

THE DECARBONIZATION POTENTIAL OF ALTERNATIVE FUEL AND VEHICLES
CHOICES IN THE US TRANSPORTATION SECTOR: BEHAVIORAL, TECHNOLOGICAL
AND POLICY DETERMINANTS

BY

JIA ZHONG

DISSERTATION

Submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy in Agricultural and Applied Economics
in the Graduate College of the
University of Illinois Urbana-Champaign, 2021

Urbana, Illinois

Doctoral Committee:

Professor Madhu Khanna, Chair and Director of Research
Professor Hayri Onal
Professor Yanfeng Ouyang
Associate Professor Benjamin Gramig

ABSTRACT

Decarbonizing the US transportation sector will require a mix of alternative vehicles and low-carbon biofuels to displace fossil fuels. Advanced biofuels and electricity are the two most anticipated alternative energy sources for advanced powertrain vehicles to use that are less carbon-intensive. However, the current consumptions of biofuel and alternative fuel vehicles fall short of the expectation. The Renewable Fuel Standard (RFS) has failed to achieve its original goal of inducing the consumption of E85 (with up to 74% blend in gasoline), and the adoption of alternative fuel vehicles is restricted by the dominating liquid fuel vehicles.

The purpose of this research is to analyze the policy incentives, technological and behavioral factors that will determine the choices and mix of alternative fuels and vehicles and their implications for the extent of decarbonization that can be achieved in the near future. This dissertation has three chapters.

The first study examines the effect of the design of RFS on creating disincentives for ethanol fuels but favoring biodiesel production. I develop a welfare-economic framework and a simulation model to examine the implications of the design features of the policy (specifically, its nested structure and the accompanying cellulosic waiver credit and biodiesel tax credit) on the mix of biofuels blended and on social welfare. The results show that the flexibility allowed for compliance reduces the incentives for selling a higher blend of corn ethanol and cellulosic ethanol and leads to an overall blend wall for ethanol. They raise the retail price of higher ethanol blend (E85) higher than the energy-equivalent price of motor fuel (E10). Though social welfare is enhanced and GHG emission reduces marginally, the design features impose welfare costs on corn ethanol producers and taxpayers.

The second study examines the behavioral and technological determinants of the adoptions of alternative fuel vehicles by incorporating the consumers' vehicle choice model with the random utility framework in a dynamic, open-economy, multi-market optimization model. We find that behavioral factors limit the adoption and distribution of battery-electric vehicles for consumers with less public charging or fast-charging coverage that increases the costs of range limitation, detour, and waiting. Idiosyncratic preferences of consumers show a persistent preference for the conventional vehicle as well as emerging interest for electric vehicles. We also find that market acceptance of battery-electric vehicles is more responsive to the market uncertainties than the GHG emissions, where the growing the electricity demand and corresponding GHG emission restricts the social benefit from GHG mitigation. The EV tax credit is the main driver of the BEV uptake even under market uncertainty, but it also leads to a net welfare loss requiring substantial government investment.

The third paper explores the role of cellulosic biofuel policy in decarbonizing US transportation while interacting with the incentives for electrification in US transportation. We first use graphical analysis to examine the interaction between the ethanol blend mandate and the electrification incentives. We find changes in the implicit price incentives for E85, E10, and diesel from blend mandate are ambiguous, which depends on the extent of E10 displacement and increased blend rate. Our numerical model using the same model developed in chapter 3 finds that the synergy between the cellulosic biofuel policy and incentives for electric vehicles reduces the total emission and carbon intensity of the mileage in the US. Though the cellulosic biofuel policy alone leads to greater net welfare loss than the federal tax credit for electric vehicles (EV) alone due to high fuel prices, the joint implementation of both policies leads to cheaper abatement costs than the cellulosic ethanol mandate alone.

This dissertation contributes to the literature with advanced understandings of the implication of decarbonization strategies, especially Renewable Fuel Standard and the electrification incentives and their interactions. The findings in Chapter 2 suggest the need to shift the structural design of RFS policy towards a non-nested structure with a separate fossil fuel base to eliminate the blend wall and to create demand for cellulosic ethanol and minimize the GHG intensity of transportation fuel. Chapter 3 identifies the pathways of overcoming the behavioral and technological barriers to stimulate the adoption of battery electric vehicles and identifies the key driver of EV adoption being the costly EV tax credit. Chapter 4 demonstrates the role of cellulosic biofuel policy in the tradeoffs between economic surplus and GHG emissions due to the policy interactions between electrification incentives and biofuel blend mandate.

ACKNOWLEDGMENTS

I would like to express my deepest appreciation to my advisor Madhu Khanna for her invaluable guidance for my research and financial support. Her persistent support and countless great advice direct me to the rigorous research training essential for my future career development. My gratitude also goes to my committee members: Hayri Onal, Ouyang Yanfeng, Ben Gramig, for the constructive advice and encouragement. Thank you to the College of Agricultural, Consumer, and Environmental Sciences for many academic opportunities and platforms to develop a graduate career. My sincere thanks also belong to my family and friends for caring, supporting, and love during the hardships.

To my beloved grandparents, Boxi Zhong, Cuina Lu, Xingrong Gou, Wenying Yang

and

To my parents, Yue Zhong and Xiaoling Gou

TABLE OF CONTENTS

CHAPTER 1: Introduction	1
CHAPTER 2: Assessing the Efficiency Implications of Renewable Fuel Policy Design in the United States	6
CHAPTER 3: Behavioral, Technological and Economic Determinants of Electric Vehicle Adoption in the United States	62
CHAPTER 4: The Imperative for Cellulosic Biofuels in an Electrifying Vehicle Market	98
CHAPTER 5: Conclusion	128
REFERENCES	132
APPENDIX A: Supplementary Material For Chapter 2	142
APPENDIX B: Supplementary Material For Chapter 3 and Chapter 4.....	162

CHAPTER 1 : Introduction

Achieving long-term transportation emission reduction will require a portfolio of strategies (US EPA 2020), including replacing petroleum fuel with low-carbon fuels, switching to alternative drivetrain vehicles, and increasing vehicle fuel efficiencies. The Renewable Fuel Standard (RFS) enacted by Environmental Protection Agency prescribes an overall target of 36 billion gallons of total biofuels by 2022 that includes minimum requirements for advanced biofuels of cellulosic biofuel (16 billion gallons) and biomass-based diesel (2 billion gallons), and mandates the rest from conventional biofuel from corn starch. The policy is expected to have a technology-forcing impact to induce more biofuel consumption by the ethanol-tolerable flex-fuel vehicles. Moreover, the growing optimism about the potential of GHG mitigation by electric vehicles (EV) lies in the all-electric technology with zero tailpipe emission and efficient electric motors (Williams et al. 2012; Meier et al. 2015; Tong and Azevedo 2020). The consumers of electric vehicles are provided with federal tax credits of up to \$7500 per vehicle for battery-electric vehicles and \$2500 for the plug-in hybrid electric vehicle. The potential restrictive ban on liquid-fuel vehicles would also indirectly push the turnover of current vehicle fleets for alternative fuel vehicles to penetrate the market. Moreover, generous incentives are granted to the electric vehicle manufacturer to increase the fuel efficiency of the vehicle fleet and comply with the Safer Affordable Fuel-Efficient standard (SAFE) and Corporate Average Fuel Efficiency standard (CAFE).

However, the current volumetric productions of biofuel and alternative fuel vehicles fall short of the expectation of either the intended requirement of the Renewable Fuel Standard or that of the estimated vehicles outlook of the Energy Information Administration. Although the average CO₂ emissions per mile of US cars driving on the road has decreased by 23% and fuel

economy has increased by 30% from 2008 to 2018 (EPA 2018a), the total GHG emissions from the transportation sector have increased annually at a rate of 0.8% (EPA 2019). This dissertation has several purposes: the first chapter aims to examine the policy implications of the policy design of Renewable Fuel Standard on fuel markets; the second chapter investigates the behavioral, technological, and economic drivers of alternative fuel vehicle adoptions; the third chapter studies the cost-effectiveness and the ability of GHG reduction by the implementation of the policy combination of biofuel policies and electrification incentives.

The chapter 2 examines the implication of the design features of the Renewable Fuel Standard (RFS) on the mix of biofuels produced for compliance. The Renewable Fuel Standard has failed to achieve its original goal of inducing the consumption of E85 (with up to 74% blend in gasoline). Blenders chose to comply with the RFS mandate by increasing the blending of biomass-based biodiesel beyond originally-targeted levels instead of creating market demand for E85 by pricing E85 at an energy-equivalent level with E10 fuel in the US. The objective of this study is to analyze the implications of the nested design of the RFS and the accompanying cellulosic waiver credit and biodiesel tax credit for the mix of biofuels blended and for social welfare. I undertake this analysis by developing a stylized economic model of the US transportation sector, which is an integrated representation of the fuel distribution system from the wholesale fuel producers to the consumers. The model endogenously determines the optimal solution that could indicate the unintended consequence of the design feature of the RFS on fuel prices. The study extends the previous research by decomposing the impacts of each designed feature of the RFS, and theoretically and numerically examines their interactive impacts on fuel prices, welfare change, and GHG emissions. The results show that the flexibility allowed for compliance by the current design of the RFS reduces the incentives for selling a higher blend of

corn ethanol and cellulosic ethanol and leads to an overall blend wall for ethanol. This flexibility benefits the consumers of diesel-blended and gasoline-blended fuels users as well as biodiesel producers but at the cost of the corn ethanol producers and taxpayers.

Chapter 3 examines the economic and behavioral determinants of alternative fuel vehicles adoptions for consumers to shift their vehicle choices. Despite the existing optimistic projections of the EV sales and penetrations in the market, the current vehicle stock of EVs is only 1.5 million by 2019 that casts doubt on wide market acceptance of electric-powered drivetrain. This paper aims to disentangle the effect of behavioral, technological, and economic drivers of the adoption of alternative fuel vehicles. I integrate behavioral preferences from a random utility framework into a dynamic, open-economy, multi-market optimization model BEPAM (Biofuel and Environmental Policy Analysis Model) with multiple markets in the fuel, transportation, and electricity sectors. The study contributes to the literature by simulating behaviorally realistic vehicle choices integrated with both the economic and intangible costs of vehicle ownership and operation as well as the idiosyncratic preferences. We find the range limitation and detour costs discourage the purchase of battery electric vehicles for consumers with access to only public charging, whereas waiting cost further deters the BEV adoption with less fast charging. Idiosyncratic preference shows the persistent preference for conventional vehicles and electric vehicles. The market uncertainty in prices and policy incentives indicates that extensive financial support will be required in the form of EV tax credits to support the adoption of electro-mobility. Additionally, the savings in GHG emissions is limited by the additional emission discharged from the rising electricity consumed by EVs.

Chapter 4 examines the cost-effectiveness and the extent of GHG reduction with multiple decarbonization policy strategies, including the cellulosic ethanol mandate, EV tax credit, and

ban on conventional liquid vehicles over the 2016-2040 period. We interact the biofuel blend policy with the incentives for electrification and examine their joint implication for the adoption of alternative fuel vehicles and energy consumption. We also examine the welfare cost of imposing the policies and estimate the abatement cost of GHG emissions. We first demonstrate the implication of the ethanol blend mandate and EV incentives by graphical analysis and find that the interaction between the ethanol blend mandate and the electrification incentives leads to ambiguous changes in the price incentives for retail fuels of E85, E10, and diesel. It depends on the extent to which both E10 is substituted, the increased consumption of E85 to meet the volumetric mandate, as well as the blend rate that determines the stringency of policy. The numerical simulations using the same integrated model BEPAM as in chapter 3 show that the cellulosic ethanol mandate complements the EV tax credit and conventional liquid vehicle ban in diversifying vehicle fleet by raising the blend rate and cutting E10 demand. The synergy between the combined policies lowers the carbon intensities for flex-fuel vehicles comparable to the levels hybrid electric vehicles could achieve. Though the cellulosic ethanol mandate increases the welfare cost, the joint implementation of EV incentives has lower abatement costs than the cellulosic ethanol mandate alone due to the higher synergized welfare gains for agriculture, light-duty consumer, and electricity than the sum of gains of separate impositions of the policies. The findings warrant the role of biofuel in expediting the decarbonization with the synergy created with the electrification of US transportation.

The findings of this dissertation inform policymakers of the intended and unintended consequences of decarbonization strategies of transportation in the US. We find that the biodiesel tax credit and the nested structure together create a 14% price gap between E85 and E10 and generate the blend wall at 10% blend of ethanol. The second chapter finds that the welfare cost

of EV adoption is as high as \$349 billion under different scenarios due to the tax credit required by government investment. Lastly, the cost-effectiveness analysis of various policy strategies for GHG mitigation shows that combining ethanol blend mandate with electrification can achieve additive cumulative GHG mitigation potential and the 11% - 13% lower abatement cost than the individual policy strategies.

CHAPTER 2 : Assessing the Efficiency Implications of Renewable Fuel Policy Design in the United States

2.1 Introduction

The US Renewable Fuel Standard (RFS), a technology-forcing policy, was revised in 2007 to accelerate the supply of various types of biofuels and to stimulate demand for high blends of ethanol in the transportation fuel as part of the primary goal. The broad categories of biofuels mandated by the RFS include conventional biofuel (corn ethanol), advanced biofuel (sugarcane ethanol), biomass-based diesel (mostly soybean oil¹), and cellulosic biofuel (from biomass feedstocks); these biofuels differ in their feedstock and savings in greenhouse gas (GHG) intensity relative to fossil fuels. The RFS set an overall target of 36 billion gallons for total biofuels, which includes a minimum target of 16 billion gallons for biofuel from cellulosic feedstocks, at least 1 billion gallons of biomass-based diesel, and 4 billion gallons for other advanced biofuels by 2022. The rest of the mandate could be met by producing conventional biofuel from corn starch to a maximum of 15 billion gallons. Although the RFS specified volumetric mandates for different types of biofuels, it is implemented by setting blend rates for different types of biofuels at the national level. The refineries or importers that supply gasoline or diesel for domestic use are required to blend biofuel in the mandated proportion to a fossil fuel base that jointly includes gasoline and diesel.

The RFS is designed to have a nested structure (see Table 1), in which cellulosic ethanol qualifies for the cellulosic, advanced, and conventional biofuel components. Biomass-based diesel certifies for biomass-based diesel, advanced, and conventional biofuel compliance.

¹ The biomass-based biodiesel is obtained from non-petroleum renewable resources such as soybean oil, rapeseed oil, and other vegetable-oil and animal fat. Soybean oil sources count for more than 80% of the total biodiesel feedstock. We use “biodiesel” as short form of biomass-based diesel in the following context.

Advanced biofuels qualify for advanced and conventional biofuel components. Corn-based ethanol can only be applied towards the conventional biofuel component. The RFS has been accompanied by two additional policies that can affect the mix of biofuels blended. The first is the cellulosic biofuel waiver credit that has been offered because the supply of cellulosic biofuel is limited and uncertain. The EPA allows obligated parties to purchase waiver credits up to the level of their cellulosic biofuel obligation to meet their annual cellulosic compliance requirements. In addition to paying the waiver fee, obligated parties are also required to blend an equivalent amount of non-cellulosic advanced biofuel to comply with total renewable fuel obligations (US EPA 2015). Second, the RFS has been accompanied by volumetric tax credits that have differentially affected the costs of blending alternative types of biofuels for complying with the RFS. Biodiesel producers have received a tax credit of \$1 for every gallon of biodiesel sold since 2010 (EPA 2018b). In contrast, the tax credit for corn ethanol was lowered over time from \$0.54 per gallon of ethanol since 1980 to \$0.45 per gallon in 2004 and was eliminated in 2011. Similarly, the cellulosic biofuel credit of \$1 per gallon provided since 2010 was eliminated in 2016.

Despite the flexibility provided in compliance, the RFS has failed to achieve its volumetric goals for ethanol as originally intended. While the supply of conventional corn ethanol has increased to about 15 billion gallons as mandated, production of cellulosic ethanol has fallen far short of the targeted amount, whereas biodiesel production has exceeded the amount originally mandated. Additionally, achieving the RFS statutory target in 2017 would have required a blend rate of 16% of ethanol and required a significant amount of ethanol sold as higher blends that

contained between 51% and 85% of ethanol (E85)² (see Appendix A1 for statutory support to create demand for the higher ethanol blends expected to be produced through compliance with the RFS)³. However, consumer demand for such higher-blend ethanol fuel has not emerged, and ethanol is primarily sold in a 10% blend as E10. Since 2012, demand for ethanol has been constrained by a “blend wall”⁴ since sales of higher blends, principally E85, have not grown at the rate needed to consume the volume of ethanol mandated originally by the RFS. Instead, blenders have chosen to comply with the mandate by increasing the blending of biomass-based diesel (BBD) with petroleum diesel. The sale of higher blends of ethanol as E85 requires the pricing of E85 to be at least at parity with the energy-equivalent price of E10 and a sufficient demand from flex-fuel vehicles that are able to use E85 on the road. However, the price of E85 has been 7-29% higher than the energy equivalent price of E10 since 2007 (as shown in Figure 2.1). The absence of demand for higher blends of ethanol, together with the unavailability of supply of cellulosic biofuels, has led to a scaling down of the mandate since 2012, largely by waiving the cellulosic biofuel component of the RFS.

The purpose of this study is to analyze the implications of the nested structure of the RFS, the cellulosic waiver credit, and the biodiesel tax credit for the mix of biofuels blended and to

²The E85 is an ethanol-gasoline blend containing a volumetric share of 51 to 83% ethanol; the exact share varies across locations and seasons (approved as active standard ASTM D5798). The 85% is an upper limit for the share of ethanol blend in the gasoline. On average, the Energy Information Administration recognizes that “winter months drivability considerations require more than a 15% share of gasoline” and that the share of ethanol added to gasoline to produce “E85” is closer to 74% (Annual Energy Outlook, 2004 and thereafter). The revised Renewable Fuel Standard (footnote 157 at 75 FR 14762) has also assumed the average blend sold as E85 has 74 % ethanol and 26 % gasoline by volume.

³ Though not requiring a specific ethanol blend, EPA envisioned that “increases in E85 will dominate efforts to increase the use of renewable fuel” (EPA 2015) and estimated that 9.2 billion gallons of E85 will be required in 2016 (see more details in Appendix 1). A large body of literature has also highlighted the role of high-ethanol gasoline blends required to meet the required ethanol blend and estimate the market demand and supply (Pouliot and Babcock 2014; Pouliot et al. 2018; Johnson and Melendez 2007).

⁴ 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 Perkins 2010; Taheripour and Tyner 2008).

creating a blend wall. Specifically, we examine the extent to which each of these policies provides incentives for increasing the production of biodiesel instead of increasing the consumption of higher blends of ethanol after we hit the blend wall. We also analyze the implications of these policies for the persistence of the blend wall and conditions under which it creates disincentives for price parity between E10 and E85 on an energy equivalent basis. Finally, we examine the welfare implications of these renewable fuel policies for consumers and producers in the fuel markets and greenhouse gas (GHG) emissions.

We undertake this analysis by developing a stylized economic model of the U.S. transportation sector with four representative agents: wholesale petroleum fuel producers (including gasoline and diesel), wholesale biofuel producers (corn ethanol, cellulosic ethanol, and biodiesel), blenders, and retail fuel consumers. We develop an integrated representation of the fuel distribution system from the wholesale producers to the consumers, similar to a social planner's problem, to endogenously determine the induced effect of the design feature of the RFS on fuel pricing strategies. This representation allows us to endogenously determine optimal prices and quantities of different types of renewable and non-renewable fuels used in the US transportation fuel as well as RIN credit volumes and their market prices under the current and alternative designs of the RFS. Our theoretical analysis first demonstrates the policy implication of nested structure and fossil fuel base on fuel prices. We then examine the effects of the cellulosic waiver credit and the biodiesel tax credit on the RINs markets, fuel markets, and welfare implications. We numerically simulate these scenarios to quantify the implications of the design features of the RFS and accompanying biodiesel tax credit for the mix of biofuels markets for complying with the RFS.

Lastly, we discuss the GHG emission implications of the design of the RFS and the accompanying policies. The RFS defines cellulosic ethanol as having at least 60% less GHG emission than gasoline; biomass-based diesel as having 50% of GHG emissions of gasoline; and corn-based ethanol as having at least 20% lower GHG intensity compared to gasoline. We analyze the overall social welfare effects of implementing the RFS, including the GHG effects valued at the social cost of carbon and the distributional implications for consumers and producers of different types of fuels.

Our paper differs from the existing literature in several ways. Early studies by de Gorter & Just (2009) and Lapan & Moschini (2012) analyzed the implications of implementing the mandate assuming a perfectly competitive market and showed that a blend rate mandate would implicitly tax gasoline and subsidize ethanol. Other studies have examined the economic impact of various biofuel policies (biofuel mandate, tax credits, fixed and variable rate subsidies) on crop prices, biofuel imports and trade in sugarcane, biofuel production, and prices (Babcock, Agroicone and Peng 2013; Tyner, Taheripour and Perkis 2010). Thompson, Meyer and Westhoff (2010) show how changes in biofuel policies, specifically, expiration of the tax credit and the specific tariff, affect RIN prices and mandate costs. These studies are considering biofuel blending rates below the blend wall. Chen et al. (2014) assume that there will be sufficient demand for E85 by flex-fuel vehicles and focused on examining the supply-side implications of the RFS for land use, greenhouse gas emissions, and fuel use. These studies were based on the assumption that with a competitive market for biofuels and a binding mandate, the blend wall problem can be implicitly avoided with a complete pass-through of the RIN value from the wholesale to the retail price of the blended fuel. None of these studies are examining the implications of the nested design of the RFS for creating the incentives for blend wall.

Among the empirical studies, Whistance and Thompson (2014) analyze RIN price behavior to test the implications of a binding RFS versus a nonbinding RFS on ethanol-gasoline and corn-gasoline price relationships. Other studies by Knittel et al. (2017), Lade & Bushnell (2018), and Li & Stock (2018) seek to analyze the extent of pass-through of RIN prices between wholesale and retail blended fuel prices. They show that retail E85 prices are higher than the energy equivalent retail price of E10 due to an incomplete RIN pass-through and speculate on various explanations for this. Lade and Bushnell (2018) and Li & Stock (2018) suggest that the market power of the blenders at the terminal and imperfect retail competition in the E85 market results in incomplete pass-through of RIN values and raises E85 prices above the energy equivalent parity value with E10. Luo and Moschini (2019) explain the price disparity between E85 and E10 by using a Hotelling spatial competition model to capture the market power and product differentiation in both spatial distributions of consumers and consumer preferences for biofuel. Irwin, McCormack and Stock (2020) analyze the effect of the biodiesel tax credit on the volatility of D4 biodiesel RIN prices. Unlike these studies, our paper provides a structural explanation for the price disparity between E85 and E10, even under the assumption of a perfectly competitive E85 market. It shows that correcting imperfect competition at the retail level alone will not correct the price disparity and eliminate the blend wall given the current nested design of the RFS.

A few studies have examined the effects of the cellulosic biofuel waiver policy on incentives for investment in cellulosic biofuel refineries (Miao, Hennessy and Babcock 2012) and on crop price levels, crop and livestock farm income, compliance costs, and greenhouse gas emissions (Meyer and Thompson 2012). These studies, however, do not examine the marginal economic conditions under which flexibility affects the choice of pathways for

compliance with the RFS and contributes to the generation of the blend wall.

