The Imperative for Cellulosic Biofuels in an Electrifying Vehicle Market

Jia Zhong
University of Illinois at Urbana-Champaign
jzhong11@illinois.edu

Madhu Khanna
University of Illinois at Urbana-Champaign
khanna1@illinois.edu

Selected Paper prepared for presentation at the 2021 Agricultural & Applied Economics Association Annual Meeting, Austin, TX, August 1 – August 3

The Imperative for Cellulosic Biofuels in an Electrifying Vehicle Market

1 Introduction

Achieving the goal of a 50% reduction in greenhouse gas emission (GHG) — addressed by the Biden administration's climate policy— will require a portfolio of strategies (US EPA 2020), especially for the transportation sector. The ambitious decarbonization plan inevitably requires a shift to low carbon fuels and alternative powertrains vehicles, such as electric vehicles and flex-fuel vehicles capable of using high blends of ethanol, both of which need to be incentivized by policies. The electric vehicle (EV) buyers are granted the federal vehicle credit, and the potential restrictive ban on gasoline-fueled vehicles indirectly proposed by California, New York City, and Massachusetts might further the market acceptance of electric vehicles. In the case of the promoting biofuel fleet, the extant ethanol blend mandate of 56 billion liters of corn ethanol has been implemented since 2007 and potentially extended after 2022. Currently also implemented are the fleet-wide fuel efficiency standard that regulates the automakers to raise the fuel economy of vehicles as well as the Renewable Portfolio Standard that reduces the carbon intensity of electricity by introducing renewable electricity. The joint implementation of these policies in the presence of a trending preference for the electric vehicle, however, may or may not achieve the targeted goals when considering the interactions in the fuel market, electricity market, and agricultural sectors. Rarely has literature discuss the interaction of the policies for both electrification and biofuel blending and their synergistic/agonistic effect on the alternative fuel vehicles.

The objective of this paper is to examine cost-effectiveness and the ability of GHG reduction of each of the policies individually and jointly together. We interact the biofuel blend policy with the incentives for electrification and study the joint implication on adoptions of alternative fuel vehicles and energy consumption, as well as the welfare and environmental impact on the US economy. The most notable low-carbon biofuel is corn- and cellulosic-based ethanol, with at least 20% and 60% lower GHG emissions intensity than petroleum gasoline fuel. Cellulosic biofuel is defined as biofuel from sources of cellulose, hemicellulose, or lignin, which has a potential of 60% lifecycle GHG reduction relative to the petroleum counterparts. The high blend of biofuel beyond the current blend level of 10% is compatible with the dual-fuel engine equipped by the flexible-fuel vehicle (FFV) that can significantly reduce GHG emissions (Dwivedi et al. 2015; Wang et al. 2012), which even outweighs the electric vehicle in the lifetime emission intensity (Gelfand et al. 2020). The electric vehicles (EV) running on the electric-powered engine enhances fuel efficiency and eliminate tailpipe emissions (US EPA 2012). The declining costs and continuing government support spur the optimism about expanding transportation electrification as electric vehicles are becoming competitive with both favorable economic and environmental performance.

Regardless of the incentives for the alternatives, petroleum liquid-fuel vehicles still dominate the US vehicle fleet. The GHG emissions of the transportation sector have increased by 9.6% from 2012 to 2019 (EPA 2019) due to growing demand for mileage, although the emission per mile reaches a record low since 2005 (EPA 2018). The recent observed conventional vehicle stocks and the future projections of petroleum-fueled vehicles show an expanding trend, whereas the alternative fuel vehicle shares are limited and projected to be only 10% by 2040 (US DOE 2019; EIA 2021). The demand rigidities in high ethanol blends is restricted by the limited incentives both for the adoption of flex-fuel vehicle (FFV) and for the retail price (Khanna, Rajagopal and Zilberman 2021). The electro-mobility also confronts the techno-economic and behavioral challenges (Zhong and Khanna 2021b), where the abatement costs of GHG mitigation of electrification are more costly than the social cost of carbon.

To accelerate the GHG reduction in the transportation sector, we consider imposing the 61 billion liters of cellulosic biofuel mandate of the Renewable Fuel Standard (RFS) in addition to the existing 56 billion liters of corn ethanol currently mandated. Although the volumetric targets of various types of biofuels beyond 2022 are yet to be determined, forward-looking analysis can inform the policy discussions of the potential economic and environmental implications on the transportation fleet of extending the corn ethanol mandate and adding the cellulosic biofuel mandate to be achieved in the long term. A substantial literature has examined the cost-effectiveness of cellulosic biofuel in reducing GHG emissions by replacing fossil fuel and soil carbon (Robertson et al. 2017; Lynd 2017; Hudiburg et al. 2016; Dwivedi et al. 2015; Pourhashem et al. 2013). However, the biofuel policy implication with consideration of the electrification of transportation is rarely studied. This study examines how the replaced gasoline consumption by EV purchase interacts with biofuel policy and the role of blend mandate in the transportation sector. The leading policy support for EVs, such as EV tax credit and gasoline-vehicle ban, are analyzed jointly with and without the extended cellulosic biofuel policy. We compare the effect of these policy scenarios and aim at the implications on vehicle fleet and fuel consumptions, as well as the lifecycle GHG emission intensity of each car type. We examine the cost-effectiveness in abating the emission by measuring the welfare cost of the transportation, electricity sectors, and government revenue in the US economy.

The environmental performance of cellulosic biofuels and electrification in transportation is ambiguous. Cellulosic ethanol production offers the highest GHG emission benefit among bioethanol feedstocks (Wang et al. 2012). The upscaling cellulosic biofuel production using the carbon capture technique could lower the carbon intensity of biofuel (−179 to 20 g CO_2 per MJ), which are comparable to electric vehicles (Gelfand et al. 2020). Meier et al. (2015) find that up to 56.4 billion gallons of cellulosic biofuel is required in addition to a 40% of mileage electrification to achieve the 80% GHG reduction target. The emission benefit of EVs can reduce GHG emission by as high as 64% (Meier et al. 2015), though restricted by the regional sources for electricity (Tong and Azevedo 2020; Holland et al. 2016). These lifecycle analyses of low carbon transportation energy do not discuss the market friction of adopting alternative fuel vehicles, neither consider the feedback effect of the fleet change back on the fuel market.

The feasibility of high ethanol-blended fuel widely accepted by US consumers (with an average blend of 74%, also known as E85) depends on the key factors of fuel prices and availability of refueling stations, as well as behavioral preferences. The demand for E85 fuel is driven by the fuel prices that are found discounted by consumers 55% to 76% of regular motor fuel (E10) for most regions, but the price ratio of E85 to E10 in California can be as high as 131% in California (Pouliot, Liao and Babcock 2018). Moreover, the owners of FFV are reported unaware of the dual-fuel capabilities and associated costs of using E85 (Liao and Pouliot 2016; Pouliot et al. 2018). The E85 demand is also driven by the geographical locations of the E85 pumps as consumers are sensitive to the inconvenience cost of detours (Pouliot and Babcock 2014). Empirical evidence shows that the increasing deployment of E85 fuel stations induces adoptions of government FFV fleet more than private FFVs (Corts 2010). However, rarely has the literature discussed the role of biofuels play in the presence of electrified transportation and the substitutable or complementary effect between FFV with the electric vehicle (EV).

Our approach of the integrated dynamic vehicle choice model also contributes to the literature of modeling the transportation sector. The Biofuel and Environmental Policy Analysis Model (BEPAM) widely studies the implications of biofuel policy on agriculture and transportation fuels, but it does not consider the endogenous vehicle choices under heterogenous driving demand. Behaviorally realistic vehicle choice models with the consideration of inconveniences costs and idiosyncratic preferences are incorporated into the energy system models to mimic the vehicle stock change under alternative policies (Bunch, Ramea and Yeh 2015; Ramea et al. 2018; McCollum et al. 2017). The model, however, does not discuss the economic mechanism of vehicle choices with varying fuel prices and traveling demand that affect the vehicle choices.

Our model contributes to the literature with the policy analysis for the market acceptance of emerging technologies, such as EVs (plug-in hybrid electric and battery electric) and low carbon fuel vehicles (flex-fuel vehicles) using the welfare framework. We first provide a conceptual graphical analysis of policy analysis to study the extent to which the combination of the policies affect the price incentives for the fuel prices that determine the cost-effectiveness and GHG mitigation. We then undertake the numerical analysis based on the vehicle choice model integrated with the dynamic, open-economy, multi-market optimization model BEPAM (Biofuel and Environmental Policy Analysis Model) that specifies the fuel, transportation, electricity, and agriculture sectors under a welfare-economic framework (Zhong and Khanna 2021b). The specification of the dynamics of vehicle fleet and the stock turnover considers five fuel types that take 99% of the total US light-duty vehicle stock (in Table S1): conventional vehicle (CV), flexible-fuel vehicle (FFV), hybrid gasoline vehicle (HBV), plug-in hybrid vehicle (PHEV), and battery electric vehicle (BEV). One feature that differentiates our model from previous literature is that we endogenously solve the consumers' choice of the vehicle type, fuel consumption, mileage driven, and charge modes by maximizing social welfare. We represent consumer heterogeneity by specifying spatial variation across 20 regions, three driving demand groups, four charging modes, and up to 24 vehicle ages, for five vehicle drivetrain types. We further apply the realistically stochastic variable of daily mileage traveled, time valuation, and idiosyncratic preference. We quantify welfare change incurred by the policy incentives and calculate the abatement cost of the GHG mitigation.

The rest of the paper is organized as follows. The following section first describes the conceptual framework of the policy analysis considering both incentives for the electrification and low carbon fuel blend mandate. We then introduce the numerical simulation model and scenarios to analyze. Section 4 presents the impact of the cellulosic biofuel policy and electrification incentives on the transportation sector, focusing on vehicle stocks, energy consumption, and welfare and environmental implications. Lastly, in Section 5, we conclude the paper with a discussion of the implications of our findings.

2 Conceptual Framework

We first analyze the implication of policy interaction between the ethanol blend mandate (denoted as M) and the policy incentive for EV, such as tax credit (denoted as T), with a simple graphical analysis in Figure 1. We examine the fuel market under four alternative scenarios: without any policy intervention (denoted as 0), with EV tax credit (T), the ethanol blend mandate (M), and the joint implementation of ethanol blend mandate and EV tax credit (M+T).

First, ethanol demand is comprised of the ethanol blended in E10 and E85 (in panel a and b of Figure 1). Without any policy intervention, the aggregated ethanol demand curve is limited at a low ethanol blend (D^e_0 in Figure 1a), whereas E85 demand is negligible. The ethanol blend mandate raises the demand for ethanol blended up to 10% (D^e_M in Figure 1a) and also for E85 (D^c_M in Figure 1b). The aggregated ethanol demand has a kink and prioritizes the ethanol blended in E10 until it reaches the blend wall[1] , and then followed by the ethanol demand in E85 (D^E_M). The price difference between the supply and aggregated demand curve is the implicit subsidy granted by the ethanol blend mandate (shown as $subsidy_M$ in Figure 1c). Theoretically, it is the shadow price of the policy constraints.

The EV tax credit alone without blend mandate promotes EV adoptions, thus reduces the dependence on E10 and the corresponding blended ethanol (D^e_T in Figure 1a) without any E85 consumption. The addition of the ethanol blend mandate at the presence of the EV tax credit (M+T) indicates a higher blend rate applied to the fossil fuel base of the sum of gasoline and diesel volumes[2] to secure the same amount of ethanol to be blended and consumed. Therefore, the EV tax credit (T+M) shifts the demand for E10 outward (D^e_{M+T} in Figure 1a), but lower than the original demand under blend mandate (D^e_M) due to the lower demand of E10 caused by the EV tax credit. The demand for E85, however, shift outwards (D^c_{M+T} in Figure 1b) as the volumetric ethanol target pushes E85 consumption as E10 demand declines. The aggregated demand for ethanol, therefore, shifts downwards with the kink moved to the left and followed by flatter E85 demand that intersects with the mandated level of ethanol with the implicit subsidy wedging between the supply and new demand (denoted as $subsidy_{M+T}$ in Figure 1c). The slopes of the piecewise demand curve (D^E_{M+T}) are greater due to the increasing blend rate corresponding to the decline in fossil fuel consumption. We find that whether the $subsidy_{M+T}$ is

[1] The literature describes the blend wall as the limit on ethanol blend rate that can be consumed by the existing fleet of vehicles due to technological constraints (Du and Li 2015; Luo and Moschini 2019; Tyner, Taheripour and Perkis 2010; Taheripour and Tyner 2008).

[2] As speficied in Federal Register, the ethanol mandate is implemented by setting blend rates applied to a fossil fuel base that jointly include gasoline and diesel. Source: https://www.epa.gov/renewable-fuel-standard-program/regulations-and-volume-standards-renewable-fuel-standards

greater or smaller than the original implicit subsidy_M is ambiguous. It largely depends on the extent to which both the E10 is substituted, how much E85 is induced, as well as the blend rate that determines the slope of the demand curve. As the case illustrated in Figure 1c, the lower E10 demand but flatter demand curve could result in lower implicit subsidy meanwhile increase the E85 consumption.

The revenue-neutral policy also imposes the same amount of implicit tax on both gasoline and diesel due to the joint base of the ethanol blend mandate (Zhong and Khanna 2021a). The implicit taxes under the joint-base policy is the multiplication of the blend rate and the shadow price of the policy constraints (Zhong and Khanna 2021a). As found in previous studies (Babcock, Agroicone and Peng 2013; Thompson, Meyer and Westhoff 2010), the ethanol blend mandate alone shifts the demand for gasoline inward from $D^g{}_0$ to $D^g{}_M$ (Figure 1d) that creates the price wedge between the demand and supply, which is the implicit tax_M. The EV tax credit without ethanol blend mandate parallelly reduces the demand for gasoline ($D^g{}_T$). If jointly implement both the biofuel blend mandate and EV tax credit, the demand curve shifts inward from $D^g{}_T$ to $D^g{}_{M+T}$ with a steeper slope with a higher blend rate than $D^g{}_T$. The quantity of gasoline is reduced to $Q^g{}_{M+T}$. We note that the change of implicit taxes is also ambiguous from tax_M to tax_{M+T}. It depends on how much gasoline is replaced by the EV tax credit ($D^g{}_T$), and the increase of the ethanol rate that determines the slope and the quantity of gasoline at the equilibrium ($Q^g{}_{M+T}$).

3 Numerical Model

We undertake this analysis by using the open-economy, price-endogenous, partial equilibrium model— Biofuel and Environmental Policy Analysis Model (BEPAM) that integrates the multiple markets of transportation, electricity, and agriculture sectors (Chen et al.

2020). The model maximizes the discounted sum of consumer and producer surplus in the three sectors, subject to policy constraints in the form of corn ethanol only mandate and cellulosic with corn ethanol mandate, and various technological and material balance constraints. The technological constraints of the transportation sector describe the assumptions about the compatible fuel type for each vehicle engine, fuel economy that determines the conversion efficiency of fuel into mileage driven. Material balance constraints ensure that demand is equal to supply, which is defined as market equilibrium achieved in the transportation, electricity, and agriculture sectors. In the transportation sector, the equilibrium of the mobility service is defined as traveling demand met by the capacity of driving mileage supplied by driving the vehicle in stock and consuming the fuel and energy.

3.1 Transportation sector

The heterogenous driving demand of transportation is specified by the downward sloping linear demand functions for vehicle kilometers traveled (VKT) of twenty electricity market regions and three driving demand groups based on the driving cost from Alternative Fuel Data Center (AFDC 2019) and annual VKT from National Household Travel Survey (Federal Highway Administration 2017). The consumers' utility of the transportation sector is incorporated with the specification of the consumer surplus from driving demand net the vehicle ownership costs, including the economic costs (procurement cost, operation and management cost) and intangible disutility costs (range limitation, waiting, and detour). The randomness in consumers' behavioral characteristics of daily driving demand, and value of time, and idiosyncratic preferences are considered to embody the realistic market dynamics.

