoline ICEs. This is because grid emission factor improves continuously over time. EVs as durable goods can therefore harvest the environmental gains from grid decarbonization in its later life years. Across the nine electricity regions, the timing when lifetime damages of EVs get lower than that of gasoline ICE cars is earlier in some region than in others (see Figure C.8). In the next section, I analyze the optimal policy timing for the state of Georgia (in SERC region) and the average U.S. scenario.

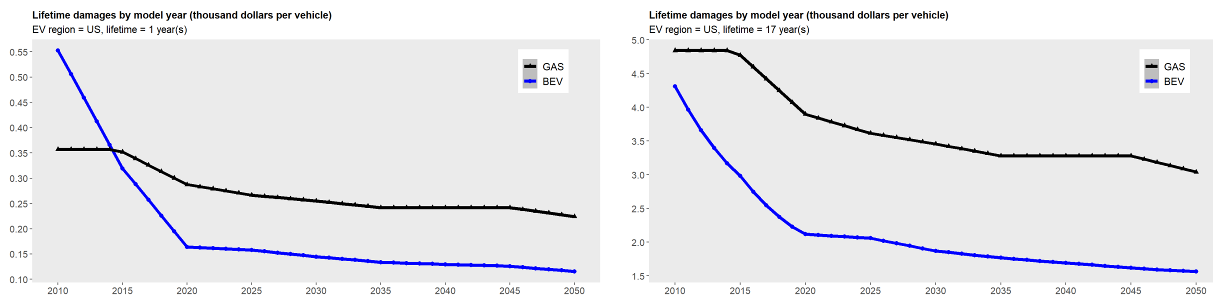

Figure 5: Lifetime damages of EV (blue line) versus gasoline ICE (black line). Estimates are based on average US grid. In terms of one-year static damages, EVs are not cleaner than ICEs until 2015 (left panel). Comparing the 17-year lifetime damages, EVs are cleaner than ICEs as early as year 2011 (right panel).

5 Benefit Analysis of Policy Timing

The environmental benefits of electric vehicles depend on the difference between damages from gasoline ICEs and EVs. From Section 4, I compute the net environmental benefits of an incremental EV sales in year t by taking the difference of their lifetime damages:

$$B(t) = -(D_{EV}(t) - D_{GAS}(t)). \tag{17}$$

$B(t)$ is positive if $D_{EV}(t) < D_{GAS}(t)$ and vice versa. The benefits estimates are assumed to be exogenous from the EV diffusion process in this paper. The upper panel of Figure 6 depicts the net environmental gains per EV sold in the state of Georgia, showing EV is not cleaner than its gasoline alternative in the SERC region until year 2017.

Following Section 3, the effect of a EV subsidy program in year x stimulates a divergent path of sales:

$$\Delta q_x(t) = q_x(t) - q_\infty(t). \tag{18}$$

Before the implementation of the subsidy program, $q_x(t) = 0$ for $v \leq x$. Given the present value of the total spending on EV subsidy, the environmental returns per government subsidy dollar is computed as

$$\frac{PVBenefit}{PVCost} = \frac{\sum_{t=2011}^{2100} \frac{B(t)\cdot\Delta q_x(t)}{(1+\sigma)^t}}{PVCost}. \tag{19}$$

The bottom panel of Figure 6 illustrates, for a selection of subsidy policy timings, the dollars of environmental benefits per government dollar spending. It is worth noticing that the timing that maximizes the environmental return of the EV policy is approximately 6 years earlier than when EVs become cleaner than gasoline cars.

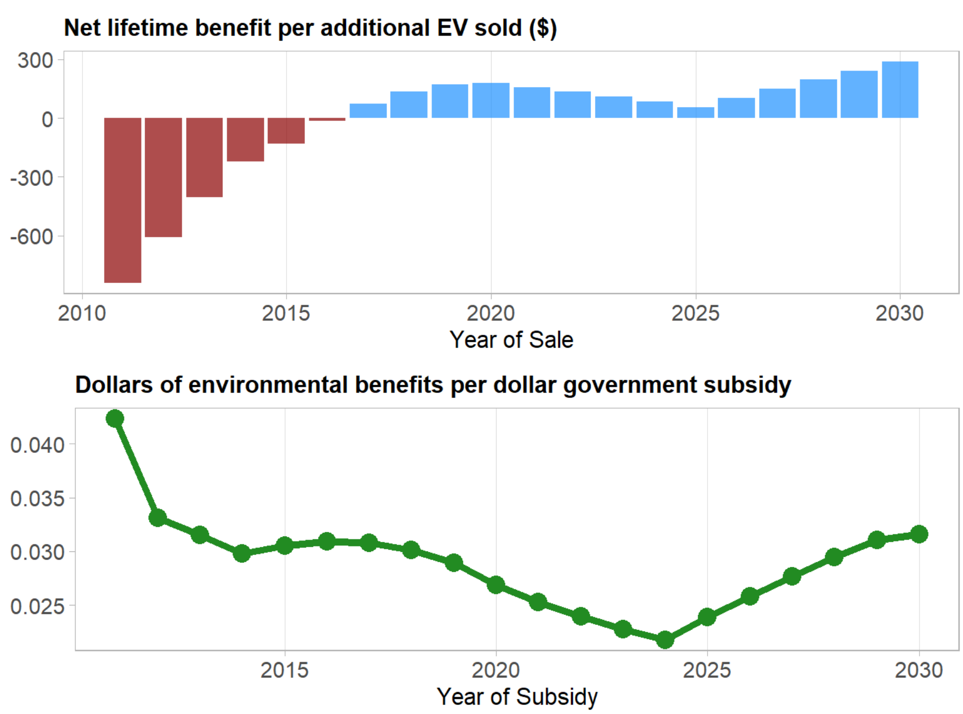

Figure 6: The upper panel presents the net lifetime environmental benefits from an incremental new EV car sold in different years. The values are calculated based on estimates of the SERC region generation profile. The new EV car is assumed to replace a gasoline ICE car. The bottom panel shows the environmental return of the EV policy, which has a present value of 2 million dollars in 2011.

The environmental returns of the EV policy can be decomposed in two components, representing the "trade-off" between the immediate environmental externality generated from subsidizing EVs with higher damages and the adoption externality generated from the spillover diffusion process following the policy. In Figure 7 (top panel), the immediate environmental externality starts negative for earlier timing, and follows the trend of net lifetime benefits of EV in Figure 6. The positive adoption externality from faster diffusion of a cleaner EV fleet is however diminishing as the policy timing gets postponed (Figure 7 bottom panel).

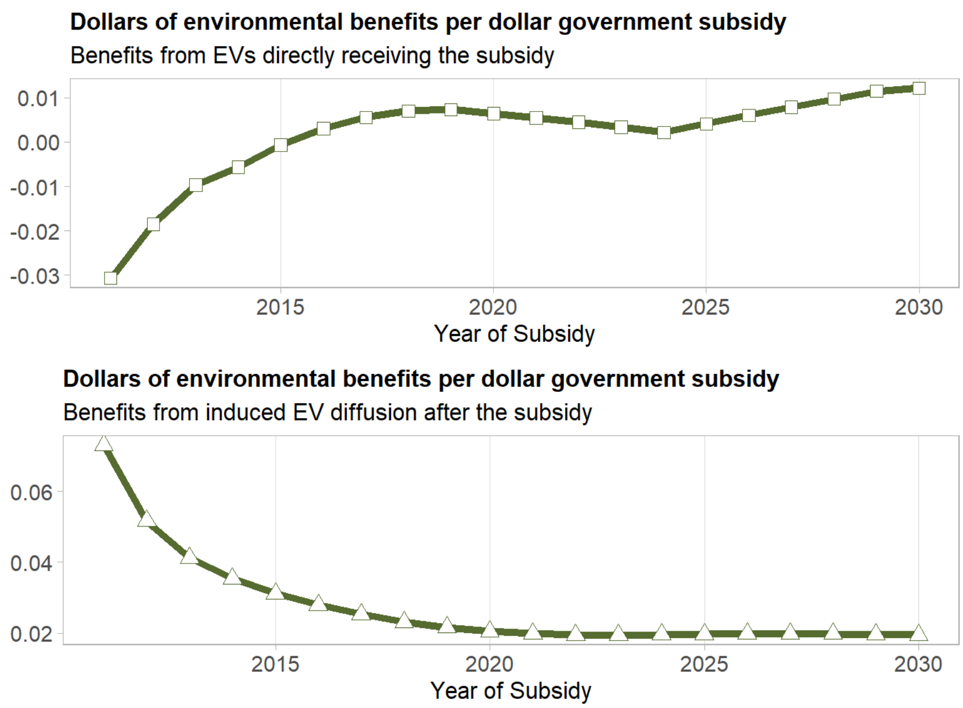

Figure 7: For Georgia state, the total environmental returns per dollar subsidy are decomposed into two components: (upper panel) the immediate environmental externalities from EV sales directly receiving the subsidy, (bottom panel) the adoption externalities from the spillover diffusion effect.