A few studies have analyzed the welfare implications of the volumetric mandates specified by the RFS for different types of biofuels and show conditions under which the RFS increases social welfare in a competitive economy (Cui et al. 2011; Lapan and Moschini 2012; Moschini, Lapan and Kim 2017; Chen et al. 2014; Chen et al. 2021). These studies do not analyze the implications of the nested design of the RFS and accompanying biodiesel tax credit and cellulosic waiver credit for the mix of biofuels produced and the blend wall or its social welfare and distributional effects. Korting, Just, and De Gorter (2019) compare welfare implications of the nested RFS with the biodiesel tax credit for ethanol and biodiesel producers and consumers of blended gasoline and diesel relative to no policy. They show that it leads to a large loss in the surplus of diesel-blended fuel consumers. Our study extends the welfare analysis in Korting, Just and De Gorter (2019) by theoretically and numerically decomposing the effects of each feature of the RFS and accompanying policies, including the joint fossil base, nested structure, biodiesel tax credit, and cellulosic waiver credit) and their interactions on fuel prices, welfare change, and GHG emissions. We show that the increased flexibility in complying with the overall mandate allowed for lower-cost biofuels to substitute for the more costly biofuels and increased overall social welfare. This flexibility benefited the consumers of diesel-blended and gasoline-blended fuels users as well as biodiesel producers but at the cost of the corn ethanol producers and taxpayers.

In the next section, we describe the design of the RFS and mechanisms for complying with it. We develop stylized features of the RFS based on this and incorporate them in the conceptual framework presented in section 2.3. This framework is used to generate analytical insights on the effects of the features of the RFS on fuel price and fuel mix and its welfare effects. The

numerical simulation and results are presented in section 2.4. We conclude in section 2.5 with a discussion of our results.

2.2 Background

Under the Energy Independence Security Act (EISA) of 2007, the Environmental Protection Agency (EPA) is responsible for administering the RFS. The law requires EPA to annually announce the total renewable fuels mandate and the corresponding sub-mandates of cellulosic biofuel and biomass-based biodiesel by November 30th of the previous year. Compliance with the RFS is tracked by associating each unit of biofuel blended with a Renewable Identification Number (RIN). When biofuel is blended with petroleum, RINs are detached from biofuel and can be traded in the RIN market, and obligated parties are required to acquire enough RINs to meet their volume obligation every year. There are four separate types of Renewable Identification Numbers (RINs) –cellulosic (D3), biomass-based diesel (D4), other advanced fuel (D5), and conventional fuel (D6). Since any of the advanced components (cellulosic, biodiesel, and other advanced biofuels) could be used to fulfill the conventional biofuel component of the mandate, the advanced RINs (D3, D4, and D5) should always be valued higher than conventional ethanol RINs.⁵ Due to the nested structure of the RFS, D3 (cellulosic), D4 (biodiesel), and D5 (advanced) RINs can be counted towards the total renewable fuel compliance; but the reverse is not allowed.

⁵ If this was not the case then an arbitrage opportunity would exist where an obligated party could sell conventional ethanol RINs and purchase an equal volume of advanced RINs for mandate compliance while profiting on the RIN trade. The reverse trade would not work since conventional ethanol RINs cannot be applied towards any of the advanced mandate classifications.

The EPA has the authority to waive the mandate and reduce the applicable volume of cellulosic ethanol if its inadequate domestic supply generates potentially severe economic harm for blenders (Coppess and Irwin 2017). Since 2010 the EPA has waived a significant portion of the cellulosic biofuel mandate and also waived the mandated total renewable fuel volume below levels originally required by the RFS. The EISA requires EPA to issue cellulosic waiver credits corresponding to the waived volume of the cellulosic biofuel mandate. The obligated parties (oil refiners and importers) can purchase those waiver credits to comply with the cellulosic mandate obligations when they are not able to produce enough such biofuel. However, unlike D3 RINs eligible for both cellulosic and total renewable fuel mandates, the cellulosic waiver credits do not count towards an obligated party's advanced biofuel or total renewable fuel obligations. In other words, when the obligated parties use cellulosic waiver credits to meet the mandate, an equivalent volume of non-cellulosic advanced RINs (D4 or D5 RINs) are required to satisfy non-cellulosic biofuel obligations. The EPA sets the price of the waiver according to a formula by taking the greater of \$0.25 or the difference between \$3.00 and the average wholesale gasoline price in the previous year (US EPA 2015). Since the issuance of the cellulosic waiver credit, the prices have been lower than the D3 RIN price (shown in Figure 2.2). It encourages the obligated parties to use waivers instead of producing more cellulosic ethanol leading to the observed shortfall in meeting the cellulosic biofuel mandate.

In 2017 the EPA used its waiver authority and reduced the cellulosic biofuel mandate from 3.67 billion to 0.21 billion gasoline-gallon equivalent (gge) while increasing the advanced biomass-based diesel requirement to 2 billion gge from the original requirement of at least 1 billion gge, keeping the implicit corn ethanol gap unchanged at 15 billion gge (Table 1). The actual volumes of different biofuel types produced by the obligated parties (refiners or oil

importers) diverged from the mandated amounts⁶: biodiesel production at the level of 2.56 billion gge exceeded the mandated level while cellulosic biofuel production at 0.17 billion gge and was lower than the mandated level in 2017. Conventional ethanol production (from corn) also fell short of its maximum allowed level by 0.74 billion gge. As a result, the total renewable fuel volume fell short of even the revised total mandate by 0.75 billion gge. Next, we develop a stylized partial equilibrium, multi-market, closed economy analytical model to analyze the market equilibrium quantities and prices of petroleum and biofuel fuels in the U.S. transportation sector subject to the RFS constraints. We seek to show the role of the design of the RFS and accompanying waivers and tax credits on the pricing and mix of biofuel blends and on the (dis-)incentives for selling E85.

2.3 Theoretical Model

2.3.1 Model Setup

The stylized transportation sector model consists of representative fuel consumers, fuel blenders, biofuel producers, and refineries. We consider a representative consumer that demands gasoline-blended fuels in the presence of the blend wall sold either as E10 (q_{E10}) or E85 (q_{E85}), where q_{E10} and q_{E85} are the endogenously determined demands for E10 and E85 measured in gasoline-gallon equivalent (gge) units. The aggregated demand for gasoline blended fuel is represented by q_{gf} and defined as $q_{gf} = q_{E10} + q_{E85}$. As flex-fuel vehicle users can shift between E85 and E10 fuel interchangeably with equivalent fuel economy at the gasoline-gallon equivalent level, we assume E10 and E85 are perfectly substitutable at the energy equivalent

⁶ Source: <https://www.epa.gov/fuels-registration-reporting-and-compliance-help/annual-compliance-data-obligated-parties-and#nested-rvo>

level ⁷

(Roberts 2008). With this assumption, the prices of E85 should be at least on par with E10 to be sold. The demand for blended biodiesel by diesel-fueled vehicles is represented by q_{df} and defined as $q_{df} = q_b + q_d$, where q_b and q_d are the volume of biodiesel and diesel demand that are assumed equivalent in diesel energy content at current level⁸.

The blender purchases gasoline (q_g) and diesel (q_d) from refineries; corn ethanol (q_e), cellulosic ethanol (q_c), and biodiesel (q_b) from biofuel producers to produce two types of gasoline blended fuel (q_{E10} and q_{E85})⁹ and biodiesel blended diesel (q_{df}). Total ethanol produced (including corn and cellulosic) is equal to the amount blended into E10 (10% of the volume of E10) and E85 (74% of the volume of E85). This is represented as $q_e + q_c = 0.1q_{E10} + 0.74q_{E85}$. Similarly, the total amount of petroleum gasoline is equal to the amount blended in E10 and E85, which contain 90% and 26% of gasoline, respectively; thus $q_g = 0.9q_{E10} + 0.26q_{E85}$.

⁷ Some studies have shown that many consumers would be unwilling to pay for E85 simply based on its energy equivalence; they show that for some consumers the price of E85 needs to be at lower or at most at energy equivalent parity to E10 for consumers to consume it (Pouliot & Babcock 2015) whereas for other consumers (for example, in California) there is a willingness to pay more for E85 than the energy equivalent value of E10. For simplicity, we assume that the representative flex-fuel vehicle owner is rational, has complete information about the energy content of E85 and E10 and treats them as functional substitutes at the energy equivalent level. This may be reasonable at the national level if consumers with various preferences are normally distributed through the population. As shown by the validation of our numerical model, our simple framework provides solutions that agree closely with observed data on fuel quantities and prices. Additionally, since it is reasonable to assume that consumer preferences are invariant across RFS design scenarios, the inclusion of consumer heterogeneity will not affect the analysis of the relative implications of RFS design for blend wall and for fuels pathways chosen to comply with the RFS. However, the model developed here can easily be extended to consider heterogeneity in consumer valuation and willingness to pay for E85 and derive a more specific relationship between the price of E10 and E85.

⁸ The biodiesel and diesel blends are perfect substitutes up to a 5% blend based on the source from the Department of Energy: https://afdc.energy.gov/fuels/biodiesel_blends.html. Since 2007, the biodiesel blends have been less than 5% that validates our assumption of perfect substitutes between biodiesel and diesel.

⁹ Considering that there is very little demand for E15 (15% ethanol blend) and for simplicity of our analysis we only consider E10 and E85 throughout our study. However, the framework developed here can be easily extended to consider three blends instead of two blends of ethanol only.

We construct the RIN market following the EPA's definition¹⁰ by specifying the RINs generated with the production of biofuels. We convert volumes of all types of fuels and RIN volumes into gasoline-gallon equivalent (gge). The blended volume of cellulosic ethanol determines the D3 RINs (q_{D3}); the amount of D4 RINs produced (q_{D4}) is determined by the volume of biodiesel produced; the total quantity of D6 RINs (q_{D6}) is determined by the volume of corn ethanol produced. The three different categories of RINs are represented as: $q_{D3} = q_c$, $q_{D6} = q_e$, and, $q_{D4} = q_b$. For simplicity, we do not consider the banking of RINs and assume that RINs produced are all used for compliance in the same year¹¹.

We solve the social planner's welfare (denoted as W) optimization problem to determine the optimal mix of transportation fuels and RINs as well as their prices as the least cost way of achieving the biofuel policy mandate.

$$\begin{aligned} \text{Max}_{\{q_{gf}, q_{df}, q_e, q_c, q_g, q_d, q_b, q_{cw}\}} W = & \int_0^{q_{gf}} D_{gf}(q_{gf}) dq_{gf} + \int_0^{q_{df}} D_{df}(q_{df}) dq_{df} - \\ & \int_0^{q_e} S_e(q_e) dq_e - \int_0^{q_c} S_c(q_c) dq_c - \int_0^{q_b} S_b(q_b) dq_b - P_{g0}q_d - P_{d0}q_d - w_{gf}q_{gf} - w_{df}q_{df} - \\ & P_{cw}q_{cw} + t_Bq_b \end{aligned} \quad (2.1)$$

Subject to

$$q_{D4} \geq \theta_{D4} (q_g + q_d); \quad (2.2)$$

$$q_{D3} \geq \theta_{D3} (q_g + q_d); \quad (2.3)$$

$$q_{D6} \geq \theta_{D6} (q_g + q_d) \quad (2.4)$$

¹⁰ As majority of the D5 RINs are generated from sugarcane ethanol imported from Brazil and since we assume a closed economy in this study, for simplicity of our analysis we only consider above mentioned three categories of RINs compliance mechanism.

¹¹ The EPA rulemaking allows obligated party to over-comply and generate more RINs than they need and "carry over" the excess RINs for use in the subsequent compliance year up to 20% of the renewable volume obligation.

For simplicity, we denote the short-term inverse demand and supply functions as $D(\cdot)$ and $S(\cdot)$, respectively. The first two integrals in equation (2.1) represent the area underneath the downward sloping consumer demand functions for blended gasoline and diesel $D_{gf}(q_{gf})$ and $D_{df}(q_{df})$ and measure the total benefit to consumers. The next three terms represent the production costs by integrating the upward sloping marginal cost functions for corn ethanol, cellulosic ethanol, biodiesel as represented by $S_e(q_e)$, $S_c(q_c)$, $S_b(q_b)$. We assume the U.S. as the price taker of the world gasoline and diesel market with constant prices P_{g0} and P_{d0} . The blending cost incurred by the blenders in producing the blended fuels is represented by $w_{gf}q_{gf}$ and $w_{df}q_{df}$, where w_{gf} and w_{df} are per unit cost of the blended gasoline (q_{gf}) and blended diesel (q_{df}) respectively. Lastly, P_{cw} is the exogenously assigned price for the cellulosic waiver credit sold (q_{cw}) and t_B is the biodiesel tax credit per unit of biodiesel blended.

The policy constraints defined in equations (2.2) to (2.4) show the biofuel requirements of each fuel type by applying blend rates on the total petroleum fuel consumed (gasoline and diesel) as specified by the RFS, which we refer to this as a “joint-base mandate”. Equation (2.2.2) indicates that the biodiesel D4 RINs requirement should be at least equal to the mandated biodiesel blend rate θ_{D4} times the total petroleum fuel ($q_g + q_d$). Equation (2.2.3) specifies that the cellulosic biofuel produced (equivalent to D3 RINs) must be at least equal to the blend rate θ_{D3} times the total petroleum fuel. In equation (2.4), the conventional ethanol is required specifically to be at least mandated blend rate θ_{D6} times the total petroleum fuel consumed. It is a counterfactual stylized non-nested RFS mandate for the three types of biofuels without any design feature of waiver and no biodiesel tax credit. We denote these policy constraints as “non-nested” in scenario (I).

We analyze three other alternative policy scenarios with policy features added one at a time, as shown in Table 2.2. Scenario (II) adds a “nested” structure of RFS but with no cellulosic waiver and no biodiesel tax credit. We replace equation (2.4) with $q_{D3} + q_{D4} + q_{D6} \geq \theta_R (q_g + q_d)$ so that the total amounts of renewable fuel RINs (D3, D4, and D6) required are obtained by multiplying the overall mandated blend rate θ_R with the total petroleum fuel consumed. This equation represents the nested feature of the RFS, which allows biodiesel to substitute for ethanol, and it is their combined production that counts towards the overall mandate. Scenario (III) is “nested+ biodiesel tax credit” of RFS with nested structure plus the biodiesel tax credit but without the cellulosic waiver, and we set t_b at \$1 in equation (2.1) whereas policy settings remain the same. Scenario (IV) shows the “nested+ biodiesel tax credit +waiver” with the status-quo structure of the nested RFS having both the cellulosic waiver and biodiesel tax credit as implemented by EPA. We add the variable of cellulosic waiver $q_{cw} > 0$ in equation (2.3) so that blenders can use both D3 RIN (physically blended cellulosic ethanol) and cellulosic waiver credit to meet the blend mandate of cellulosic components: $q_{D3} + q_{cw} \geq \theta_{D3} (q_g + q_d)$.

We also theoretically analyze the policy implication of a non-nested mandate with a “separate-base” structure where the ethanol blends are defined using only gasoline as the base, and the biodiesel blend is defined using only diesel as the base. Specifically, we target the same volumetric target but define the biodiesel blend mandate in equation (2.2.2) as $q_{D4} \geq \theta_{D4} q_d$ by applying the biodiesel blend rate to diesel only as base fuel; and we define the cellulosic and

corn ethanol blend rates relative to gasoline as base fuel: $q_{D3} \geq \theta_{D3}q_g$ and $q_{D6} \geq \theta_{D6}q_g$ in equations (2.2.3) and (2.2.4)¹².

2.3.2 Lagrangian Model

We solve the Lagrangian model to determine the Karush-Kuhn-Tucker (KKT) optimality conditions for the key decision variables with interior solutions, as summarized in Table 2.3. The solutions in Table 2.3 are derived for the general form of RFS policy, regardless of the scenario. Different scenario settings change the magnitude of implicit subsidies and taxes. A detailed description of the Lagrangian representation and mathematical derivation can be found in Appendix A1.

Equations (i) to (iii) in Table 2 show that the wholesale price of each of the three biofuels is equal to its marginal cost of production net of the RIN value to biorefineries (as in Miao et al. 2012). Equation (i) shows that the wholesale price of corn ethanol is equal to its marginal cost ($S_e(q_e)$) minus the D6 RIN credit price (p_{D6}). Similarly, the wholesale price of cellulosic ethanol is equal to its marginal cost ($S_c(q_c)$) minus the D3 RIN credit price (p_{D3}) in equation (ii). Since we assume that conventional and cellulosic ethanol are perfectly substitutable based on their energy content, the wholesale prices of corn and cellulosic ethanol are identical (p_E^w)¹³. Equation (iii) shows that the wholesale price of biodiesel (p_d^w) is determined by the marginal cost of biodiesel $S_b(q_b)$ minus D4 RIN credit price (p_{D4}) and the biodiesel tax credit (t_B) if applied.

Equations (iv) and (v) show that gasoline and diesel wholesale prices are obtained by adding the implicit taxes imposed by the mandate to the marginal costs of gasoline P_{g0} and diesel

¹² We do not consider the nested with separate-base design of the RFS because it would not be logical to define a cross blend mandate (share of a renewable fuel mandate (ethanol+biodiesel) in gasoline only or in diesel only).

¹³ We use w to denote wholesale price, and r to denote retail price.

P_{d0} . The implicit taxes for gasoline and diesel are denoted by $\tau_g = \tau_d = \lambda_{D3}\theta_{D3} + \lambda_{D4}\theta_{D4} + \lambda_R\theta_R$, which is the sum of the shadow prices of the three blend mandates times their respective blend rates. Gasoline and diesel are subject to the same tax because both petroleum fuels are jointly used as the base for the biofuel mandate.

Equations (vi) and (vii) show that the retail prices of E10 (p_{E10}^r) and E85 (p_{E85}^r) in \$ per gallon are the volume-weighted sum of the ethanol and gasoline wholesale prices plus the blending cost. The retail prices of E10 and E85 obtained from the demand function are at energy equivalent parity at the optimal level of fuel consumption from equation (viii). But this condition holds only when E85 consumption is nonzero. Similarly, the retail price of blended diesel obtained from the demand curve for blended diesel is equal to the wholesale price of blended diesel plus the blending cost at the market equilibrium in equation (ix).

We also show the difference in the RIN prices across the scenarios in Table 2.4. The equilibrium RIN prices are derived from the first-order conditions of RIN volumes of the three different biofuels. They are functions of shadow prices of constraints (2)-(4) as shown in Table 2.4, varying by RFS scenarios. RIN prices under the non-nested structure are equal to the corresponding shadow prices of the biofuel-specific mandates. These RIN prices are independent and reflect the market value of each biofuel to meet the corresponding mandate. However, under the nested structure, the D3 RIN price (p_{D3}) is equal to the sum of shadow prices of the cellulosic (λ_{D3}) and the total renewable fuel mandates (λ_R); the D4 RIN price (p_{D4}) is the sum of shadow prices of the biodiesel (λ_{D4}) and the total renewable fuel mandates (λ_R); lastly, the D6 RIN price (p_{D6}) is equal to the shadow price of the total renewable fuel mandate (λ_R). The advanced RINs (D3 and D4 RINs) are, therefore, more valuable than D6 RINs because advanced fuels are eligible for compliance with both the advanced and conventional mandates. The nested

structure with or without the biodiesel tax credit or cellulosic waiver credit will lead to the same relative RIN price structure. However, the presence of biodiesel tax credit and cellulosic waiver credit provide more flexibility in compliance that undermine the stringency of the blend mandate and reduce the value of shadow prices. We discuss them in section 2.3.3.

2.3.3 Policy Determinants of RFS in Retail Blended Fuel Prices

As shown by equations (vi) to (ix) in Table 2, we obtain the retail prices of blended fuels from wholesale fuel prices. Since the wholesale prices of corn ethanol and cellulosic ethanol are assumed to be identical, we get the wholesale price of ethanol as a volume-weighted average of the marginal cost of production net of RIN prices of the two ethanol types in equation (2.5). The wholesale price of diesel is also a volume-weighted average of biodiesel wholesale price (equation (iii) of Table 2.3) and petroleum diesel wholesale price (equation (v) of Table 2.3).

$$p_E^w = (S_e(q_e) - p_{D6})q_e/(q_e + q_c) + (S_c(q_c) - p_{D3})q_c/(q_e + q_c) \quad (2.5)$$

$$p_d^w = (S_b(q_b) - p_{D4} - t_B)q_b/(q_b + q_d) + (P_{d0} + \tau_d)q_d/(q_b + q_d) \quad (2.6)$$

We then use these wholesale prices in the expressions for the retail prices of blended fuels in equations (vi) and (vii) of Table 2.3 and get the retail fuel prices with the implications of RIN prices. The retail fuel prices of E85, E10, and blended diesel are provided below in equation (2.2.7) – (2.2.9) (in \$ per gge). The first parentheses within the bracket in equations (2.2.7) – (2.2.9) represent the volumetric weighted average marginal production cost of producing the blended fuel. The second parentheses show the RFS incentives for E85, E10, and blended diesel of $0.74\kappa - 0.26\tau_g$, $0.1\kappa - 0.9\tau_g$, and $(p_{D4}q_b - q_d\tau_d)/(q_b + q_d)$, respectively, passed from wholesale prices to the retail fuel price. If this RFS incentive is positive, it is a net implicit subsidy; a negative term indicates a net implicit tax. The terms outside of the brackets w_{gf} and

w_{df} are blending costs per gge of blended fuel. The derivation of these expressions is shown in Appendix A1.2 and A1.3 in equations (A.8)-(A.12).

$$p_{E85}^r = [(0.74(S_e(q_e)q_e + S_c(q_c)q_c)/(q_e + q_c) + 0.26P_{g0}) - (0.74\kappa - 0.26\tau_g)] + w_{gf} \quad (2.7)$$

$$p_{E10}^r = [(0.1(S_e(q_e)q_e + S_c(q_c)q_c)/(q_e + q_c) + 0.9P_{g0}) - (0.1\kappa - 0.9\tau_g)] + w_{gf} \quad (2.8)$$

$$p_{df}^r = [(S_b(q_b)q_b + P_{d0}q_d)/(q_b + q_d) - (p_{D4}q_b - q_d\tau_d)/(q_b + q_d)] + w_{df} - t_B q_b/(q_b + q_d) \quad (2.9)$$

where κ is defined as weighted per gge ethanol incentive from D3 and D6 RINs: $\kappa = (P_{D6}q_e + P_{D3}q_c)/(q_e + q_c)$; τ_g and τ_d denote the implicit taxes on gasoline and diesel as $\tau_g = \tau_d = \lambda_{D3}\theta_{D3} + \lambda_{D4}\theta_{D4} + \lambda_R\theta_R$. The expressions κ , τ_g , and τ_d remain unchanged under the nested and non-nested design of the RFS with a joint-base for the blend mandate composed of gasoline and diesel. In the case of a blend mandate with a separate-base, such that ethanol blend rate is defined relative to a gasoline base only while biodiesel blend rate is defined relative to diesel only, the implicit tax on gasoline will be $\tau_g = \lambda_{D3}\theta_{D3} + \lambda_{D6}\theta_{D6}$ and implicit tax on diesel will be $\tau_d = \lambda_{D4}\theta_{D4}$. The implicit subsidy for ethanol, κ , is the same for both the joint- and separate-base cases. Equation (2.9) shows that the biodiesel tax credit if present, $t_B q_b/(q_b + q_d)$, is partially passed to the retail price of the blended diesel based on the blend rate.

In order to identify the effect of the design of the RFS on the retail prices of fuels and the choice of biofuel for compliance, we first analyze the effect of policy design on the relative magnitude of κ , τ_g , and τ_d and their relative incentive on blended fuels: $0.74\kappa - 0.26\tau_g$ for E85, $0.1\kappa - 0.9\tau_g$ for E10, and $(p_{D4}q_b - q_d\tau_d)/(q_b + q_d)$ for blended diesel. Based on the revenue-neutrality condition by the assumption of a perfectly competitive market, blenders earn a zero profit from selling three blended fuels. The blenders' spending on the implicit tax imposed on fossil fuel is offset by the RIN subsidy for blending biofuel, as presented in equation (2.10). The

detailed derivations are shown in Appendix A2 (equation (A.12)-(A.13)). The first term indicates the total RFS effect on E10 and E85 prices, and the second term is the net effect on blended biodiesel price.

$$[\kappa(q_e + q_c) - \tau_g q_g] + [P_{D4} q_b - \tau_d q_d] = 0 \quad (2.10)$$

2.3.3.1 Implicit Tax and Subsidies Imposed by RFS

We first show how the effects of the RFS on blended fuel prices depend on whether the overall ethanol blend mandate is above or below the blend wall and on the design of the RFS.