We address economic costs and intangible disutility costs associated with ownership of alternative powertrain vehicles (range limitation, waiting, and detour). Range limitation cost quantifies the cost of the alternative modes of transportation if BEV runs out of battery. Waiting cost is the valuation of time summing over all the visits to the public charging stations. Detour cost is measured by the time cost to find the nearest station. The idiosyncratic preference term for each vehicle type is added to the consumer utility that mimics the random utility framework following Gumbel distributions (Bunch and Rocke 2016). We also incorporate the stochastic process by randomly drawing the preference terms, daily driving demand, and value of time from predefined distributions. The full details of mathematical modeling and data source are described in Appendix in Zhong and Khanna (2021).

The fuel supply of the transportation module in BEPAM model includes the crude oil markets for both US and the rest of the world, the refinery product of petroleum gasoline and diesel used for blended retail products, and the regional electricity grid. Following the same fuel modeling assumption in Chen et al. (2021), gasoline and diesel are jointly distilled products from crude oil and US as a price-taking exporter of petroleum products as US only export a small portion of the petroleum product to the rest of the world. The gasoline and diesel prices are capped by the prices of world markets. The model endogenously determines the implicit cost of VKT depending on the marginal cost of oil, costs of conversion of oil to gasoline and diesel, extent and mix of biofuels blended, and the operation and maintenance costs of vehicles.

3.2 Electricity sector

We also include the regional supply and demand of the electricity generation at the electricity market region, where the generation capacity, cost of generation, and conversion efficiency are specified for each energy source in each region. The electricity demand is specified in each region with a linear demand curve that is an aggregation of demand across residential, commercial, and industrial sectors. The model endogenously determines prices and quantities of electricity consumption in the electricity sector (Oliver and Khanna 2017b). We further update the electricity markets with the updated eGRID data (EPA 2016). The additional electricity demand due to the increasing electric vehicle use shifts the aggregate demand outward. The endogenous solutions of market equilibrium of electricity prices determine the energy sources and fuel costs of driving EV. We estimate the cost of expanding the charging portals for both L2 and fast-charging by using the estimates of a single outlet from DOE (2015) times the numbers of the portals required for stations, assuming each station on average having three portals.

3.3 Agricultural sector

The agricultural sector endogenously determines the quantities of row crops, biomass feedstock, biofuels, and fossil fuels and their prices that ensure that market demand and supply are in equilibrium. It incorporates domestic agricultural and fuel markets in the U.S. and trade in agricultural commodities and petroleum products with the rest of the world. The model considers spatial heterogeneity in crop and livestock production, where costs of production, yields, and land availability differ across crop reporting districts (CRDs). Crops can be produced using alternative rotation, tillage, and irrigation practices. The model simulates optimal land use allocation for major row crops and energy crops on active cropland endogenously based on the availability of land, the net returns to crop production, endogenously determined crop prices, historical land mix constraints, policy, and technology constraints. More details are documented in Chen et al. (2021).

3.4 Welfare Analysis

To determine the social welfare effects of the policy incentives for decarbonization, we assess the change in fuel prices, energy consumptions, and vehicle kilometer traveled (VKT) and, thus, on the discounted value of the sum of consumer and producer net benefits of agricultural, transportation, and electricity sectors relative to the existing policy scenario. The consumer utility gained from the transportation service is calculated as the consumer surplus from VKT demand net the vehicle ownership cost, disutility cost, and the cost of home charging. We demonstrate the welfare change for consumers of each vehicle type as well as diesel users. The profit of fuel producers is the total benefit from retail fuel sales less the crude oil production cost, crude oil process cost, and excise taxes of gasoline and diesel. We calculate the surpluses for both producers and consumers of the electricity sector the same way as (Oliver and Khanna 2017a). We also consider the government costs and benefit from fuel tax revenue, the investment in the tax credit, and establishing the charging infrastructure. We assume a social discount rate of 3% (for more discussion of the welfare framework of the agriculture sector, see Chen et al. 2020).

3.5 GHG Estimation

Unlike EPA and NHTSA overlook the upstream emission with only consideration of tailpipe emissions, we investigate the lifecycle GHG emission sources from the agriculture, transportation, and electricity sectors following Chen et al. (2021) by multiplying the lifecycle carbon intensity with the fuel consumptions of gasoline, diesel, biofuels, and electricity of different sources. We estimate the carbon intensity per km for each vehicle type by dividing the vehicle emission by the vehicle kilometer traveled (VKT) under each scenario. We examine the cumulative emissions and their social costs of each scenario from 2016 to 2040 and the GHG emission in 2040. We calculate the total social cost of GHG emissions from agriculture, transportation, electricity sectors based on the carbon price. There is a wide disparity in the range of estimates of the social cost of carbon but a considerable consensus that $50 per metric ton of CO_2 equivalent (Mg CO_2) is a reasonable estimate with the same 3% social discount rate assumed here (Watkiss and Downing 2008; Tol 2005).

3.6 Scenarios

We first investigate three potential policy scenarios that promote electrification in the transportation sector over 2016 - 2040 period. Baseline scenario (1) defines the existing policy mix of 56 billion liters of corn ethanol blend mandate, the underlying fuel efficiency standard featuring the increasing fuel economy of all vehicle types, as well as the Renewable Portfolio Standard with minimum percentage requirement for renewable energy. Scenario (2) extends the federal tax credit policy for battery and plug-in hybrid vehicles in addition to scenario (1). Scenario (3) imposes the ban on conventional vehicles with only internal combustion engines starting 2020 in addition to scenario (2) that jointly represent the most aggressive incentives to facilitate the decarbonization.

We then analyze the above three scenarios under the extended cellulosic biofuel mandate to achieve 61 billion liters of cellulosic biofuel production of the Renewable Fuel Standard (RFS) by 2040 and we number the three scenarios (4) to (6). We assume the cellulosic ethanol production grows linearly from 0.87 billion liters in 2016 to 61 billion liters in 2040 while annual corn ethanol levels are constant at 56 billion liters.

4 Results

We validate the model by comparing simulated outcomes in the fuel and vehicle sectors under scenario (1) over 2016-2019 period with observed data. We find the fuel consumption and production both in the US and the rest of the world generally deviate by less than 2% from observed data (Table A3 in appendix A.4). The fuel prices are within a 12% deviation. The vehicle stocks are within a 9% deviation from the observed level from 2016 to 2019. The deviations of the simulated outcomes of the updated BEPAM for 2016–2019 from their observed values over the 2016–2019 period are generally within a similar level of tolerance as in previous studies applying BEPAM (Chen et al. 2020; Hudiburg et al. 2016; Oliver and Khanna 2017b).

4.1 Effect of Policy Interaction on Fuel Incentives

The implicit price incentive of biofuel policy on gasoline, diesel, and ethanol are provided in Table 1. We find that implicit subsidy of ethanol blend mandate on ethanol production increases from \$0.33 L^{-1} of baseline scenario (1) to \$0.39 L^{-1} with EV tax credit in scenario (2), and implicit tax also increases from \$0.04 L^{-1} to \$0.06 L^{-1} in 2040. The gasoline and diesel share the same amount of implicit tax as the volumetric total of gasoline and diesel are jointly used for the ethanol blend mandate. As we illustrated in Figure 1, the price incentive increases when the demand for E85 does not grow fast enough to meet the volumetric target of ethanol production and requires greater subsidy. The addition of the CV ban on the top of the EV tax credit, however, reduces the implicit subsidy to \$0.31 L^{-1} when E85 market demand rise more than the decrease in the E10 consumption (as illustrated in Figure 1), whereas the implicit tax on petroleum fuels remains the same with increased blend rate despite the lower incentive.

The scenarios (4) to (6) with cellulosic ethanol mandate increase the implicit subsidies and taxes because of more stringent policy relative to counterpart scenarios without cellulosic ethanol mandate. Follow the same direction as above, and the EV tax credit increases the implicit subsidy from \$0.38 L^{-1} to 0.56 L^{-1} and implicit tax from \$0.10 L^{-1} to \$0.18 L^{-1}, driven by the reduced E10 demand. Similarly, the CV ban reduces the implicit tax and subsidy relative to otherwise when E85 demand is pushed by the volumetric target.

4.2 Effect of Electrification Incentives

The outcome of vehicle choices, energy consumption, and vehicles kilometer traveled (VKT) are presented in **Error! Reference source not found.** for policy scenarios under study 2040. As EIA predicted, the VKT demand in 2040 is 23% above the 2016 level; BEVs are 11% cheaper, and vehicles of all types are more efficient (details in Appendix A.1 and A.2). By 2040, the total amount of vehicle stock expands to 298 million (as shown in Table 2) with a diversified alternative-vehicle fleet. Though the BEVs stock is only 4 million by 2040, the electrification jointly achieved by BEVs and PHEVs rises to 10%, whereas the ethanol blend of the VKT remains at 10%. The efficient and diversified vehicle fleet saves E10 consumption in 2040 by 11% compared to the baseline scenario that reversely pushes the E85 consumption and FFV purchase to maintain the 56 billion liters of corn ethanol production. However, the detour distances for E85 and charging stations decline as the infrastructure slowly diffuses across the country (2% annually), which needs less price incentive for the E85 users to offset the inconvenience cost to switch fuel choices. E85 price is higher than the level in 2016. The increasing driving demand raises the E10 price above the 2016 level, despite the fact that the vehicles are more efficient and E10 are displaced by other fuel types.

In case tax credit of $7,500 and $2,500 for BEV and PHEV extended to 2040 in scenario (2), BEVs and PHEVs stocks are further enlarged to 46 million and 51 million and together account for 32% of the total vehicle fleet. They contribute to the electrification of the vehicle fleet to 36% but only 15% of reduction in total energy consumption compared to scenario (1) without the tax credit. We find E85 consumption increases by 12 billion liters to meet the 56 billion liters of ethanol mandate and 29 billion increase of gasoline-equivalent liters of electricity offset the reduction of 74 billion liters of E10 consumption. The EV tax credit lowers the E85 price due to higher incentives received in 2040. The higher incentive indicates E10 displacement reducing the ethanol demand dominates the increase in the price incentive.

Under the aggressive policy restriction of tax credit and CV bans over the 2016-2040 period, the new CV purchases are replaced entirely by the alternative fuel vehicle, with only 5 million stocks remaining in 2040. The PHEV becomes the next popular vehicle type with a drastic increase in the stock to 108 million, followed by FFV of 84 million and BEV of 72 million. E10 consumption drops by 224 million liters in the E10 consumption, and E85 increases by 24 billion liters compared to the baseline scenario. The electricity consumption increases by 54 billion liters, whereas diesel consumption remains unchanged as an implicit tax on both diesel and gasoline does not change (Table 1). Altogether, they contribute to 148 billion liters of reduction (-22%) in the total energy consumption compared to the baseline scenario (1) in 2040. The regulated market favoring advanced vehicles raises the overall ownership cost that marginally reduces both the total light-duty VKT and total vehicle stocks but enhances the fuel efficiency to 24 km per liter.

4.3 Effect of Cellulosic Ethanol Mandate

The implementation of Corn + Cellulosic Ethanol Mandate increases the requirement of cellulosic ethanol linearly to the goal of 61 billion liters by 2040 in addition to the extant production capacity of 56 billion liters of corn ethanol and thus doubles the ethanol consumed for light-duty VKT to 18% (Table 2). The stringent ethanol policy induces 50 million FFV adoption and 90 billion liters of E85 in 2040 than the baseline scenario (1) without cellulosic biofuel mandate (Table 2). The total energy consumption reduces by 2% due to the cellulosic ethanol mandate, contributed mostly by 71 billion liters and 5 billion liters less E10 and diesel consumption, respectively, but they are offset with the addition of 68 billion liters of E85 and 2 billion energy equivalent electricity. The fuel prices of E85 decrease by $0.02 per liter, whereas E10 increases by $0.05 per liter compared to the baseline scenario (2). The E85 is thus priced 25% lower than the E10 to secure the market demand, which is also found in Pouliot et al. (2018).

The cellulosic biofuel policy with the extended EV tax credit in scenario (5) synergizes the adoptions of alternative fuel vehicles. Compared to scenario (1), the stock increases of FFV by 40 million and BEV by 48 million are greater than the sum of the increase from EV tax credit and from cellulosic ethanol mandate alone. It is because EV tax credit contracts the demand for gasoline that furthers the ethanol blend rate required to meet the required 61 million cellulosic biofuel mandate. The higher blend rate and increased implicit tax raises the E10 prices and consequently reduces CVs stock to only 130 million. The reduction in total energy consumption by 84 billion liters compared to the baseline scenario (1) is higher than the sum of the reduction (by 74 billion liters) achieved by the single EV tax credit in scenario (2) and the cellulosic ethanol policy (by 6 billion liters) in scenario (4).

The cellulosic ethanol mandate with the ambitious EV tax credit and CV ban in scenario (6) increases the FFV adoption to 111 million, which becomes the primary choice of vehicle. The BEVs increases by 5 million by the cellulosic ethanol mandate, whereas PHEV is replaced by FFV stock. FFVs and BEVs are complementary in taking the market share while replacing the E10 fuels. An increase of 66 billion liters of E85 consumption replaces 49 billion liters of E10 fuel use. The total energy reversely increases by 5 billion liters compared to the counterpart without cellulosic blend mandate in scenario (3) as electrification minorly decline due to the shift of the primary vehicle choice from PHEV to FFV and increased E85 consumption surpasses the reduced E10. Though FFVs dominate the market now, the E85 price is higher than the case without the CV ban in scenario (5). It is because of the synergy of the CV ban and cellulosic ethanol mandate that is similar to the analysis we discussed in Figure 1 that reduces the implicit tax and subsidy of the cellulosic ethanol mandate.

4.4 GHG Intensity of Vehicle

The greenhouse gas (GHG) emissions per mile of five vehicle types under different policy scenarios are displayed in Figure 2. Enhanced fuel efficiency predicted in 2040 leads to reduced emission intensities for all vehicles across scenarios. Under the baseline policy scenario (1) in Figure 2, the CV still has the highest emission intensity for all three scenarios, followed by FFV with 26% less emission due to the consumption of E85 fuel that has lower carbon intensity. HBV and PHEV with higher efficiency show a 30% and 67% less emission than CV, whereas BEV has zero-emission intensity as the electricity sources are marginally from clean sources. Scenario (2) with EV tax credit further reduces the emission intensities for FFV even lower than the level of HBV as EV tax credit synergically induces the FFV adoption. The joint imposition of EV tax credit and CV ban of scenario (3) raises the intensity of CVs by 15% compared to scenario (2) as they are the remaining aged and inefficient vehicles still in use since 2016. FFVs also have a 19% increase in the average emission intensity as they mostly consume E10 as the second cheapest vehicle option substituting for CV. Whereas HBV, PHEV, and BEV relative remain the same intensity.

Lastly, we find the Cellulosic Ethanol Mandate in 2040 cuts the emission intensity of FFV by 47% compared to scenario (1) without cellulosic ethanol. The emission intensities of all other vehicles reduce by 3% universally in 2040 relative to no cellulosic ethanol mandate in scenario (1). It is because the higher E10 prices induce the adoption of alternative fuel vehicles that raise the average fuel efficiency, whereas the retirement of the old CVs also reduces the intensity. The cellulosic biofuel mandate further downgrades the emission levels of FFV close to PHEV, which are 60%-67% lower than that of the CV and driven by the high ethanol blend. The Cellulosic Ethanol Mandate with the EV tax credit lowers the carbon intensity for FFV but barely for others, whereas the CV ban together with the EV tax credit raises the carbon intensity of CV by 15% and that of FFV by 12% and reduces 0.1% for PHEV, for the same reason discussed above without Cellulosic Ethanol Mandate.