This analysis of environmental returns is repeated for the U.S. average. Different from the SERC region, accounting for the lifetime damages, EVs are cleaner than an alternative gasoline ICE at the beginning of the simulation time horizon (top panel in Figure 8). In this case, subsidizing more EV adoptions would certainly generate a positive environmental return. There are however significant losses in holding the policy stimulate program until a later year. As shown by the bottom panel of Figure 8, the benefits from reducing pollutant emissions drop over 50% if the year of subsidy is shifted one year later from the beginning of the time periods. Similar to the case of Georgia, this environmental return is a sum of two components (Figure 9). The values of immediate environmental benefits from subsidized EVs are dominated by the relative cleanness of EVs versus gasoline ICEs, while the long-run adoption externalities diminish due to waiting the policy. This is because the later policy diverges the EV diffusion from its business-as-usual scenario, the more damages from driving gasoline cars are generated in years before the policy is introduced. Examining the magnitude of the two benefit components, the adoption externality is multiple times higher than the immediate environmental externality.

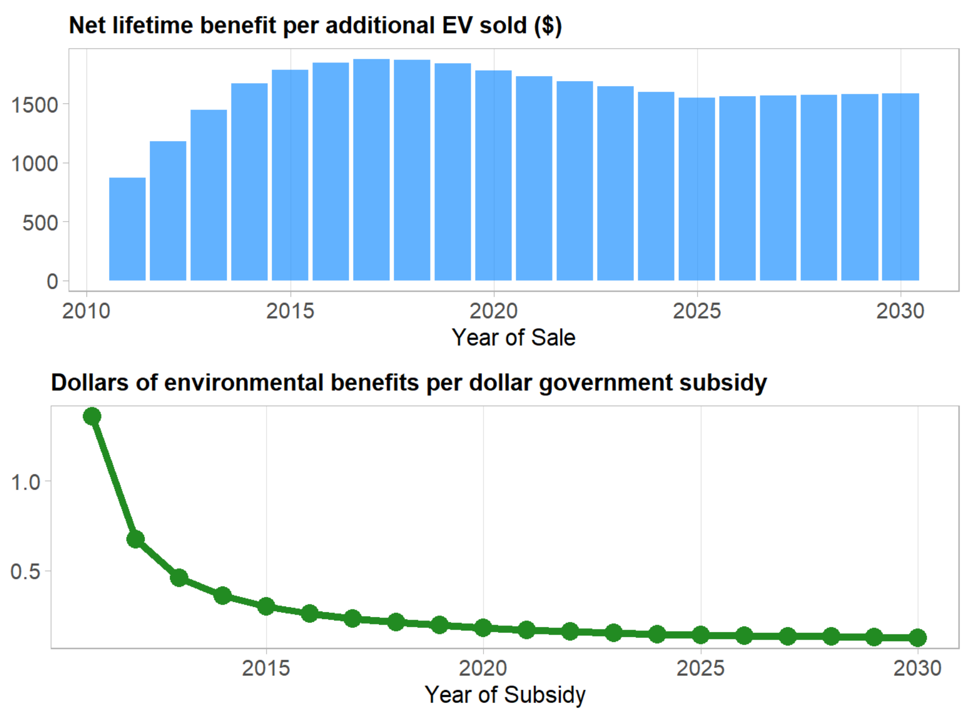

Figure 8: The upper panel presents the net lifetime environmental benefits from an incremental new EV car sold in different years. The values are calculated based on estimates of average US generation profile. The new EV car is assumed to replace a gasoline ICE car. The bottom panel shows the environmental return of the EV policy, which has a present value of 100 million dollars in 2011.

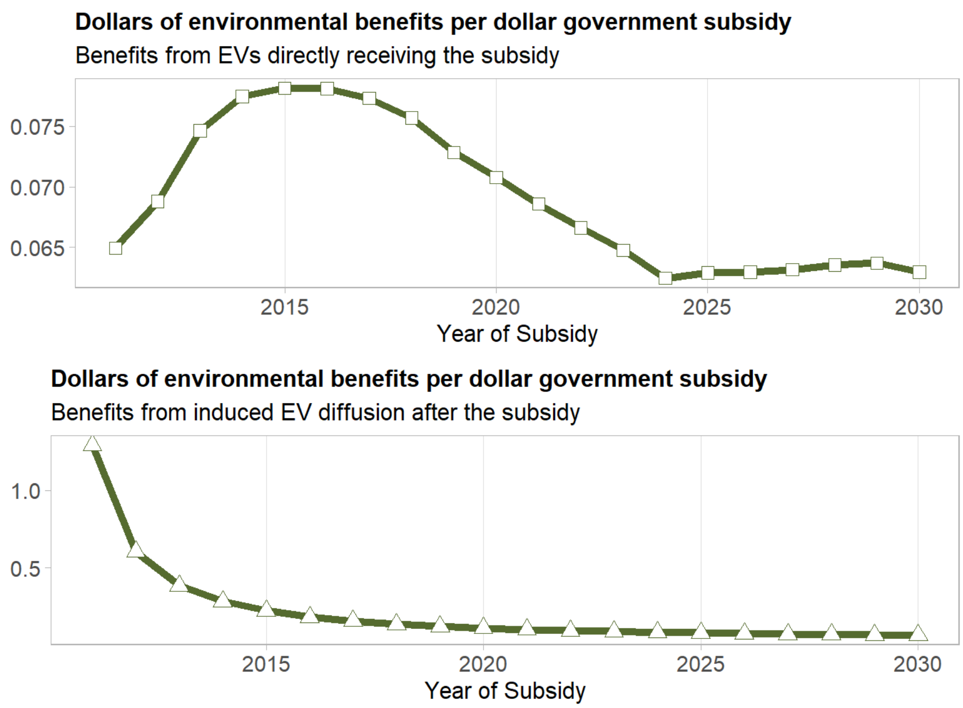

Figure 9: For the U.S. average, the total environmental returns per dollar subsidy are decomposed into two components: (upper panel) the immediate environmental externalities from EV sales directly receiving the subsidy, (bottom panel) the adoption externalities from the spillover diffusion effect.

6 Discussion

The environmental benefits of EVs relative to ICEs depend upon the mix of electricity generators. They vary with dynamics of the power sector and are expected to grow as power grids decarbonize to combat climate change. However, the static environmental benefits of EVs are presently negative in some regions of the U.S. and the world. Because vehicles are long-lived durable goods, power sector decarbonization varies over time and space, and there are EV adoption dynamics, the optimal timing of EV subsidies is not obvious. Using both a theoretical model and empirical analyses, I show that EV subsidies should be introduced before EVs are cleaner than ICEs in a static sense, that is, in the year of EV adoption. Policies that subsidize EVs before they are cleaner than ICEs induce immediate climate damages in the adoption year, but they have compounding effect on the diffusion process and lead to long-run environmental gains as the grid gets cleaner over the vehicle lifetime. Delaying subsidies until net emissions from replacing an ICE with an EV drop below zero forgoes environmental benefits associated with the diffusion process. The optimal policy may tradeoff negative environmental externalities in the short run for positive adoption externalities in the long run. While these results are relevant in the U.S. where EVs are estimated to be dirtier than ICEs in some regions, my analysis is also relevant in non-U.S. context—e.g. countries like China and India, where power generation is still relatively emissions intensive.