PROPOSITION 1. When ethanol blend rate is less than blending limit, and the biofuel mandate has a non-nested structure and separate base (for the ethanol blends and for the diesel blend), the retail price of E10 is the volume-weighted marginal cost of gasoline and ethanol, and the price of blended diesel is the volume-weighted marginal cost of diesel and biodiesel with zero net incentive from RFS. When the blend mandate has a joint base with both gasoline and diesel, E10 is subsidized and blended diesel is taxed under both non-nested and nested structures of RFS if the ethanol RIN prices and overall ethanol blend rate in gasoline fuel are higher than biodiesel RIN prices and biodiesel blend rate in petroleum diesel fuel.

When the mandated volume of ethanol is less than the blend wall limit where the ethanol blend rate of the gasoline fuel is less than 10%, $(q_e + q_c)/q_g < 1/9$, ethanol is first blended into E10 and there is no incentive to blend it into E85; thus, E10 and blended diesel are the only two retail fuels sold in the market. As proved in Appendix A2.1, the separate base and non-nested structure impose a tax on diesel ($\tau_d = \lambda_{D4} \theta_{D4}$) which is offset by the biodiesel subsidy of $P_{D4} q_b$ and lead to zero net RFS incentive for blended diesel because $(p_{D4} q_b - q_d \tau_d)/(q_b + q_d) = 0$. With this term being zero in the revenue-neutral condition in equation (2.10), the first term is

also zero with $\kappa(q_e + q_c) - \tau_g q_g = 0$, and that E10 also gets a zero net RFS incentive.

Therefore, the retail prices of E10 and blended diesel are equal to the volume-weighted average of the marginal production costs of their component fuels.

A joint base structure (in scenario I) leads to the implicit tax on gasoline equal to the implicit tax on diesel as, $\tau_g = \tau_d = \lambda_{D3}\theta_{D3} + \lambda_{D4}\theta_{D4} + \lambda_{D6}\theta_{D6}$. As shown in equation (A.14), $\tau q_g = \kappa(q_e + q_c) - q_g q_d / (q_g + q_d) \times [(q_e + q_c)\kappa / q_g - q_b p_{D4} / q_d]$, the total tax imposed on gasoline is equal to the total ethanol RIN incentives net of the multiplied term of $q_g q_d / (q_g + q_d)$ with $\kappa(q_e + q_c) / q_g - p_{D4} q_b / q_d$. We then discuss the conditions when the derivation above defines the policy effect of RFS on retail fuel prices.

A mandate with a joint-base structure will tax a blended fuel with a relatively lower marginal production cost of biofuel, lower biofuel quantity requirement, and lower biofuel blend rate. As proved in Appendix A2.2, when the implicit subsidy for ethanol is greater than the subsidy for biodiesel $\kappa > p_{D4}$ (or $(P_{D6}q_e + P_{D3}q_c) / (q_e + q_c) > p_{D4}$), and ethanol blend in gasoline is higher than biodiesel blend in diesel $((q_e + q_c) / q_g > q_b / q_d)$, the RFS will subsidize E10 ($\kappa(q_e + q_c) - \tau q_g > 0$) and tax blended diesel $((p_{D4}q_b - q_d\tau_d) / (q_b + q_d) < 0)$. It can be easily seen that a sufficient condition for $\kappa \geq p_{D4}$ is $P_{D6} \geq P_{D4}$ and $P_{D3} \geq P_{D4}$. Without any loss of generality, the RIN prices are higher when the marginal production costs are higher, or the quantity mandate is more stringent, vice versa. Additionally, if the blend rate of biofuel is relatively low, the effect of the RIN subsidy on the volume-weighted price of the biofuel blend could be offset by the implicit tax passed through to petroleum fuel. In other cases where the above two conditions don't hold, which are an implicit subsidy for ethanol is less than the subsidy ($\kappa < p_{D4}$) or ethanol blend rate in gasoline is lower than biodiesel blend in diesel

(or $(q_e + q_c)/q_g < q_b/q_d$), the impact of the RFS on the relative prices of E10, E85, and blended biodiesel will be ambiguous.

PROPOSITION 2: For blends rates larger than the 10% blend wall, a mandate defined with a separate base for the ethanol and biodiesel blends and a non-nested structure will tax E10 and subsidize E85 such that their energy equivalent prices are at parity. However, with a mandate defined with a joint base with either a non-nested or nested structure, E85 and E10 will be subsidized while blended diesel will be taxed only if RIN price and blend rate are higher for ethanol than those for biodiesel.

When overall ethanol blend in gasoline is higher than the 10% blend wall, E85 consumption is required to comply with the mandate. With a separate base and given the revenue neutrality condition in equation (2.10), there will be price parity between E10 and E85 such that the tax on gasoline offsets the subsidy on ethanol $\kappa(q_e + q_c) - \tau_g q_g = 0$. With an overall blend rate greater than 10% of $\theta_{D3} + \theta_{D6} = (q_e + q_c)/q_g \geq 1/9$ and $\tau_g/\kappa \geq 1/9$, there will be a net tax on E10 as $0.1\kappa - 0.9\tau_g < 0$ and a net subsidy on E85 as $0.74\kappa - 0.26\tau_g > 0$. The price parity reduces the price gap between the energy equivalent price of E10 and E85 to zero. In this case, the diesel tax of $\tau_d = \lambda_{D4}\theta_{D4}$ will be offset by the biodiesel subsidy of $P_{D4}q_b$ with $p_{D4}q_b - q_d\tau_d = 0$, which will lead to the blended diesel price being the weighted sum of the marginal cost of diesel and biodiesel.

Similar to Proposition 1, we find that a joint base blend mandate in scenario (I) will tax blended diesel with a negative term $P_{D4}q_b - \tau_d q_d < 0$ and subsidize both E85 and E10 as $0.74\kappa - 0.26\tau_g > 0.1\kappa - 0.9\tau_g > 0$. They hold under the condition that the weighted RIN price of ethanol is greater than biodiesel $\kappa > p_{D4}$ and the ethanol blend rate in gasoline is higher than the biodiesel blend rate in diesel $(q_e + q_c)/q_g > q_b/q_d$. The sufficient conditions for

weighted RIN price of ethanol being higher than for biodiesel ($\kappa > p_{D4}$) are the same as discussed above for the joint base case in Proposition 1 to satisfy both $P_{D6} \geq P_{D4}$ and $P_{D3} \geq P_{D4}$. Under other conditions, the effect of the implicit tax or subsidy on the different biofuel blends is ambiguous. The proof is provided in appendix A2.4. Table 2.5 summarizes the finding of propositions 1 and 2. This provides the analytical rationale for the blended diesel being taxed by the joint-base nested RFS structure in the presence of the blend wall and the finding of a welfare loss for the blended diesel consumers by Korting et al. (2018). It also shows that with the joint base blend rate mandate, both E10 and E85 are subsidized and gasoline fuel users benefit from the policy.

2.3.3.2 Economic Rationale for Biodiesel Over-production

As discussed before, the marginal costs of producing different types of biofuels determine not only the RIN incentives that affect their retail prices and fuel sales, but also the blenders' fuel choices to comply with RFS. We now discuss the economic rationale for blenders choosing biodiesel to over-comply with the RFS mandate.

PROPOSITION 3: A mandate with a nested structure and a joint-base without a waiver will induce blenders to comply with over-production of biodiesel instead of ethanol when the elasticity-weighted marginal cost of using biodiesel is lower than that of conventional biofuel.

In policy scenario II with nested structure, we show in Appendix 2.5 in equations (A.15) to (A.18) that over-production of biodiesel occurs when the lower elasticity-weighted marginal production cost of biodiesel reduces the total blending cost and $(1/\eta_b + 1) S_b(q_b) < (1/\eta_e + 1) S_e(q_e)$, where η_b and η_e are the price-elasticities of the supply for biodiesel and conventional corn ethanol and $S_b(\cdot)$ and $S_e(\cdot)$ are the marginal costs of producing biodiesel and corn ethanol, respectively.

Beyond the finding of Korting and Just (2017) that biodiesel over-production is one of the channels to comply with the RFS, we find that only if the supply function of biodiesel is flatter than that of ethanol at equilibrium marginal cost, the nested structure RFS would induce blenders to use biodiesel for over-compliance. The economic rationale for over-producing biodiesel hinges on the relative elasticities of biodiesel and ethanol fuels and their marginal cost at the market equilibrium and the design of the RFS. The over-production of biodiesel will continue until the marginal cost ratio drops such that $S_e(q_e)/S_b(q_b) = (1/\eta_b + 1)/(1/\eta_e + 1)$.

PROPOSITION 4: The provision of a cellulosic biofuel waiver with the nested RFS and a joint base will lead blenders to further substitute biodiesel for cellulosic ethanol to meet the total renewable fuel mandate only when $(1/\eta_b + 1)S_b(\cdot) < (1/\eta_e + 1)S_e(\cdot) < (1/\eta_c + 1)S_c(\cdot)$.

The cellulosic biofuel waiver provides another incentive for over-producing biodiesel when the RFS has a nested structure with a joint base, and the elasticity-weighted marginal cost of biodiesel is the lowest among the three biofuel types. Biodiesel will be used to replace cellulosic ethanol first and then to substitute for corn ethanol if the marginal cost savings by using biodiesel to use the cellulosic waiver credit is greater than the difference in the marginal cost when biodiesel is used to substitute for corn ethanol, as $(1/\eta_c + 1)S_c(\cdot) - (1/\eta_b + 1)S_b(\cdot) > (1/\eta_e + 1)S_e(\cdot) - (1/\eta_b + 1)S_b(\cdot)$.

The extent to which biodiesel is used to substitute for corn or cellulosic ethanol depends on the relative elasticity-weighted marginal production cost of biodiesel, corn ethanol, and cellulosic ethanol at the equilibrium production level. The over-produced biodiesel will be used to displace cellulosic ethanol as long as the weighted marginal cost of producing biodiesel is marginally lower than the weighted marginal cost of producing cellulosic ethanol $((1/\eta_b + 1)S_b(\cdot) \leq (1/\eta_c + 1)S_c(\cdot))$. Biodiesel will be over-produced to meet the total renewable fuel

mandate as long as the marginal cost of biodiesel is higher than that of conventional corn ethanol, that is, $(1/\eta_b + 1) S_b(\cdot) \leq (1/\eta_e + 1) S_e(\cdot)$.

PROPOSITION 5: The provision of the biodiesel tax credit exacerbates incentives for over-production of biodiesel to comply with the RFS under the nested structure.

In scenario III, as shown in equations (A.18) and (A.19) in Appendix, the provision of the biodiesel tax credit reduces its marginal blending cost for blenders and enhances the condition for over-production of biodiesel derived in Propositions 3 and 4. This tax credit passes through to the retail biodiesel price and lowers this price by $t_B q_b / (q_b + q_d)$ per gge, as shown by the last term in equation (2.9). It, therefore, also incentivizes consumer demand for blended diesel and allows blenders to bypass the ethanol blend wall constraint. The extent of biodiesel over-production depends on the level of marginal cost at market equilibrium and tax credit. Meanwhile, as biodiesel tax credit reduces the compliance cost of using biodiesel to comply with the RFS policy, the value of D4 RINs will diminish, as demonstrated by Irwin et al. (2020). We quantify the effect of the biodiesel tax credit on RIN prices and the overall blend rate through the numerical analysis below.

2.3.3.3 Structural Effect of RFS On Price Spread between E85 and E10

With the implicit subsidies and taxes, we represent the retail price difference between E85 and E10 by rearranging equations (2.2.7) and (2.2.8) into terms representing the marginal costs of gasoline and ethanol and their RIN incentives in equation (2.11). The first bracket in equation (2.11) represents the difference in the marginal cost in producing E85 and E10; the second bracket shows the difference in the RIN incentive between E85 and E10 passed through from wholesale fuels. Theoretically, if the net RFS incentive of $\kappa + \tau_g$ completely offsets the marginal cost gap $(S_e(\cdot)q_e + S_c(\cdot)q_c)/(q_e + q_c) - S_g(\cdot)$, the E85 and E10 are priced at parity then the

price gap in equation (11) is zero. Otherwise, the positive price difference between E85 compared to E10 on the energy equivalent base discourages the flex-fuel vehicle users from buying E85. Furthermore, neither the level of biodiesel production nor the D4 RIN price directly affects the price gap.

$$p_{E85}^r - p_{E10}^r = 0.64[(S_e(q_e)q_e + S_c(q_c)q_c)/(q_e + q_c) - S_g(q_g)] - 0.64[\kappa + \tau_g] \quad (2.11)$$

PROPOSITION 6: When the elasticity-weighted marginal cost of blending biodiesel is lower than that of conventional biofuel $(1/\eta_b + 1) S_b(q_b) < (1/\eta_e + 1) S_e(q_e)$ as proved in PROPOSITION 4, the nested structure of the RFS will result in price disparity between E85 and E10 and zero E85 consumption so that it creates a blend wall.

The proof is shown in the equation (A.20) in Appendix A2.6. The over-production of biodiesel as a substitute for ethanol reduces the need to produce E85. Additionally, it reduces the demand for ethanol fuels, and thus their corresponding RIN prices drop so that the ethanol RIN price is not enough to close the retail price gap in equation (2.11). As a result, a blend wall is generated with zero E85 consumption.

With the provision of the cellulosic waiver together with the nested structure of the RFS, there is likely to be a greater level of biodiesel over-production $q_{D4} - \theta_{D4}(q_g + q_d) > 0$ than in the case without waiver because the waiver enables additional substitution of biodiesel for cellulosic ethanol and reduces incentives for consuming E85 if the marginal condition is satisfied as in proposition 4. Theoretically, the cellulosic waiver purchase depends on the waiver price and compliance benefit of using waiver as derived in Table 2.4. If EPA sets the cellulosic waiver credit price P_{cw} lower than the compliance cost of the cellulosic biofuel mandate (λ_{D3}), the obligated party will purchase the cheaper waiver instead of D3 RIN.

2.4 Numerical Model

The numerical model used for this analysis follows the exact same analytical framework of partial equilibrium modeling of the U.S. fuel sector that simulates decisions by fuel wholesalers, blenders, and fuel consumers described in equations (2.1) to (2.4) and policy scenarios. We investigate the impact of the structural design of RFS and accompanying waiver and tax credit policies on the values of RIN prices (D3, D4, D6) and their compliance in 2017, as well as the implication on GHG emissions and social welfare. We consider a closed economy with linear downward sloping functions for fuel demands, upward-sloping short-run linear supply functions for corn ethanol, cellulosic ethanol, and biodiesel. For simplicity, we assume all the biofuels are domestically produced, although there were international trades of ethanol and biodiesel in 2017 (EIA 2019b) ¹⁴. We select values for the price elasticities of fuel demand and supply from the range reported in the literature in Table A.2. We then use the observed volumes and prices of fuels to obtain slopes and intercepts to calibrate these functions in equation (2.1) numerically. We run the model of the nested with waiver and biodiesel tax credit scenario and examine how closely the equilibrium solution matched the observed reality in 2017. We show that the wholesale and retail fuel prices deviate by less than 5% from observed data. The quantities of simulated fuel production deviate by less than 9% from observed levels. The simulated outcomes of the model are within a similar level of tolerance as in previous studies applying a partial equilibrium model with the transportation sector (Chen et al. 2021; Chen et al. 2014). Even

¹⁴ The international trade of ethanol and biodiesel is not expected to affect domestic biofuel production as traded share is small relative to the domestic production (<https://www.epa.gov/fuels-registration-reporting-and-compliance-help/annual-compliance-data-obligated-parties-and->). Neither will they affect the RIN market as they are not eligible for compliance. Although the US is the leading exporter of ethanol according to USDA (<https://www.fas.usda.gov/ethanol-2019-export-highlights>), the world price is higher than the US market and is not affected by the US price. Since the ethanol exported is not eligible for RINs, the export market is an outlet for excess production of ethanol and not a substitute for domestic sales of ethanol. The US is also a price-taker in the world markets for petroleum products, gasoline and diesel in recent years (see Chen et al, 2021); thus the policies analyzed here are not likely to affect the terms of trade and domestic fuel prices in the US.

though the simulated D4 RIN price is 13% lower than the observed \$1.17 per gge and the D6 RIN price is 18% higher than the observed \$ 0.86 per gge in 2017, the absolute deviation is only \$0.16 and \$ 0.15 per gge.

We calibrate the percentage blend rates recursively according to the endogenously solved gasoline and diesel to approach the volumetric targets for each type of biofuel. As the simulated levels of all fuel quantities in this scenario are closest to actual volumes of fossil fuels and biofuels produced in 2017 (as shown in Table 2.6), blend rates in the nested with waiver and biodiesel tax credit scenario are calibrated to be similar to the announced blend rates by the EPA. We also recursively calibrate the counterfactual blend rate mandates for four other counterfactual RFS scenarios without biodiesel tax credit only, without the cellulosic waiver credit only, without both credits, and non-nested scenarios, based on the endogenous model outcome for gasoline and diesel levels so that the biofuel production levels matched the observed level in 2017.

The lifecycle emission factors per gge of the various fuels are obtained by multiplying EPA emission factors (US EPA 2016) and Oak Ridge National Laboratory (2019) energy density estimates (as shown in Table A.4). We use these emission factors to calculate the total life cycle emissions associated with the outcome volumes of different types of fossil fuels and biofuels for each policy scenario in 2017. Lastly, we compute the social welfare in each scenario as the sum of consumer and producer surplus in the wholesale and retail fuel markets, we find the change in

government revenue and the change in GHG emissions valued at the social cost of carbon of \$50 per metric ton of CO₂¹⁵.

2.4.1 Simulation Results

The model simulates five RFS policy scenarios with a joint base¹⁶. These include (I) Non-nested structure of RFS; (II) Nested structure without waiver and no biodiesel tax credit; (III) Nested structure with cellulosic waiver credit added (Nested+waiver); (IV) Nested structure with biodiesel tax credit but without cellulosic waiver (Nested+ biodiesel tax credit); as well as (V) Nested structure jointly with cellulosic waiver scenario and biodiesel tax credit (Nested + waiver + biodiesel tax credit). We first validate the model by comparing the simulated outcome in scenario (V) nested with waiver and biodiesel tax credit scenario. Scenario (V) mimics the current policy landscape, and we compare our model outcomes with the observed prices and quantities in relevant markets in 2017 (Table 2.6).

2.4.1.1 Impact of RFS Design on RIN Volumes

Figure 2.3 compares the biofuel-RIN volumetric compliance of the five scenarios in 2017. The total required volume of biofuels in 2017 was 12.2 billion gge, including 10 billion gge of conventional ethanol, 2 billion gge of biodiesel, and 207 million gge of cellulosic ethanol (as shown by the stacked dashed lines in Figure 2.3). The non-nested structure without biodiesel tax

¹⁵ There is a wide disparity in the range of estimates of the social cost of carbon, but we follow the extensive review that \$50 per Mg CO₂ is a reasonable estimate (Tol, 2005; Watkiss and Downing, 2008). Moreover, a recent re-assessment of the social cost of carbon under the Biden administration reestablished the estimates of the social cost of carbon at \$51 per ton (IWG, 2021), which is similar to the estimates obtained under the Obama Administration.

¹⁶ We do not simulate a non-nested with separate-base scenario because biodiesel is not overproduced with the same result as the non-nested with joint-base scenario and does not provide insight on how the design features of RFS leads to divergence in compliance.

credit (scenario (I) in the first stacked column of Figure 2.3) is found to produce the exact volume of each type of biofuel required by the law as the optimal solution.

In the nested only scenario (II), we find that 0.42 billion gge of biodiesel is over-produced, and it replaces a corresponding 0.42 billion gge of conventional ethanol, as shown in Figure 2.3. The nested + waiver structure in scenario (III) leads to the same amount of biodiesel over-production, but 0.11 billion of this is used for compliance with the cellulosic waiver first and the rest, 0.31 billion gge, to fill the gap in corn ethanol. When the biodiesel tax credit is added to the nested structure in scenario (in scenario IV), the excess biodiesel produced increases to 0.85 billion gge and reduces corn ethanol production by 8.5% relative to the mandated level. In the final scenario (V), with the joint addition of both cellulosic waiver and biodiesel tax credit (nested + waiver + biodiesel tax credit), 0.72 billion gge of biodiesel are used to displace the corn ethanol and another 0.13 billion gge of biodiesel are blended to accompany the cellulosic waiver credits purchased to meet the total renewable fuel mandate. The total 0.85 billion gge of over-production of biodiesel reduces the production of corn ethanol by 8% and cellulosic ethanol by 60% relative to the non-nested scenario (scenario I). The expansion of biodiesel production in response to the policy design is found to be the efficient pathway to fill the gap in total renewable fuel mandate (Korting and Just 2017; Moschini et al. 2017). But we show that over-production of biodiesel can be induced by the nested features of RFS and the biodiesel tax credit, whereas the cellulosic waiver prioritizes the use of the biodiesel to fill the advanced fuel gap.

2.4.1.2 Impact of RFS Design on RIN Prices

Figure 2.4 compares the estimated prices of D3, D4, and D6 RINs obtained under the five different scenarios in 2017. The non-nested scenario without biodiesel tax credit leads to the highest price of D3 RINs at \$4.78 per gge among the five scenarios. It reflects the compliance

cost of producing cellulosic ethanol without flexibility. The D6 RIN (conventional ethanol) price is at \$1.79 per gge and is higher than the D4 RIN (biodiesel) price of \$1.40 per gge. This result is consistent with our theoretical findings in section 2.3.3 that biodiesel RIN price has the lowest value compared to the other RIN prices because of the relative costs of producing biodiesel determined by the mandate level (2 billion gge of biodiesel versus 10 billion gge of corn ethanol).

The RIN values of nested only structure inducing the over-production of biodiesel are shown in the second column in Figure 2.4. D3 RIN price remains constant, but D6 RIN price drops to \$1.66 per gge and converges with the D4 RIN price rising to \$1.66 per gge. As long as biodiesel overproduces beyond the mandated level, the zero shadow price of the biodiesel constraint ($\lambda_{D4} = 0$ in equation (2.2.2)) under KKT theory will result in converging D4 and D6 prices.

The addition of the cellulosic waiver to the nested structure in scenario III (third column in Figure 2.4) reduces the cellulosic D3 RIN value from \$4.76 to \$4.67 per gge when waivers are used to comply with the cellulosic mandate. The D6 and D4 RINs are relatively stable. However, when adding biodiesel tax credit to the nested without waiver in “nested + biodiesel tax credit” scenario IV (fourth column in Figure 2.4), all the RIN values reduce: cellulosic D3 RIN reduces to \$4.26 per gge, the converging D6 RIN and D4 RIN prices drop to \$1.01 per gge. The addition of the \$1 per gge biodiesel tax credit reduces the D4 RIN value by \$0.66 per gge, which is within the range of the D4 RIN drop (\$0.615 - \$0.696 per gge) caused by biodiesel tax credit found in the literature (Irwin et al. 2020). Under scenario V “nested + waiver +biodiesel tax credit”, when both biodiesel tax credit and cellulosic waiver are in place, the D4 and D6 RIN prices remain at \$1.01 per gge (fifth column in Figure 2.4), but the D3 RIN price declines further to \$4.01 per

gge. Though the D6 RIN prices capped by D4 RIN price is not new (Irwin et al. 2020; Kortting et al. 2019), we show the unintended lower ethanol RINs values is caused by the appended policy feature and the continuing biodiesel displacement.