4.5 Total GHG Emission

We calculate the GHG emissions of transportation, electricity, and agriculture sectors, as shown in Table 3. In 2040, the transportation and electricity sectors account for 47% and 50% of the total emissions, whereas the share of cumulative GHG emissions by both transportation and electricity sector are 48%. It shows a declining emission intensity with the improving fuel efficiency to reduce the transportation emission in the long run. The addition of EV tax credit in scenario (2) enhances the GHG reduction in the transportation sector by 17% in 2040 but reversely increases the emission of the electricity sector by 4% for transportation that leads to a net decrease of 6% of the GHG emissions compared to the baseline scenario (1). The magnitude of cumulative emission reduction caused by the EV tax is relatively smaller compared to the 2040 reduction as the fuel efficiency and GHG reduction potential is the highest in 2040 over the 2016- 2040 period. The joint implementation of EV tax credit and CV ban enlarges the GHG reduction to 11% in 2040 and 5% cumulatively from 2016-2040.

The imposition of the cellulosic policy in scenario 4-6 contributes to an overall 3% reduction in the cumulative emission over 2016-2040 compared to that of the counterpart scenarios 1-3 without cellulosic ethanol mandate, whereas 2040 reductions reach 6-7% less GHG emission compared to the counterparts. The percentage emission reductions in agricultural sectors are as high as 24%-27%, but the absolute contribution is not comparable to that of the transportation sector. The Cellulosic Ethanol Mandate alone in scenario (4) outperforms the EV tax credit in scenario (2) in cumulative emission reduction. The joint implementation of the cellulosic ethanol mandate and EV tax credit increases the GHG reduction in 2040 and is additive in achieving a 5% reduction in cumulative GHG emissions over the 2016-2040 period. The CV ban jointly implemented with the cellulosic ethanol mandate also shows the additive cumulative reduction of 8% compared to the EV tax credit and CV ban in scenario (3) and cellulosic ethanol mandate in scenario (4) by itself, but the 2040 emission shows the GHG reduction is less than the sum of those of scenario (3) and (4) when FFV compete PHEV to be the primary vehicle type with the addition of the cellulosic ethanol mandate.

4.6 Welfare analysis

We find that the EV tax credit will lead to an overall decrease of $125 billion in the economic net benefit over 2016-2040 relative to the baseline scenario. In the transportation sector, consumers of light-duty vehicle fleet benefit with a net of $287 billion relative to the baseline scenario (1) by increasing the consumers' utility of the BEV and PHEV owners but reducing those of the CV and HBV. The higher implicit subsidy discussed in section 4.1 driven by less fuel demand reduces the consumer benefit of diesel fuels by $72 billion. Electricity producers' benefit increases by $95 billion (1%) as more electrification is created for transportation use, but the higher electricity price reduces the consumers' benefit. The government revenue from fuel taxes falls by $62 billion (-5%) with less petroleum consumption and is further exacerbated by $369 billion of EV tax credit expenditure on the EV purchase. We find the expense of EV tax credit is greater than the gain in the transportation fuel sector and electricity sector. As the cumulative GHG emission reduces by 2,334 million Mg CO_2 (-2%), the abatement cost of CO_2 with the tax credit for EV is \$54 per $MgCO_2$. It is close to the widely accepted value of the social cost of carbon at \$50 per $MgCO_2$.

The additional CV ban in scenario (3) forces drivers to buy more expensive alternative fuel vehicles, leading to a net economic loss of \$607 billion. The declining CV stocks lead to a drastic loss of \$44,518 billion (-30%) for the CV fleet but enhance consumers surplus of all other alternative fuel vehicles that offset the CV loss with a net gain of \$117 billion (-0.1%) for light-duty vehicles compared to the baseline scenario (1). The electricity sector further enhances the economic benefit by \$202 billion by benefiting the producers but reducing the welfare for consumers with higher electricity prices. The welfare loss exacerbates for the government as fuel tax revenue cut by \$145 billion and vehicle tax credit required \$678 billion. The abatement cost of implementing the CV ban more than doubles to \$111 per Mg CO_2 as the economic loss grows faster than the GHG reduction.

The cellulosic ethanol mandate reduces the economic surpluses by a loss of \$417 billion (-0.1%). The stringent policy raises the E10 and diesel prices and reduces the profits of CV, HBV, and diesel fuel drivers by \$6,045 billion (-4%), \$454 billion (-5%), and \$412 billion (-3%) compared to the baseline scenario (1). The increased benefit for EVs and FFV drivers reduces the net welfare loss by 478 billion (-0.1%), which is greater than the sum of \$53 billion in the agricultural sector, \$1 billion increase in the electricity sector synergistically caused by the cellulosic ethanol mandate, and the \$7 billion increase of the fuel tax revenue from ethanol import tariff. The cumulative GHG emission of 2,945 Million Mg CO_2 (-3%) is higher than that of the scenario with EV Tax credit in scenario (2) and leads to an abatement cost of \$142 per Mg CO_2.

The cellulosic ethanol mandate, together with the EV tax credit, worsens the overall economic benefit by $668 billion (-0.3%). It is greater than the sum of welfare loss from the EV tax credit in scenario (8) and cellulosic ethanol mandate in scenario (10). Though the light-duty consumers benefit from the EV tax credit by $237 billion, the diesel fuel users bear the loss of $606 billion that leads to a net of $370 billion loss in the transportation sector. And the substantial government payment of $462 billion further deteriorates welfare loss despite the electricity sector benefits by $98 billion. The overlapping EV tax credit and the cellulosic ethanol mandate have a synergistic effect on welfare gain of the agricultural sector and electricity sector, as well as on welfare loss of diesel consumer surplus and government revenue. The cumulative GHG emission reduction of the policy interaction between the EV tax credit and cellulosic ethanol mandate at 5,425 Million Mg (-5%) is also more than the sum of the reduction of single implementation of the EV tax credit and cellulosic ethanol mandate. The abatement cost reduces to $123 per Mg CO_2, lower than the level of cellulosic ethanol alone ($142 per Mg CO_2) but higher than that of the EV tax credit ($54 per Mg CO_2). It is because the light-duty consumer gain from the EV tax credit, but bear the high fuel cost caused by the cellulosic ethanol mandate that reduces the net costs of the transportation sector. As a result, the joint implementation of EV tax credit and cellulosic ethanol mandate achieves 5 % of GHG reduction but reducing the abatement cost by 13%, compared to the cellulosic ethanol mandate alone.

The addition of the CV ban to the EV tax credit and the cellulosic ethanol mandate deteriorates the total welfare loss by $1,022 billion compared to the baseline scenario (1). Compare the results summing the cellulosic ethanol mandate in scenario (4) and EV tax credit and CV ban in scenario (3), the joint imposition of these policies does not bring the synergy for the economic surplus, nor for the GHG emissions. The abatement cost is \$126 per Mg CO_2, between \$111 per Mg CO_2 and \$142 per Mg CO_2.

5 Discussion

This paper estimates the economic and environmental implications of decarbonization policies of the biofuel mandate, EV tax credit, and conventional vehicle ban on the transportation, electricity, and agricultural sectors in the US over the 2016-2040 periods. We apply a multi-period, multi-market, partial equilibrium, open-economy model (BEPAM) of the transportation, electricity, and agricultural sectors to endogenously determine vehicle choices, fuel mix, electricity demand, and prices to meet the policy mandate. We also examine the change of GHG emissions associated with each sector in response to the decarbonized strategies and their abatement costs.

Our findings show that the interaction between the ethanol blend mandate and the electrification incentives affect the implicit price incentive of the ethanol blend mandate, but the direction is ambiguous depends on the extent to which both E10 is substituted, the increase of E85 to meet the volumetric mandate as well as the blend rate that determines the stringency of policy. The numerical results show that the EV tax combined with ethanol blend mandate increases the price incentives for ethanol and petroleum fuels. The aggressive electrification effort of the CV ban and EV tax credit, however, reduces the subsidy of E85 as market demand is high enough chosen by the market,

The numerical simulations show the EV tax credit alone and scenario with both the EV tax credit and CV ban diverse the vehicle fleet with 34% and 53% of VKT electrification, but liquid fuel vehicles running on the gasoline still dominate the fleet. Cellulosic Ethanol Mandate induces the flexible-fuel vehicle (FFV) adoptions and E85 consumption by replacing the conventional vehicle (CV) and E10 use. The Cellulosic Ethanol Mandate synergizes with the EV tax credit in diversifying the vehicle adoptions by raising the blend rate and cutting the E10 demand. The aggressive CV ban even prioritizes the flex-fuel vehicle and eases the pressure for wide adoption of E85 fuels.

The cellulosic ethanol mandate helps to lower the carbon intensity of FFV from being the second-highest emission-intensive vehicle to close to what PHEV can achieve by raising the ethanol blend. Overall, the cellulosic ethanol mandate mitigates the GHG emissions by 6-7% and has better performance in reducing GHG emissions from both transportation and agricultural sectors than the counterparts without the cellulosic ethanol mandate. The synergy between cellulosic ethanol mandate and EV tax credit as well as CV bans leads to additive results in GHG emissions reduction in 2040 by 16 % and 8% of cumulative reduction over the 2016-2040 period.

We find the abatement cost of the EV tax credit is comparable to the social cost of carbon at \$54 per $MgCO_2$ that reduces 2% of the cumulative GHG emission compared to the baseline scenario. The scenario with the CV ban and EV tax credit doubles both the emission reduction and abatement cost relative to the scenario with EV tax credit alone. The cellulosic ethanol mandate increases the abatement cost to \$142 $MgCO_2$, born mainly by the fuel consumers. The synergy between the cellulosic ethanol mandate and EV tax credit reversely reduces the abatement cost to \$123 per $MgCO_2$ and the cumulative GHG emissions by 5%, which is due to the benefit of EV tax credit offsetting the loss caused by the ethanol blend mandate. The abatement cost of the CV ban, together with the EV tax credit, is also lower than the cellulosic ethanol only for the same reason.

While the agriculture producers benefit from the cellulosic ethanol mandate, the majority of consumers pay for expensive liquid fuels that lead to net economic loss compared to the counterpart scenario without cellulosic ethanol policies. However, the extended EV tax credit benefits the consumers with cheaper vehicle choices and welfare gain in the electricity market, but the required government investment for the increased EV adoption still surpasses the benefit and leads to a net welfare loss. In the scenario combining cellulosic ethanol mandate with EV tax credit and the CV ban, both transportation consumers and government pay more than the benefit obtained from the agriculture and electricity sectors, which leads to a substantial welfare loss. But they are not as high as the cellulosic ethanol mandate alone achieved in 2040.

Our analysis has several policy implications. It shows the conditions under which cellulosic biofuel mandate has the potential to reduce energy consumption, reduce GHG emissions, and the complementary effect with other climate policy and would, therefore, warrant policy support. The complementary electrification and biofuel displacement by raising E10 price is effective in reducing both energy consumption and emission. Our findings should also provide normative evidence to policymakers to extend the blend rate requirement to 2040 for the cellulosic mandate. Our approach does provide the first estimation of the implication of the biofuel mandate implementation amid the trend of electrification and enables an assessment of the distributional welfare considering the consumers’ utility obtained by vehicle choices associated with behavioral considerations.

Tables and Figures

Table 1 Effect of policy scenarios on implicit tax and subsidy ($ per liter)

	Baseline policy (1)	(1) +EV Tax credit (2)	(2) + CV ban (3)	(1) +Cellulosic Ethanol Mandate (4)	(4) +EV Tax credit (5)	(5) + CV ban (6)
Implicit subsidy						
Ethanol	0.33	0.39	0.31	0.38	0.56	0.41
E85						
Implicit tax						
Gasoline	-0.04	-0.06	-0.06	-0.10	-0.18	-0.16
Diesel	-0.04	-0.06	-0.06	-0.10	-0.18	-0.16
E10						

Table 2 Effect of policy scenarios on transportation sector in 2040

	2016	Baseline policy (1)	(1)+EV Tax credit (2)	(2)+ CV ban (3)	(1)+Cellulosic Ethanol Mandate (4)	(4)+EV Tax credit (5)	(5)+ CV ban (6)
Total Vehicle Stock (million)	**241**	**298**	**299**	**298**	**298**	**298**	**298**
CV	216	221	166	5	191	130	4
FFV	20	21	25	84	50	61	111
HBV	4	20	11	29	17	9	21
PHEV	0	32	51	108	35	47	83
BEV	0	4	46	72	5	52	77
Energy Consumption by Transportation (billion liter)*	**758**	**656**	**582**	**508**	**650**	**572**	**513**
E10	523	351	237	127	280	169	78
E85	0	22	34	46	90	101	111
Diesel fuel	234	269	267	267	264	258	259
Electricity	0.3	14	43	68	16	44	65
VKT by light-duty fleet (billion km)	4,423	5,827	5,834	5,823	5,823	5,830	5,820
VKT by diesel fleet (billion km)	699	1,072	1,065	1,066	1,053	1,026	1,031
Fuel efficiency (km per liter)	8	15	19	24	15	19	23

Electrification (% of total VKT)	**0**	**10**	**34**	**53**	**11**	**35**	**52**
Low	0	2	7	21	2	8	18
Medium	0	4	24	51	5	28	47
High	0	20	57	71	22	56	72
Ethanol (% of total VKT)	**7**	**10**	**9**	**10**	**18**	**18**	**19**
Low	6.9	10	11	22	13	15	37
Medium	7.0	9	11	10	17	22	20
High	6.9	9	8	4	22	16	8
Fuel prices ($ per liter)*							
E10	0.64	0.83	0.83	0.85	0.88	0.94	0.94
E85	0.44	0.55	0.49	0.58	0.53	0.37	0.52
Blended diesel	0.43	0.44	0.44	0.44	0.44	0.44	0.44
Electricity ($ per MWh)	120	108	112	115	108	112	114

* Volumes are converted to gasoline-equivalent liter.