Although this paper focuses on the environmental return of EV subsidies, the model and analyses can be applied to alternative policy instruments that stimulate EV diffusion and compound the environmental effects over time. Closely related to EV rebates, regulators in U.S. and other countries have provided funding and set mandatory standards for EV charging infrastructures. China is the country with the most charging stations in the world, and the Chinese central government announced a stimulus package for building new charging facilities in March 2020.[20] In the U.S., state governments played a more active role than the federal government in making charging network policies.[21] Subsidizing charging facilities induces more EV adoption than a direct rebate to vehicle purchases (Li et al., 2017; Springel, 2020). Charging network policies are likely to have geographic spillover effect on EV adoptions and driving patterns, which might lead to bi-directional biases in the empirical analyses on optimal timing of the policies. Expanding the charging network of a state with a clean grid could lead to more aggregate environmental damages if the spillover effect triggered more

[20] A look inside China's timely charging infrastructure plan. `https://www.greenbiz.com/article/look-inside-chinas-timely-charging-infrastructure-plan` (accessed on November 11, 2020).

[21] New Jersey announced in April 2020 that \$45 million will be allocated to EVs and EV charging. In March 2020, \$5 million was added to the Charge Ready NY program for the state of New York, which offers \$4,000 rebates for building Level 2 charging stations. The California Energy Commission approved in September 2019 the budget of more than \$60 million for charging infrastructures (\$32.7 million for light-duty vehicles and \$30 million for medium- and heavy-duty vehicles). The state of Georgia has a 10% tax credit (up to \$2500) for businesses installing public charging equipment and a \$250 rebate for residential Level 2 chargers installed in 2020.

EV adoption in less-clean states, and vice versa. Further research is needed to examine the welfare trade-offs empirically between different EV policy instruments and their appropriate timings.

In practice, technology policies usually extend across multiple years. For instance, the U.S. government has set a federal tax credit for new battery EVs and plug-in EVs purchased in or after 2010. My demonstration of diminishing environmental returns due to diminishing technology adoption externalities suggests that the marginal returns of a subsidy policy are likely to decline over their durations. As technology diffuses, the magnitude of adoption externalities falls, lowering the environmental benefits due to the ongoing policy. Though I model a one-period subsidy regime, the results can be generalized to a regime that seeks to subsidize a fixed number of EVs regardless of when they are adopted.

In some related policy settings, ongoing technology adoption subsidies are likely yielding diminishing environmental benefits. As the grid gets cleaner, for instance, the environmental benefit of a marginal unit of solar capacity falls. A solar subsidy regime should perhaps be terminated before the marginal benefit in the adoption year is dominated by the marginal cost of the subsidy because the environmental benefits are expected to decline further over the 20-30-year lifetime of the solar capacity.

The framework of this paper can be utilized to design policies for innovation and technologies that facilitate the transition to a low-carbon economy. To combat global climate change in the next decade, ambitious actions are required to cut carbon emissions in the power sector, in food production,[22] and in the transportation system. Energy storage technology, e.g. battery storage, enables integrating large capacity of intermittent low-carbon generation, which is essential for transition to an emission-free power system. However, due to the high cost of batteries, the diffusion rate of the storage technology is quite slow in the

[22]The environmental impact from food production might increase by 50–90% in the next three decades unless technological changes and dedicated mitigation measures occur (Springmann et al., 2018). Clark et al. (2020) show that food-related emissions alone would make it impossible meet the goals of the Paris Agreement, even if all fossil fuel emissions were cut to zero immediately.

absence of policy intervention. And the uncertainty in the short-run environmental benefits from deploying energy storage bias policy prescriptions towards limiting diffusion.[23] unless the dynamics of storage diffusion were included in the analysis.

For the food production system as well as the transportation system, a key challenge in the green transition is to reshape social norms or to induce societal shifts in behaviors. To smooth the transition to a plant-based diet, technology that produces meat substitutes have emerged in the market[24]. However, life cycle assessments find that carbon footprint of meat substitutes tends to range between poultry (medium carbon intense) and beef (high carbon intense) (Nijdam et al., 2012).[25] Dynamically, the optimal policy timing is relevant given that innovative food technologies could outperform conventional meat in carbon intensity in the long run and will lead to compounding environmental benefits via high adoption rate of plant-rich diets. An analogy can be drawn for designing public transit reforms and/or urban planning policies to switch people from driving to taking public transit. Whereas increasing accessibility of public transit might raise social costs as it might be initially operated under-capacity before widely adopted, switching transportation model entirely will remarkably increase the environmental gains in the long run. The mechanisms in my analysis that drive the optimal timing of policies are therefore relevant for technologies and innovations that can smooth the transition to a low-carbon economy.

[23] The environmental engineering literature asserts that bulk energy storage may increase emissions from the grid (Hittinger and Azevedo, 2015). Decentralized home batteries would not automatically reduce emissions or conserve energy unless they enable more renewable energy (Fares and Webber, 2017). Depending on the charging behavior of users, residential energy storage could unintentionally increase emissions when users seek to minimize their energy cost (Babacan et al., 2018).

[24] Some of the recent successful companies like Beyond Meat and Impossible Burger have developed plant-based meat substitutes.

[25] Besides the plant-based products, lab-grown meat (or in vitro meat) is the cell-based alternative, whose energy intensity can possibly fall on the high end of the spectrum comparing with livestock meat (Mattick et al., 2015).

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Appendices

A Analysis of a simple model

A.1 Impact of policy timing to EV diffusion

The policy intervention, e.g. EV subsidies, at time x temporally increases EV adoption by s. This leads to a diverging path from the business-as-usual diffusion process staring $t \geq x$. The market penetration rate of EV is expressed by (A.1):

$$F(t,x) = \frac{1}{1+\phi_x e^{-\beta(t-x)}}, \quad \phi_x = \frac{1-Y(x)-s}{Y(x)+s}. \tag{A.1}$$

Hence,

$$\phi_x' = -\frac{\beta Y(x)(1-Y(x))}{(Y(x)+s)^2} > 0 \tag{A.2}$$

I can then derive the derivative of this diffusion path with respect to the subsidy starting time x.

$$\begin{aligned} \frac{\partial F(t,x)}{\partial x} &= -e^{-\beta(t-x)} \frac{\phi_x' + \beta\phi_x}{(1+\phi_x e^{-\beta(t-x)})^2} \\ &= \beta e^{-\beta(t-x)} \frac{Y(x)(1-Y(x)) - (Y(x)+s)(1-Y(x)-s)}{(Y(x)+s)^2(1+\phi_x e^{-\beta(t-x)})^2} \\ &= \frac{s(2Y(x)+s-1)}{\phi_x (Y(x)+s)^2} \cdot \frac{\partial F(t,x)}{\partial t} \end{aligned} \tag{A.3}$$

It is reasonable to assume that the policy intervention occurs before EV takes 50% market share, i.e. $Y(x) < 0.5$, and that $Y(x)+s \leq 0.5$, then for any positive s, (A.3) has a negative sign, as $\frac{\partial F(t,x)}{\partial t} > 0$

$$2Y(x)+s-1 = Y(x)+(Y(x)+s)-1 < 0 \quad \longrightarrow \frac{\partial F(t,x)}{\partial x} < 0. \tag{A.4}$$

This implies that the earlier the subsidy, the faster the diffusion process drives EV to a larger installed market base. Figure A.1 is a numerical illustration of this statement.