2.4.1.3 Impact of RFS Design on the Blend Wall

Next, we study the impact of the policy on the retail price gap between E10 and E85 and the corresponding overall ethanol blend rate in gasoline. We divide the price gap defined in equation (2.11) by the E10 price to show the percentage disparity in the price of E85 relative to the price of E10. The blue bars in Figure 2.5 show that the blend rates go beyond 10% under non-nested (10.8%), nested only (10.4%), and nested with the waiver (10.4%) scenarios. The over-produced biodiesel under nested structure (scenario II) reduces the overall ethanol blend in gasoline, but the extent of excess production is limited to 0.42 billion gge due to marginal costs conditions (as discussed in proposition 3 and 4), which still requires E85 blend sold at price parity to meet the mandate. The addition of the biodiesel tax credit in scenario (III), however, undermines the value of the RIN prices, generates a blend wall at 10%, and raises the E85 price 14% greater than that of E10 on an energy equivalent basis. The cellulosic waiver credit together with the nested and biodiesel tax credit in “Nested+waiver+ biodiesel tax credit” scenario (V) further widens the price spread and raises the E85 price to 15% more than the price of E10.

2.4.1.4 Impact of RFS Design on GHG reduction

The GHG emissions and fuel consumption under each policy scenario are displayed in Table 2.7. The non-nested scenario (I) leads to GHG emissions of 2,281 million metric tons (MMT) in 2017, 62% and 33% of which are from gasoline and diesel consumption, respectively. The remaining 5% of emissions are generated by the production of biofuels. We compare these

GHG emissions with those under the four alternative policy designs to examine the GHG implication of each policy feature.

The nested structure of the RFS in scenario (II) reduces GHG emissions by a net amount of 1.6 MMT compared to the non-nested scenario (0.07% reduction) by allowing a greater blend of biodiesel that is less carbon-intensive to replace corn ethanol. This results in 4.1 MMT less emissions from corn ethanol and reduces emissions from petroleum diesel by 5.4 MMT relative to the non-nested scenario. However, emissions from over-produced biodiesel and gasoline consumption increase by 3.0 MMT and 4.8 MMT, respectively.

The cellulosic waiver credit in scenario (III) replaces the production of cellulosic ethanol with biodiesel. The reduction in cellulosic ethanol that has the lowest carbon intensity increases GHG emission by 0.3 MMT. Corn ethanol production increases and thus increase emissions by 3.4 MMT. With all other emissions unchanged compared to the nested only scenario (II), the cellulosic waiver reduces the total GHG savings to 0.6 MMT (0.02% reduction) compared to the non-nested scenario.

The biodiesel tax credit added to the nested structure in scenario (IV) increases the over-production of biodiesel that reduces demand for corn ethanol and petroleum diesel, resulting in 8.2 MMT and 10.8 MMT less emissions, respectively, compared to the non-nested scenario. However, the over-produced biodiesel and gasoline emissions increase by 6.0 MMT and 9.6 MMT, respectively; hence net emission reduction relative to the non-nested scenario is by 3.3 MMT (0.15% reduction in total emissions).

The net effect of nested feature, cellulosic waiver credit, and biodiesel tax credit in scenario (V) is a marginal reduction in GHG emissions by 1.6 MMT (0.07%) compared to the

non-nested structure. The GHG mitigation benefit of biodiesel consumption is offset by the lower cellulosic biofuel production and lower corn ethanol.

2.4.1.5 Impact of RFS Design on Social Welfare

The estimates of welfare change due to the RFS and accompanying policies compared to a no-policy scenario are displayed in Table 2.8. We define the no-policy scenario as the free market scenario without policy constraints; in the absence of any policy, market equilibrium occurs at 7.7 billion gge of corn ethanol. Compared to the no-policy scenario, the non-nested RFS policy (scenario (I)) enhances biodiesel producer surplus by \$1,139 million, cellulosic ethanol producer surplus by \$34 million, and corn ethanol producer surplus by \$6,377 million. In contrast, the consumer surplus of gasoline-blended fuel and diesel-blended fuel reduces by \$7,283 million and \$10,295 million, respectively. The value of GHG emissions saving increases by \$891 million. Overall social welfare is lower by \$9,136 million compared to the no-policy scenario.

The welfare changes due to the nested feature compared to the no-policy scenario (scenario (II)) are listed in the second column of Table 2.8. The nested structure increases biodiesel producer surplus by \$1,680 million but reduces the gain of the corn ethanol producers to \$5,075 million. The consumers of both diesel-blended fuel and gasoline-blended fuel lose surplus by \$6,669 million and \$10,017 million, respectively, because retail fuel prices are lower than those with the non-nested RFS. Including the increased value of GHG savings by \$976 million, the welfare loss reduces to \$8,922 million. This differs from previous studies, which only show the welfare change of the nested RFS relative to no RFS policy structure without showing the implication of nested structure (Korting et al. 2019; Moschini et al. 2017). In contrast, we find that the nested structure increases total welfare by \$215 million compared to the non-nested

scenario (I) because the inclusion of biodiesel in the total renewable fuel standard benefits the diesel markets more than the loss in the gasoline fuel market.

The addition of the cellulosic waiver credit (scenario (III)) increases the biodiesel producer surplus by \$1,728 million and the surplus of corn ethanol producers by \$5,299 million. The waiver reduces the gain in the cellulosic ethanol producer surplus to \$14 million and undermines the surplus for consumers of gasoline-blended fuels and diesel-blended fuels. The government gains \$222 million in revenue from the cellulosic waiver sales, but GHG savings reduce to \$927 million. The total social welfare loss reduces to \$8,716 million (a \$206 million increase and 4.6% increase in welfare compared to the non-nested scenario I).

The addition of the biodiesel tax credit of \$1 per gge in scenario IV significantly increases the biodiesel producer surplus by \$2,506 million but reduces the gain in the corn ethanol producer surplus to \$3,817 million. Consumers of gasoline and diesel blended fuel gain from the provision of the biodiesel tax credit with reduced losses at \$6,045 million and \$7,413 million, respectively. The biodiesel tax credit imposes a cost of \$2,850 million on taxpayers. The overall welfare in the fuel sector falls by \$55 million due to the biodiesel tax credit compared to scenario (II) with only nested structure: diesel/biodiesel markets gain \$580 million, and gasoline/ethanol markets lose \$635 million). This welfare loss is offset by GHG savings of \$1,061 million that results in an overall social welfare loss of \$8,891 million (\$245 million and 2.6% increase compared to the non-nested scenario).

A similar welfare gain in consumer surplus of diesel-blended fuel due to biodiesel tax credit is observed in Korting et al. (2018) by comparing the same scenario settings in (II) and (IV). Their finding of a \$3.8 billion increase in consumer surplus of diesel-blended fuel is greater than the \$2.6 billion increase in our study due to their assumption of a more inelastic diesel demand

curve than is assumed in our study. That also explains the zero change in GHG savings and only 0.1 billion gge increase in biodiesel over-production with \$1 per unit of the biodiesel tax credit in their paper.

The joint implementation of both cellulosic waiver credit and biodiesel tax credit leads to a drop in the surplus of cellulosic ethanol producers by \$5 million. It is lower than that with cellulosic waiver alone in scenario (III) because biodiesel tax credit exacerbates the extent of the displacement of ethanol by biodiesel. However, government revenue increases due to waiver sales by \$382 million. The change in surplus of corn ethanol producers and gasoline-blended fuel consumers are between levels found in scenarios (III) and scenario (IV) with either the cellulosic waiver or biodiesel tax credit feature alone. The biodiesel producer surplus remains at \$2,506 million, but the joint implementation of the biodiesel and cellulosic waiver tax credit reduces the loss of consumer surplus in the diesel-blended fuel market by \$7,397 million. The value of GHG savings is \$978 million and close to that in the nested only scenario (II), which shows the offsetting effects of the biodiesel tax credit and cellulosic waiver credit. The overall total social welfare is highest compared to the other scenarios, and the welfare loss is reduced to \$8,572 million (\$564 million and 6% increase compared to the non-nested scenario).

2.4.2 Sensitivity Analysis

We conduct a sensitivity analysis to examine the robustness of our findings about the extent of the price disparity between E10 and E85 to assumptions of the supply elasticities of corn ethanol and biodiesel; and to the values of cellulosic waiver credit and biodiesel tax credit. Since there are significant variations in the corn ethanol and biodiesel supply elasticities reported in the literature (as shown in Table A.2), we carry out a Monte-Carlo simulation by randomly drawing values from an assumed uniform distribution within the range of 0.2-5.5 and 1.5-2.5,

respectively (Table A.2). We draw two values 1000 times simultaneously from the two distributions and simulate the price disparity, as displayed in Figure 2.6. We find that the percentage disparities between E85 and E10 are positive across the range of biofuel elasticities and follow a skewed distribution ranging from 13% to 21% higher price of E85 than E10 with a mean of 19% and a standard deviation of 1.3%. The result is comparable to the observed higher E85 price than E10 with an average of 21%, ranging from 6% to 36% since 2000 (Figure 2.1).

We next analyze the effect of three levels of the biodiesel tax credit with the setting of “nested+waiver+biodiesel tax credit” in scenario (V) on the extent of overproduction of biodiesel and corresponding price disparity between E85 and E10: \$1 per gge (current level of the tax credit), half of the current tax credit at \$0.5 per gge credit, and no credit. The results in Figure 2.7 show that lowering the tax credit from \$1 to \$0.5 per gge does not have much impact on the extent of D4 RIN over-production. Both cases result in 0.85 billion gge of D4 RIN over-production, 15% of which replaces cellulosic biofuel, and the rest is used to count toward conventional ethanol compliance. However, the absence of the biodiesel tax credit causes biodiesel D4 RIN over-production to drop to 0.42 billion gge, with 0.35 billion gge and 0.074 billion gge used to displace corn ethanol and cellulosic ethanol, respectively. We also find that the price difference between E85 and E10 significantly reduced from 14% higher with \$1 per gge of biodiesel tax credit to only 1% higher with only \$0.5 per gge of the biodiesel tax credit. Without the tax credit, the E85 and E10 are priced equivalently without the price gap. The elimination of the biodiesel tax credit limits the amount of over-production of biodiesel and increases the incentive for E85 that is priced at energy equivalent parity with E10,

Lastly, we compare the effect of cellulosic waiver credit price on the amount of cellulosic waiver purchased and price disparity between E85 and E10 price with the setting of

“nested+waiver +biodiesel tax credit” in scenario (V). The effects of four levels of the cellulosic waiver credit are analyzed: 1) \$2.3 per gge (following the EPA’s method of calculation¹⁷ using 2017 gasoline wholesale price), 2) the benchmark price of \$3.0 per gge as announced by the EPA in 2017, 3) \$3.2 per gge as an intermediate level and 4) \$ 4.0 per gge from compliance cost of P_{D3} by blending cellulosic ethanol from the model outcome of scenario V “nested+waiver+biodiesel tax credit”. Our analysis shows that when the cellulosic waiver price is at \$2.3 per gge, 207 million gge cellulosic waiver credits are purchased to meet the cellulosic ethanol mandate without any cellulosic D3 RIN compliance. As the cellulosic waiver price gradually increases from \$2.3 to \$4.0, the waiver purchase gradually declines to zero, as shown in Figure 2.8. The reduction in cellulosic waiver credits requires less biodiesel to be counted toward the overall mandate, which in turn leads to reduced price disparity between E85 and E10 from 16.1% to 14.1%. Nonetheless, the overall role of the cellulosic waiver in affecting the price gap is limited. Even in the absence of cellulosic waiver credit and scenario reduces to biodiesel tax credit only scenario (IV) (nested+biodiesel tax credit), we find that there is still a 14.1% price gap between E85 and E10.

2.5 Conclusions

The RFS was intended to be a technology-forcing policy and in the long run to induce a transition from corn ethanol to cellulosic ethanol and other advanced fuel by creating incentives for selling higher blends of ethanol. This paper shows the disincentives created by the design of the RFS and accompanying policies, specifically the nested structure, joint-base blend rate, biodiesel tax credit, and cellulosic waiver credit in creating a blend wall and analyzes its welfare

¹⁷ As discussed in Background section, the EPA sets the price of the waiver according to a formula by taking the greater of \$0.25 or the difference between \$3.00 and the average wholesale gasoline price in the previous year.

and GHG implications. Our theoretical findings show the economic mechanism through which the RFS design favors biodiesel production and operates against increased production of cellulosic ethanol, thereby contributing to the creation of a blend wall for ethanol at 10%. The blend rate mandate with the joint base of gasoline and diesel leads to an implicit tax on diesel consumers and an implicit subsidy on gasoline-ethanol consumers that results in price disparity between E10 and E85 in the presence of a blend wall. The nested feature results in biodiesel over-production only when its elasticity-weighted marginal production cost is relatively low, which hinders the sales of E85 and leads to the under-production of corn and cellulosic ethanol production. These disincentives are further exacerbated by the provision of a biodiesel tax credit and cellulosic waiver credit, which increases the competitiveness of biodiesel that does not have the same blend limits as ethanol.

Our calibrated numerical simulation model quantifies and decomposes the effects of the design of the RFS and accompanying policies on biodiesel over-production and RIN prices. Compared to the non-nested RFS structure, the nested structure leads to 21% more biodiesel production, the biodiesel tax credit leads to an additional 21% of biodiesel overproduction, and the cellulosic waiver credit does not further increase the level of biodiesel. The conventional D6 RIN price and cellulosic D3 RIN price decrease while the D4 RIN price increase due to the nested structure and biodiesel tax credit. The biodiesel tax credit, together with the nested structure, creates a 14% price gap between E85 and E10 and generates the blend wall at 10% blend of ethanol. The price gap widens to 15% with the cellulosic waiver credit. Lastly, flexibility in compliance enhances both the GHG reduction and welfare benefit as expected in the short run but only marginally. The interaction between the biodiesel tax credit and cellulosic waiver offsets the impact on GHG emission compared to the nested-only structure.

The design of the RFS results in an unintended market failure by preventing energy-equivalence pricing of E85. It limits the demand for E85 by flexible-fuel vehicles and deters the long-term goal of displacing demand for gasoline fuel. Since gasoline constitutes more than half of the total energy consumed in the US transportation sector, it is imperative to get past the blend wall and enable demand for higher blends of ethanol. Though we show positive welfare and GHG implications with the nested structure of the RFS in the short run, the policy has detrimental impacts on ethanol fuel producers, especially cellulosic ethanol producers, and will delay efforts to reduce dependence on gasoline in the long run. Our findings suggest the need to shift towards a non-nested structure with a separate fossil fuel base in order to enable incentives to eliminate the blend wall and to create demand for cellulosic ethanol, which has significantly greater potential to reduce the GHG intensity of fuel than biodiesel.

Our analysis was conducted with several restrictive assumptions to maintain tractability. First, we developed a static, partial equilibrium conceptual framework here and the numerical simulation was based on inverse demand and supply functions calibrated using short-term elasticities. Since the goal of this paper is to conduct a comparative static analysis of the effects of various policy parameters and compare effects across policy scenarios at a point in time, this limitation does not affect the general direction of findings we obtain. Second, we assumed a closed economy with no trade-in oil or biofuels for simplicity. The US is a price-taking small exporter of gasoline and diesel and a small importer of biodiesel. The US is a larger exporter of corn ethanol, but exported ethanol does not qualify for RIN compliance; thus, there is a large difference in ethanol price between domestic and export markets, and the export market has been an outlet for excess ethanol production beyond the level needed to comply with the RFS. Thus changes in the design of the RFS and accompanying policies do not affect pathways for

compliance with the RFS, since these choices depend on the relative marginal costs of biodiesel and ethanol, which are unaffected by world markets. Third, for simplicity, we assume a representative consumer that is willing to pay for E85 based on its energy parity with E10. The framework developed here can be extended in the future to show the effect of heterogeneity in consumer preferences on the relationship needed between the price of E85 and E10 in order to avoid a blend wall.

Tables and Figures

Table 2.1 Volumetric Standards Under the RFS in 2017 and Observed Production (billion gasoline gallon equivalent)

	Cellulosic biofuel (D3)	Biomass- based diesel (D4)	Conventional biofuel (D6)	Advanced fuel (D3+D4+D5)	Total renewable fuel (D3+D4+D5+D6)
Statutory target	3.67	1.00	10.00	6.00	16.00
Revised target	0.21	2.00	10.00	2.85	12.85
Observed Production	0.17	2.57	9.26	2.84	12.10

Source: <https://www.epa.gov/fuels-registration-reporting-and-compliance-help/annual-compliance-data-obligated-parties-and>

Table 2.2 The Policy Target of Each Scenario Settings under Each Category

	Equation (2.2): Biodiesel	Equation (2.3): Cellulosic Biofuel	Equation (2.4): Overall/Conventional Biofuel
Scenario I: Non-nested	$q_{D4} \geq \theta_{D4} (q_g + q_d)$	$q_{D3} \geq \theta_{D3} (q_g + q_d)$	$q_{D6} \geq \theta_{D6} (q_g + q_d)$
Scenario II: Nested	$q_{D4} \geq \theta_{D4} (q_g + q_d)$	$q_{D3} \geq \theta_{D3} (q_g + q_d)$	$q_{D3} + q_{D4} + q_{D6} \geq \theta_R (q_g + q_d)$
Scenario III: Nested + Biodiesel tax credit	$q_{D4} \geq \theta_{D4} (q_g + q_d)$	$q_{D3} + q_{cw} \geq \theta_{D3} (q_g + q_d)$	$q_{D3} + q_{D4} + q_{D6} \geq \theta_R (q_g + q_d)$
Scenario IV: Nested + Biodiesel tax credit + waiver	$q_{D4} \geq \theta_{D4} (q_g + q_d)$	$q_{D3} + q_{cw} \geq \theta_{D3} (q_g + q_d)$	$q_{D3} + q_{D4} + q_{D6} \geq \theta_R (q_g + q_d)$
Separate-base + Non-nested	$q_{D4} \geq \theta_{D4} q_d$	$q_{D3} \geq \theta_{D3} q_g$	$q_{D6} \geq \theta_{D6} q_g$

Table 2.3 The First-order Conditions in Nested Without Waiver RFS Scenario

Decision variable	First-order Condition*	Equation
Biofuel producers		
q_e	$p_E^w = S_e(q_e) - p_{D6}$	i
q_c	$p_E^w = S_c(q_c) - p_{D3}$	ii
q_b	$p_d^w = S_b(q_b) - p_{D4} - t_B$	iii
Refiners		
q_g	$p_g^w = P_{g0} + \lambda_{D3}\theta_{D3} + \lambda_{D4}\theta_{D4} + \lambda_R\theta_R$	iv
q_d	$p_d^w = P_{d0} + \lambda_{D3}\theta_{D3} + \lambda_{D4}\theta_{D4} + \lambda_R\theta_R$	v
Blenders		
q_{E10}	$p_{E10}^r = D_{gf}(\cdot) = (0.9p_g^w + 0.1p_E^w) + w_{gf}$	vi
q_{E85}	$p_{E85}^r = D_{gf}(\cdot) = (0.26p_g^w + 0.74p_E^w) + w_{gf}$	vii
q_{gf}	$p_{E10}^r = p_{E85}^r = D_{gf}(\cdot)$	viii
q_{df}	$p_{df}^r = p_d^w + w_{df} = D_{df}(\cdot)$	ix

*w stands for wholesale and r stands for retail.

Table 2.4 The First-order Condition of RIN Credits and Cellulosic Waiver Credit

RIN Volumes	Non-nested RFS	Nested RFS (with/without waiver)
q_{D3}	$p_{D3} = \lambda_{D3}$	$p_{D3} = \lambda_{D3} + \lambda_R$
q_{D4}	$p_{D4} = \lambda_{D4}$	$p_{D4} = \lambda_{D4} + \lambda_R$
q_{D6}	$p_{D6} = \lambda_{D6}$	$p_{D6} = \lambda_R$
q_{cw}		$p_{cw} = \lambda_{D3}$

Table 2.5 The RFS Incentive for Retail Price under Different Policy Design and Blend Rate

Ethanol Blend Rate in the Gasoline Fuel	Fossil Fuel Base ^a	Structure ^b	Implicit tax or subsidy by RFS ^c on		
			E10	E85	Blended diesel
Below 10%	Separate	Non-nested	0	-	0
Below 10%	Joint	Non-nested, Nested	>0	-	<0
Above 10%	Separate	Non-nested	<0	>0	0
Above 10%	Joint	Non-nested, Nested	>0	>0	<0

a. Separate-base only applies to non-nested structure, where ethanol blends were defined using gasoline only base and the biodiesel blend was defined using diesel as the base only where $q_{D3} \geq \theta_{D3}q_g$, $q_{D6} \geq \theta_{D6}q_g$, and $q_{D4} \geq \theta_{D4}q_d$; Joint-base defines the blend rate based on the total gasoline and diesel.

b. Nested structure is inclusive of scenarios with and without the cellulosic waiver.

c. E10, E85, and blended diesel have RFS incentive of $0.1\kappa - 0.9\tau_g$, $0.74\kappa - 0.26\tau_g$, and $(p_{D4}q_b - q_d\tau_d)/(q_b + q_d)$, respectively. A positive sign indicates a net subsidy; a negative sign indicates a net tax. The results hold only when both $(q_e + q_c)/q_g > q_b/q_d$ and $\kappa > p_{D4}$ hold as discussed in Proposition 1 and 2.