Table 3 GHG emissions of last year and cumulative GHG emissions in 2040

	Baseline policy (1)	(1) +EV Tax credit (2)	(2) + CV ban (3)	(1) +Cellulosic Ethanol Mandate (4)	(4) +EV Tax credit (5)	(5) + CV ban (6)
	Million Mg CO_2	% change relative to (1)				
GHG emission in 2040	4,100	-6%	-11%	-6%	-7%	-16%
Transportation	1,918	-17%	-32%	-10%	-27%	-40%
Electricity	2,007	4%	9%	0%	4%	8%
Agriculture	175	0%	1%	-24%	-28%	-27%
Cumulative GHG emissions over 2016-2040	107,844	-2%	-5%	-3%	-5%	-8%
Transportation	51,946	-6%	-14%	-5%	-11%	-18%
Electricity	51,572	1%	3%	0%	1%	3%
Agriculture	4,326	-1%	-1%	-14%	-13%	-14%

Table 4 Effect of alternative biofuels mandate on social welfare over 2016-2040

	Baseline policy (1)	(1) +EV Tax credit (2)	(2) + CV ban (3)	(1) +Cellulosic Ethanol Mandate (4)	(4) +EV Tax credit (5)	(5) + CV ban (6)
	($ billion)	Relative change to (1) ($ billion)				
Economic surplus (a)	**217,541**	**-125**	**-607**	**-417**	**-668**	**-1,022**
Agricultural sector	*4,586*	*-3*	*-2*	*53*	*67*	*55*
Agricultural consumers	3,203	1	0	-9	-9	-10
Agricultural producers	1,383	-4	-1	62	76	64
Transportation fuel sector	*196,982*	*214*	*16*	*-478*	*-370*	*-471*
VKT light-duty consumers	179,038	287	117	-65	237	69
CV consumers	150,158	-10,540	-44,518	-6,045	-17,839	-45,633
FFV consumers	13,770	631	12,248	5,728	7,026	15,643
HBV consumers	8,774	-2,265	3,574	-454	-2,382	2,178
PHEV consumers	5,524	4,425	14,772	577	4,091	13,004
BEV consumers	812	8,036	14,041	129	9,342	14,878
VKT diesel fuel consumers	16,353	-72	-99	-412	-606	-538
Fuel producer	1,591	-1	-1	-1	-2	-2
Electricity sector	*14,643*	*95*	*202*	*1*	*98*	*192*
Electricity consumers	10,173	-124	-263	-6	-140	-261
Electricity producers	4,470	220	465	8	238	452
Government revenue	*1,330*	*-431*	*-823*	*7*	*-462*	*-798*
Fuel tax	1,330	-62	-145	7	-59	-131
EV tax credit	0	-369	-678	0	-403	-667
Cumulative GHG emissions (Million Mg)	**107,589**	**-2,334**	**-5,480**	**-2,945**	**-5,425**	**-8,143**
Abatement cost ($ per $MgCO_2$)		**54**	**111**	**142**	**123**	**126**

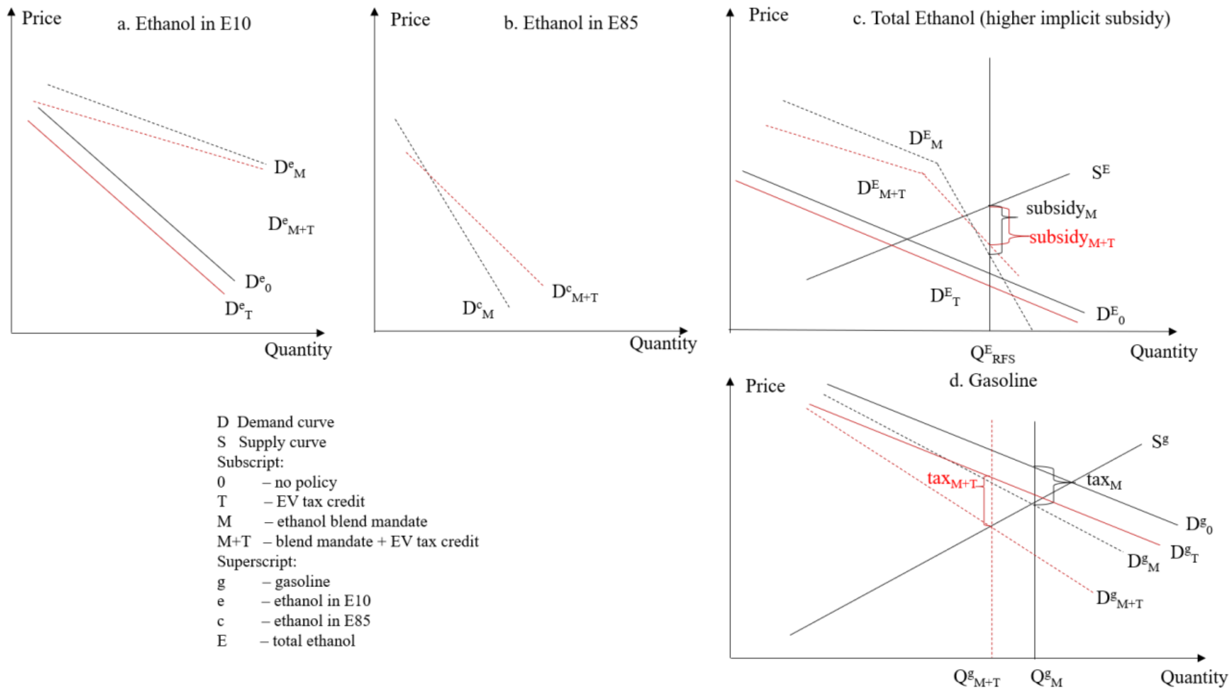

Figure 1 Policy Implication of joint implementation of biofuel policy and EV tax credit

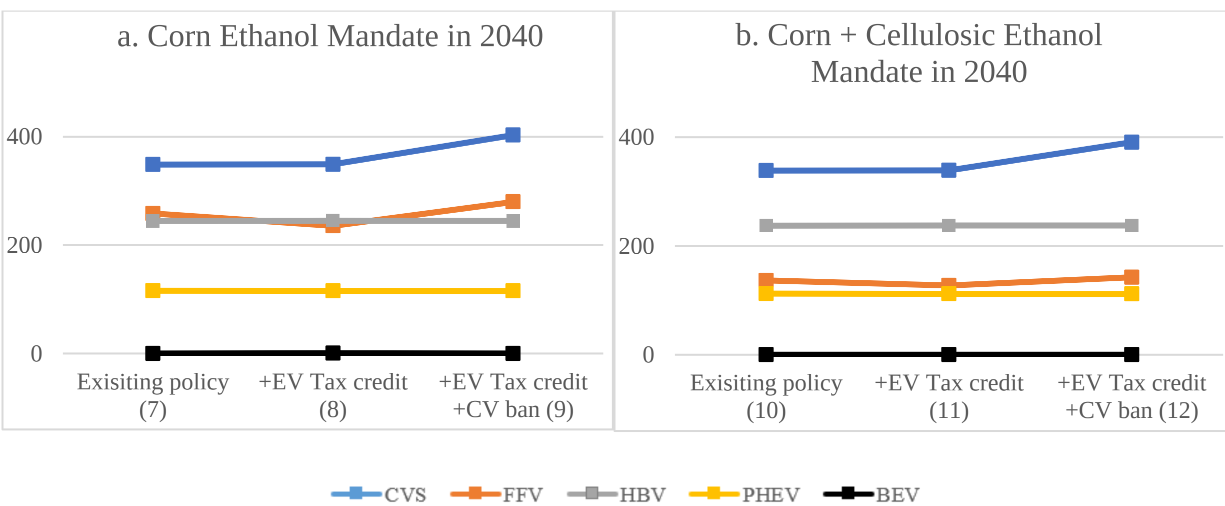

Figure 2 The carbon intensity of vehicle mileage under each scenario (g CO_2 per mile)

Reference

AFDC. 2019. “Vehicle Cost Calculator Assumptions and Methodology.” *Vehicle Cost Calculator*. Available at: https://afdc.energy.gov/calc/cost_calculator_methodology.html [Accessed July 26, 2019].

Alternative Fuels Data Center, D. 2020. “Vehicle Cost Calculator Assumptions and Methodology.” Available at: https://afdc.energy.gov/calc/cost_calculator_methodology.html [Accessed June 11, 2019].

Babcock, B.A., M. Agroicone, and Y. Peng. 2013. “Biofuel Taxes, Subsidies, and Mandates: Impacts on US and Brazilian Markets Recommended Citation.” Available at: http://lib.dr.iastate.edu/card_staffreports/4 [Accessed June 11, 2019].

Belzowski, B.M., W. Mcmanus, Bruce M. Belzowski, W. Mcmanus, B.M. Belzowski, and W. Mcmanus. 2010. “Alternative powertrain strategies and fleet turnover in the 21st century.”

Bunch, D.S., K. Ramea, and S. Yeh. 2015. “Incorporating Behavioral Effects from Vehicle Choice Models into Bottom-Up Energy Sector Models.” Institute of Transportation Studies, University of California, Davis.

Bunch, D.S., and D.M. Rocke. 2016. “Variance-component-based nested logit specifications: Improved formulation, and practical microsimulation of random disturbance terms.” *Journal of Choice Modelling* 21:30–35. Available at: https://www.sciencedirect.com/science/article/pii/S1755534515300853 [Accessed August 2, 2018].

Chen, L., D. Debnath, J. Zhong, K. Ferin, A. VanLoocke, and M. Khanna. 2020. “The Economic and Environmental Costs and Benefits of the Renewable Fuel Standard.”

Chen, L., D. Debnath, J. Zhong, K. Ferin, A. VanLoocke, and M. Khanna. 2021. “The Economic and Environmental Costs and Benefits of the Renewable Fuel Standard.” *Environmental Research Letters*.

Corts, K.S. 2010. “Building out alternative fuel retail infrastructure: Government fleet spillovers in E85.” *Journal of Environmental Economics and Management* 59(3):219–234. Available at: http://dx.doi.org/10.1016/j.jeem.2009.09.001 [Accessed October 5, 2016].

Davis, S.C., and R.G. Boundy. 2018. “Transportation Energy Data Book: Edition 37.”

DOE. 2019. “Alternative Fueling Station Locator.”

DOE. 2015. “Costs Associated With Non-Residential Electric Vehicle Supply Equipment Factors to consider in the implementation of electric vehicle charging stations.”

DOT. 2015. “2015 Revised Value of Travel Time Guidance.” Available at: https://www.transportation.gov/sites/dot.gov/files/docs/2015 Revised Value of Travel Time Guidance.pdf [Accessed May 5, 2020].

Du, X., and S. Li. 2015. “Flexible-Fuel Vehicle Adoption and the U.S. Biofuel Market.” Available at: https://ssrn.com/abstract=2583808 [Accessed June 7, 2019].

Dwivedi, P., W. Wang, T. Hudiburg, D. Jaiswal, W. Parton, S. Long, E. DeLucia, and M. Khanna. 2015. “Cost of Abating Greenhouse Gas Emissions with Cellulosic Ethanol.” *Environmental Science & Technology* 49(2512–2522):2512–2522. Available at: http://pubs.acs.org/doi/pdf/10.1021/es5052588 [Accessed June 19, 2017].

EIA. 2021a. “Annual Energy Outlook.” Available at: https://www.eia.gov/outlooks/aeo/ [Accessed January 29, 2020].

EIA. 2021b. “Light-Duty Vehicle Stock by Technology Type.” *Annual Energy Outlook 2019*.

Available at: https://www.eia.gov/outlooks/aeo/data/browser/#/?id=49-AEO2019&cases=ref2019&sourcekey=0 [Accessed June 17, 2019].
EPA. 2016. "Emissions & Generation Resource Integrated Database (eGRID)." Available at: https://www.epa.gov/energy/emissions-generation-resource-integrated-database-egrid [Accessed August 2, 2019].
EPA. 2019. "Greenhouse Gas Inventory Data Explorer." Available at: https://cfpub.epa.gov/ghgdata/inventoryexplorer/index.html [Accessed June 22, 2019].
EPA. 2018. "Highlights of the Automotive Trends Report." Available at: https://www.epa.gov/automotive-trends/highlights-automotive-trends-report [Accessed August 17, 2019].
Federal Highway Administration. 2016. "Highway Statistics 2016." *Highway Statistics 2016*. Available at: https://www.fhwa.dot.gov/policyinformation/statistics/2016/ [Accessed June 12, 2019].
Federal Highway Administration. 2017. "National Household Travel Survey." Available at: https://nhts.ornl.gov/ [Accessed July 26, 2019].
Gelfand, I., S.K. Hamilton, A.N. Kravchenko, R.D. Jackson, K.D. Thelen, and G.P. Robertson. 2020. "Empirical Evidence for the Potential Climate Benefits of Decarbonizing Light Vehicle Transport in the U.S. With Bioenergy from Purpose-Grown Biomass with and without BECCS." *Environmental Science and Technology* 54(5):2961–2974.
Holland, S.P., E.T. Mansur, N.Z. Muller, and A.J. Yates. 2016. "Are There Environmental Benefits from Driving Electric Vehicles? The Importance of Local Factors." *American Economic Review* 106(12):3700–3729. Available at: http://dx.doi.org/10.1257/aer.20150897 [Accessed April 16, 2019].
Hudiburg, T.W., W. Wang, M. Khanna, S.P. Long, P. Dwivedi, W.J. Parton, M. Hartman, and E.H. Delucia. 2016. "Impacts of a 32-billion-gallon bioenergy landscape on land and fossil fuel use in the US." *Nature Energy* 1. Available at: https://www.nature.com/articles/nenergy20155.pdf [Accessed November 17, 2017].
Khanna, M., D. Rajagopal, and D. Zilberman. 2021. "Lessons Learned from US Experience with Biofuels: Comparing the Hype with the Evidence." *Review of Environmental Economics and Policy* 5(1). Available at: https://doi.org/10.1086/713026 [Accessed April 25, 2021].
Kubendran, K.R. 2016. *Integration of vehicle consumer choice in energy system models and its implications for climate policy analysis*. University of California, Davis.
Liao, K., and S. Pouliot. 2016. "Estimates of the Demand for E85 Using Stated-Preference Data off Revealed-Preference Choices." In *Agricultural & Applied Economics Association Annual Meeting*. Boston.
Lin, Z., and D.L. Greene. 2011. "Promoting the Market for Plug-In Hybrid and Battery Electric Vehicles,Role of Recharge Availability." *Journal of the Transportation Research Board* 2252:49–56. Available at: http://trrjournalonline.trb.org/doi/pdf/10.3141/2252-07 [Accessed March 30, 2018].
Luo, J., and G. Moschini. 2019. "Pass-through of the policy-induced E85 subsidy: Insights from Hotelling's model." *Energy Economics* 84:104478. Available at: https://linkinghub.elsevier.com/retrieve/pii/S0140988319302592 [Accessed May 22, 2020].
Lynd, L.R. 2017. "The grand challenge of cellulosic biofuels." *Nature Biotechnology* 35(10):912–915. Available at: https://www.nature.com/articles/nbt.3976 [Accessed May 11, 2021].
McCollum, D.L., C. Wilson, H. Pettifor, K. Ramea, V. Krey, K. Riahi, C. Bertram, Z. Lin, O.Y.