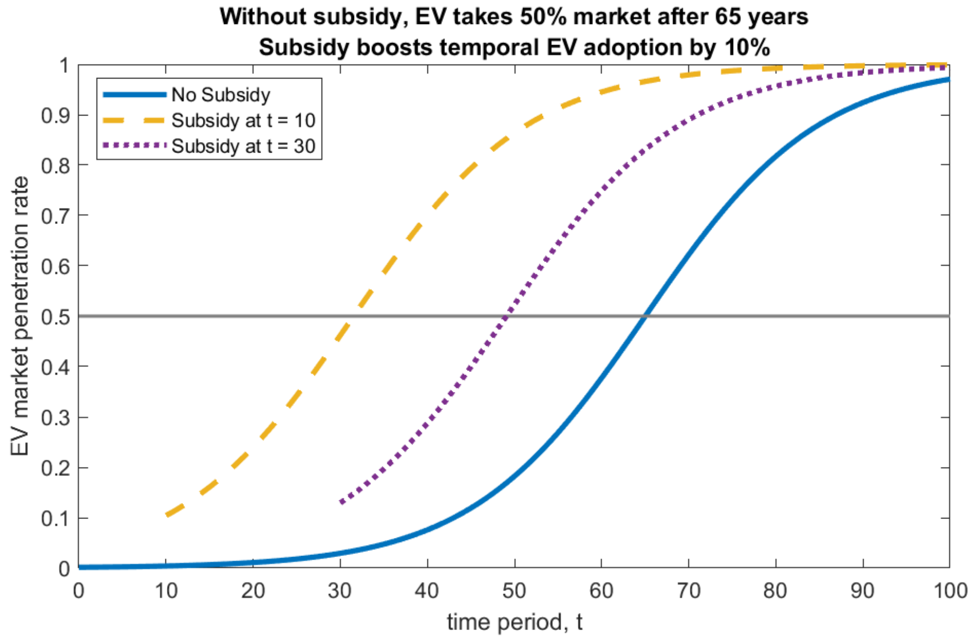

Figure A.1: It is assumed that the subsidy boosts adoption temporally by 10%. Starting the EV subsidy in year 30 instead of year 10 would postpone the time point when EV takes half the automobile market.

A.2 Deriving the first-order condition for optimal timing

In the social planner's problem, the optimization objective is

$$E(x) = \underbrace{\int_0^x [Y(t)\delta_e(t) + (1 - Y(t))\delta_g]dt}_{A(x)} + \underbrace{\int_x^T [F(t,x)\delta_e(t) + (1 - F(t,x))\delta_g]dt}_{B(x)} . \tag{A.5}$$

Following the fundamental theorem of calculus, I get

$$\frac{dA(x)}{dx} = Y(x)\delta_e(x) + (1 - Y(x))\delta_g = \frac{\delta_0 e^{-\theta x} + \delta_g \phi e^{-\beta x}}{1 + \phi e^{-\beta x}} . \tag{A.6}$$

By Leibniz Rule, I get

$$\begin{aligned} \frac{dB(x)}{dx} &= \int_x^T \left[(\delta_e(t)-\delta_g)\cdot\frac{\partial F(t,x)}{\partial x}\right]dt - [F(x,x)\delta_0 e^{-\theta x} + (1-F(x,x))\delta_g] \\ &= \int_x^T \left[(\delta_e(t)-\delta_g)\cdot\frac{\partial F(t,x)}{\partial x}\right]dt - \left[\frac{\delta_0 e^{-\theta x}+\delta_g\phi_x}{1+\phi_x}\right]. \end{aligned} \tag{A.7}$$

Therefore, the first-order derivative of $E(x)$ with respect to x is $\frac{dE(x)}{dx} = \frac{dA(x)}{dx} + \frac{dB(x)}{dx}$.

Condition on $x=\tau$, i.e. subsidy starts when EV becomes cleaner than gasoline vehicles, where $\tau = (1/\theta)ln(\delta_0/\delta_g)$, the value of derivative is positive,

$$\frac{dE(x)}{dx}|_{x=\tau} = \int_\tau^T \left[(\delta_e(t)-\delta_g)\cdot\frac{\partial F(t,x)}{\partial x}\right]dt > 0, \tag{A.8}$$

as $\delta_e(t) < \delta_g \forall t > \tau$ and $\frac{\partial F(t,x)}{\partial x} < 0$ (shown in Appendix A.1).

Condition on $x=0$, i.e. subsidy starts from the current time point, the value of derivative becomes

$$\begin{aligned} \frac{dE(x)}{dx}|_{x=0} &= \int_0^T \left[(\delta_e(t)-\delta_g)\cdot\frac{\partial F(t,x)}{\partial x}|_{x=0}\right]dt - \left[\frac{\delta_0+\delta_g\phi_{x=0}}{1+\phi_{x=0}}\right] + \left[\frac{\delta_0+\delta_g\phi}{1+\phi}\right] \\ &= \int_0^T \left[(\delta_e(t)-\delta_g)\cdot\frac{\partial F(t,x)}{\partial x}|_{x=0}\right]dt - \left[\frac{\delta_0+\delta_g(\frac{1-Y_0-s}{Y_0+s})}{1+(\frac{1-Y_0-s}{Y_0+s})}\right] + \left[\frac{\delta_0+\delta_g(\frac{1-Y_0}{Y_0})}{1+(\frac{1-Y_0}{Y_0})}\right] \\ &= \int_0^T \left[(\delta_e(t)-\delta_g)\cdot\frac{\partial F(t,x)}{\partial x}|_{x=0}\right]dt - (\delta_0-\delta_g)s \\ &= \int_0^T \left[(\delta_e(t)-\delta_g)\cdot\left(\frac{s(2Y_0+s-1)}{(1-Y_0-s)(Y_0+s)}\right)\cdot\frac{\partial F(t,0)}{\partial t}\right]dt - (\delta_0-\delta_g)s \\ &= \left(\frac{s(2Y_0+s-1)}{(1-Y_0-s)(Y_0+s)}\right)\left(\int_{t=0}^{t=T}(\delta_e(t)-\delta_g)dF(t,0)\right) - (\delta_0-\delta_g)s \end{aligned} \tag{A.9}$$

Assuming $Y_0=0$, equation (A.9) becomes

$$\frac{dE(x)}{dx}|_{x=0} = \underbrace{-\int_{t=0}^{t=T}(\delta_e(t)-\delta_g)dF(t,0)}_{>0 \text{ for large } T} - (\delta_0-\delta_g)s \tag{A.10}$$

For small s, (A.10) is likely to be positive. This implies that a later subsidy timing will lead to higher emission, hence suggesting an early optimal timing of the policy. To the extreme, when $s \to 0$, $\frac{dE(x)}{dx}|_{x=0} \to 0$.

For large s, the sign of (A.10) can be reversed to negative. If the initial emission gap between the grid generation and gasoline vehicle engine is sufficiently large — $\delta_0 >> \delta_g$ — implying significant environmental damage from driving EVs at the current time, then the "$\frac{dE(x)}{dx}|_{x=0} < 0$" case is more likely to hold true. This therefore suggests a latter optimal timing of the policy.

B Numerical simulation of the simple model

Figure B.1 illustrates the process of numerical simulation and corresponding parameter values that compute accumulated emission from the transportation sector which consists two type of fleet – electric vehicles (EV) and gasoline vehicles. The dynamic equations for EV diffusion and grid decarbonization are presented by equation (1) to (3). The installed base for EV and gasoline vehicles are expressed by

$$N_e(t,x) = MF(t,x), \quad N_g(t,x) = M(1 - F(t,x)). \tag{B.1}$$

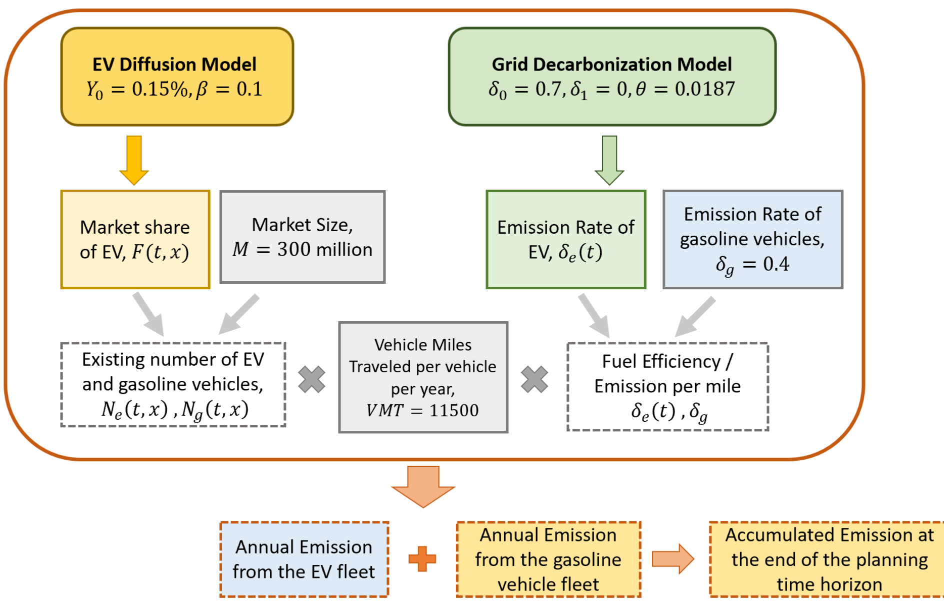

Figure B.1: Flow chart of the simulation practice. The social planner decides the starting time of the EV subsidy x. Varying the value of x, the accumulated emission at the end of the planning time horizon ($T = 100$ years) is simulated.