Table 2.6 Validation of Simulated Outcomes in the Status Quo (Nested with Waiver and Biodiesel Tax Credit) Scenario

Item	2017 observation	Simulated outcomes	Difference	Source
Prices (\$ per gge)				
Wholesale petroleum diesel	1.45	1.45	0%	EIA ¹
Wholesale biodiesel	3.55	3.73	5%	AFDC ²
Wholesale gasoline	1.98	1.98	0%	EIA ³
				Nebraska
				Ethanol
Wholesale ethanol	2.43	2.34	-4%	Board ⁴
Retail E85	2.58	2.62	1%	AFDC ²
Retail E10	2.26	2.27	1%	AFDC ²
Retail diesel	2.21	2.28	3%	AFDC ²
D3	3.77	4.01	6%	EPA ⁵
D4	1.17	1.01	-13%	EPA ⁵
D6	0.86	1.01	18%	EPA ⁵
Volumes (billion gge)				
Diesel	68.5	66.70	-3%	EIA ⁶
Biodiesel	2.61	2.85	9%	EPA ⁷
Gasoline	128.58	126.32	-2%	EIA ⁸
Ethanol	9.62	9.36	-3%	EIA ⁹

* Fuel prices are converted to per unit gge by using the energy content coefficient obtained from EIA sources: <https://www.eia.gov/energyexplained/units-and-calculators/energy-conversion-calculators.php>, where 1 gallon of gasoline = 0.88 gallons of diesel = 1.5 gallons of ethanol=1 gallons of biodiesel

1. https://www.eia.gov/dnav/pet/pet_pri_spt_s1_a.htm

2. <https://afdc.energy.gov/fuels/prices.html>

3. https://www.eia.gov/dnav/pet/pet_pri_refoth_dcu_nus_a.htm

4. <http://www.neo.ne.gov/statshtml/66.html>

5. <https://www.epa.gov/fuels-registration-reporting-and-compliance-help/rin-trades-and-price-information>

6. https://www.eia.gov/dnav/pet/pet_cons_psup_dc_nus_mbb1_a.htm

7. https://www.eia.gov/dnav/pet/pet_sum_b100_dcus_nus_a.htm

8. <https://www.eia.gov/outlooks/steo/data/browser/#/?v=9&f=A&s=&id=&maptype=0&ctype=linechart&linechart=MGTCBUSX~EOTCPUS&map=>

9. <https://www.epa.gov/fuels-registration-reporting-and-compliance-help/annual-compliance-data-obligated-parties-and>

Table 2.7 Effects of RFS features on GHG Emissions and Fuel Volumes

Scenarios	(I) Non-Nested	(II) Nested only	(III) Nested + waiver	(IV) Nested + biodiesel tax credit	(V) Nested + waiver + biodiesel tax credit
Change relative to Non-Nested scenario (I)					
GHG emissions (MMT)					
Conventional biofuel	96.8	-4.1	-3.4	-8.2	-7.0
Biomass-based diesel	14.3	+3.0	+3.0	+6.0	+6.0
Cellulosic biofuel	-0.7	+0.0	+0.3	+0.0	+0.4
Gasoline	1,414	+4.8	+4.8	+9.6	+9.6
Diesel	757	-5.4	-5.4	-10.8	-10.8
Total	2,281	-1.6	-0.6	-3.3	-1.6
Fuel volumes (billion gge)					
Conventional biofuel	10	-0.42	-0.35	-0.85	-0.72
Biomass-based diesel	2	+0.42	+0.42	+0.85	+0.85
Cellulosic biofuel	0.21	-0.00	-0.08	-0.00	-0.13
Gasoline	125.5	+0.39	+0.39	+0.82	+0.82
Diesel	59.5	-0.37	-0.37	-0.80	-0.80

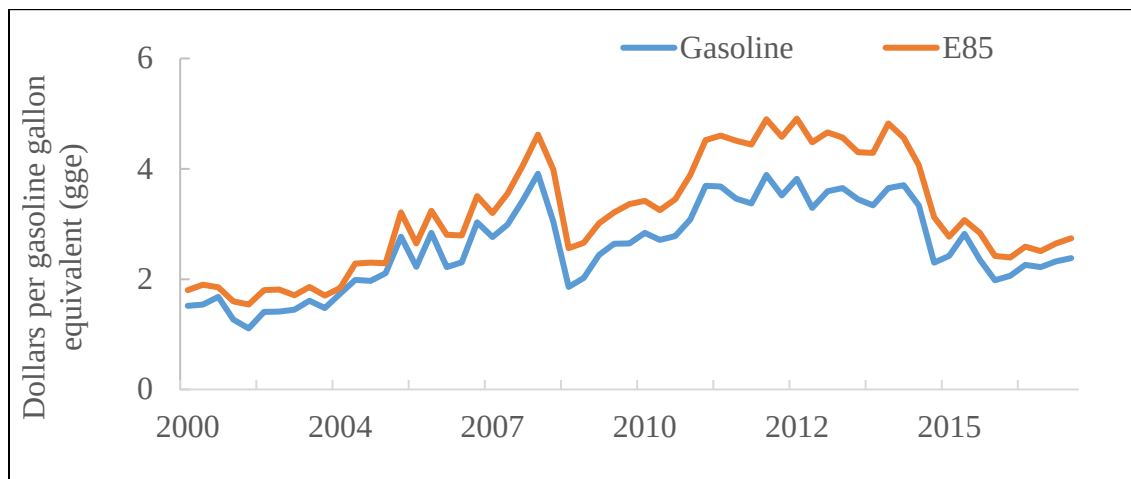
Table 2.8 The Change in the Social Welfare Due to the Design Feature of RFS (relative to no RFS scenario) (million \$)

	(I) Non-Nested	(II) Nested	(III) Nested + waiver	(IV) Nested + biodiesel tax credit	(V) Nested + waiver + biodiesel tax credit
P.S. Biodiesel	1,139	1,680	1,728	2,506	2,506
P.S. Cellulosic ethanol	34	34	14	34	5
P.S. Corn ethanol	6,377	5,075	5,299	3,817	4,186
C.S. Gasoline-blended fuel	-7,283	-6,669	-6,821	-6,045	-6,382
C.S. Diesel-blended fuel	-10,295	-10,017	-10,086	-7,413	-7,397
Cellulosic waiver revenue	-	-	222	-	382
Biodiesel tax credit payment	-	-	-	-2,850	-2,850
Economic surplus	-10,027	-9,897	-9,644	-9,952	-9,551
Value of GHG savings	891	976	927	1,061	978
Change in total social welfare	-9,136	-8,922	-8,716	-8,891	-8,572
Change in total social welfare relative to Non-Nested scenario (I)	0	215	420	245	564

Note: P.S. is short for producer surplus, C.S. is short for consumer surplus.

No RFS policy scenario is defined as the social welfare maximization problem without any RFS policy constraint

Figure 2.1. US Gasoline and E85 Retail Fuel Price Trends



Source: <https://afdc.energy.gov/fuels/prices.html>

Figure 2.2 Comparison between Cellulosic (D3), Biodiesel (D4), Conventional (D6) RIN Prices, and Cellulosic Waiver Price

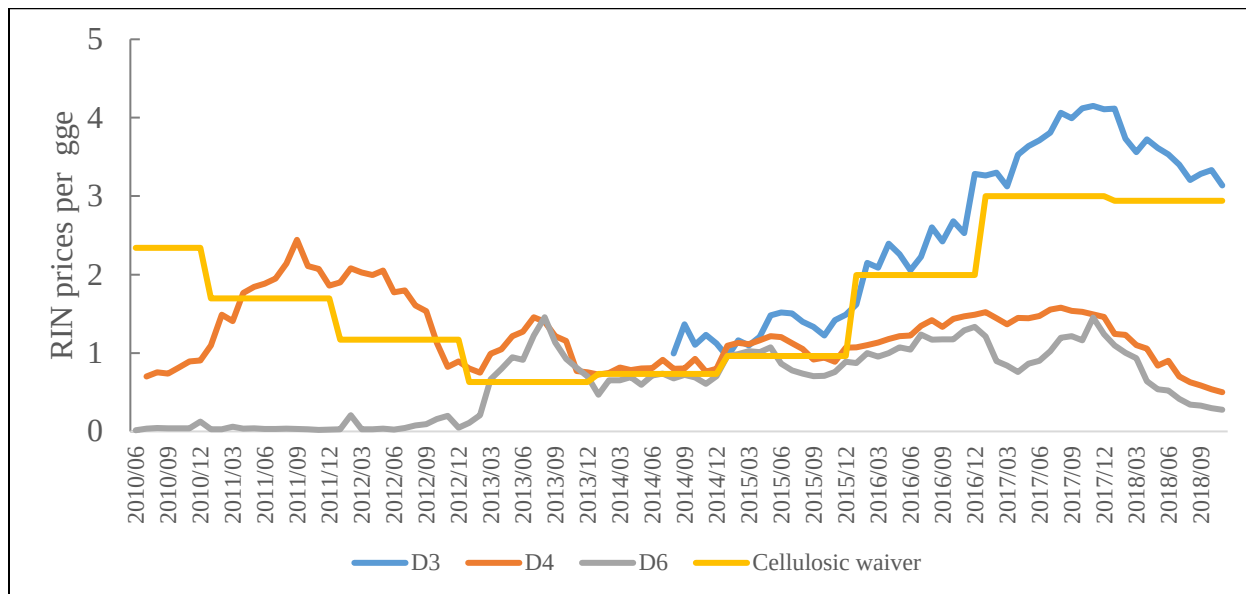
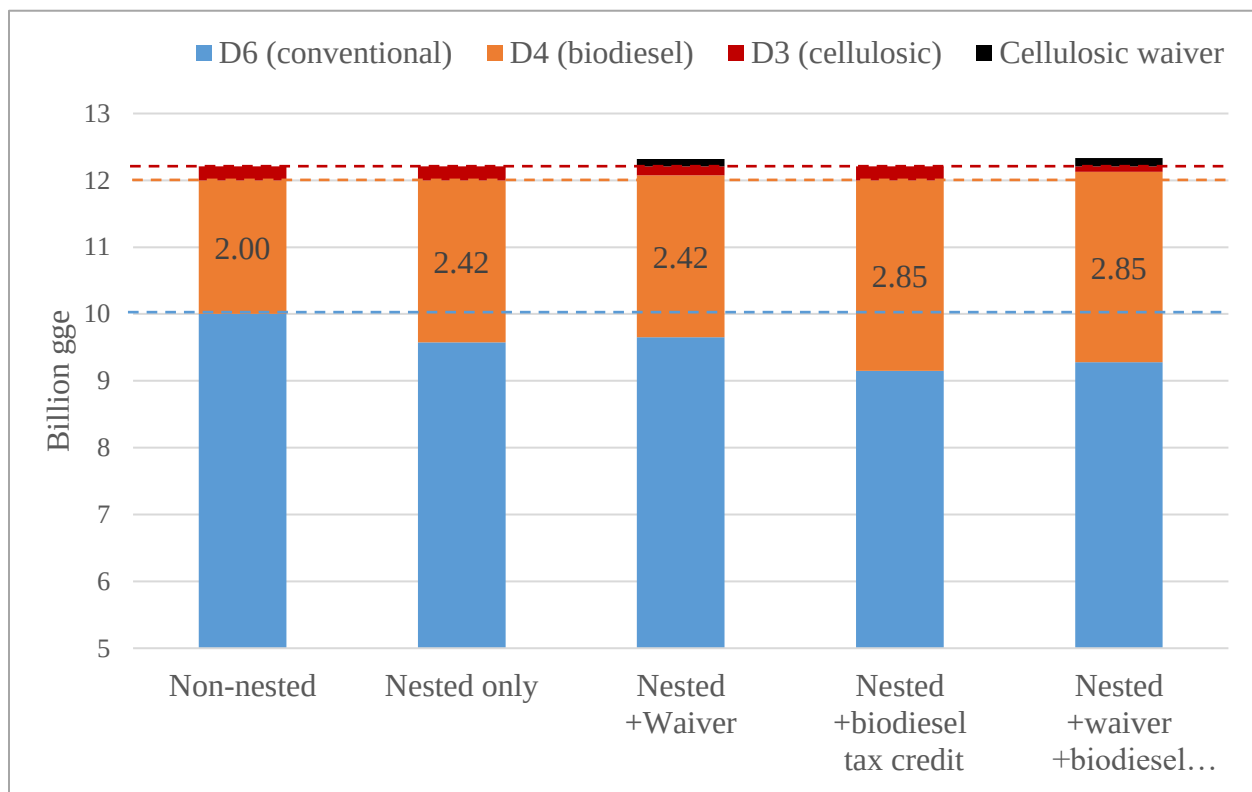


Figure 2.3. Volumetric Compliance of RINs by Simulated Policy Scenarios and Actual Blended RINs in 2017 (in billion gasoline gallon equivalent)



Note: The dashed lines show the mandated levels of corn ethanol, biodiesel, and cellulosic ethanol. Numbers inside the orange box indicate the D4 compliance.

Figure 2.4. Effect of the Design of RFS on RIN Prices

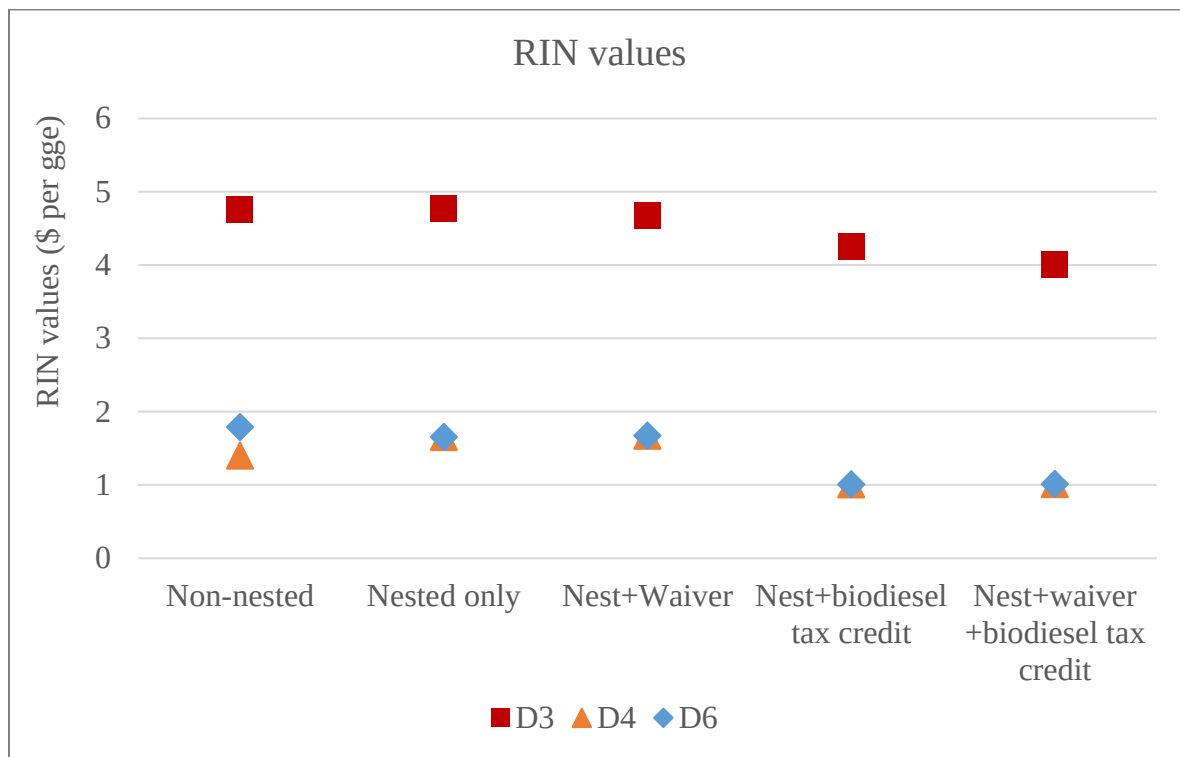


Figure 2.5. Effect of Design of RFS on Percentage Disparity of E85 and E10 and Corresponding Blend Wall

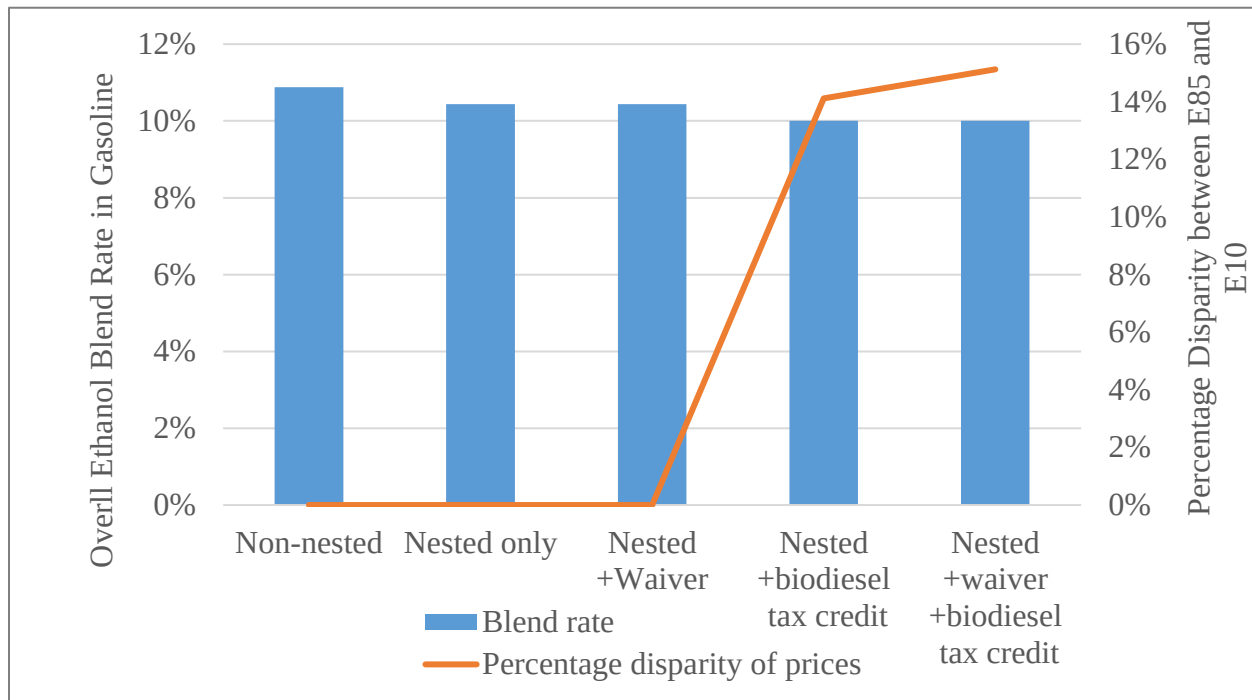


Figure 2.6. Monte-Carlo Simulation on Biodiesel and Corn Ethanol Supply Elasticities on E85 and E10 Price Difference

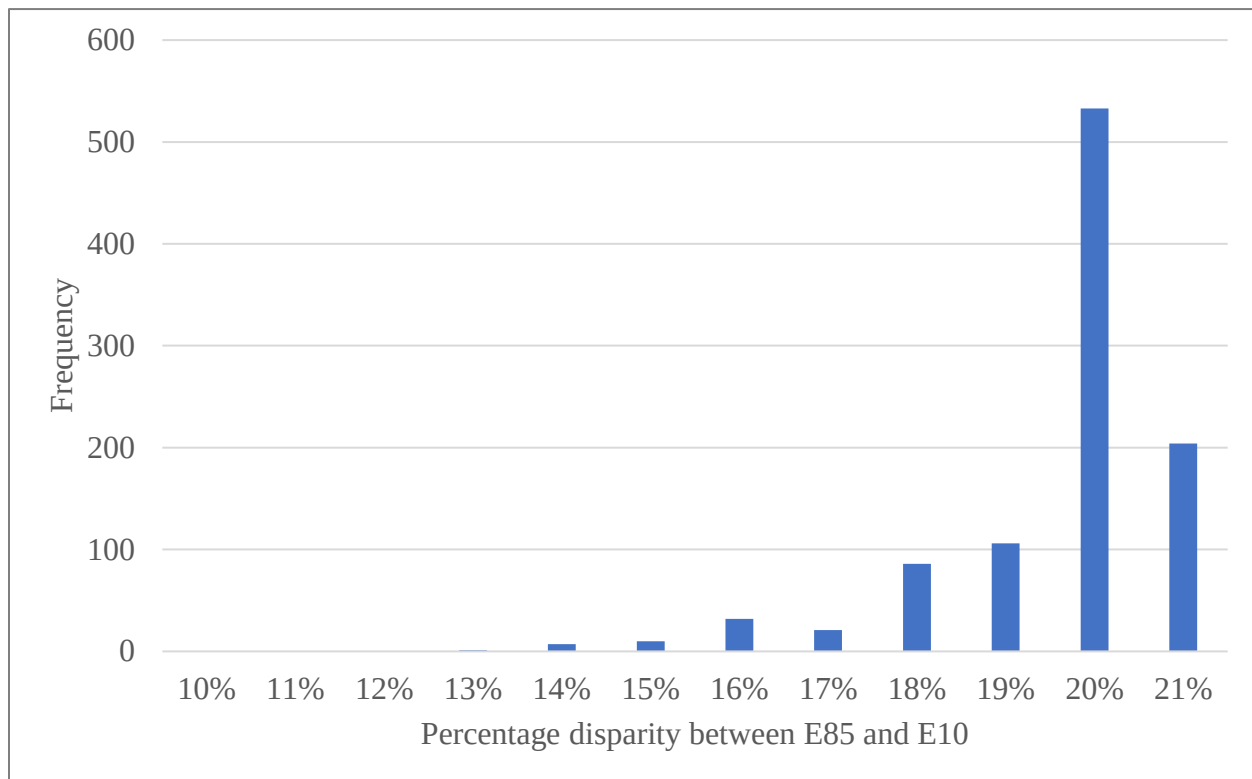


Figure 2.7. Effect of the Biodiesel Tax Credit on D4 RIN Over-production and Price Differential

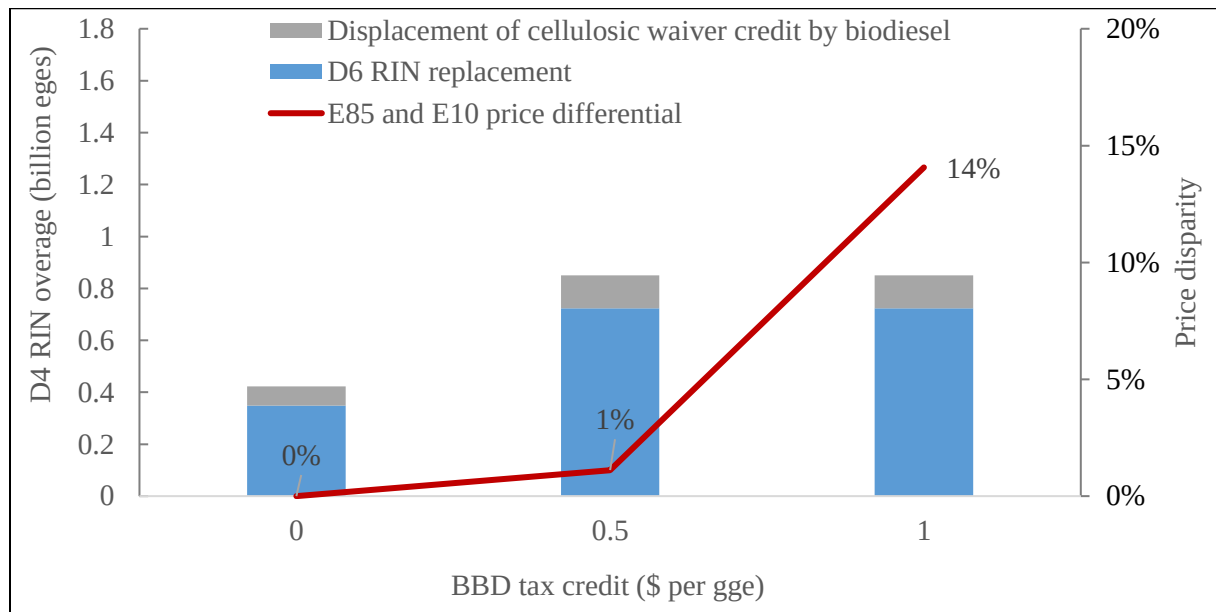
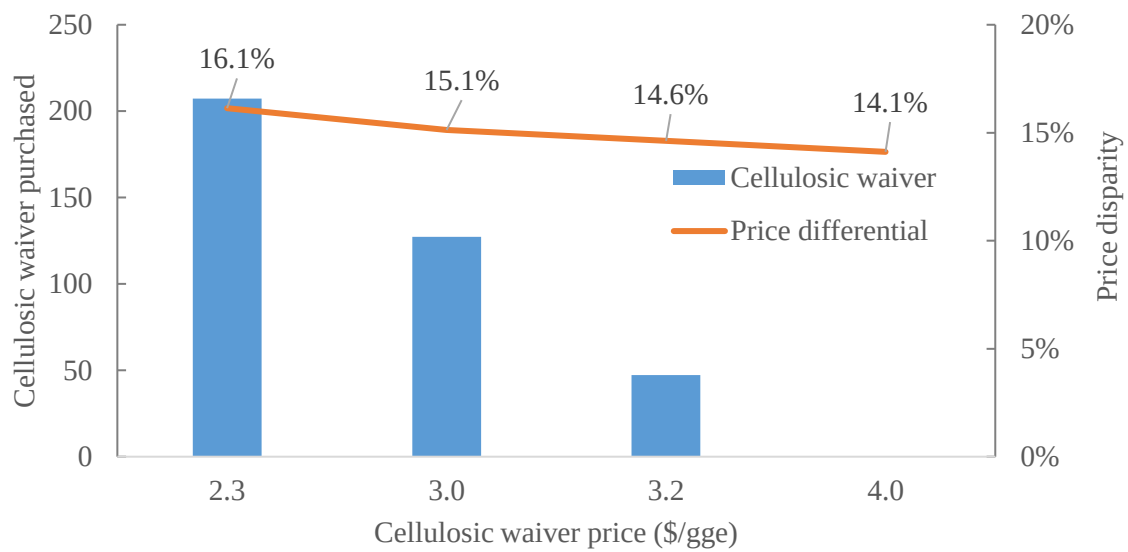


Figure 2.8. Effect of Cellulosic Waiver Price on Purchased Credit and Price Disparity between E85 and E10



CHAPTER 3 Behavioral, Technological and Economic Determinants of Electric Vehicle Adoption in the United States

3.1 Introduction

Biden Administration pledged to boost the market share of electric vehicle (EV) sales to 50% in 2030 and to reduce the economy-wide greenhouse gas emissions (GHG) emissions by 50% (The White House 2021). The optimism of EV technology stems from the falling lithium-ion battery price (BloombergNEF 2019) as well as the estimated price drop ranging from \$5,700 to \$7,100 per electric vehicle by McKinsey (Baik et al. 2019). Moreover, fuel cost savings from switching to EVs can be as high as \$500 to \$900 per year (Krupa et al. 2014; Hidrue et al. 2011). The federal tax credit incentivizes EV buyers with up to \$7,500 for the new battery electric vehicles (BEV) and \$2,500 for plug-in hybrid electric vehicles (PHEV), which is likely to extend under Biden's infrastructure bill. Electric vehicle technology is also predicted to mature in 5 to 10 years when EV production scales up (Gartner 2020).