Edelenbosch, and S. Fujisawa. 2017. “Improving the behavioral realism of global integrated assessment models: An application to consumers’ vehicle choices.” *Transportation Research Part D: Transport and Environment* 55:322–342. Available at: https://www.sciencedirect.com/science/article/pii/S1361920915300900 [Accessed August 28, 2018].
Meier, P.J., K.R. Cronin, E.A. Frost, T.M. Runge, B.E. Dale, D.J. Reinemann, and J. Detlor. 2015. “Potential for Electrified Vehicles to Contribute to U.S. Petroleum and Climate Goals and Implications for Advanced Biofuels.” *Environmental Science & Technology* 49(14):8277–8286. Available at: http://pubs.acs.org/doi/10.1021/acs.est.5b01691 [Accessed March 18, 2019].
NREL. 2016. “AFDC TransAtlas.” Available at: https://maps.nrel.gov/transatlas/?aL=lyQBvX%255Bv%255D%3Dt&bL=clight&cE=0&lR=0&mC=40.212440718286466%2C-91.58203125&zL=4 [Accessed July 25, 2019].
Oliver, A., and M. Khanna. 2017a. “Demand for biomass to meet renewable energy targets in the United States: implications for land use.” *GCB Bioenergy* 9(9):1476–1488. Available at: http://doi.wiley.com/10.1111/gcbb.12437.
Oliver, A., and M. Khanna. 2017b. “What Is the Cost of a Renewable Energy-Based Approach to Greenhouse Gas Mitigation?Approach to Greenhouse Gas Mitigation?” *Land Economics* 93(3):437–458.
Pouliot, S., and B.A. Babcock. 2014. “The demand for E85: Geographical location and retail capacity constraints.” *Energy Economics* 45:134–143. Available at: http://www.sciencedirect.com/science/article/pii/S0140988314001558 [Accessed May 18, 2016].
Pouliot, S., K.A. Liao, and B.A. Babcock. 2018. “Estimating Willingness to Pay for E85 in the United States Using an Intercept Survey of Flex Motorists.” *American Journal of Agricultural Economics* 100(5):1486–1509. Available at: https://academic.oup.com/ajae/article-abstract/100/5/1486/5047906 [Accessed October 31, 2018].
Pourhashem, G., P.R. Adler, A.J. McAloon, and S. Spatari. 2013. “Cost and greenhouse gas emission tradeoffs of alternative uses of lignin for second generation ethanol.” *Environmental Research Letters* 8(2):25021–25034. Available at: https://iopscience.iop.org/article/10.1088/1748-9326/8/2/025021 [Accessed May 11, 2021].
Ramea, K., D.S. Bunch, C. Yang, S. Yeh, and J.M. Ogden. 2018. “Integration of behavioral effects from vehicle choice models into long-term energy systems optimization models.” *Energy Economics* 74:663–676. Available at: https://www.sciencedirect.com/science/article/pii/S0140988318302573 [Accessed August 13, 2018].
Robertson, G.P., S.K. Hamilton, B.L. Barham, B.E. Dale, R.C. Izaurralde, R.D. Jackson, D.A. Landis, S.M. Swinton, K.D. Thelen, and J.M. Tiedje. 2017. “Cellulosic biofuel contributions to a sustainable energy future: Choices and outcomes.” *Science* 356(6345). Available at: http://science.sciencemag.org/ [Accessed September 21, 2020].
Semega, J.L., K.R. Fontenot, and M.A. Kollar. 2017. “Income and Poverty in the United States: 2016.” Available at: https://www.census.gov/library/publications/2017/demo/p60-259.html [Accessed March 19, 2021].
Taheripour, F., and W. Tyner. 2008. “Ethanol policy analysis—what have we learned so far.” *Choices*. Available at: http://www.choicesmagazine.org/UserFiles/file/article_38.pdf

[Accessed May 31, 2016].
Thompson, W., S. Meyer, and P. Westhoff. 2010. “The New Markets for Renewable Identification Numbers.” *Applied Economic Perspectives and Policy* 32(4):588–603. Available at: https://onlinelibrary.wiley.com/doi/abs/10.1093/aepp/ppq021 [Accessed May 4, 2021].
Tol, R.S.J. 2005. “The marginal damage costs of carbon dioxide emissions: An assessment of the uncertainties.” *Energy Policy* 33(16):2064–2074.
Tong, F., and I.M.L. Azevedo. 2020. “What are the best combinations of fuel-vehicle technologies to mitigate climate change and air pollution effects across the United States?” *Environ. Res. Lett* 15:74046. Available at: https://doi.org/10.1088/1748-9326/ab8a85 [Accessed July 21, 2020].
Train, K.E. 2003. *Discrete choice methods with simulation*.
Tyner, W.E., F. Taheripour, and D. Perkis. 2010. “Comparison of fixed versus variable biofuels incentives.” *Energy Policy* 38(10):5530–5540. Available at: http://dx.doi.org/10.1016/j.enpol.2010.04.052.
U.S. DOE. 2019. “Highway Statistics.” Available at: https://www.fhwa.dot.gov/policyinformation/statistics.cfm [Accessed September 26, 2020].
U.S. EPA. 2012. *2017 and Later Model Year Light-Duty Vehicle Greenhouse Gas Emissions and Corporate Average Fuel Economy Standards*.
US Energy Information Administration. 2019. “Assumptions to the Annual Energy Outlook 2019: Transportation Demand Module.” (February):1–29. Available at: https://www.eia.gov/outlooks/aeo/assumptions/pdf/transportation.pdf.
US EPA. 2020. “Routes to Lower Greenhouse Gas Emissions Transportation Future.” Available at: https://www.epa.gov/greenvehicles/routes-lower-greenhouse-gas-emissions-transportation-future [Accessed September 26, 2020].
Wang, M., J. Han, J.B. Dunn, H. Cai, and A. Elgowainy. 2012. “Well-to-wheels energy use and greenhouse gas emissions of ethanol from corn, sugarcane and cellulosic biomass for US use.” *Environmental Research Letters* 7(4):045905. Available at: http://stacks.iop.org/1748-9326/7/i=4/a=045905?key=crossref.bc2d92022ddca565108ad62fb6e4201d [Accessed June 25, 2017].
Watkiss, P., and T. Downing. 2008. “The social cost of carbon: Valuation estimates and their use in UK policy.” *Integr. Assess* 8.
Zhong, J., and M. Khanna. 2021a. “Assessing the Efficiency Implications of Renewable Fuel Policy Design in the United States.”
Zhong, J., and M. Khanna. 2021b. “Beyond the Hypes: Behavioral and Techno-Economic Determinants of Electrification in US.”

Appendix

A.1 Existing vehicle and driving demand

We construct the demand for vehicle fleet specifically for the light-duty fleet in 2016. We consider both light-duty vehicles and medium-/heavy-duty trucks in the vehicle sector. The fuel compatibility varies across vehicle types: CV, HBV, and PHEV under charge-sustaining mode drive on conventional fuel (currently with 10% ethanol blend E10); BEV and PHEV under charge-depleting mode run on electricity; FFV can run on any ethanol-gasoline blends of E10 and E85 (higher ethanol blend of 53% to 74%). The medium- or heavy-duty trucks are mostly freight trucks consuming diesel.

The annual mileage and the vehicle count for each age group and mileage group are from 2017 National Household Travel Survey (as shown in Figure A3 and Figure A4). We roughly categorize the driving demand into three groups first and demonstrate the annualized demand by using the data statistics from NHTS. The low driving demand group categorizes the consumers having similar yearly driving mileage of less than 8 thousand miles; the medium group drives between 8 and 16 thousand miles per year, whereas the high group has greater demand of more than 16 thousand miles. Due to the lack of information for alternative vehicles and for simplicity, we assume that the maximum annual mileages driven by alternative vehicles follow the same pattern as the conventional vehicle owners.

Following the same practices of establishing the demand of transportation in BEPAM model (Chen et al. 2021), we first aggregate the vehicle demand into national demand function and further disaggregate the total mileage of the US for each of 20 regions and three driving demand groups based on the distributional pattern from 2017 National Household Travel Survey.

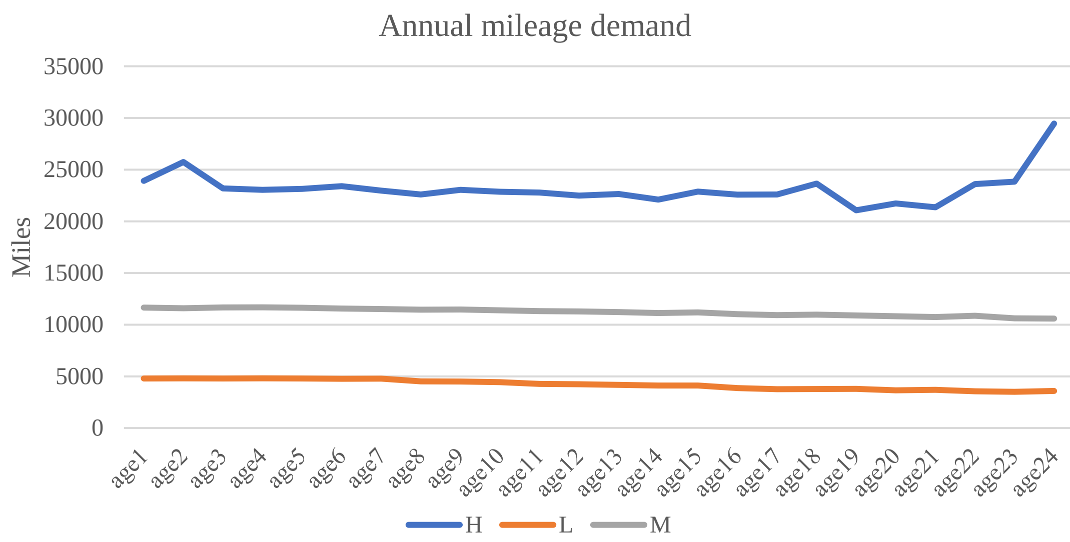

Figure A3 The annual mileage demand for each driving group across ages (NHTS, 2017)

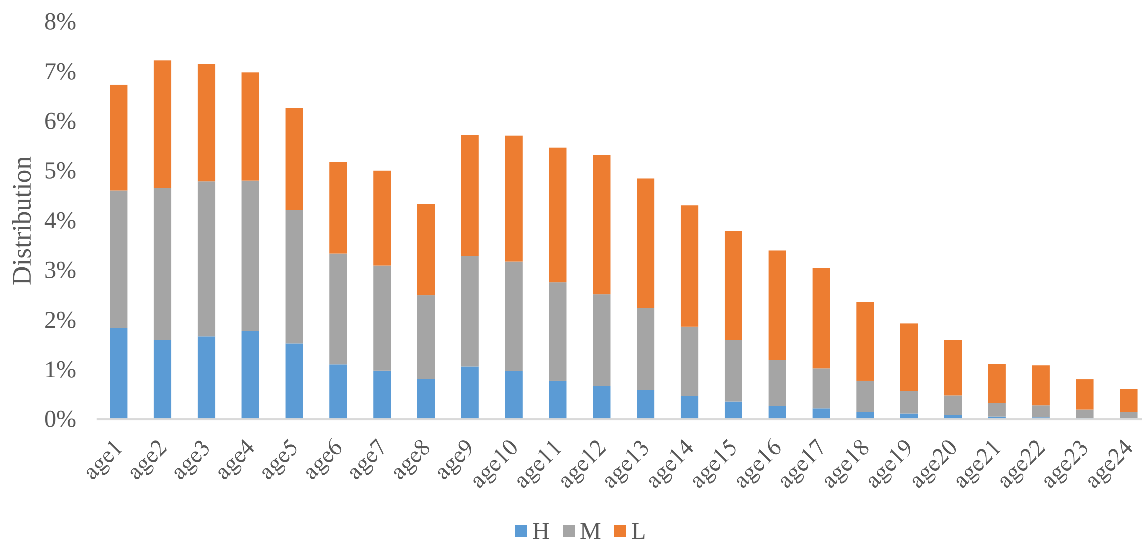

Figure A4 Vehicle count probability distribution in age and mileage group (NHTS, 2017)

We obtain the vehicle registration in the vehicle stocks by fuel types, by state, by driving behavior group, and by age in 2016. The initial vehicle stock by fuel type is based on the observed data from EIA (2019). The age distribution of the CV is obtained from NHTS and age distributions of other alternative fuel vehicles are from Transportation Energy Data Book (Davis and Boundy 2018). The spatial distribution of liquid-fuel vehicle (CV and HBV) are from Highway Statistics Series (Federal Highway Administration 2016). FFV spatial distribution by state is from IHS automotive purchase, and PHEV and BEV spatial distributions are from the vehicle density of NREL (2016). We assume the above distributions are independent to get the joint distribution by fuel type, by age, and by region. We use the electricity market region (EMR) to identify the spatial variation across the region given the defined electricity prices at EMR level. Further, the vehicle purchase and driving behavior are not restricted by any jurisdictions. We therefore analyze the spatial variation and distribution across the electricity market region.

We calibrate the fuel economy of the existing conventional vehicle with the data from NHSTA (Federal Highway Administration 2016a) in 2016. For other alternative fuel vehicles (FFV, HBV, PHEV, and BEV), we use the fuel efficiencies from the vehicle database of the alternative fuel data center (DOE 2017). The increasing efficiencies of the new vehicles of all vehicle types beyond 2020 are based on the AEO database, which implies the vehicles produced by the automakers are in compliance with Corporate Fuel Efficiency Standard (US Energy Information Administration 2019).

The vehicle stock dynamics are defined by equations A2 to A3 with the specification of the vehicle age, which allows us to update the age distribution of the vehicle stock at each year t. Equation A2 defines the number of new purchases of vehicle type i as the group of age 1 (denoted as a1) in year *t*. Equation A3 shows the turnover of the existing vehicles (age a that is greater than 1) is equal to the amount of vehicle stock from the previous year *t-1* at age *a-1* times the functional retirement (r) minus the possible early retirement. We apply the vehicle scrappage rate (r) by age (Belzowski et al. 2010) to allow functional retirement due to tears and wears for all five powertrains vehicles. The vehicle stocks defined for each powertrain type, at age a and time t define the maximum amount of the mileage the fleet is capable of running, where m_{cap} is denoted as the annual mileage from NHTS discussed in Figure A3. The numbers of the new vehicle purchase (*N*), existing vehicle fleet (*V*), early retirement (*R*), and yearly mileage driven (M) are endogenously determined by the model.

$$N_{t\ i,t}^{i} = V_{a1,t}^{i} \ \ \forall i,\mathrm{t} \tag{A2}$$

$$V_{a,t}^{i} = V_{a-1,t-1}^{i} \times r_{a-1} - R_{a-1,t-1}^{i} \ \ \forall i, a24 \geq a \geq a2, T \geq t \geq t2 \tag{A3}$$

$$V_{a,t}^{i} \times m_{cap} \geq M_{a,t}^{i} \ \ \forall i, a, t \tag{A4}$$

Because vehicles are still drivable before reaching the extreme of the vehicle life span (age 24)[3] , we take into account their depreciated vehicle value remained by the end of the simulation period *T* in the objective function of total welfare as the term $\rho^{T}\beta\sum_{i,a}\phi^{i}\pi_{a}V_{a,t}^{i}$. By selling the auto parts to the dealer or recycling center, or sending the vehicle to the auto parts auction, the driver could recover the scrappage value, as showed in the last term of equation **Error! Reference source not found.** in year *T*. The coefficient β represents the vehicle market value loss once the vehicle is sold by the vehicle dealer (85% in this study). Further depreciation π_a is relevant to the aging problems after *a* years of wear and tear.

A.2 Vehicle Ownership cost

As shown in Table A5, we take the average of the purchase price and fuel efficiency of the new vehicles from AEO by using the market share of each vehicle class from AEO as weights from 2016 to 2050. The data showed that except for the battery electric vehicles, the prices for the other vehicles are projected to be leveling up. It is due to the incremental costs in the newly adopted technology cost, whereas the BEV price is proportionally reduced with battery costs

[3] For purpose of setting up the age property of vehicle fleet, we use the full age range of the vehicle up to age 24 that is observed from the National Household Transportation Survey.

(BloombergNEF 2019). The fuel economies of all vehicle types are also projected to increase from 2016 to 2040. PHEV has two efficiencies in charge-depleting mode (all-electric), and charge-sustaining mode (only on gasoline). The report statistics indicate around 40% of the VMT driven by the PHEV are on charging-depleting mode. We apply this assumption to calculate the electrified mileage and electricity consumed by the PHEV.

We account for the annual operating and maintenance costs per mile of driving for each powertrain (Alternative Fuels Data Center 2020) and the vehicle registration cost, insurance, and license cost per vehicle at $1,616 per year from the American Automobile Association (AAA). We take the operational and maintenance cost from AAA 2016 report for CVS, HBV, and BEV. We assume the FFV has the same operational cost as CVS, and PHEV has the same operational cost as HBV. The depreciation rate of the vehicle values due to wears and tear is applied to the vehicles still in use at the end of the study period from the National Automobile Dealers Association (2014).

Table A5 Specification of Light-Duty Vehicle in 2016.

Vehicle type	Energy sources	Fuel efficiency (miles per gasoline gallon)	Purchase cost ($)	Operational and maintenance cost ($ per mile)
CVS	E10	20	25,720	0.0683
FFV	E10, E85	19	25,750	0.0683
HBV	E10	33	32,400	0.0699
PHEV	E10, Electricity	35, 85	39,700	0.0699
BEV	Electricity	90	51,500	0.0655

According to the EIA outlook projection, the increasing fuel economy of all vehicle types results from the compliance of CAFE standards and the technology improvement. We take the

MPG projection from AEO data and apply the factor of 0.7 to alter the compliance MPG to the actual non-experimental on-road MPG, according to the EPA (2016).