The evolution paths of emission rate from the grid and of gasoline engines are shown in Figure B.2. By construction, EV is assumed to be cleaner than an average gasoline combustion engine by year 30. If without any policy intervention, EV would take 65 years to take half of the total market share,and the adoption rate of EV by that time point would be low, at approximately 3 percent.

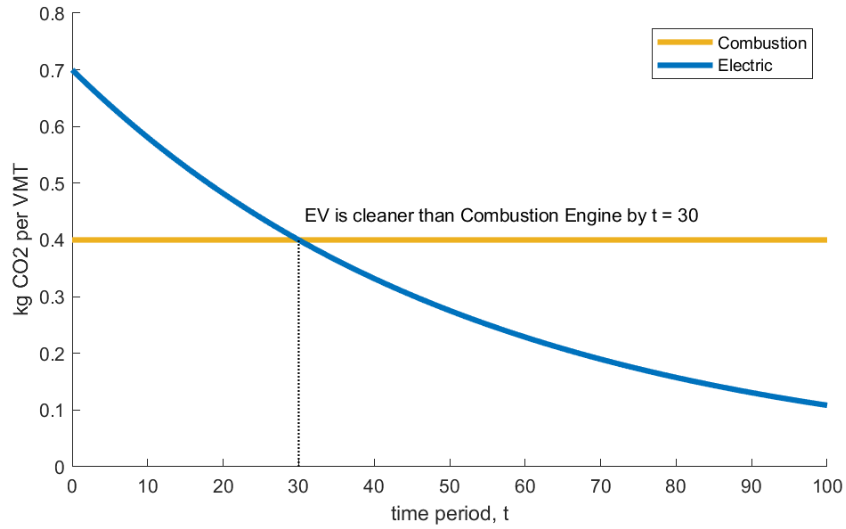

Figure B.2: The grid decarbonization process starts at 0.7 kg CO2 per vehicle mile traveled and decreases to 0.1 kg CO2 per vehicle mile traveled.

Assume the subsidy policy can temporally boost EV adoption by $s = 10\%$, then the simulated emission in this scenario varies with the policy starting time $x \in [0, 65]$ (Figure B.3). The point corresponding to the lowest commulated emission implies the "optimal" timing of subsidy should be earlier than the time when EV is cleaner than gasoline vehicles.

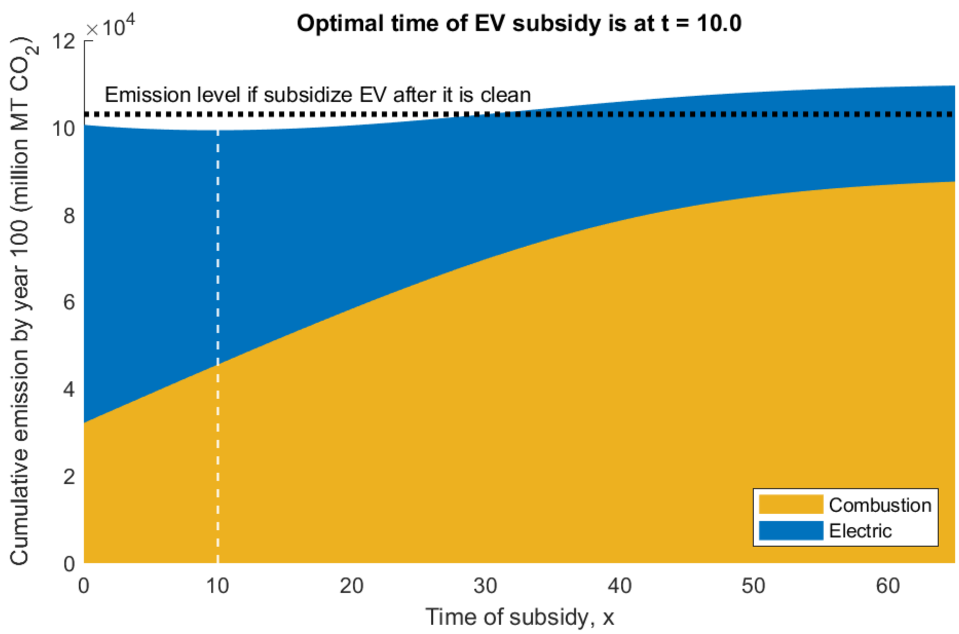

Figure B.3: Simulation result illustrating optimal timing of policy

C Supplementary figures

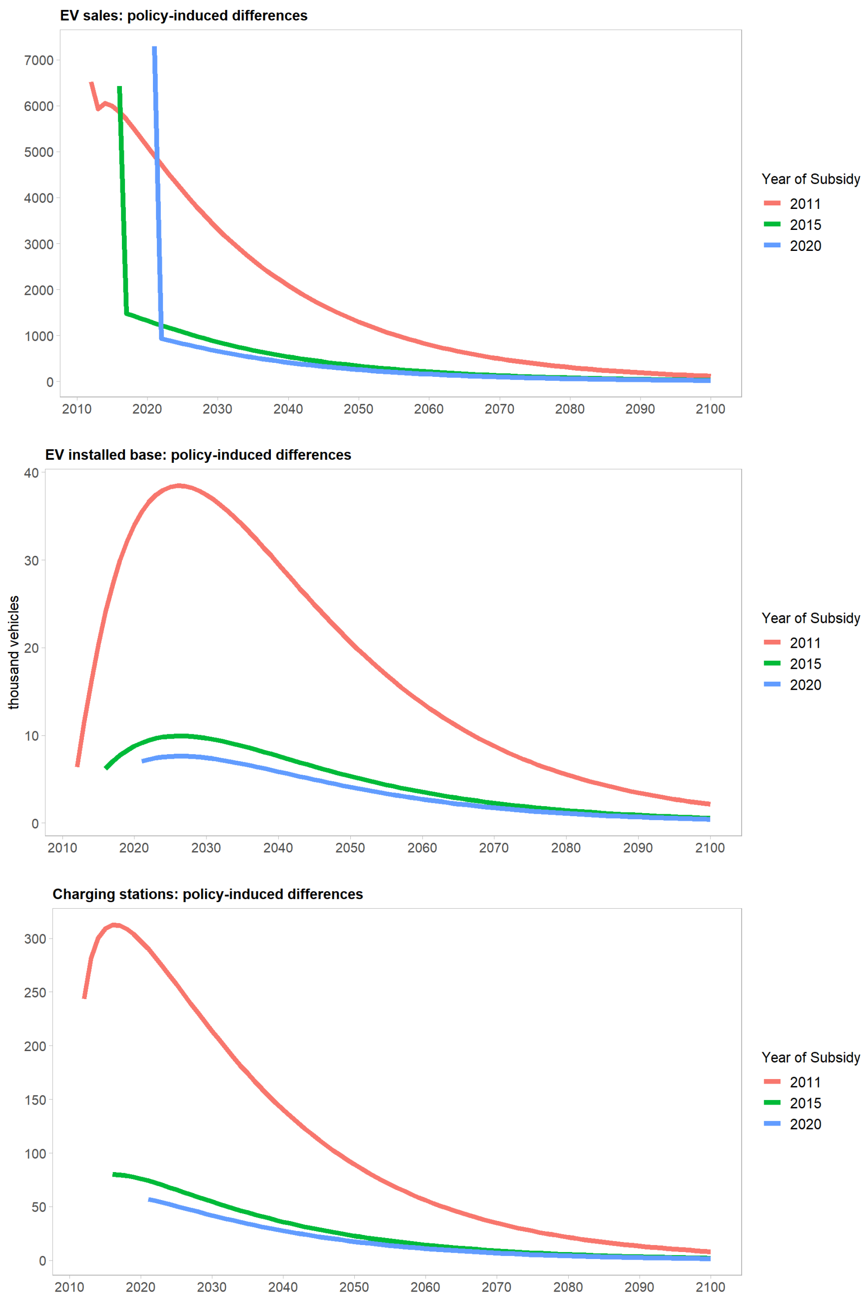

Figure C.1: The figures depict the policy-induced differences in the diffusion process comparing to baseline. For three selected subsidy payment years, the lines present the all-state aggregated net increase in EV sales (top panel), installed EV base (middle panel) and charging stations (bottom panel).