However, there is great uncertainty in EV penetration. Studies have projected that the share of new EV sales (including plug-in hybrid and battery electric vehicles) will range from 24%-30% by 2030 in the US vehicle stock (Plotkin et al. 2009; Noori and Tatari 2016; Sen, Noori and Tatari 2017) by reducing the vehicle costs and improving the charging availability. The recent projections of the Annual Energy Outlook (AEO), however, lower the estimated EV stock share from 5% to 1% (13.9 million to 2.3 million) of total vehicle stocks by 2030 (EIA 2021a) due to changing gasoline prices and driving demand (DOE 2021b). The current vehicle stock of the EVs is only 1.5 million in 2019 (0.6% of the total light-duty vehicle fleet) that further casts doubt on the goal of achieving EV sales of 50% by 2030.

This paper aims to project the likely outcome of alternative fuel vehicle penetrations given the various behavioral, technological, and policy drivers. The welfare economic analysis allows us to calculate the societal cost of achieving the ambitious target of electrification of transportation and weighing the cost of GHG mitigation benefit. We consider rational economic drivers of vehicle purchase and driving costs, the intangible costs associated with advanced technology, and the future changes of technological pathways, as well as idiosyncratic preference towards the fuel types. The BEV are more costly than conventional vehicles (Miller 2020; Lévy, Drossinos and Thiel 2017) though the battery pack price fell by 85% from 2010-2018 (Souloupoulos 2017). Besides the economic consideration, various intangible costs associated with driving behaviors also hinder the consumers from driving BEVs: the range limitation of EV imposes the risk of alternative transportation cost if running out of battery (Ramea et al. 2018; Lin 2014; Mccollum et al. 2018; Needell et al. 2016); detour distance to the sparse charging stations (Hu, Dong and Lin 2019; Yang et al. 2016) and the waiting time to charge inside the stations (Ashkrof, Homem de Almeida Correia and van Arem 2020) increase the additional time cost. They jointly lead to range anxiety to meet the varying mileage demand that inhibits the broad adoption of BEVs. In addition to the inconveniences, consumers show their irrational preferences towards EV for the iconic acceleration performance, privileged private charger, and pro-environment identity of electrified vehicles, contributing to surging interests and preferences (Okada, Tamaki and Managi 2019). However, rarely have the previous studies jointly considered all the above technological and economic factors and their interactions evolving over time.

Empirical evidence shows that electric vehicle adoption not only is affected by the economic factors of vehicle price incentives (Muehlegger and Rapson 2018) and the operating driving cost savings compared to conventional vehicles (Busse, Knittel and Zettelmeyer 2013; Allcott and

Wozny 2014; Anderson et al. 2011; Sallee, West and Fan 2016), but also the availability of charging stations (Li et al. 2017; Springel 2020; Li 2019) that could otherwise derive the range anxiety (Bonges and Lusk 2016). The perceptions of vehicle attributes, attitudinal valuations, and environmental consciousness play an important role in EV adoption (Mohamed et al. 2016; Wang et al. 2018; Sexton and Sexton 2013; Ferguson et al. 2018; Schuitema et al. 2013; Axsen, Bailey and Castro 2015). These studies, however, provide limited insights about the consumers' preference only for the existing vehicle models under the technology and market conditions due to the data availability. The projected future changes in market conditions, potential technology features, and increasing infrastructure availability are not captured by the revealed preference study.

Simulation studies estimate the market share by integrating the consumers' utility with the energy system modeling (US Energy Information Administration 2019; Noori and Tatari 2016; Stephens et al. 2017) based only on the observed characteristics and assumptions of key variables of the total number of vehicle purchases, fuel prices, and vehicle mileage traveled (Mccollum et al. 2018; Xie and Lin 2017). The energy system optimization model of MARKAL (Kannan et al. 2007) and TIMES (Yang et al. 2015; Babaee, Nagpure and Decarolis 2014) that rely solely on one single representative decision-maker, as shown by Ramea et al. (2018), lead to the limitation of corner solution of technology choice. Ramea et al. (2018) develop A novel methodology of incorporating heterogeneous consumer demand with unobserved preferences based on the cost minimization framework. Unlike the above studies, we further improve the consumer choice modeling by using a welfare economic model with intercorrelated fuel, vehicle, and electricity markets by maximizing the total economic benefits of both producers and

consumers. The model allows us to isolate the factors of technology improvement, economic and behavioral factors that determine the adoption behavior of alternative fuel technologies.

We undertake this analysis by establishing the random utility-based approach for the vehicle choice modeling, assuming consumer decision of the vehicle depends on utility from the observed tangible and intangible costs and benefits as well as the random error terms based on idiosyncratic preferences. This is a self-consistent framework, in which the new vehicle sales and old vehicle retirement are determined by the relative consumer utility associated with the forecast of technological, economic, and behavioral factors and specify the dynamic of vehicle stock. We represent consumer heterogeneity with spatial variation across 20 regions of electricity markets, three driving demand groups, four charging modes, and up to 24 vehicle ages for five vehicle drivetrain types. We further apply the stochastic daily mileage traveled, time valuation, and idiosyncratic preference with ten representative consumers of each segment above to capture the realistic consumers demand in the vehicle market. We incorporate the vehicle choice model into an open-economy, multi-market, partial equilibrium, social welfare optimization model BEPAM (Biofuel and Environmental Policy Analysis Model), which is widely used to analyze the effects of implementing biofuel policies in the transportation sector (Chen et al. 2021; Chen et al. 2014; Huang et al. 2013). We quantify welfare change incurred by the market uncertainty in the transportation sector and policy incentives by considering the social cost of GHG emissions.

The rest of the paper is organized as follows. The following section describes the modeling specification of transportation, fuel, electricity, and agricultural sectors, as well as the scenarios to investigate. Section 3.3 presents the impact of behavioral factors on the transportation sector. Section 3.4 examines the uncertainty scenarios with varying market conditions and policy

incentives. Lastly, in Section 3.5, we conclude the paper with a discussion of the implications of our findings.

3.2 Methods

We first integrated a dynamic vehicle choice model with the open-economy, price-endogenous, partial equilibrium model — Biofuel and Environmental Policy Analysis Model (BEPAM), which has a comprehensive energy modeling system (Oliver and Khanna 2017b; Chen et al. 2021). The optimization model determines the market equilibria for multiple markets of fuel, electricity, and agriculture sectors simultaneously by maximizing the sum of consumers' and producers' surpluses, subject to material balance, technological limit, land availability, and policy constraints from 2016 to 2030. We then extend the BEPAM model with the vehicle market and demonstrate the demand of vehicle kilometer traveled (VKT) for the transportation sector, as illustrated by Figure 3.1.

We specify the consumers' utility with consumer surplus obtained from meeting the aggregated demand for VKT minus the ownership costs, including vehicle prices, fuel costs, maintenance costs, and also the behavioral inconvenience costs of range limitation, detour, and waiting. We further consider the idiosyncratic preference using the error terms of the nested multinomial logit model to complete the modeling of the random utility of representative consumers of the transportation sector.

$$U_n(\mathbf{x}_j, \mathbf{d}, \varepsilon_j) = \text{Consumer Surplus} - C_{\text{Purchase}} - C_{\text{Fuel}} - C_{\text{Maintainence}} - C_{\text{Range}} - C_{\text{Wait}} \\ - C_{\text{Detour}} + \varepsilon_{nj}$$

3.2.1 Transportation Sector

Like Ramea et al. (2018), we coarsely categorize the drivers into three driving demand groups (high, medium, and low) based on the annual VKT from National Household Travel Survey (Federal Highway Administration 2017) and capture their daily VKT probability distribution. The consumers of the high driving demand group have a greater VKT, and their daily mileage distribution has a broader variance skewed to the left (Figure B3) with a greater probability of driving long distances than the other two groups with fewer driving demands. We further capture the heterogeneity in annual driving capacity by vehicle age to reflect the driving demand in response to the turnover of the fleet based on the National Household Travel Survey (Figure B1 to B2) (Federal Highway Administration 2017). We aggregate the total annual mileage demand functions of each fuel type established by Chen et al. (2021)¹⁸ so that the model allows consumers to switch vehicle choices. We further proportionate the VKT demand functions for twenty electricity market regions and three driving demand groups based on the observation from NHTS. Unlike many literature assuming the fixed mileage for vehicle choice modeling, the downward sloping demand functions allow vehicle owners to adjust the traveling demand based on endogenous fuel prices and quantify the consumer benefit of meeting the driving demand. Similarly, consumers shift their vehicle choice only if the utility obtained from the ownership of the alternative vehicle is greater than the current one. We also consider the traveling demand of medium/heavy-duty fleet that consumes primarily diesel fuel.

We develop a dynamic vehicle fleet turnover for five representative types of powertrains that account for 99% the total US light-duty vehicle stock that includes conventional vehicle

¹⁸ Within each driving demand group and region, we assume that the drivers are indifferent to mileage using different types of vehicles.

(CV), flexible-fuel vehicle (FFV), hybrid gasoline vehicle (HBV), plug-in hybrid vehicle (PHEV), and battery electric vehicle (BEV). We simulate vehicle choice decisions considering new vehicle purchases, early scrappage, and vehicle age distribution (Equation B2 to B4 in Appendix B.2). The projections of vehicle technology improvements such as fuel economy, battery range, and corresponding vehicle prices are from EIA (2019). Details about the assumptions can be found in Appendix B.1. We test the sensitivity of technological assumptions of BEV vehicle prices, charging station availability, and fuel prices in the later sections.

3.2.2 Behavioral Disutility Costs of Driving

The data sources of economic costs, including procurement cost, operation, and management cost, are provided in Appendix B.2. We also quantify the behavioral disutility costs of range limitation, waiting, and detour, and then calibrate the idiosyncratic preference term to complete the specification of the random utility function. We incorporate the stochastic representation of the idiosyncratic preference, daily driving demand, and value of time from predefined distributions.

As in many literature (Ramea et al. 2018; Needell et al. 2016; Lin and Greene 2011), we quantify the range limitation cost for BEV users as the cost of the alternative modes of transportation, only when the mileage demand exceeds the efficient range capacity obtained from available charging portals and allowed by the battery capacity. We leverage the data of annual mileage driven from the NHTS (Federal Highway Administration 2017) and generate the Gamma probability distribution of daily VKT for three driving groups by using the mean and variance of the annual mileage of vehicles with each driving demand. We quantify the effective mileage range as the total mileage allowed by the charging portals available at home or work based on the daily routines (Hu et al. 2019), public charging availability, and mileage range

capacity (details are provided in Appendix B.2.1). The consumers could spend \$2,500 on installation costs to obtain home charging. Unlike the previous literature using the deterministic value of the range limitation cost per vehicle (Ramea et al. 2018), we randomize the daily driving demands from the parameterized Gamma distributions and compare them to the efficient ranges to calculate the probability of running out of the battery. The details of quantifying the range limitation cost varying across the regions, driving demand groups, charging modes, and vehicle ages are provided in Appendix 2.1.

We quantify the waiting cost as the valuation of time spent during all the visits to the public charging stations for BEV owners, using a similar approach used by US EPA and NTHSA (2018). The waiting cost is the multiplication of the probability of public charging visits based on the availability of charge mode at home or work, the time duration spent in the available charging portals of regular L2 or fast-charging portals, as well as the value of time. To show the representative economic value of time people attach to waiting across the US, we randomly draw the per-hour value of time from the income distribution (Semega, Fontenot and Kollar 2017) and then apply the 50% for traveling purposes, as suggested by the Department of Transportation (2015). The calculation details are provided in Appendix A2.2.

We then follow Pouliot and Babcock (2014) to measure the detour cost by the monetary value of extra time to find the nearest station. By obtaining the distance data from NREL (2021), the value of time, and the probability of visit public charging discussed above, we update the linear detour cost function (see Appendix B2.3). We also randomize the value of time as in waiting cost.

Lastly, we capture the unobserved idiosyncratic preferences for each vehicle type with the error terms under the nested multinomial logit model to show substitution patterns. We apply the

same nested structure suggested by the Ramea et al. (2018) that liquid-fuel vehicle types of conventional vehicles and flex-fuel vehicles clustered together with the same inner combustion engine, and they then further cluster with hybrid electric and plug-in hybrid vehicles that rely on liquid fuels but also have electric motors, whereas the electric vehicles being relatively independent parallel to the nest of the inner combust engine. So that the error terms of alternatives within the same nest of the liquid-fuel vehicle are correlated, whereas the terms of two alternatives in different nests (liquid-fuel versus electric) are uncorrelated. We further adjust the mean of the error terms and follow the scaling approach to calibrate the heteroscedastic errors across the regions (Train 2003; Bradley and Daly 1994) by using the cross-sectional data of Google Trend. We then randomly draw the unobserved preference terms from the formulated Gumbel distribution and add to the consumer utility to complete the representation of the random utility for consumers of three driving demand groups, twenty spatial regions, and with four charging modes. The calibrated error terms are used to validate the output of vehicle choices from 2016 to 2019. The details are in Appendix B.3 and B.4.

3.2.3 Fuel Supply

The fuel supply of the transportation module in the BEPAM model includes the crude oil markets of both US and the rest of the world, the refinery products of petroleum gasoline and diesel, and the regional electricity grid. Following the same fuel modeling assumption in Chen et al. (2021), gasoline and diesel are generated proportionally from crude oil, and the US is a price-taking exporter of petroleum products as the US only exports a small portion of the petroleum product to the rest of the world. Most gasoline is sold as blended motor fuel with 10% of ethanol E10 and high ethanol blend (up to 74%) product E85. The model endogenously determines the implicit cost of VKT depending on the marginal cost of oil, conversion costs of

oil to gasoline and diesel, the mix of biofuels blended, and the operation and maintenance costs of vehicles. This study assumes the current production capacity of 56 billion liters of corn ethanol remains the same after 2016 and onwards. The biofuel is produced from the cropland, of which the land productivity and land use allocation are endogenously solved. More details of the agricultural modeling can be found in Chen et al. (2021).

3.2.4 Agricultural Sector

The agricultural sector endogenously determines the quantities of row crops, biomass feedstock, biofuels, and fossil fuels and their prices under market equilibrium. It connects the domestic agricultural and fuel markets in the US as well as trades of 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 different rotation, tillage, and irrigation practices. The model simulates optimal land use allocation for major row crops and energy crops on cropland based on the constraints of 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).

3.2.5 Electricity Sector

We also include the regional supply and demand of the electricity for twenty electricity market regions (Oliver and Khanna 2017b), where the generation capacity, cost of generation, and conversion efficiency are specified for each energy source. The electricity demand is specified with a linear demand curve that includes demand across residential, commercial, and industrial sectors for each region by using the 2016 eGRID data (EPA 2016). The additional electricity demand due to the increasing demand for EV shifts the aggregate demand outward.

The market equilibrium of electricity prices determines the electricity sources and thus 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 portal (\$3,000 for L2 and \$21,000 for fast charging) from DOE (2015) times the numbers of the portals required for stations, assuming each station on average having three portals.

3.2.6 Scenarios

We undertake this analysis by first addressing the technological and behavioral factors in affecting over the 2016-2030 period. In scenario (1), we define the benchmark scenario with the feasible technological and economic assumptions from Annual Energy Outlook for vehicle price, vehicle attributes (fuel efficiency and battery capacity), improvement of charge availability, as well as the world petroleum price ¹⁹. The technical details and assumptions about are provided in appendix. We also include the federal EV tax credits for consumers at \$7,500 for BEV and \$2,500 for PHEV from 2016 to 2030 as the baseline policy landscape.

Based on the benchmark scenario above, we then add the behavioral factors on top of each other sequentially to reflect the Likely Outlook of the transportation sector (as listed in Table 3.1). We first add factors that only apply to the BEV users: range limitation cost in scenarios (2) and then waiting cost in scenarios (3) in addition to range limitation cost. We then include the detour cost that affects driving experience of both the BEV and FFV in scenario (4) on the top of scenario (3). Adding the idiosyncratic preference term to scenario (4) with all the above inconveniences completes the representation of the consumers' utility that comprehensively includes both observed and unobserved factors in the scenario (5). With that, we assume the

¹⁹ The US is assumed to be price taking exporter of the gasoline and diesel, same as Chen et al (2020).

owners of conventional gasoline vehicles (CV), hybrid gasoline vehicles (HBV), and plug-in hybrid electric vehicles (PHEV) are not subject to any inconvenience costs²⁰. The policy constraints remain the same as benchmark scenario (1) for all four Likely Outlook scenarios. Finally, the model is validated from 2016 to 2019 based on scenario (5) settings with inclusive consideration of all the above behavioral factors. The details of the model validation can be found in Appendix B.4.

We further examine the uncertainty scenarios associated with different market conditions and policy incentives on the basis of the behavioral representation in scenario (5), as listed in Table 3.1. In scenario (6), we cancel the vehicle tax credit starting 2019. But we also simulate the increase in the federal tax by 50% in scenario (7) to reflect the continuing support from the government. Scenario (8) lowers the exported gasoline and diesel prices by 2%, given the volatile fuel costs for liquid-fuel vehicles. In scenario (9), we raise the exported gasoline and diesel prices by 2%, increasing fuel costs for liquid-fuel vehicles. In scenario (10), we simulate the case of achieving 500 thousand charging stations by 2030 in the US, assuming the numbers of stations grow at a constant rate at 26% annually and proportionally across the regions for both L2 and fast-charging stations starting from 41 thousand in 2020 (DOE 2021a). In addition, we also demonstrate the declining BEV price in scenarios (11) by \$3,000.

3.2.7 Welfare Analysis and GHG Emission Estimation

To determine the social welfare effects of the decarbonization, we assess the impact of uncertainties in fuel prices, vehicle prices, policy incentives, and recharging improvement upon

²⁰ We assume owners of PHEV have dual-energy system and can shift to gasoline fuels when running out of the battery. Based on the statics showing 40% of the mileage is on charging-depleting mode whereas PHEV only has 40 to 60 mileage capacity, we assume the PHEV owners are equipped with charging portals at home or at work that are sufficient to get full charge.

the discounted sum of consumer and producer net benefits of agricultural, transportation, and electricity sectors relative to the benchmark scenario (6) without EV tax credit. The consumer utility obtained from meeting the driving demand is calculated as the consumer surplus from VKT demand net the economic cost of vehicle ownership and disutility costs as demonstrated in the previous sections. 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's benefit from fuel tax revenue, the investment in the tax credit, and the cost of 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. 2021).

We estimate the lifecycle GHG emissions from the agriculture, transportation, and electricity sectors following Chen et al. (2021) by multiplying the lifecycle carbon intensity of each fuel type with the counterpart fuel consumptions of gasoline, diesel, biofuels, and electricity of different sources. We examine the cumulative emissions and their social costs under each scenario over 2016 - 2030 period. 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 CO₂ equivalent (Mg CO₂) is a reasonable estimate with the same 3% social discount rate (Watkiss and Downing 2008; Tol 2005).

3.3 Results of Behaviorally Realistic Interpretation

3.3.1 Benchmark Scenario

The benchmark scenario indicates the vehicle adoption by consumers considering only the economic costs including vehicle purchase, maintenance, and fuel costs, as illustrated in Figure 3.2, without any concerns of inconveniences. We find that conventional vehicles (CV) are the cheapest option for consumers of low and medium driving demand groups in terms of the

average annualized lifetime cost over 2016-2030 period, whereas Battery Electric Vehicle (BEV) are the cheapest for the high driving demand group. It is because the substantial cost savings of fuel and maintenance by the EVs, due to the intensive driving, that offsets the cost differences in vehicle prices. The per-km costs (in Figure 3.2b), measured by the annualized cost over the yearly vehicle kilometer traveled (VKT), diminishes as the yearly VKTs of medium and high mileage demand groups are 2.6 times and 4.5 times greater than that of low mileage demand group.

As shown in Table 3.3, the total vehicle stock increases from 241 million in 2016 to 272 million in 2030 under the benchmark scenario, with a significant amount of alternative fuel vehicles penetrated the market. Without considering any inconveniences, CVs stocks sharply decline to 160 million but still dominate the fleet, which is substituted by the BEVs (42 million), FFVs (35 million), and PHEVs (32 million), which altogether account for 40% of the total vehicle stock. The electrified VKT contributed by both BEVs and PHEVs reaches 75% within the high driving demand group, and 17% in the medium driving demand group, whereas the electrifications of the low driving demand group are negligible (shown in Table 3.3). The spatial distribution of the CV and FFV stocks under the benchmark scenario in 2030 generally shows similar patterns as 2016 observations (in Figure 3.3), whereas BEVs and PHEVs increase in the area where market demands of driving are relatively large.

The benchmark scenario shows a simplified specification of vehicle choices where a rational consumer only focuses on the economic costs of the vehicle, fuel, and maintenance costs. However, the consumers of different market segments across the region have disparate driving behaviors and preferences that might interact with the properties of drivetrains and vehicle

attributes. We then study the heterogeneity in the driving behaviors and the intangible costs associated with the psychological preference.

3.3.2 Impact of Range Limitation

The disutility of range limitation cost is quantified by the expected penalty cost of the alternative transportation mode if running out of power for battery electric vehicles (BEV). The ex-ante average estimated range limitation costs are displayed in Table 3.2 for BEV owners with access to different charging modes and with different driving demands over the 2016-2030 period, assuming driving at full capacity of annual mileage (as illustrated in Figure B1). The range limitation costs increase with greater driving demand and less available charging at either home or work, ranging from \$0 - \$65 per year for consumers having both work and home charging; and to \$0 - \$212 per year with only home charging and \$0 - \$346 per year with only work charging. We find the estimated range limitation costs are low for consumers having at least one fixed charging portal because the effect ranges provided by the available charging portals are as high as 289-441 km, leading to low chances of running out of battery. However, the consumers rely solely on the public charging only have an effective range of 27 km, which leads to a substantial increase in the range limitation cost to \$4,130 - \$6,681 per year. The ex-post optimized range limitation costs of new BEV purchases in Figure 3.2a showed that consumers adjust the actual purchase and driving VKT to avoid the high range limitation cost with only \$0, \$11, and \$173 per year for the low, medium, and high driving demand. The average range limitation costs of each kilometer driven are only \$0, \$0.001, and \$0.003 per kilometer. About 17 million BEV owners used to have access to only public charging in scenario (1) turn to use work charging and even give up the ownership and shift to PHEVs and HBVs, leaving the BEVs stocks to 35 million. The other vehicle stocks remain relatively the same. The

BEV stock drops mainly in the area with fewer available charging stations, as displayed in Figure 3.3. As a result, the VKT electrification of the high driving demand market reduces to 66% in 2030, whereas that of medium-driving demand remains the same. The fuel efficiency falls to 16.4 km per liter when the fleet stock has fewer BEVs.

3.3.3 Impact of Waiting Cost

Another inconvenience causing the range anxiety is having to wait in the public charging station for hours until BEV is sufficiently charged. The time duration depends on the mix of fast-charging and regular L2 portals, where many metropolitan areas, such as New York and California, have a high density of charge stations but less fast-charging coverage (Figure B4). People with the same availability of home/work charging portals face the equal probabilities of visiting public charging stations across the US as chances of running out of battery given the home or work charging availability are the same. Table 3.2 shows that the estimated waiting costs for consumers with accessible home or working charging are up to \$46 per year, whereas the consumers relying only on public charging face the waiting costs of \$177 to \$735 per year. The optimal solution by the model shows that the waiting costs are adjusted to \$73, \$12, and \$140 per year for the existing BEV owners of the low, medium, and high driving demand groups who still mostly have work charging (Figure 3.2). The low waiting cost is due to the minimal probability of visiting the public charging for people with either home or work charging. The joint imposition of the waiting cost and the range anxiety cost significantly impact the BEV adoptions in regions with less available charging, less fast-charging coverage, and higher electricity prices. They together lead to inhibited BEV's adoptions in California and Texas, where are subject to high waiting costs (Figure 3.3). The BEV stock drops to 11 million, with the 25 million drivers shifting to PHEVs in North and East areas as the second cheapest options.