A.2.1 Range limitation cost

Based on Lin et al. (2011), the range limitation cost is quantified by the cost of the backup plans of reaching the destination when EV is running out of battery. That includes many alternative costs of renting a car, car tolling service, and ride-hailing service as alternative transportation modes when the vehicle runs out of battery in the middle of the trip. We use a conservative cost of $10 per day as a conservative estimate of alternative transportation mode. We estimate the number of days in a year running out of battery based on the daily vehicle miles traveled (VMT) demand distribution calibrated using the average mileage capacity for three driving demand groups following the gamma distributions (Figure A5). The parameters of the gamma distribution of three driving groups are adjusted with the data from National Travel Household Survey (2017) for all age groups.

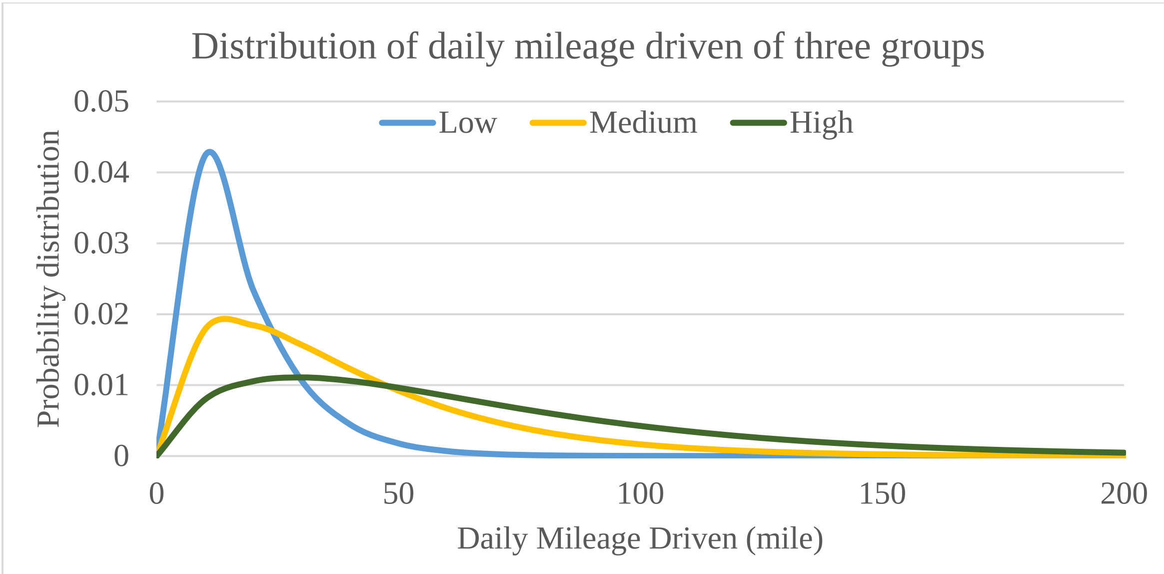

Figure A5 The Gamma distribution of the daily mileage driven

The effective mileage (eVMT) is defined as the sum of total mileage it can get from the available fixed charging (home and work if applied) and the public charging sources. The available charging portals (Q_{chrg}) depends on the options of charge modes chosen by the drivers and are endogenously solved by the model, plus the public charging. And Q_H=1 when the home charge is selected, Q_W=1 when the work charge is selected, Q_p is the ratio of the numbers of public charging to the gasoline charging stations in each region based on the data of alternative fuel data center and North American Industry Classification System. We assume four charging groups in 2016: Home and Work, Home only, Work only, and None of above. We follow the same assumption as Ramea et al. (2018) that of all BEV owners, 52% have home charges, 5% have work charging). The model endogenously solves the optimal number of vehicle adoption given the option of each charging mode, where the home charging requires a $2,500 installation fee and public charging is subject to the substantial range limitation cost, the work only charging group is the most optimal choice.

The effective mileage is a function of the availability of the fixed charging portals, the time required for charging, and the charging capacity.

$$\mathrm{eVMT}_{\mathrm{chrg}} = min(R^{max}, E_H T_H Q_H) + min(R^{max}, E_W T_W Q_W) + min\left(R^{max}, \sum_k T_k E_k Q_{P,k}\right)$$

where T is the time spent at the charging place (8 hour at home and working place); E is the charging capacity (assuming 6.6 kW for L2 charging portal mostly at home, at working, and public charging has 6.6 kW and 50 kW for L2 and fast charging respectively); The R^{max} is the maximum range of a fully charged BEV. We take the minimum of the mileage from charging and the range capacity to have a conservative upper bound of the effective mileage. It determines the probability of driving demand exceeds the driving ability. The probability of the VMT demand (X) exceeds the effective mileage range (eVMT) is 1 minus the integral of the probability distribution function from 0 to eVMT miles. The number of days running out of the battery is the probability times the 365 days in a year. The final range limitation cost per vehicle (C_{range}) for both the existing vehicle and new purchase is the penalty cost from the cost of alternative transportation mode times the days out of battery.

$$P_a(X > \mathrm{eVMT}) = 1 - \int_0^{\mathrm{eVMT}} p(x)\, dx \ \ (\%)$$

$$N_a = 365 \times P_a \ \ (day/vehicle)$$

$$C_{range} = N_a \times \$20/day \quad (\$/veh)$$

Unlike the deterministic range limitation cost from Kubendran (2016), we add the stochastic choice of the daily miles traveled based on the Gamma distribution shown in Figure A5 and redefine the probability of running out of the battery as the total number of days in a year when mileage demand exceeds the effective mileage (eVMT). We randomly pick the VMT 10 times for each age group (age from 1 to 24), charge group (4 groups), mileage demand group (3 groups), electric market region (20 regions), and each day (365 days per year). The total range limitation cost is the penalty cost ($10 per day) times the total number of days where the demand of VMT exceeds the mileage capacity given the charging availability.

$$P_a = \sum_{day=1}^{365} 1(VMT_{day} > eVMT)\,/365$$

$$C_{range} = \sum_{day=1}^{365} 1(VMT_{day} > eVMT) \times \$10/day \quad (\$/veh)$$

A.2.2 Waiting cost

We define the waiting cost as the time spent in the stations waiting for the recharge, specifically for the charging of a battery-electric vehicle. We quantify the number of visits to the public charging needed for the electric vehicle based on the mileage demand (VMT_v) and a mileage range of the vehicle (R^{max}), as well as the probability ($p_{pub,k}$) of public charging and time spent in the charging station. To determine the probability of using public charging and the average time spent in the charging, we use the similar the probability of running out of battery based on the daily mileage distribution described above, but only including the efficient mileage from fixed charging portals at home or work in the efficient mileage ($eVMT_{fix}$). The probability of exceeding the efficient mileage at fixed charging portal then is interpreted as the need to visit the public charging to meet the mileage demand ($P_{a_{fix}}$). Note that the probability of the using public charging is not related to the availability of the public charging portals.

$$\mathrm{eVMT_{fix}} = min(R^{max}, E_H T_H Q_H + E_W T_W Q_W)$$

$$P_{a,fix}(X > \mathrm{eVMT}) = 1 - \int_0^{\mathrm{eVMT_{fix}}} p(x)\, dx$$

Rather, the time spent in the charging station is related to the availability of the fast-charging portals. Based on the point data of the public charging stations (DOE 2019), we have the coverage rate of the regular portal of L2 portal and DC fast-charging for public charging versus the gasoline station differentiated by the electricity market region. The time spent in the public charging stations is assumed to be limited by a 2-hour duration for simplicity. Fast DC charging needs less time to fully charge an electric vehicle with a capacity of 50 kW. Considering the vehicle owner mostly likely would search for charging when the battery state-of-charge (SOC) is 20% and stop at 80% of SOC, the time fast charging requires is $\min(2, \frac{R^{max}}{\gamma_{BEV} \times 50})$. The weighted time spent at the fast-charging station thus varies across regions based on the availability of the fast charging.

$$T = (2 \times Q_{P,L2} + \min(2, \frac{R^{max}}{\gamma_{BEV} \times 50}) \times Q_{P,DC}) / (Q_{P,L2} + Q_{P,DC})$$

The value of time (V^t) is the opportunity cost of half of the income based on the (DOT 2015). We further randomly draw the value of the time from the income distribution of the US population from the Census Bureau (Semega, Fontenot and Kollar 2017) for ten times for each VMT demand group, vehicle age, and each year from 2016 to 2040 to show the representative value of time across US. The valuation of the waiting cost therefore is formulated as the multiplication of the total number of visits, the probability of public charging, the average time spent in the charging station, and the valuation of the time.

$$C_{waiting} = \frac{VMT}{R^{max}} \times P_{a,fix} \times T \times v^t$$

We assume the plug-in hybrid vehicle (PHEV) owner has the closer option to fuel gasoline thus will not spend any extra time in the charging station or detour. Also, we assume the PHEV owner has the accessibility of charging at home or at work that would be sufficient for use on the charge-depleting mode. We, therefore, exclude the waiting costs from the PHEV ownership costs.

A.2.3 Detour cost modeling

Pouliot and Babcock (2014) used the upward-sloped curves to show the increasing per gallon cost when the refueling stations sit farther away. It is the cost of time spent to find the nearest station, which is a function of the value of time, mileage, time, and speed. The linear form of the cost shows the economic calculation and differentiates it from the range limitation cost associated with psychological anxiety. The increasing detour cost function with respect to the detour distance indicates the consumers' aversion to the long-distance searching.

$$C_{detour} = V_t \times \frac{\mathrm{VMT}_v}{R^{max}} \times \mathrm{d}_{\mathrm{detour}} \times P_{a,fix} \times \frac{2\times 1.3 \text{ Euclidean coefficient}}{32 \text{ mph}} = 0.082 \times V_t \times \frac{\mathrm{VMT}_v}{R^{max}} \times \mathrm{d}_{\mathrm{detour}}$$

The detour cost is rewritten as above as the total amount of time visiting the public station running the detour distance that is monetized by the value of time, where the V_t is the value of the time; VMT is the total VMT consumption endogenously determined by the model; d is the detour distance that varies across states. We note that the improved accessibility of the charging station with a shorter distance reduces the detour cost of refueling. Following the same method, we apply the mileage range of a FFV or a BEV (R^{max}) that increases over time and the value of time (V_t) from the income distribution. We assume a representative car with a running speed of 32 miles per hour and a fuel tank volume of 16.2 gallons as Pouliot (2014), the detour price of E85 is calculated to be $0.06 per gallon per mile of the detour distance. In the paper, we randomly draw the value of time from income distribution based on the source of the Bureau of Census for each representative consumer of each segment to show the heterogeneity of consumers. Similarly, we construct the detour cost function for BEV to the nearest charging station based on the value of time, total VMT, the mileage range of BEV, and the distance to the nearest charging.

$$C_{detour}^{E85} = 0.082 \times V_t \times \frac{\mathrm{V}MT_{FFV}}{\gamma_{FFV} \times 16.2} \times \mathrm{d}_{\mathrm{E85}}$$

$$C_{detour}^{electricity} = 0.082 \times V_t \times \frac{\mathrm{V}MT_{BEV}}{R^{max}} \times P_{a,fix} \times \mathrm{d}_{\mathrm{charging}}$$

We obtain the detour distance (denoted as d in the unit of mile) by measuring the distance from the centroid of the zip code zone to the nearest refueling stations of charging or E85 refueling stations. The dataset is available from the developer API request of NREL for the nearest stations[4]. The state-level detour distance is shown in Figure A6 and averaged to the electricity market region.

Based on the estimated value of time during the commuting trip is about half of the income (DOT 2015), and that income distribution does not correlate with VMT demand or ages of vehicle they own, we randomly draw the value of time ten times for each age group of the

[4] https://developer.nrel.gov/docs/transportation/alt-fuel-stations-v1/

vehicle, VMT demand group, and each year from 2016 to 2040 and divided by 2 to show the representative value of time across US. However, the value of time might be correlated across the region and vehicle choice. Therefore, we did not consider the random draw of the value across the region and vehicle choices.

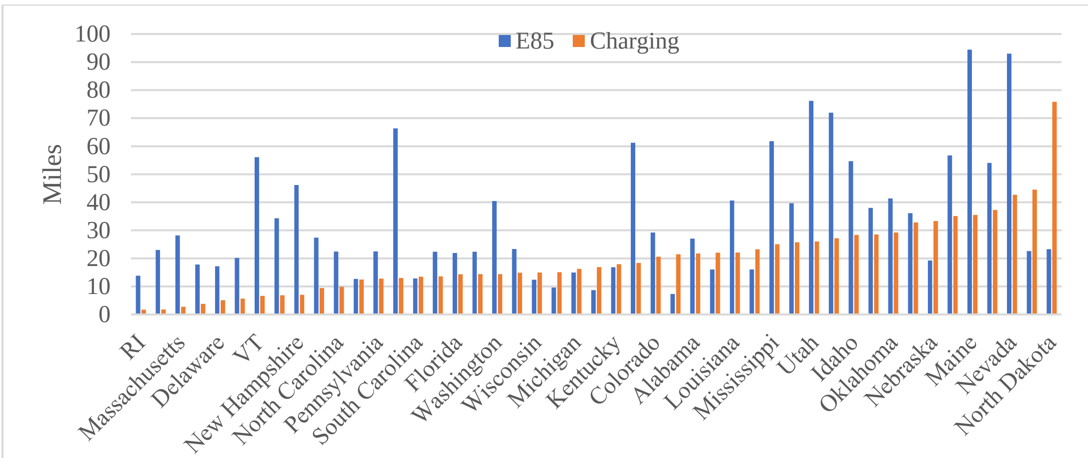

Figure A6 State average mileage distance to the nearest station in the US

A.3 Idiosyncratic preferences

We capture the idiosyncratic preference towards the vehicle fuel type by adjusting the error terms of the random utility framework. In the theory of discrete choice model, the relative difference between error term determines the probability of the choice over other alternatives and define the relative correlation between options (Train 2003). We apply the correlated error term provided by Ramea et al. (2018) that represents the choices under nested multinomial logit model that has correlated error term within the nest of choices with the same drivetrain but independent across the different drivetrain nests (Bunch and Rocke 2016). It is a marginal distribution of standard Gumbel distribution with the location parameter of 0 and scale parameter of 1 for each vehicle type but correlated within the nests. We adjust the mean of distribution for each vehicle and scale the error terms with the regional multipliers from Google Trend to show the systematic differences in the variance of choices across regions, and for different driving demand groups.

The adjustment of the error terms reflects the alternative-specific constants and the scaling approach (across regions and the driving demand groups) that captures the average effect on the utility of all factors that are not included in the model and normalizes the heteroskedastic errors in different segments of the market. By doing so, the adjustment keeps the correlation coefficient matrix of the error terms and the variance-covariance matrix following the same pattern as the original nested error terms (as shown Figure A7).