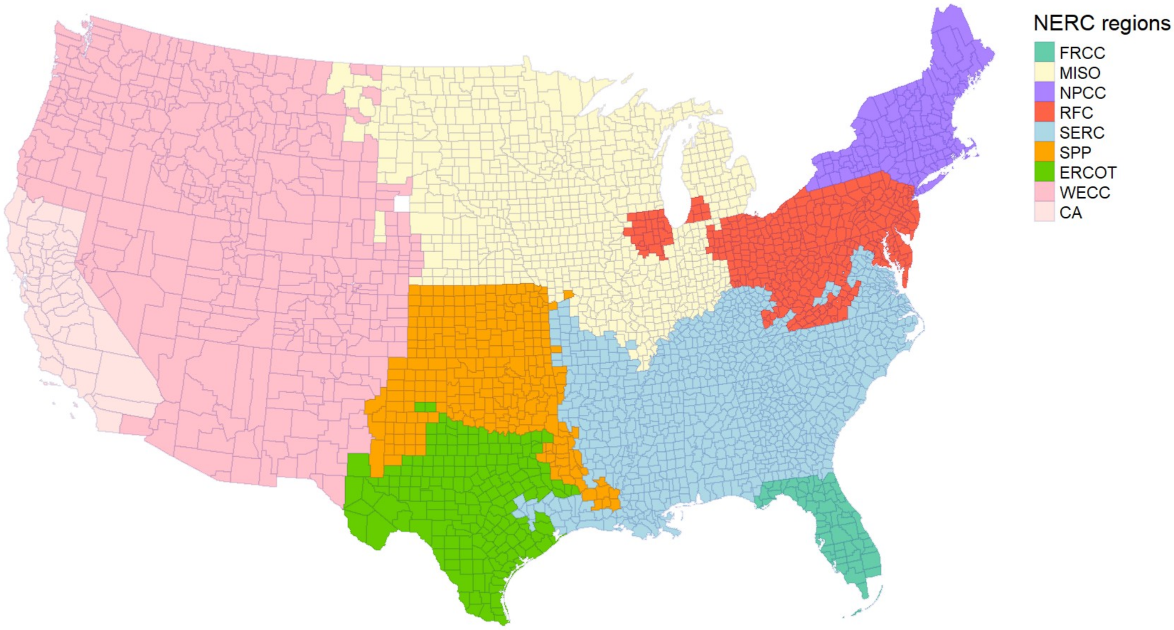

Figure C.2: Map of electricity regions.

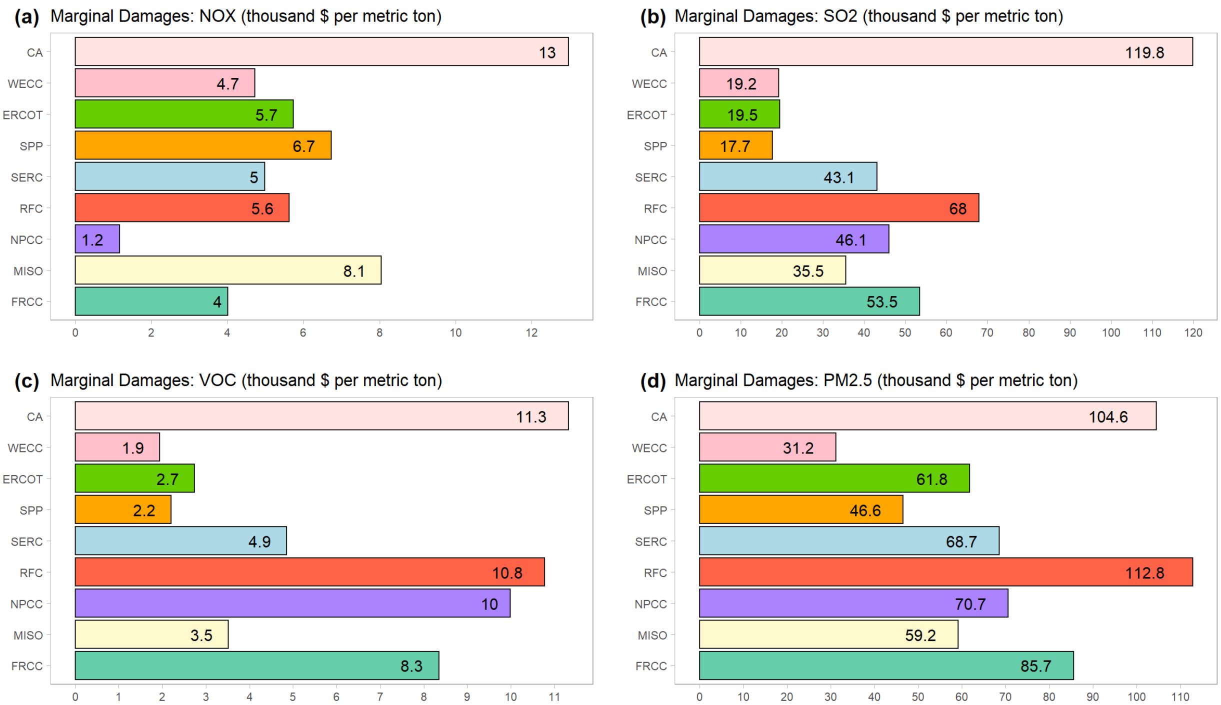

Figure C.3: Average marginal damages of local pollutants by different electricity regions.