3.3.4 Impact of Detour Cost

Both the BEV and FFV owners are subject to the inconvenience of detours, which indicates the extra time searching for the nearest stations. The estimated detour cost of BEV owners ranges widely from \$0-\$40 for the consumers with both home and work charging to as high as \$5,530 - \$26,615 for the consumers without fixed charging portals (Table 3.2). The drastic increase for consumers without home or work charging is due to the fact that the consumers solely rely on the public charging and need to detour for every recharge. The consumers therefore adjust their vehicle ownerships with detour costs of \$17, \$13, and \$41 for three mileage demand groups as the optimal solutions (Figure 3.2). The detour costs of refueling E85 for FFVs users are \$189, \$460, and \$785 per year, and higher than BEVs as E85 stations are sparser than charging stations and primarily clustered in the Midwest, which induces FFV buyers to move towards the Midwest to avoid detour costs (Figure 3.3). Meanwhile, the E85 fuel price is lowered by about the same amount of detour cost per liter. The increasing implicit subsidies for E85 provided by the ethanol policy offset the detour costs to maintain the price parity of E85 relative to E10.

The results in Table 3.3 show that the addition of the detour cost further reduces the BEV stock to only 9 million in 2030, whereas increase the FFV stock to 44 million and HBV to 12 million. The increasing FFVs stocks are mainly shifted from CV only in the area where the consumer cost of using E85 could be lower than E10 (including the detour cost), whereas the FFV stocks in the rest regions use only E10 and retire over time. The consequent electrification of VKT further dampens to 43% in the high-mileage demand group and to 24% in general. The fuel economy of the fleet marginally declines to 15.5 km per liter.

3.3.5 Impact of the Idiosyncratic Preference

We leverage the random error terms with the correlated nested vehicle choices and the heteroscedastic variance across market regions calibrated by Google Trend data (as formulated in Appendix A.3) to fully represent the random utility of consumers. The monetary values of the consumers' idiosyncratic preferences are shown as the error bar in Figure 3.2. The distribution of the error terms and their correlations are displayed in Figure B7 and Figure B9. The idiosyncratic preference term indicates the non-economic reason to own a vehicle, where the positive terms indicate the reluctance of buying the vehicle, and the negative preferences indicate the intention of paying premium and reduces the ownership cost of the vehicle. On average, CVs are attached with a value of \$825 per year, followed by \$234 for PHEVs, \$195 for BEVs, \$190 for FFVs, and \$148 for HBVs. The spatially heteroskedastic error terms for each vehicle type scaled by the Google Trend data result in standard errors of \$587 for CVs, \$590 for FFVs, \$556 for HBVs, \$564 for PHEVs, and \$557 for BEV. The dominating preference led by the CVs indicates the reluctance of the population to shift to the new technology.

The preference terms increase the new vehicle purchases to a total of 275 million, together with a 1% increase in the total VKT when overall vehicle ownership costs are cheaper. The estimated CVs stocks regain back to 208 million and BEVs gain the market share to 6%, whereas FFVs stocks in 2030 are close to the observation of 2019 vehicle stock (Table B3) with the rest 11% of the vehicle stocks are diversified with advanced vehicles. This vehicle stock change reduces the overall fuel efficiency of the fleet to 13.8 km per liter. The electrification of the low driving demand market increases to 3%, but those of the medium and high driving demand group declines with an overall electrification drops to 14% as PHEV are substituted by CVs. California becomes the most welcoming region in the US for alternative fuel vehicles, mostly HBVs,

PHEVs, and BEVs (as shown in Figure 3.3). The FFVs stocks spread broader around the Mid-West area.

3.4 Sensitivity Analysis

The market acceptance of battery electric vehicles and their contribution to the environment are uncertain as they are impacted by many exogenous technical and market factors, such as gasoline prices, policy incentives, EV technology improvement, and public charging availability. We examine their impacts on the transportation sector as well as the US economy on the basis of the Likely Outlook in scenario (5) (discussed in section 3.3.5). We also examine the welfare and environmental effects of these exogenous changes to the US economy.

3.4.1 No Tax Credit

In scenario (6), BEV and PHEV stocks drop to 1 and 9 million without the tax credit, and new vehicle sales share reduced to 0% and 8%, displaced by the CV and HBV options. The reduced electrification increases the GHG emissions in 2030 to 2,005 million MgCO₂ (7% increase) from 1,870 million MgCO₂ of the benchmark scenario (5). However, the emission level in 2030 is still 12% lower than the 2016 level (2,282 Mg CO₂) when the overall vehicle fleet improves the fuel economy over time.

3.4.2 Extended tax credit

With the 50% more tax credit on BEV and PHEV, the BEV stock increases to 46 million with a 28% share of the total new vehicle sale in 2030 and substitutes the CV stocks in the market. The electrification of VKT reaches 29% with the extended and aggressive EV tax credit with the most fuel-efficient vehicle fleet. The energy consumptions for transportation saves by 596 billion liters, whereas the electricity consumption for transportation reaches 33 gasoline-

equivalent billion liters. The GHG emission in 2030 reduced to 1,677 million MgCO₂, 26% less than the 2016 level. The average carbon intensity of the fleet reduces to 90 gCO₂ per km.

3.4.3 Volatile Gasoline Prices

The volatile fuel prices increase the uncertainty in fuel costs saving for BEV owners compared to driving conventional vehicles. Both the fuel savings and the BEV adoptions are expected to reduce if the prices of petroleum fuels are low (or vice versa). We examine the extent to which this is the case by simulating scenario (8) in which the world prices of gasoline and diesel are 2% lower than those in scenario (5), all else being equal. We also study the case in scenario (9), when world prices increase by 2% higher than scenario (5).

The results show that the stocks of alternative fuel vehicles are sensitive to the fuel prices. Compared to scenario (5) shown in Table 3.4, the 2% decrease in the fuel prices reduces the BEV stocks by 2 million and new vehicle sales in 2030 by 2%, replaced mostly by the CV. The electrification reduces mainly in the high driving demand group, in which consumers are sensitive to the fuel cost. The E10 consumption increases by 1%, and that leads to a 2% increase in the 2030 GHG emission of 1,889 million Mg CO₂. But the cumulative GHG emissions from 2016 to 2030 increase by only 0.2%. The average carbon intensity of the fleet increases to 115 gCO₂ per km (1% increase).

We find the 2% higher prices have a similar change of 2 million reductions in CV stocks but are then substituted by the HBV and PHEV relative to scenario (5) without changing the BEV stock. E10 reduces by 4 billion liters. The GHG emission reduces by 15 million Mg CO₂ (-1%) in 2030, and the cumulative GHG reduces by 80 million Mg CO₂ over the 2016-2030 period (-0.6%). The average carbon intensity of the fleet reduces to 113 gCO₂ per km (1% decrease). We

find that the change in GHG emission is robust to the price change as the demand elasticities of gasoline and diesel fuels are relatively low and fuel consumptions are relatively constant.

3.4.4 Impact of Charging Station Expansion

As the Biden administration rolls out the infrastructure investment plan, the goal of 500 thousand charging stations requires a tenfold increase from the current level of 47 thousand stations. Without details of how the plan will be implemented, we assume in this study an optimistic outlook of recharging station distribution of both L2 and fast-charging stations increasing at an annual rate of 26% starting from 2020 (47 thousand stations) to 500 thousand by 2030. By doing so, we increase the measurements of availability of charging portals relative to the gasoline station annually²¹, and also reduce the detour distances to the station by the same annual rate.

We find the consumers with better charging availability in scenario (10) face less than \$1 per year of range limitation cost, and the average detour cost reduces to \$0.02 to \$1.12 for the BEV consumers. However, the potential buyers with intensive driving demand without any home or working charging are still subject to the range limitation and waiting costs as high as \$79 to \$723 per year. Overall, improving only the charging availability may not be enough to offset the dominating preference of CVs over BEVs. The results show only 19 million BEV stocks (13% of the new vehicle sales in 2030) and overall electrified VKT increase marginally from 16%, compared to the 14% in scenario 5 (Table 3.4). The 2030 GHG emission reduces to 1,847 million Mg CO₂ (1% decrease), and cumulative GHG emissions from 2016 to 2030 reduce by 199 million Mg CO₂ (0.6% decrease).

²¹ The gasoline stations are assumed to be fixed from 2016 to 2030.

3.4.5 Technological Improvement of BEV Price Reduction

We also examine the reduced BEV prices by \$3,000 per vehicle in scenario (11), which are believed to be feasible with strategic manufacturing designs and a dedicated product platform by McKinsey (Baik et al. 2019). By including both the tax credit and the price reduction, the scenarios with significant drops in BEV cost induce adoptions up to 40 million, raising the overall electrification of VKT to 25%.

Compared to scenario (5), the \$3,000 price reduction per BEV reduces the E10 consumption by 52 billion liters but increases E85 by 5 billion liters and electricity consumption by 11 billion gasoline-equivalent liters. It is due to the ethanol mandate that requires a fixed amount of ethanol that the cut of E10 consumption by the electrification pushes the E85 consumption. The GHG emission in 2030 reduces to 1,732 million Mg CO₂ (24% lower than scenario 5). The cumulative GHG emissions from 2016 to 2030 drop by 910 million Mg CO₂ (3%). The percentage of GHG mitigation in 2030 greater than the cumulative emission reduction is due to the gradually enhanced fuel efficiency of the vehicle fleet, which achieves the highest level in 2030. The percentage changes in the GHG emissions are still slower than the changes in the BEV fleet as the additional GHG emission from electrification offset the emission mitigation credit.

3.4.6 Welfare Effect

We analyze the sensitivity of the social welfare distribution of the US economy to the policy, technological, and economic changes with the pessimistic and optimistic settings for BEV owners. Scenario 6 without any tax credit serves as a benchmark for welfare analysis. We find that the fully extended tax credit for BEVs and PHEVs until 2030 in scenario 5 enlarges the consumers' benefit of owning BEVs and PHEVs as well as FFVs, but reduces those of CVs and HBVs owners. However, the benefits of \$14 billion for light-duty consumers, \$53 billion for

diesel consumption, \$27 billion for the electricity sector, and \$17 billion from the social benefit of GHG mitigation are less than the government expenditure of \$150 billion mostly on the tax credit. The net total social welfare ends up with a \$40 billion loss.

The extended and 50% higher EV tax credit in scenario (7) further increases the magnitude of the above economic benefits for light-duty vehicle drivers to \$17 billion, electricity sector to \$72 billion, as well as the social benefits of GHG reduction to \$54 billion. However, the economic costs of the additional tax credit government paying for enlarges that leads to a \$422 billion total social welfare loss.

The lower world fuel market prices, in addition to the EV tax credit in scenario (8), enhance the consumer surpluses of liquid-fuel vehicle owners (CV and HBV) and diesel consumers, but reduces the crude oil producer surplus compared to the previous EV tax credit scenario. But the gains from the transportation (\$67 billion) and electricity sectors (\$27 billion) are offset by the government investment of \$135 billion. Overall, the total economic surplus reduces by \$25 billion. The social benefit of GHG (\$18 billion) results in a net total social welfare loss of \$10 billion. On the contrary, the 2% increase in the world fuel price in scenario (9) reduces the consumer surplus for both light-duty consumers and diesel consumers and increases the producer surplus of crude oil. The economic surplus reduces by \$89 billion, but the social benefit of GHG of \$19 billion is still lower than the economic loss and thus results in a net welfare loss of \$70 billion.

The optimistic scenarios considering the technological and economic improvements, however, show the higher total social welfare costs. The improved infrastructure charging distribution and the full tax credit worsen the total economic surplus of the transportation sector by \$7 billion. We find a better charging profile benefits the light-duty consumers with a

substantial increase in consumer surplus for BEV owners, but it reduces the economic benefit for diesel consumers due to the increased implicit taxes compared to the full-tax credit-only scenario offsetting the benefit of the light-duty market. This is exacerbated by the loss of \$8 billion, \$151 billion, and \$21 billion in government revenue in charging stations establishment, EV vehicle credit, and the reduced fuel tax revenue. Though the GHG emission benefit by \$22 billion, the net social welfare loses by \$156 billion.

When the prices of BEV reduce by \$3,000 beyond 2019, the BEV consumers lead the welfare gain followed by the FFV and PHEV and offset the welfare loss by the reduced CV and HBV stock. The light-duty consumers have an overall net benefit of \$74 billion. The diesel consumer surplus drops due to the higher diesel price raised by increasing implicit tax compared to the fully extended EV tax scenario. It is the result of the lower demand in E10 that widens the price differential between supply and demand of ethanol. But the required vehicle tax credit from the government still substantially increases by \$273 billion that offsets the gain from the transportation, electricity, and GHG mitigations. As a result, the net total social welfare loss is \$245 billion.

3.5 Discussion

This paper analyzes the behavioral determinants in vehicle choices and examines the uncertainties in the technological and economic changes that affect the decarbonization of transportation in the US over the 2016-2030 period. We construct and integrate a vehicle choice model into a dynamic, open-economy, multi-market optimization model (BEPAM) of US transportation, electricity, and agriculture sectors to endogenously determine the vehicle choices and fuel consumptions with a welfare-economic framework. Our study provides a first approximation of vehicle choices amid a rising trend of electrification in transportation using a

welfare framework approach that allowing for nested vehicle choices and capturing the randomized idiosyncratic preference. We also assess the social welfare impacts under market uncertainties of the electrification.

Another contribution of modeling electrified transportation to the literature is the joint consideration of consumers' behavioral characteristics together with the partial equilibrium energy system model. We examine the mechanism of each behavioral factor separately affecting the market acceptance of BEVs. Our analysis shows that BEVs can reach 42 million if behavioral concerns are not considered. The realization of the range limitation cost induces the BEV users away from without home or work charging but towards with access to the work charging or shift to PHEV and HBV as the next cheapest choices. The waiting cost further deters the BEV purchase in need of public charging in the area with relatively low availability of fast charging, coinciding with relatively higher regional electricity prices. The detour cost discourages BEVs adoption with less public charging availability but requires more FFV adoptions in the Midwest region to avoid the high detour costs of E85 fuel. Finally, together with all the above behavioral factors, the randomized preference representing the passion for the vehicle technology only induces the BEV adoption to 16 million in 2030 in the US.

The market acceptance of battery electric vehicles is subject to changes in policy incentives, vehicle prices, fuel prices, charging availability. BEV uptake is limited without any policy support but still achieves 12% in GHG emissions lower than the 2016 level with the overall efficient vehicle fleet. The aggressive 50% more EV tax credit increases the BEV share to 28% and reduces the GHG emission by 26% compared to 2016 level. Under optimistic scenarios, the proposed charging infrastructure of 500 thousand stations does not eliminate the inconvenience cost and is not enough to reverse the dominating preference of CVs over BEVs. But the lower

BEV prices by \$3,000 and \$5,700 with the presence of the tax credit significantly enlarge the BEV adoptions. We also find the BEV adoption is more responsive than GHG mitigation.

The results of welfare analysis show a general conclusion that the social welfare cost rises as BEVs adoptions increase. Compared to the no-tax credit scenario, the EV tax credit benefits the light-duty consumers and diesel consumers, and the electricity sector. But environmental benefits of GHG are not enough to cover the expenses on the EV tax credit by the government that leads to a net welfare loss. We find the fuel prices affect the decision of EV adoptions and thus proportionally change the government investment in EV tax credit. The other optimistic scenarios with improved charging and lower BEV prices increase the government expenses that dominate the welfare loss despite increasing welfare gain for light-duty consumers and slow GHG mitigation benefits.

Our analysis has several policy implications. First, it shows the behavioral and technological, and economic determinants of vehicle and fuel choices in different market segments across regions. We suggest the combination of strategies including increasing range capacity, expanding the diffusion of the public charging infrastructure and fast charging portals, reducing fast charging duration, and finally attracting the buying interest to minimize irrational behavioral factors that inhibit the EV adoptions. Second, we find the EV tax credits are costly to induce the EV adoption when the GHG emission benefits are much less than the government expenditure on the tax credit. We also find the GHG mitigation is less responsive to electrification than BEV's adoption in the transportation market, despite substantial government support for the EV tax credit. It is because the diesel market is robust to the electrification in the light-duty vehicle fleet, and the increased emission from electricity generation for expanded electrified mobility would reversely deter the GHG mitigation in the transportation sector. This

paper suggests the need to include other decarbonization strategies (such as low-carbon advanced biofuel) combined with electrification efforts to expedite the GHG mitigation in the transportation sector.

Tables and Figures

Table 3.1 The scenario settings

	Scenario number	Settings
Likely outlook	1	Benchmark
	2	Benchmark + Range limitation
	3	Benchmark + Range limitation+ Waiting cost
	4	Benchmark + Range limitation+ Waiting cost + Detour cost
	5	Benchmark + Range limitation+ Waiting cost + Detour cost + Idiosyncratic preferences
Scenario outlook	6	Scenario (5) + No tax credit
	7	Scenario (5) + 50% higher tax credit
	8	Scenario (5) + 2% lower gasoline and diesel prices
	9	Scenario (5) + 2% higher gasoline and diesel prices
	10	Scenario (5) + 500 thousand stations by 2030
	11	Scenario (5) + \$3,000 cut in BEV price beyond 2019

Table 3.2 The ex-ante arithmetic average inconvenience costs of new battery electric vehicle owners with different charging availability and VKT driving demand over the 2016-2030 period (\$ per year)

Charging mode ¹	Driving demand	Range limitation	Waiting cost	Detour cost
Both home and work charging	Low	0	0	0
	Medium	3	0	0
	High	65	1	40
Home charging	Low	0	0	0
	Medium	15	1	48
	High	212	30	1,208
Work charging	Low	0	0	0
	Medium	30	3	83
	High	346	46	1,754
No home or work charging	Low	4,130	177	5,530
	Medium	6,017	430	12,353
	High	6,681	735	26,615

Table 3.2 The ex-ante arithmetic average inconvenience costs of new battery electric vehicle owners with different charging availability and VKT driving demand over the 2016-2030 period (\$ per year) (Cont.)

Note of Table 3.2:

1. All charging groups are still provided with public charging.
2. Back-of-the-envelope calculation:

2.1 Range limitation cost

Based on the quantification method and data introduced in Appendix B.2.1, the average efficient ranges ($eVMT_{\text{chrg}}$) for four charging groups are 441 km (both home and work), 327 km (home), 289 km (work), and 27 km (none). The average probability of running out of battery depends on the randomized mileage, which are 0% (low), 0.04% (medium), 0.89% (high) for the charging group with both home and work portals; 0% (low), 0.21% (medium), and 2.9% (high) for the home charging; and 0% (low), 0.41% (medium), and 4.74% (high) for the work charging; and 57%, 82%, and 91% for the group without fixed charging portals. We multiply the probability by 365 days to get the total number of days running out of battery and proxy of \$20 per day rental cost to get the estimated range limitation cost.

2.2 Waiting cost

We assume the consumers of each driving demand group driving to their full capacity of VKT for new vehicles: 8139 km, 21,666 km, and 37,337 km for consumers with low, medium, and high driving demand (based on the average annualized mileage driven from the National Household Traveled Survey illustrated in Figure B1). The average range capacity of a representative EV model over the 2016-2030 period after full charge is 365 km. Consumers without home or work charging rely solely on public charging, whereas the probabilities of using public charging are close to 0%. The average time value is \$14 per hour and requires charge duration on average across regions is 1.8 hours. Based on the calculation steps (Appendix B.2.2), the estimated waiting costs are as in Table 2.

2.3 Detour cost

With the same driving demand, range capacity, the value of time, and probability of using public charging used as note 2.2, and the average detour distance across the US of 13.9 km, the detour costs for consumers with different availability of charging and driving demand following the steps are provided in Appendix B.2.3.

Table 3.3 Effect of behavioral factors on the transportation sector in 2030

	Calibrated Outcome in 2016	Benchmark (1)	+ Range (2)	+Range +Waiting (3)	+Range +Waiting +Detour (4)	+Range +Waiting +Detour +Idiosyncratic preference (5)
Total Vehicle Stock (million)*	241	272	272	272	272	275
CV	216 (90%)	160 (59%)	159 (59%)	163 (60%)	153 (56%)	208 (76%)
FFV	20 (8%)	35 (13%)	35 (13%)	32 (12%)	44 (16%)	20 (7%)
HBV	4 (2%)	3 (1%)	7 (2%)	7 (3%)	7 (2%)	12 (4%)
PHEV	0 (0%)	32 (12%)	36 (13%)	60 (22%)	59 (22%)	19 (7%)
BEV	0 (0%)	42 (16%)	35 (13%)	11 (4%)	9 (3%)	16 (6%)
Overall Electrification (% of total VKT)	0	37	33	25	24	14
Low driving demand	0	0	0	0	0	3
Medium driving demand	0	17	17	17	16	8
High driving demand	0	75	66	44	43	25
VKT by light-duty fleet (billion km)	4,423	5,333	5,332	5,330	5,330	5,370
VKT by diesel fleet (billion km)	699	909	909	909	898	897
Fuel efficiency of light-duty fleet (km per liter)**	8.4	16.8	16.4	15.6	15.5	13.8

* The numbers in the parentheses are stock share

** Volumes are converted to gasoline-equivalent liter.

Table 3.4 Effect of market uncertainties on transportation in 2030

	Benchmark +Range +Waiting +Detour +Idiosyncratic preference (5)	+ No Tax credit (6)	+ 50% More tax credit (7)	+ 2% Lower exported gasoline and diesel price (8)	+ 2% Higher exported gasoline and diesel price (9)	+ Improved Charging (10)	+ Reduced EV price by 3,000 (11)
Vehicle Stock (million)*	275	275	275	275	275	275	275
CV	208 (76%)	230 (85%)	177 (64%)	210 (76%)	206 (75%)	206 (76%)	190 (70%)
FFV	20 (7%)	18 (6%)	24 (9%)	20 (7%)	20 (7%)	20 (7%)	20 (8%)
HBV	12 (4%)	17 (6%)	10 (4%)	12 (4%)	13 (5%)	12 (4%)	11 (4%)
PHEV	19 (7%)	9 (3%)	19 (7%)	19 (7%)	20 (7%)	19 (7%)	13 (5%)
BEV	16 (6%)	1 (0%)	46 (17%)	14 (5%)	16 (6%)	19 (7%)	40 (15%)
New Vehicle Sales share (%)							
CV	58%	77%	42%	59%	54%	58%	48%
FFV	8%	4%	8%	7%	7%	6%	6%
HBV	9%	11%	9%	9%	11%	9%	10%
PHEV	14%	8%	13%	14%	15%	14%	10%
BEV	13%	0%	28%	11%	13%	13%	26%
Electrification (% of total VKT)	14	3	29	13	14	16	25
Low driving demand	3	0	5	2	3	3	3
Medium driving demand	8	2	23	8	8	8	18
High driving demand	25	5	48	23	26	30	43
VKT by light-duty Fleet (billion km)	5,370	5,368	5,372	5,371	5,369	5,370	5,371
VKT by diesel fleet (billion km)	897	898	892	900	894	895	893
Fuel efficiency of light-duty fleet (km per liter)**	13.8	12.8	15.6	13.7	13.9	14.0	15.1

Table 3.4 Effect of market uncertainties on transportation in 2030 (Cont.)