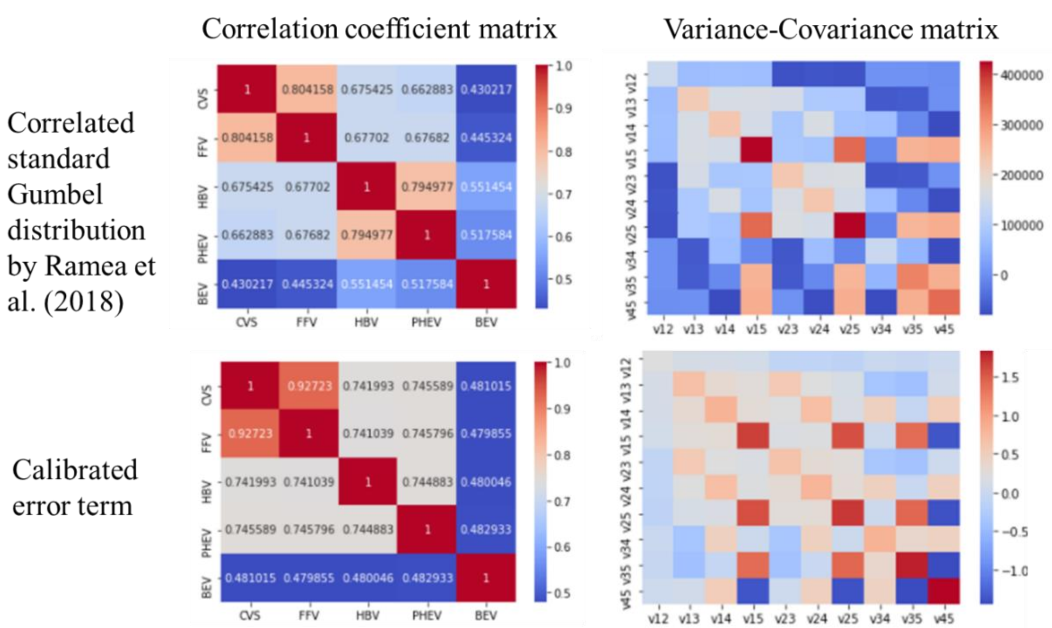

Figure A7 The heatmap of the correlation coefficient matrix and variance-covariance matrix compared to the nested error terms by Ramea et al. (2018)

Google Trend provides the normalized count of the total number of search requests made to Google in a given time frame and across the region. We first use representative car models or brands as the keywords for three vehicle types: Toyota Camry for the conventional vehicle (CV), Tesla for battery electric vehicle (BEV), and Toyota Prius for Plug-in Hybrid Electric Vehicle

(PHEV). To represent the search interest for the flex-fuel vehicle (FFV) and hybrid electric vehicle (HBV) that do not have a representative vehicle model in the US market, we use “E85” and “Hybrid Electric” as the search keyword. We also use the normalized cross-sectional data at the state level for each vehicle type for each year from 2016 to 2040 from Google Trend. Within each year and each vehicle type, the regional data are normalized relative to the state with the highest search volume and show the spatial variation of search interest across the state. We repeat the data retrieval process for all five keywords and each year between 2016 to 2020 and have a total of 5×5 sets of cross-sectional data. The data of five keywords in 2020 is illustrated in Figure A8 as an example. These 25 sets of cross-sectional data, however, are not comparable between vehicles and across time as each data is normalized to 100, relative to its peak value. For example, the highest search interest to Toyota Camry is at the state of Mississippi, but the data shows a relatively universal interest spreading across the states, whereas the searches of electric vehicles (Tesla, Toyota Prius, and hybrid electric) are mostly concentrated in California; and searches for E85 cluster in the Midwest. We rescale this dataset from 0% to 100% and denote it as $InterestR_{v,t,r}$ for vehicle type v, year t, and state r. To convert the data into the scale of 20 electric market regions, we take the average of the states within the same electric market region.

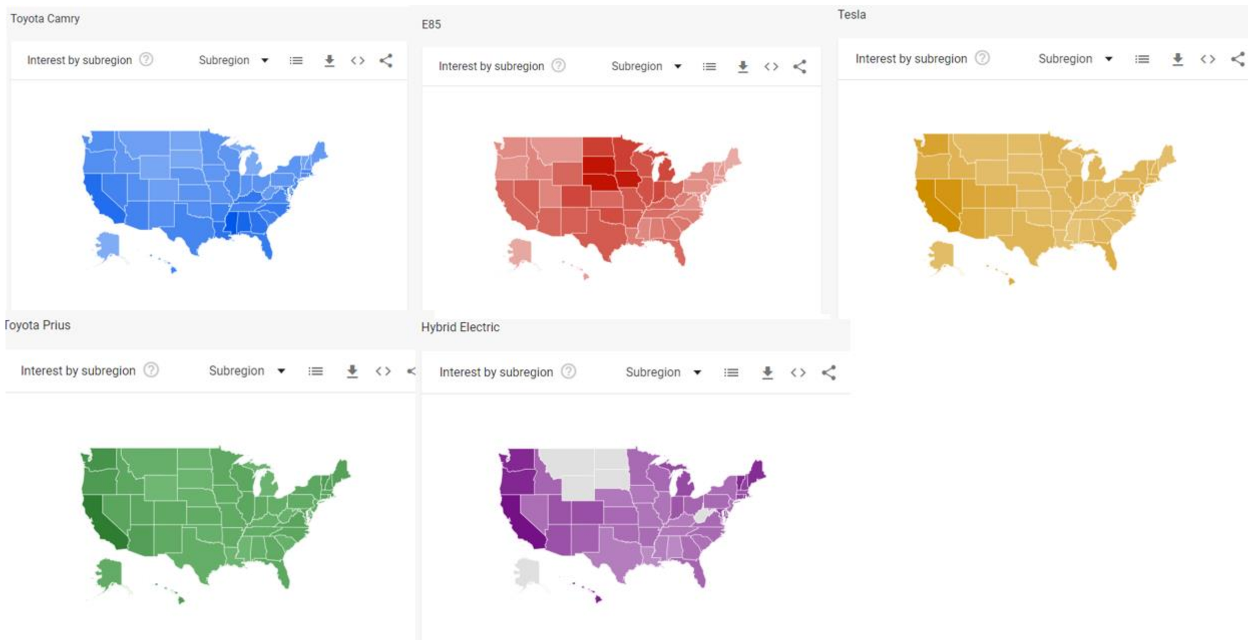

Figure A8 The normalized cross-sectional data of search interest for five keywords in 2020

To show the heterogeneous preference across driving demand group (low, medium, and high) for each vehicle type, we apply the vehicle stock distribution from 2016 based on the National Household Travel Survey as we mentioned in section A1, denoted as $Vgroup_{v,m}$ for vehicle v and driving group m. The $Vgroup_{v,m}$ indicates the relative extent of acceptance across driving demand groups compared to the group with the highest share of the stock for each vehicle type v. Using the same normalization strategy as Google Trend, we rescale the data from 0% to 100% relative to the highest stock share within each vehicle type. We observe that three liquid-fuel vehicles (conventional, flex-fuel, and hybrid) have the highest vehicle stock in the low VMT demand group ($Vgroup_{v,low}$ = 100%), whereas the electric vehicles (battery, plug-in hybrid) have a $Vgroup_{v,medium}$ of 100% for medium VMT demand group. We multiply this distribution across the driving demand group with the cross-sectional dataset from Google Trend abovementioned to obtain heterogeneity across driving demand.

The multiplication of two-level normalization processes ($InterestR_{v,r} \times Vgroup_{v,m}$) together indicate the relative purchase interests for each vehicle type v, in time t, in region r, of driving demand group m. By doing so, the battery electric vehicle ("Tesla") has the highest interest of 100% in the year 2019 in California with a medium driving demand will have the highest purchase interest ($InterestR_{v,t,r} \times Vgroup_{v,m}$=100%). Because $InterestR_{v,t,r}$=100% for Tesla in California, and $Vgroup_{v,m}$=100% for Tesla in medium driving demand group.

$$\text{Idiosyncratic Preference}_{v,t,r,m} = InterestR_{v,t,r} \times Vgroup_{v,m} \times A \times \varepsilon_v$$

Finally, we use the universal scalar (A) to validate the model from 2016 to 2040. The systematic differentiation of preference across vehicle type, region, and driving demand ($\text{Idiosyncratic Preference}_{v,t,r,m}$) would help identify the unobserved psychological preference (Train 2003) under the nested multinomial logit model framework.

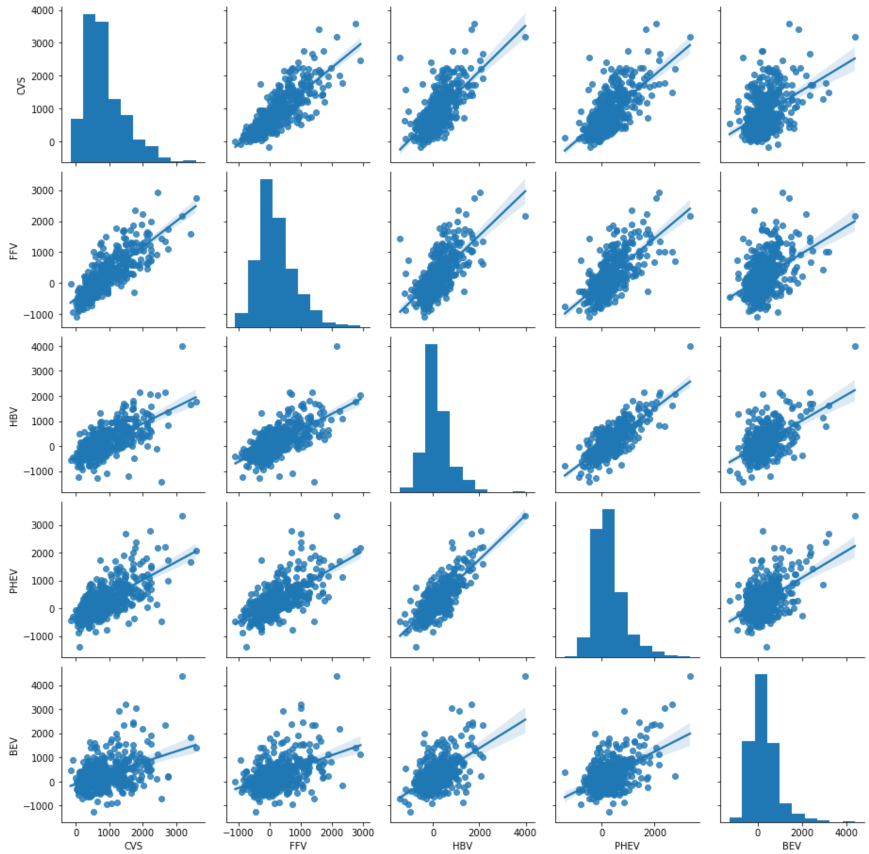

Figure A9 The descriptive statistics of the error term

A.4 Model validation

The validation of the model is shown by comparing the closeness of model outcomes for several endogenous variables in the past four years from 2016 to 2019 with observed data for key variables. The 2020 year is abnormal in fuel consumption and production due to pandemics; thus, we do not include 2020 for validation. We calibrate the elasticity for the crude oil market for US supply and rest of the world supply to 1.5 and 0.8 and keep the demand function of the rest of the world same as Chen et al. (2020) to be -4. The results compared to the observed price and quantity are shown in **Error! Reference source not found.**. We find the fuel consumption and production both in the US and the rest of the world generally deviate by less 2%. The fuel prices are within 12% deviation. We calibrate the vehicle stocks by incorporating the behavioral factors as well as the idiosyncratic preference by scaling the error term universally. The vehicle stocks are within 9% deviation from the observed level from 2016 to 2019. The deviation of 9% could be explained by the smaller scales of alternative fuel vehicle stocks compared to the conventional vehicle. The deviations of the simulated outcomes of the updated BEPAM for 2016–2019 from their observed values over the 2016–2019 period are generally within a similar level of tolerance as in previous studies applying BEPAM (Chen et al. 2020; Hudiburg et al. 2016; Oliver and Khanna 2017b).

Table A6 Model validation from 2016 to 2019

	Observed				Model outcome				Source	Average difference%
	2016	2017	2018	2019	2016	2017	2018	2019		
Fuel gallons (billion gallon)										
US oil consumption	249	254	260	254	260	265	256	262	DOE	2%
US oil supply	136	144	168	188	144	144	185	175	DOE	2%
ROW oil use	1,124	1,132	1,176	1,196	1,122	1,124	1,191	1180	DOE	0%
ROW oil supply	1,238	1,243	1,268	1,262	1,239	1,244	1,262	1267	DOE	0%
E10	143	143	143	143	143	143	140	141	EIA	-1%
Blended diesel	51	52	55	54	53	53	53	53	EIA	0%
Prices ($ per gge)										
US oil price	1.03	1.21	1.55	1.36	1.04	1.15	1.49	1.37	WTI	-2%
ROW oil price	1.04	1.29	1.70	1.53	1.04	1.15	1.49	1.37	Brent	-9%
US wholesale ethanol	1.55	1.45	1.23	1.26	1.59	1.46	1.49	1.46	NEO price	10%
US retail E10 ($/gge)	2.13	2.36	2.74	2.62	2.44	2.54	3.19	2.85	AFDC	12%
US retail diesel	1.94	2.05	2.38	2.29	2.44	2.54	3.19	2.85	AFDC	0%
Vehicle miles traveled (billion miles)										
Gasoline vehicle miles	2,747	2,836	2,883	2,917	2,747	2,787	2,835	2,970	EIA	0%
Diesel vehicle miles	410	415	437	433	434	444	444	449	EIA	4%
Vehicle stocks (million)										
CV	215	228	228	229	216	212	214	224	AEO	-4%
FFV	19.8	19.4	19.7	20.2	20.0	19.2	18.7	18.2	AEO	-4%
HBV	4.07	4.21	4.68	4.69	4.17	3.93	3.86	4.16	AEO	-9%
PHEV	0.32	0.36	0.53	0.64	0.32	0.30	0.34	0.84	AEO	-2%
BEV	0.29	0.37	0.57	0.87	0.31	0.30	0.55	1.15	AEO	9%
Total	239	252	254	255	241	235	238	248	AEO	-4%

A.5 Model output of 2030

The policy analysis with a shorter time scale over the 2016-2030 period is also studied. We discuss the results of 2030 and cumulative results from 2016-2030 as below.

A.5.1 Effect of Electrification Incentives

Under the baseline policy scenario (1) in 2030, the battery electric vehicle (BEV) fails to penetrate the market with at most 1 million stock. The plug-in hybrid (PHEV) and hybrid (HBV) vehicles gain 10% of the market share. The liquid fuel vehicles (CVs and FFVs) remain to dominate the vehicle stocks. Though the electrification is low at 3%, the increasingly efficient fleet raises the fuel economy of the whole US fleet to 13 km per liter (63% above 2016 level of 8 km per liter) and saves total energy to 673 billion liters (-11%), of which 59% is from E10.

The extended federal tax credits of $7,500 and $2,500 for BEV and PHEV significantly increase the stocks of BEVs and PHEVs to 16 million and 19 million units in 2030 by replacing the CV and HBV stocks. The overall electrification of light-duty VKT improves to 14%, mostly contributed by the high driving demand group. About 46 billion liters reduction in E10 consumption is replaced by an increase of 13 billion gasoline-equivalent liters in electricity compared to no tax credit scenario (1). The E85 consumption rises to meet the 56 billion liters of ethanol mandate that slightly drive FFV purchases. However, the E85 price rises, and the diesel fuel price falls due to the decline of the implicit subsidy and tax from the ethanol mandate. The shrinking demand for E10 reduces the E10 price, whereas the increased E85 fuel demand requires less price incentive to meet the energy equivalent parity with E10 after including the detour costs.

The ban on the new conventional vehicle in addition to federal tax credit scenario (2) significantly reduces the existing stock of CVs to only 75 million, whereas FFV becomes the next cheapest option and picks up the market with a total of 83 million of stock, followed by PHEV, HBV, and BEV with total stocks of 50 million, 34 million, and 32 million. Compared to the existing policy scenario, the E10 consumption drops by 30%, whereas E85 increases by 29%, and electricity for transportation increases to 34 billion gasoline-equivalent liters. The VKT running on electricity and ethanol reach 28% and 9%, respectively.

A.5.2 Effect of Cellulosic Ethanol Mandate

The implementation of Corn + Cellulosic Ethanol Mandate in the short run requires 61 billion liters of cellulosic ethanol to be blended in addition to the extant production capacity of 56 billion liters of corn ethanol and thus doubles the ethanol consumed for light-duty VKT to 18%. The stringent ethanol policy induces 41 million FFV adoption and 68 billion liters of E85 in 2030 compared to scenario (1) baseline policy without cellulosic biofuel mandate (Table A7**Error! Reference source not found.**). Compared to the existing policy scenario (1), the total energy consumption reduces by 2%, contributed mostly by less E10 and diesel consumption under high implicit taxes. The stringent biofuel mandate achieves a lower VKT consumption than scenario (2) with the EV tax credit.