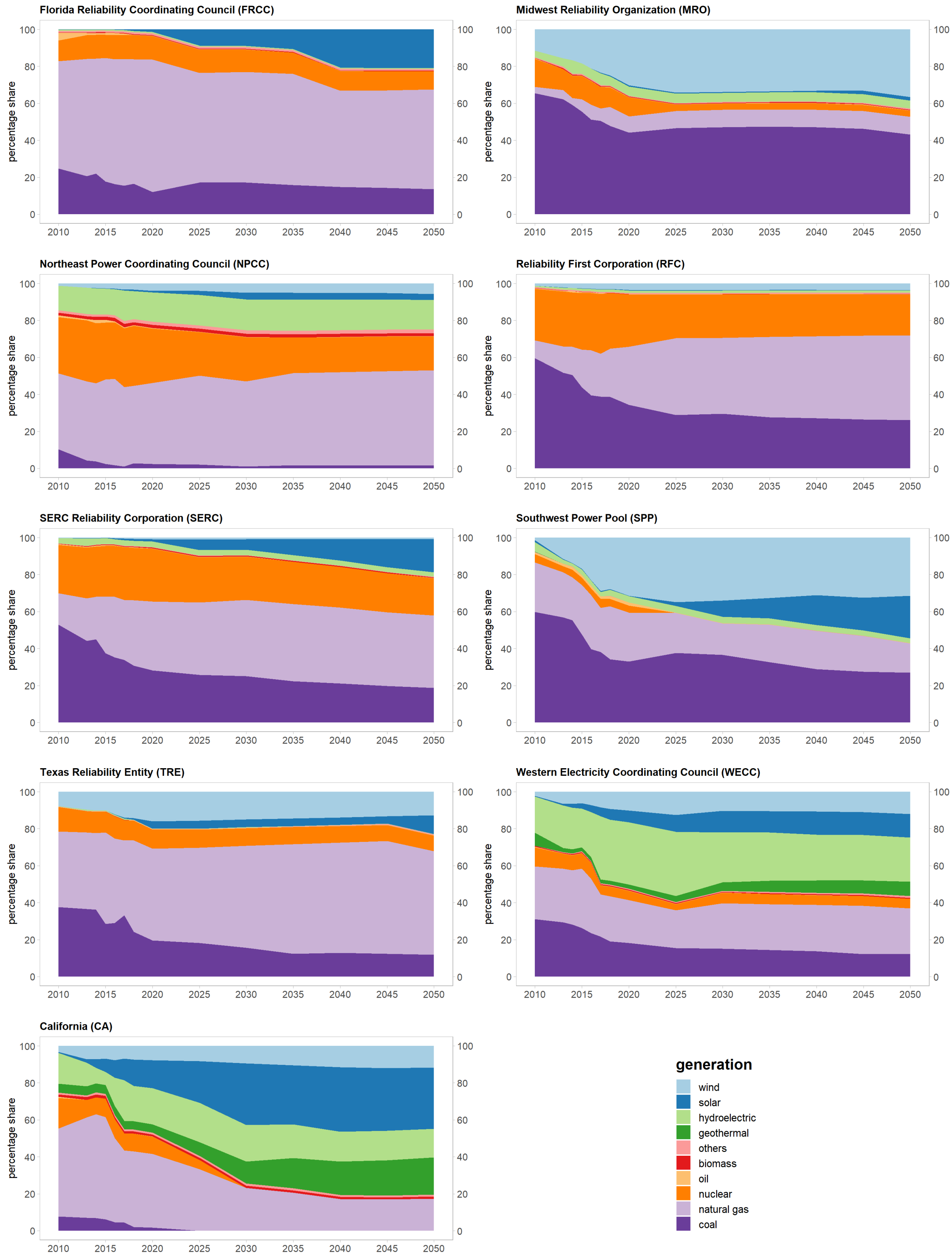

Figure C.4: Projections of generation mix from the GREET model.

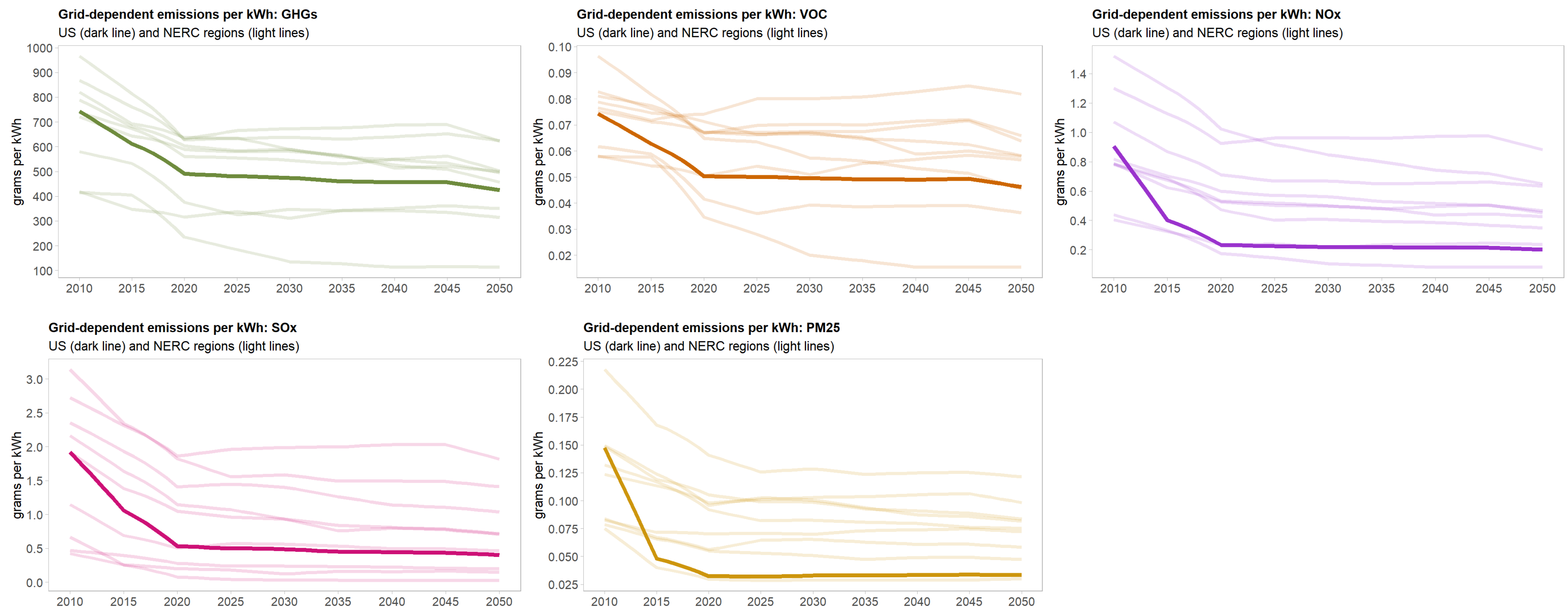

Figure C.5: Emission per kWh of five pollutants. The dark solid lines represent estimates based on the US average. The light-colored lines represent estimates for different electricity regions.

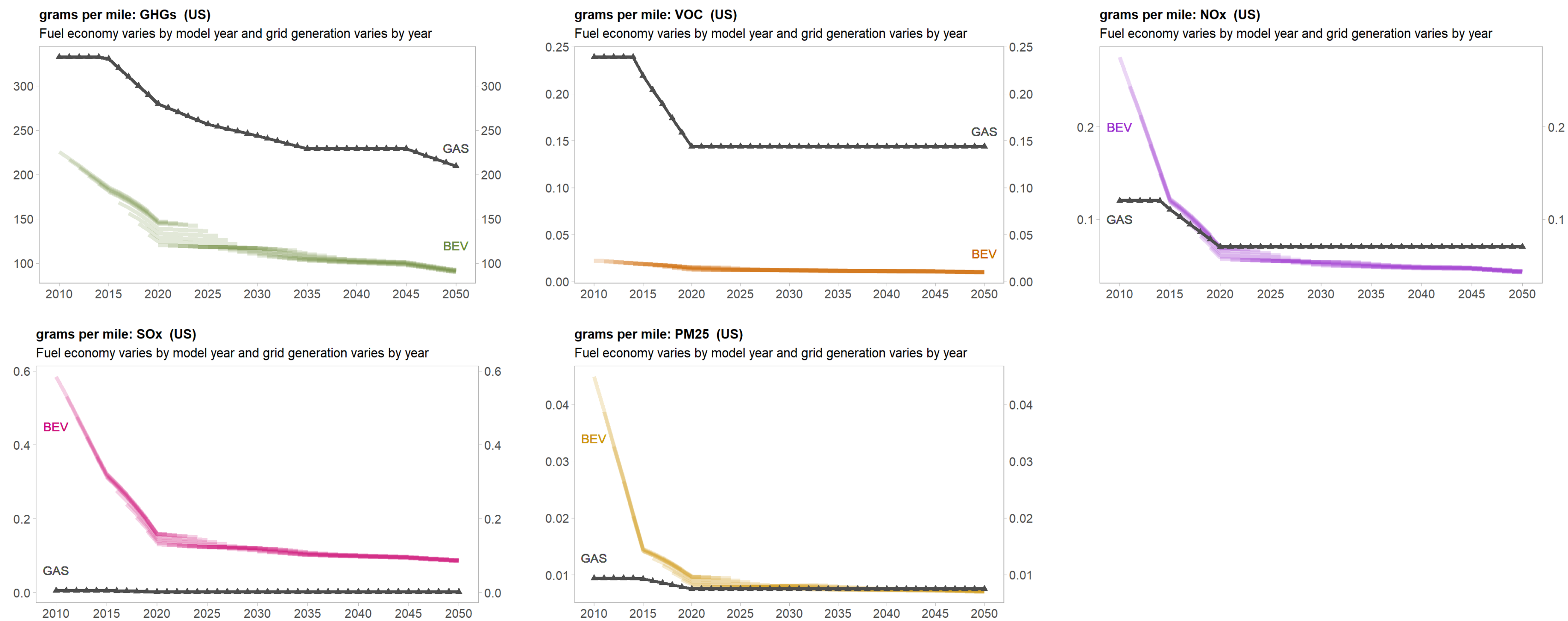

Figure C.6: Emission per mile by vehicle technology of five pollutants (US average). The black lines with triangle-shaped markers represent values for the gasoline ICE cars by model years (no variation by driving years as this technology is grid-independent). The light-colored lines represent estimates for EVs by different model years and driving years.