The cellulosic biofuel policy with the extended tax credit for electric vehicles of scenario (5) synergizes the adoptions of alternative fuel vehicles. FFV stock increases by 4 million by tax credit compared to otherwise; both PHEV and BEV increases by 1 million by cellulosic ethanol mandate compared scenario (2). It is because EV tax credit contracts the demand for gasoline that furthers the ethanol blend rate required to meet the required 61 million cellulosic biofuel mandate. The higher blend rate and increased implicit tax raises the E10 prices and consequently reduces CVs stock to 181 million. The reduction in total energy consumption of 40 billion liters compared to the existing policy (1) is higher than the sum of the reduction achieved by the single EV tax credit in scenario (2) and the cellulosic ethanol policy in scenario (4).

The Cellulosic Ethanol Mandate added to the ambitious EV tax credit, and CV ban in scenario (6) only increases 12 million of FFV and decreases 3 million CVs in addition to the counterpart scenario without the Cellulosic Ethanol Mandate. We find the price differential between E85 and E10 is reduced to $0.39 per liter and needs less incentive than those of scenarios (4) and (5) to offset the differences between FFVs and CVs in vehicle price and the idiosyncratic preferences for CVs. As a result, the reduced implicit subsidy raises the E85 price even if more E85 is required to meet the 61 million cellulosic mandate.

Table A7 Effect of alternative biofuels mandate on transportation sector in 2030

	Corn Ethanol Mandate				Corn+Cellulosic Ethanol Mandate		
	2016	Baseline policy (1)	+ EV Tax credit (2)	+ EV Tax credit + CV ban (3)	Baseline policy (4)	+ EV Tax credit (5)	+ EV Tax credit + CV ban (6)
Vehicle Stock (million)	**241**	**275**	**275**	**274**	**275**	**275**	**274**
CV	216	230	209	75	205	181	72
FFV	20	18	19	83	41	45	95
HBV	4	17	12	34	17	11	28
PHEV	0	9	19	50	11	20	46
BEV	0	1	16	32	1	17	32
Energy Consumption for Transportation (billion liter)*	**758**	**673**	**641**	**589**	**659**	**623**	**584**
E10	523	398	352	278	327	275	207
E85	0	17	18	22	85	90	97
Diesel fuel	234	254	255	256	242	239	246
Electricity	0.3	4	17	34	5	18	33
VKT by light-duty fleet (billion km)	4,423	5,368	5,370	5,355	5,367	5,368	5,354

VKT by diesel fleet (billion km)	699	898	900	906	856	844	869
Fuel efficiency (km per liter)*	8	13	14	16	13	14	16
Electrification (% of light-duty VKT)	**0**	**3**	**14**	**28**	**4**	**15**	**27**
Low	0	0	2	8	0	3	8
Medium	0	2	8	25	3	9	25
High	0	5	27	41	6	27	40
Ethanol (% of light-duty VKT)	**7**	**9**	**8**	**9**	**18**	**18**	**19**
Low	6.9	8.5	8.7	11	12	12	29
Medium	7.0	8.4	8.5	10	15	17	19
High	6.9	9.7	8.0	6	24	22	14
Fuel prices ($ per liter)*							
E10	0.64	0.75	0.75	0.75	0.84	0.87	0.83
E85	0.44	0.40	0.47	0.62	0.15	0.10	0.44
Diesel fuel	0.43	0.44	0.43	0.43	0.44	0.44	0.44
Electricity ($ per MWh)	120	104	108	111	104	107	110

* Fuel volumes are converted to gasoline-equivalent liter.

A.5.3 GHG Intensity of Vehicle

The greenhouse gas (GHG) emissions per mile of five vehicle types under different policy scenarios are displayed in Figure A10. Under the baseline policy scenario (1) in Figure 2, the CV has the highest emission intensity for all three scenarios, followed by FFV with 20% less emission due to the E85 fuel that has lower carbon intensity. HBV and PHEV with higher efficiency show a 31% and 69% less emission, whereas BEV has zero-emission intensity as the electricity sources are marginally from clean sources. Scenario (2) with EV tax credit slightly deteriorates the emission intensities for CV and FFV as their average fuel efficiencies are lower with less new and efficient vehicles purchased. The joint imposition of EV tax credit and CV ban of scenario (3) raises the intensity of CVs by 14% compared to scenario (2) as they are the remaining aged and inefficient vehicles still in use since 2016. FFVs also have a 10% increase in the average emission intensity as they mostly consume E10 as the second cheapest vehicle option substituting for CV. The aggressive adoption of HBV and PHEV reduces the intensity by 2% and 1%, respectively.

The implementation of the Cellulosic Ethanol Mandate not only reduces the carbon intensity of FFV by 49% with a doubled ethanol blend but also those of all other vehicles by 2-3%. It is because the higher E10 prices induce the adoption of alternative fuel vehicles that raise the average fuel efficiency, whereas the retirement of the old CVs also reduces the intensity. The emission intensity of FFV is even lower than that of HBV and close to PHEV, driven by the ethanol blend. The Cellulosic Ethanol Mandate with the EV tax credit lowers the carbon intensity for FFV but barely for others, whereas the CV ban together with the EV tax credit raises the carbon intensity of CV by 12% and that of FFV by 32% and reduces 1% and 0.1% for HBV and PHEV, for the same reason discussed above without Cellulosic Ethanol Mandate.

Table A8 GHG emissions of last year and cumulative GHG emissions in 2030

		Corn Ethanol Mandate in 2030			Corn+Cellulosic Ethanol Mandate in 2030		
	2016 (Million Mg CO_2)	Baseline policy (1)	+EV Tax credit (2)	+EV Tax credit + CV ban (3)	Baseline policy (4)	+EV Tax credit (5)	+ EV Tax credit + CV ban (6)
GHG emission of last year	% change relative to 2016						
Total	4,639	-10%	-11%	-15%	-14%	-18%	-21%
Transportation	2,277	-12%	-18%	-27%	-21%	-28%	-35%
Electricity	2,182	-8%	-5%	-3%	-7%	-6%	-6%
Agriculture	180	-5%	-7%	-9%	-22%	-25%	-28%
Cumulative GHG emissions		Over 2016-2030					
		Million Mg CO_2	% change relative to (1)				
Total		66,232	-1%	-2%	-3%	-4%	-5%
Transportation		32,449	-2%	-6%	-4%	-7%	-10%
Electricity		31,249	1%	2%	0%	1%	1%
Agriculture		2,534	0%	-1%	-12%	-14%	-13%

A.5.4 Total GHG Emission

We calculate the GHG emissions of transportation, electricity, and agriculture sectors, as shown in Table A8. In 2016, the transportation and electricity sectors account for 49% and 47% of the total emissions. Compared to the benchmark year of 2016, the baseline scenario in 2030 still achieves a 12% reduction in transportation emissions with an increasingly efficient vehicle fleet. The emission of the electricity sector reduces by 8% due to the underlying Renewable Portfolio Standard. The increasing crop yield reduces the emission-intensive agriculture land use and also emission by 4%. The cumulative GHG emissions of transportation and electricity sectors still account for 49% and 47% of the total emission over the 2016-2030 period. The EV tax credit enhances the GHG reduction in the transportation sector by 18% in 2030 but reversely increases the emission of the electricity sector that overall contribution by EV tax credit in addition to the existing policy is minimal. The ban on CV purchases pushes the 2030 emission 15% below the 2016 level and cumulatively reduces by 2% compared to the existing policy.

The implementation of the Cellulosic Ethanol Mandate in scenario 4-6 contributes to an overall 3% - 5% reduction in the cumulative emission over 2016-2030 compared to that of the existing policy scenario (1) and reduce 14% - 17% of the emission in 2030 below the 2016 level. The Cellulosic Ethanol Mandate alone in scenario (4) outperforms the EV tax credit in scenario (2) and has lower cumulative GHG emission than scenario (3) with the CV ban. The changes in the transportation emission contribute most to the GHG emission mitigation. The comparable percentage changes in agricultural emissions in Table 3, however, have smaller effects with lower absolute changes in million Mg CO_2.

A.5.5 Welfare analysis

We find that the EV tax credit will lead to an overall increase of $17 billion in the economic net benefit over 2016-2030 relative to the existing policy scenario 1 (Table A9). In the transportation sector, consumers of light-duty vehicle fleet benefit with a net of $49 billion relative to the existing policy scenario (1) by increasing the consumers' utility of the BEV and PHEV owners but reducing those of the CV and HBV. The less implicit subsidy discussed in section 4.1 driven by less fuel demand raises the consumer benefit of diesel fuels by $59 billion. Electricity producers' benefit increases by $136 billion (1%) as more electrification is created for transportation use, but the higher electricity price reduces the consumers' benefit by $70 billion. The government revenue from fuel taxes falls by $17 billion (-8%) with less gasoline consumption and is further reduced by $137 billion of EV tax credit expenditure on the EV purchase. We find the expense of EV tax credit is greater than the gain in the transportation fuel sector. However, the net benefit of the electricity sector offset the above loss. As the cumulative GHG emission reduces by 351 million Mg CO_2, the abatement cost of CO_2 with the tax credit for EV is negative at -$49 per Mg$CO_2$, which indicates an efficient GHG reduction with a welfare gain.

The additional CV ban in scenario (3) forces drivers to buy more expensive alternative fuel vehicles and leads to a net economic loss of $411 billion. The declining CV stocks lead to a drastic loss of $21,808 billion (-18%) for the CV fleet but enhance consumers surplus of other alternative fuel vehicles that results in net welfare loss of $222 billion (-0.1%) for light-duty vehicles compared to the Existing policy scenario (1). The electricity sector further enhances the economic benefit for the producers but reduces the benefit for consumers with higher electricity prices. The welfare loss exacerbates for the government as fuel tax contracts by $47 billion and vehicle tax credit needed grows by $294 billion. The abatement cost of implementing the CV ban turns out to be $304 per Mg CO_2 even though the cumulative GHG emissions reduction is 3.8 times greater than that of the EV tax credit of scenario (2).

Cellulosic ethanol mandate in scenario (4) leads to an overall $352 billion loss. The stringent policy raises the E10 prices and diesel prices and thus reduces the profits of CV, HBV, and diesel fuel drivers by $4,723 billion (-4%), $195 billion (-3%), and $354 billion (-3%) compared to the Existing policy scenario (1). They lead to a net loss of $386 (-0.2%) even after considering the increased benefit for EVs and FFV drivers. The addition of a net of $30 billion in the agricultural sector with support for biomass. The cumulative GHG emission of 1,670 Million Mg CO_2 is higher than that of the EV Tax credit and CV ban in scenario (3) and leads to an abatement cost of $211 per Mg CO_2. The cellulosic ethanol mandate, together with the EV tax credit, worsens the overall economic benefit by $461 billion (-0.2%). Similar to the EV tax credit without Cellulosic Ethanol Mandate, the light-duty consumers benefit from the EV tax credit, but this gain is then offset by the government expenses on the vehicle tax credit. On the contrary, the consumers' surplus of diesel reduces with a higher diesel price. The abatement cost decreases to $192 per Mg CO_2. The addition of the CV ban imposed with the tax credit deteriorates the welfare loss by $862 billion compared to the Existing policy scenario (1) for light-duty vehicle consumers, diesel consumers, and also the government expenditure. The 3,148 million Mg CO_2 of emission reduction upscales the abatement cost to $274 per Mg CO_2.

Table A9 Effect of alternative biofuels mandate on social welfare over 2016-2030 (billion $)

	Corn Ethanol Mandate			Corn+Cellulosic Ethanol Mandate		
	Existing policy (1)	+EV Tax credit (2)	+EV Tax credit + CV ban (3)	Existing policy (4)	+EV Tax credit (5)	+EV Tax credit + CV ban (6)

	($ billion)	Relative change to (1) ($ billion)				
Economic surplus (a)	**168,742**	**17**	**-411**	**-352**	**-461**	**-862**
Agricultural sector	*3,004*	*-2*	*-3*	*30*	*30*	*31*
Agricultural consumers	2,111	1	2	-7	-9	-10
Agricultural producers	893	-3	-5	36	39	40
Transportation fuel sector	*154,774*	*107*	*-164*	*-386*	*-356*	*-621*
Light-duty vehicle consumers	143,580	49	-222	-30	38	-267
CV	123,945	-4,160	-21,808	-4,723	-10,197	-23,609
FFV	11,425	119	7,042	4,536	5,431	9,977
HBV	5,953	-1,078	2,267	-195	-1,058	1,336
PHEV	1,901	2,022	6,346	302	2,426	6,395
BEV	358	3,146	5,930	51	3,436	5,633
VKT diesel consumers	10,270	59	60	-354	-391	-351
Crude oil producer	924	-1	-2	-1	-2	-3
Electricity sector	*10,023*	*66*	*98*	*1*	*30*	*56*
Electricity consumers	6,943	-70	-135	1	-44	-105
Electricity producers	3,080	136	233	0	74	161
Government revenue	*941*	*-154*	*-342*	*3*	*-165*	*-328*
Liquid fuel taxes	941	-17	-47	3	-17	-41
Vehicle tax credit	0	-137	-294	0	-148	-287
Cumulative GHG emissions (Million Mg)	**66,232**	**-351**	**-1,351**	**-1,670**	**-2,396**	**-3,148**
Abatement cost ($ per MgCO$_2$)		**-49**	**304**	**211**	**192**	**274**

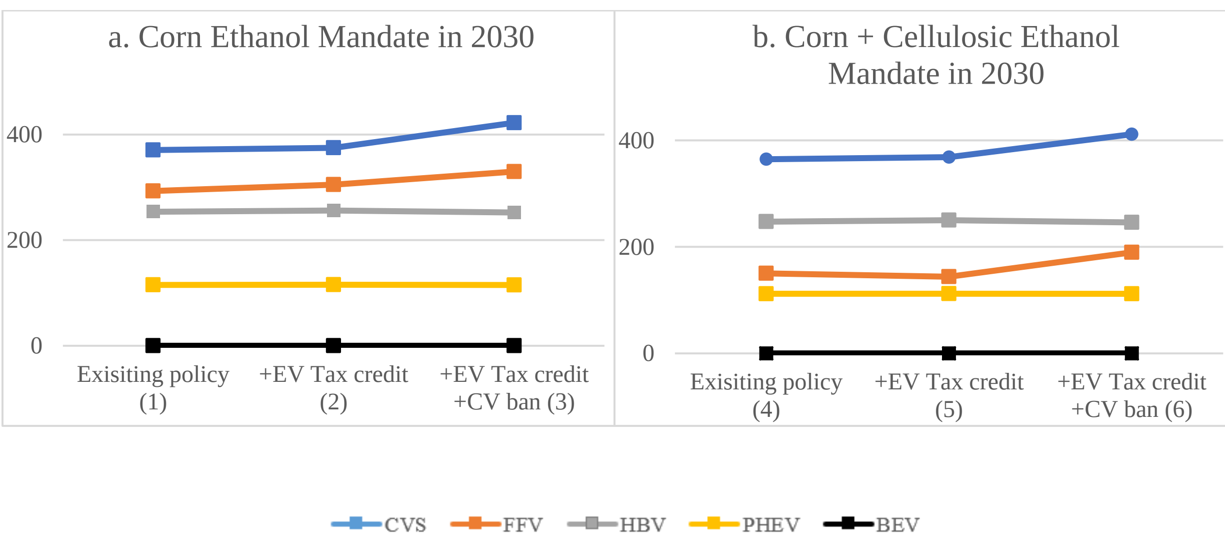

Figure A10 The carbon intensity of vehicle mileage under each scenario (g CO_2 per mile)