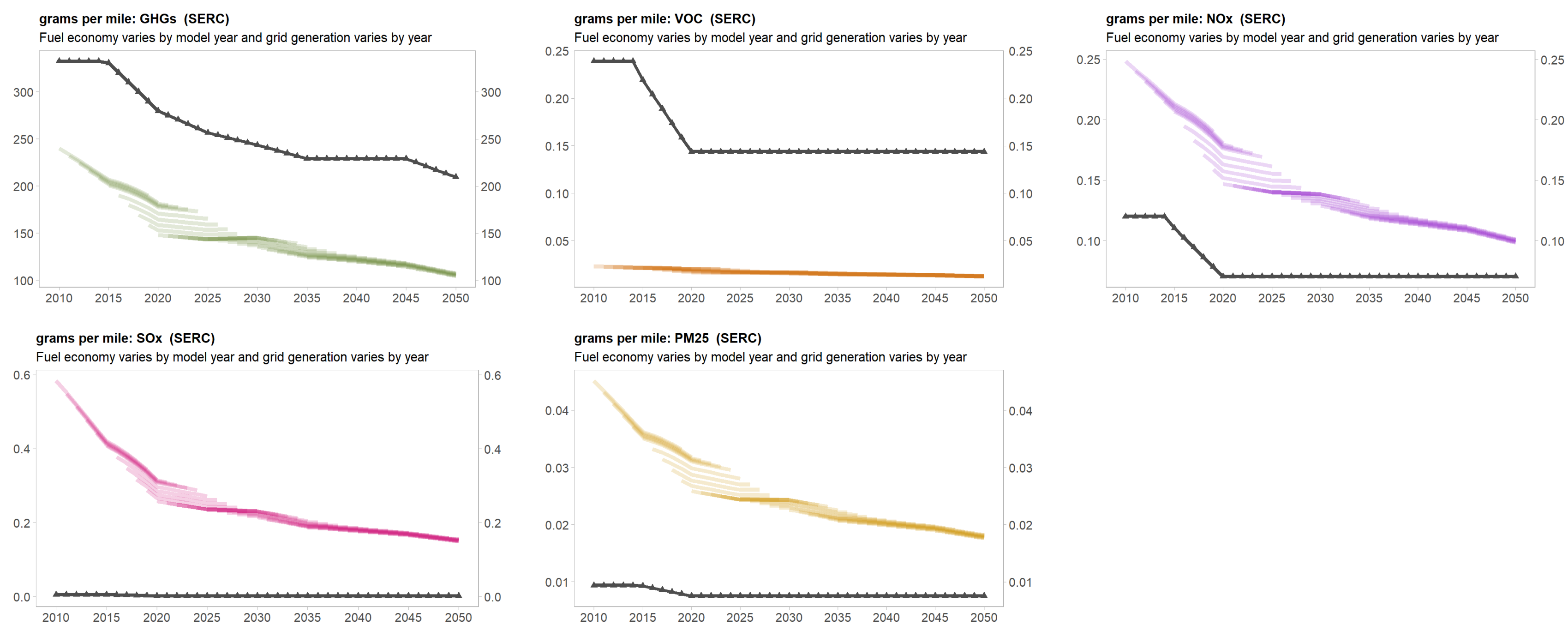

Figure C.7: Emission per mile by vehicle technology of five pollutants (SERC region). The black lines with triangle-shaped markers represent values for the gasoline ICE cars by model years (no variation by driving years as this technology is grid-independent). The light-colored lines represent estimates for EVs by different model years and driving years.

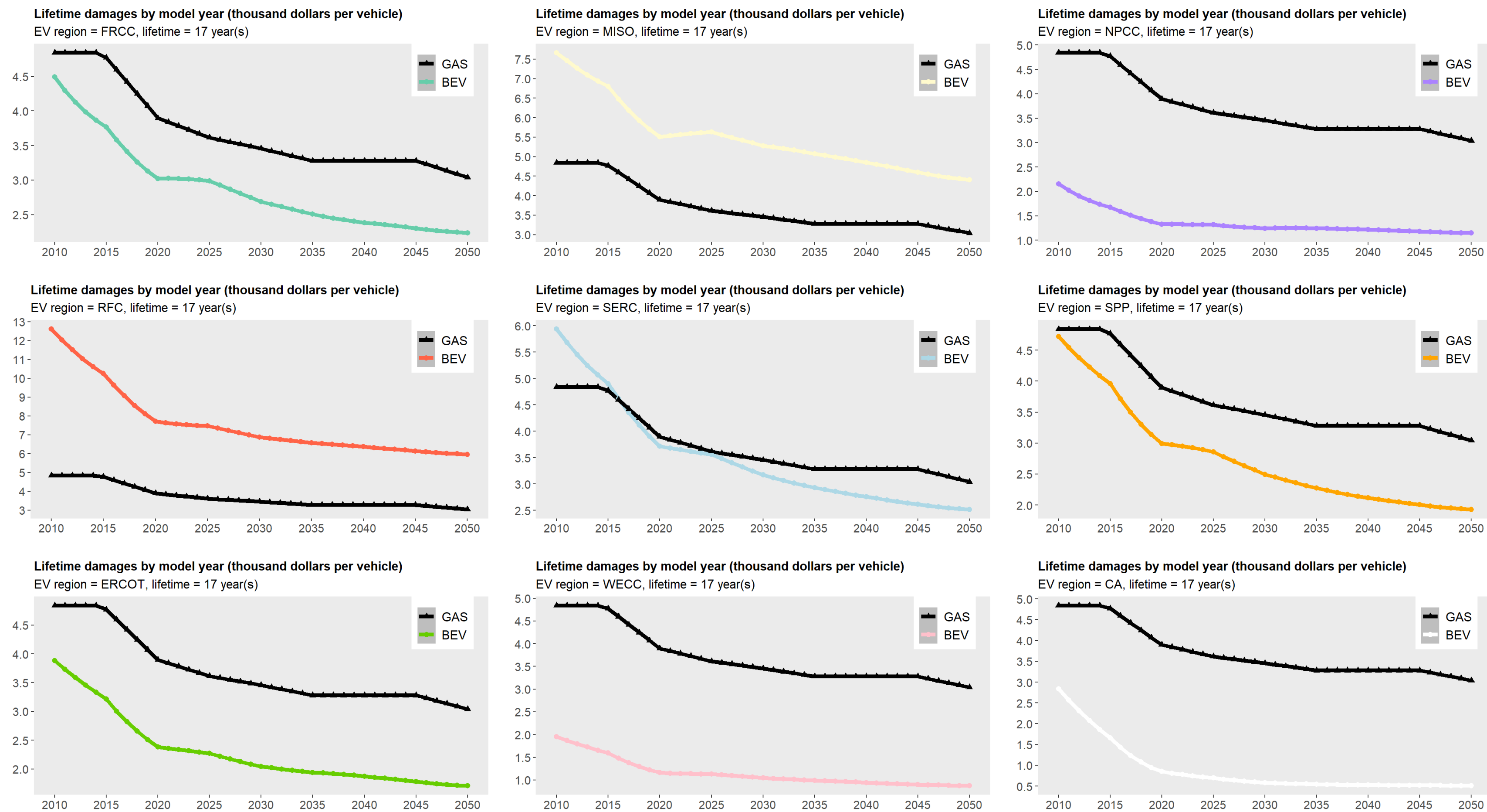

Figure C.8: Lifetime damages of EV versus gasoline ICE in 9 electricity regions. Vehicles are assumed to have 17 years of life.