Energy Consumption for Transportation (billion gasoline equivalent liter)	642	673	596	647	652	636	609
E10	349	398	281	355	362	342	300
E85	22	17	29	21	21	23	27
Blended diesel	254	254	252	255	256	253	253
Electricity	17	4	33	15	14	18	28
GHG emission in 2030 (million Mg CO ₂)	1,870	2,005	1,677	1,889	1,855	1,847	1,732
GHG reduction relative to 2016 (%)	18	12	26	17	19	19	24
Cumulative GHG emissions from 2016-2030 (million Mg CO ₂)	31,775	32,449	30,455	31,860	31,695	31,580	30,869
Average carbon intensity of the fleet (gCO ₂ per km)	114	130	90	115	113	111	97

* The numbers in the parentheses are stock share

**Volumes are converted to gasoline-equivalent liter.

Table 3.5 Effect of market uncertainties on social welfare over 2016-2030 (billion \$)

	No Tax Credit (6)	EV tax credit (5)	EV tax credit+ 50% More tax credit (7)	EV tax credit+ 2% Lower exported gasoline and diesel price (8)	EV tax credit+ 2% Higher exported gasoline and diesel price (9)	EV tax credit+ Improved Charging (10)	EV tax credit+ Reduced BEV price by 3,000 (11)
Relative change to No Tax Credit scenario							
Economic surplus (a)	168,758	-57	-475	-25	-89	-178	-289
Agricultural sector	2,999	0	-1	0	-1	5	5
Agricultural consumers	2,110	0	0	0	0	1	1
Agricultural producers	888	0	-1	0	-1	5	5

Table 3.5 Effect of market uncertainties on social welfare over 2016-2030 (billion \$) (Cont.)

Transportation fuel sector	154,771	67	-6	88	42	-7	-12
Light-duty vehicle consumers	143,578	14	17	46	-15	48	74
CV	123,972	-4,254	-11,941	-3,682	-4,581	-4,986	-8,512
FFV	11,403	362	1,124	303	382	401	607
HBV	5,974	-1,090	-1,646	-1,071	-1,071	-1,139	-1,321
PHEV	1,871	2,150	1,747	2,085	2,328	2,034	469
BEV	358	2,844	10,733	2,410	2,928	3,738	8,830
VKT diesel consumers	10,269	53	-21	59	26	-54	-84
Crude oil producer	924	-1	-2	-17	30	-1	-2
Electricity sector	10,048	27	72	23	27	4	29
Electricity consumers	6,953	-33	-97	-27	-33	-48	-104
Electricity producers	3,095	59	170	50	60	52	133
Government revenue	941	-150	-541	-135	-157	-181	-312
Fuel tax revenue	941	-16	-49	-14	-18	-21	-39
Vehicle tax credit	0	-134	-492	-121	-139	-151	-273
Infrastructure	0	0	0	0	0	-8	0
Social benefit of GHG emissions (b)	-2,724	17	54	14	19	22	44
Agriculture	-112	0	0	0	0	0	0
Transportation	-1,337	24	73	21	27	31	57
Electricity	-1,285	-7	-19	-6	-7	-8	-13
Total social welfare							
(a) + (b)	166,034	-40	-422	-10	-70	-156	-245

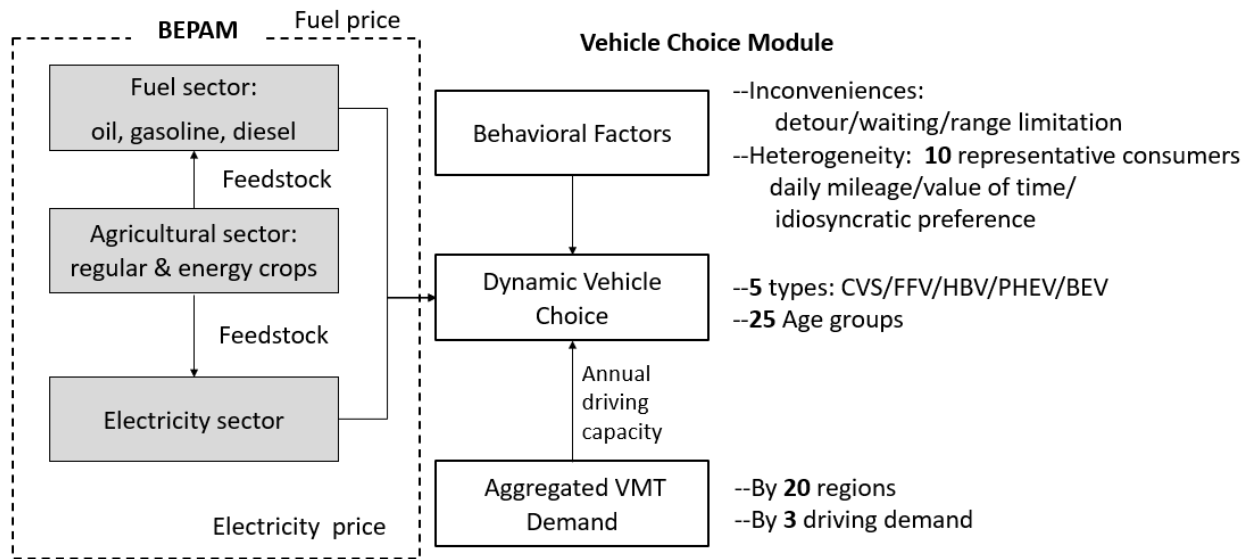


Figure 3.1 The integrated model structure of vehicle choice module with BEPAM

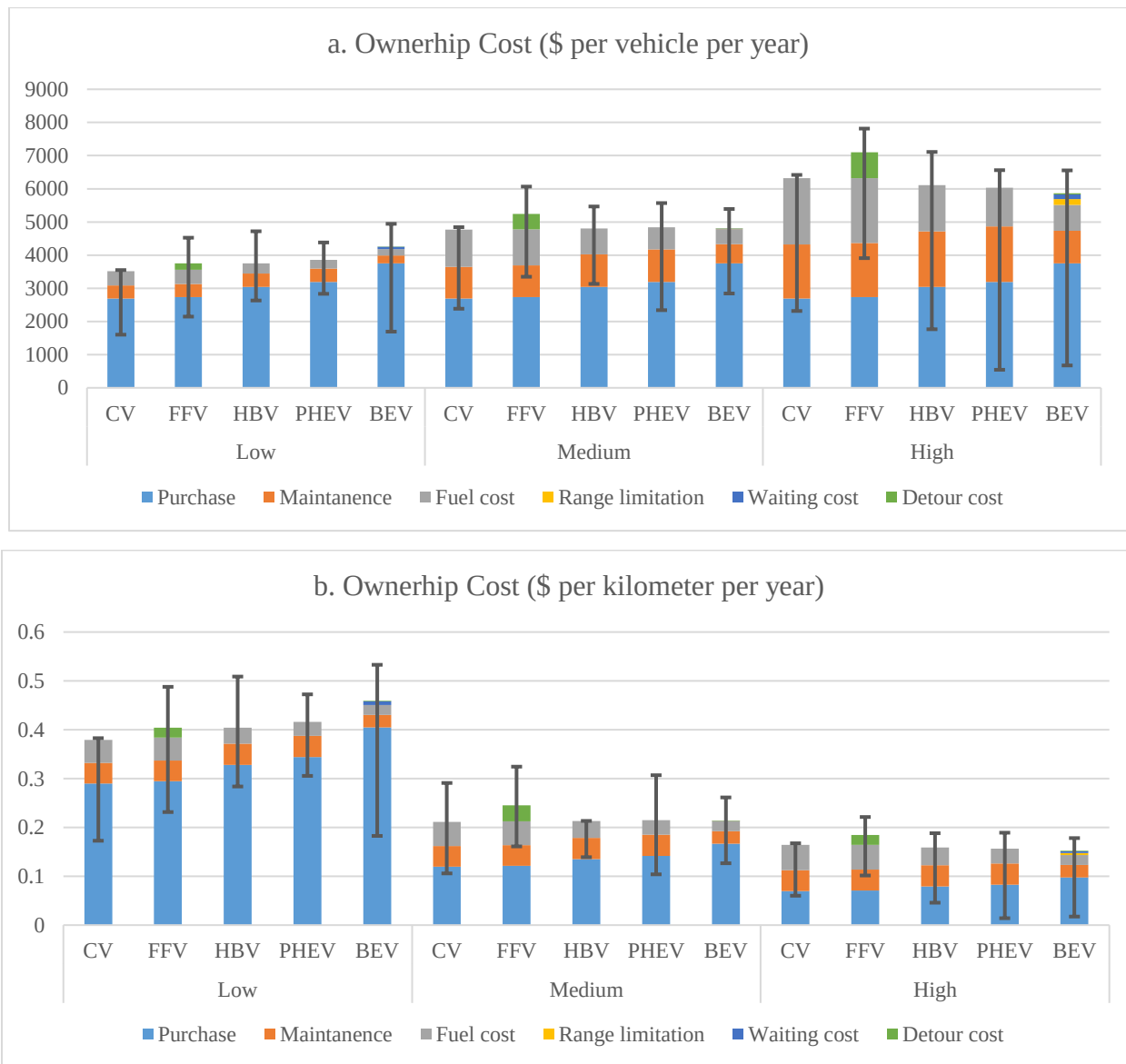


Figure 3.2 The annualized cost for owners of five vehicle powertrains of three driving demand groups from 2016 to 2030. Panel a shows the itemized ownership costs for each vehicle, and panel b shows the itemized ownership cost per kilometer driven per year. The error bars show the random error term of the idiosyncratic preference. Scenario (1) only considers the purchase cost, maintenance cost, and fuel costs; scenario (2) adds range limitation cost into consideration; scenario (3) adds the waiting cost; scenario (4) adds the detour cost; and scenario (5) includes the error bars representing idiosyncratic preference.

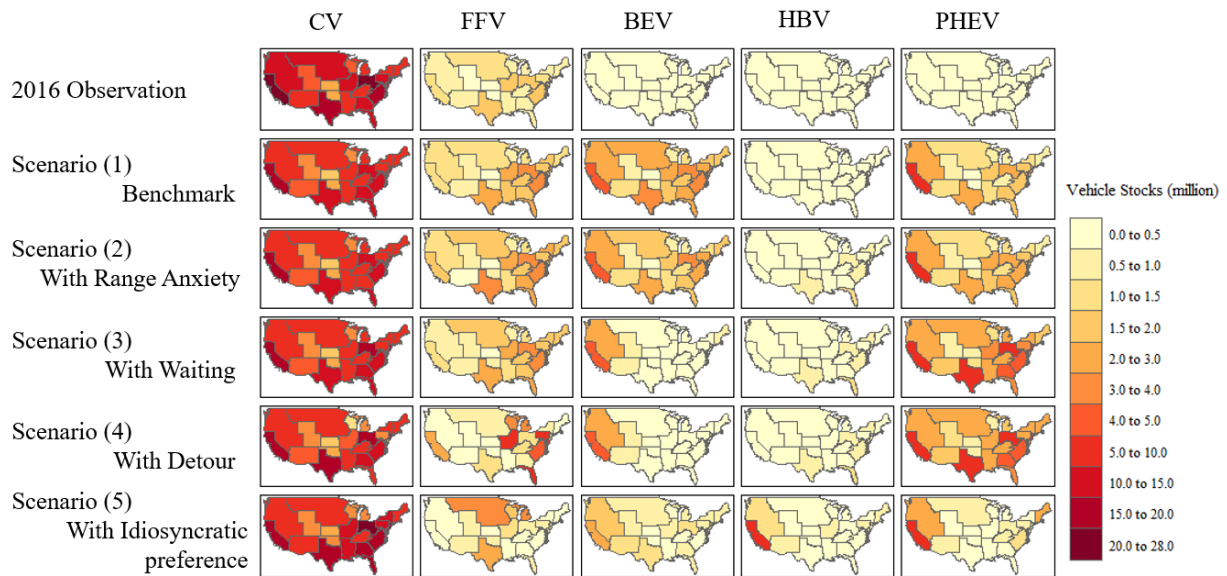


Figure 3.3 Effect of behavioral factors on the regional distribution of vehicle powertrain in 2030

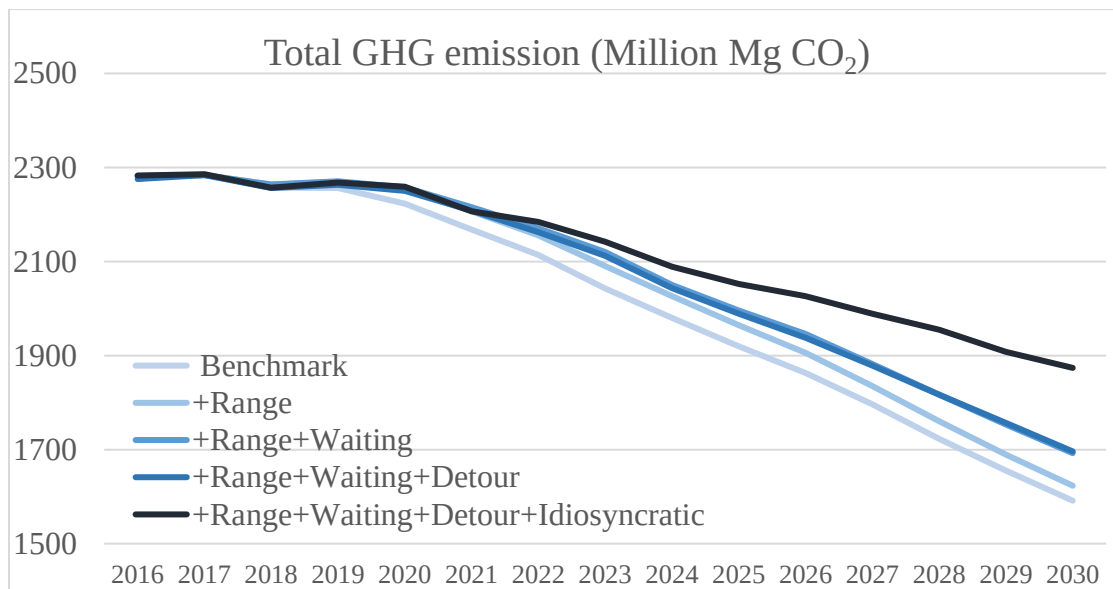


Figure 3.4 Annual GHG emissions from transportation

CHAPTER 4 The Imperative for Cellulosic Biofuels in an Electrifying Vehicle Market

4.1 Introduction

Achieving the goal of a 50% reduction in greenhouse gas emission (GHG) by 2030 lower than the 2005 level and net-zero emission by 2050— addressed by the Biden administration's climate policy— will require a portfolio of strategies (US EPA 2020), especially for the transportation sector. That inevitably requires a shift to low carbon fuels and alternative powertrains vehicles, such as electric vehicles running on electricity and flex-fuel vehicles capable of using high blends of ethanol. The electric vehicle (EV) buyers of battery electric vehicles and plug-in hybrid vehicles are granted federal vehicle credits of \$7,500 and \$2,500 respectively. The restrictive bans on gasoline-fueled vehicles proposed by California, New York City, and Massachusetts also indirectly push EV sales²². In promoting the biofuel vehicle fleet, the existing ethanol blend mandate of 56 billion liters of corn ethanol and potential extension of 61 billion liters of cellulosic ethanol raise the ethanol blend in motor fuels with at least 20% to 60% less emission intensity than gasoline. 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 increasing the 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 their interactive effects on the fuel market, electricity market, and agricultural sectors. Rarely has literature discussed the interactions of the policies of both electrification incentives and biofuel blend mandate and their synergistic/agonistic effects on the alternative fuel fleets and US economy.

²² Four states in the US have proposed banning the sale of passenger vehicles (primarily cars and buses) powered by fossil fuels such as petrol, liquefied petroleum gas and diesel at some time in the future.

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 their joint implications on adoptions of alternative fuel vehicles and energy consumption, as well as the welfare and environmental impacts on the US economy. The volumetric target of the ethanol blend mandate is implemented as the blend mandate on the total volume of gasoline and diesel to increase the production of high ethanol blended fuel. The high blend of ethanol fuel beyond the current blend level of 10% is compatible with the dual-fuel engine equipped by the flexible-fuel vehicle (FFV), which can significantly reduce GHG emissions (Dwivedi et al. 2015; Wang et al. 2012). The performance of FFV running on advanced biofuel could even outperform the electric vehicle with the low lifetime emission intensity (Gelfand et al. 2020). The electric vehicles (EV) running on the electric-powered engine enhances fuel efficiency and eliminates 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, despite the emission per mile reaches a record low since 2005 (EPA 2018a). Both the recent observation and the future projections show an expanding petroleum-fueled vehicle fleets, whereas the alternative fuel vehicle shares are limited and projected to be only 10% by 2040 (US DOE 2019; EIA 2021). The electro-mobility confronts the behavioral, technological, and economic challenges (as discussed in Chapter 3). The demand rigidities in high ethanol blends are restricted by the limited

incentives for the adoption of flex-fuel vehicles (FFV) and retail prices (Khanna, Rajagopal and Zilberman 2021).

To accelerate the GHG reduction in the transportation sector, we consider imposing the 61 billion liters of cellulosic biofuel mandate in addition to the existing 56 billion liters of corn ethanol as mandated by the Renewable Fuel Standard (RFS). Although the volumetric targets of biofuels beyond 2022 are yet to be determined, forward-looking analysis can inform the policy discussions of the potential economic and environmental implications of extending the corn ethanol mandate and the cellulosic biofuel mandate in the long term. A substantial literature has examined the cost-effectiveness of cellulosic biofuel in reducing GHG emissions by replacing fossil fuel and sequestering 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 the leading policy support for EVs, such as EV tax credit and gasoline-vehicle ban, jointly with the extended cellulosic biofuel policy. 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. Wang et al. 2012 find cellulosic ethanol production provides the highest GHG emission benefit among bioethanol feedstocks. The upscaling cellulosic biofuel production using the carbon capture technique could lower the carbon intensity of biofuel (-179 to 20 g CO₂ per MJ) that are comparable to electric vehicles (Gelfand et al. 2020). Meier et al. (2015) find that up to 56.4 billion gallons of cellulosic biofuel are required in addition to a 40% of mileage electrification in order to achieve the target of GHG reduction by 80%. The EVs can reduce

GHG emission by as high as 64% compared to the counterpart (Meier et al. 2015), depending on 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 buying alternative fuel vehicles, neither do they consider the effect of the overall fleet change 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. For most consumers, the price of E85 needs to be lower or at most at energy equivalent parity to regular motor fuel (E10) for consumers to consume it (Pouliot & Babcock 2015), whereas for other consumers (for example, in California), there is a willingness to pay more for E85 than the energy equivalent value of E10. The E85 demand is also affected by the geographical distribution 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) in taking the market share.

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 (Chen et al. 2014; Chen et al. 2021). The Annual Energy Outlook estimates

vehicle choices by the US Energy Information Administration (2019) by applying three-stage linear utility functions of coefficients from the work of Greene (2001), which only considers the observable characteristics. Similar approaches of the reduced form of utility functions are applied to other simulation models to estimate the vehicle shares (Stephens et al. 2017). The Agent-Based Model developed by Noori and Tatari (2016) estimates the market share of EV also based on a similar framework of discrete choices using the reduced form of utility. These linear forms of the utility, however, only specify the observed terms with the underlying assumption of uncorrelated unobserved terms that determine the probability of purchase. There are behaviorally realistic vehicle choice models considering inconveniences costs and idiosyncratic preferences that 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 explain the economic drives behind the vehicle choices with fixed fuel prices and traveling demand. We build on their linear framework of vehicle ownership costs and further extend the transportation module with vehicle choice under the partial equilibrium framework by addressing the consumers' utility of owning the vehicle to satisfy the driving need with endogenously choices of vehicles, fuel mix, and mileage driven.

Our model contributes to the literature with the normative 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). We first provide a conceptual graphical analysis of policy analysis to study the extent to which the combination of the policies affects 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 that specifies the fuel,

transportation, electricity, and agriculture sectors under a welfare-economic framework (as discussed in Chapter 3). 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 B1 in Appendix B): 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 simultaneously solve the consumers' choices of the vehicle type, fuel consumption, mileage driven, and charge modes by maximizing social welfare. The solutions of the partial equilibrium show the least-cost solutions of meeting the driving demand under the trending electrifications of US transportation with technical-economic and behavioral considerations. 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 to 10 representative consumers for each demand segment described above. 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 impacts considering both incentives for the electrification and low carbon fuel blend mandate. We then introduce the numerical simulation model and scenarios in section 4.3. Section 4.4 presents the numerical impacts of the cellulosic biofuel policy and electrification incentives on the transportation sector, specifically on vehicle stocks, energy consumption, and welfare and environmental implications. Lastly, in Section 4.5, we conclude the paper with a discussion of the implications of our findings.

4.2 Conceptual Framework

We first analyze the implication of policy interaction between the ethanol blend mandate (denoted as M) and policy incentive for EV, such as tax credit (denoted as T), with a graphical analysis in Figure 4.1. We examine the fuel market under four alternative scenarios: without any policy intervention (denoted as 0), with the EV tax credit (T), the ethanol blend mandate (M), and the joint implementation of ethanol blend mandate and EV tax credit ($M+T$).

The quantity of ethanol is aggregated from the ethanol blended in E10 and E85 (as shown in panels a and b of Figure 4.1). The aggregated ethanol demand curve prioritizes the ethanol blended in E10 until it reaches the blend wall²³, and then followed by the ethanol demand in E85 (D_M^E in Figure 4.1c). Without any policy intervention, the aggregated ethanol demand curve is limited at a low ethanol blend (D_0^e in Figure 4.1a), whereas E85 demand is negligible. The ethanol blend mandate raises the demand for E10 (D_M^e in Figure 4.1a) and E85 (D_M^c in Figure 4.1b). The price difference between the supply and aggregated demand curve in the ethanol market (Figure 4.1c) is the implicit subsidy granted by the ethanol blend mandate (shown as $subsidy_M$ in Figure 4.1c), which theoretically is the shadow price of the policy constraints and RIN values as in chapter 2.

The EV tax credit alone without blend mandate promotes EV adoptions, thus reduces the consumption of E10 and the blended ethanol 10% of E10 (D_T^e in Figure 4.1a and Figure 4.1c). The addition of the ethanol blend mandate at the presence of the EV tax credit ($M+T$) indicates a

²³ 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).

higher blend rate applied to the fossil fuel base of the sum of gasoline and diesel volumes²⁴ to secure the same amount of ethanol as mandated. Therefore, the ethanol blend mandate (T+M) shifts the demand for E10 outward (D_{M+T}^e in Figure 4.1a) from without ethanol mandate (D_T^e), but lower than the original demand under blend mandate (D_M^e) due to the lower overall demand of E10 caused by the EV tax credit. The demand for E85, however, shift outwards (D_{M+T}^c in Figure 4.1b) as the volumetric ethanol target pushes E85 consumption instead as ethanol blended in E10 declines. The aggregated demand for ethanol (D_{M+T}^E) shifts downwards with the kink moved to the left and followed by flatter E85 demand that intersects with the mandated level of ethanol (Q_M^E) with a new implicit subsidy wedging between the supply and new demand (denoted as subsidy_{M+T} in Figure 4.1c). The flatter slopes of the piecewise demand curve (D_{M+T}^E) result from the increasing blend rate. Whether the subsidy_{M+T} is greater or smaller than the original implicit subsidy_M is ambiguous. It largely depends on the extent to which the E10 is substituted, how much E85 is induced, as well as the blend rate that determines the slope of the demand curve. The Figure 4.1c illustrate the case when the reduced E10 demand but flatter demand curve lower implicit subsidy while increasing the E85 consumption.

The revenue-neutral ethanol blend mandate policy also imposes implicit taxes on both gasoline and diesel with the same amount due to the joint base of the ethanol blend mandate (as found in Chapter 2). Many previous studies find the ethanol blend mandate alone shifts the gasoline demand inward from D_0^g to D_M^g (Figure 4.1d), creating the price wedge between the demand and supply with the implicit tax_M (Babcock et al. 2013; Thompson et al. 2010). The EV tax credit without ethanol blend mandate parallelly reduces the gasoline demand (D_T^g) relative to

²⁴ As specified 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>

no policy scenario. If jointly implement both the biofuel blend mandate and EV tax credit, the demand curve shifts inward from D_T^g to D_{M+T}^g with a steeper slope and a higher blend rate than D_T^g . The quantity of gasoline is reduced to Q_{M+T}^g . We note that the change of implicit taxes is also ambiguous comparing tax_M to tax_{M+T} . It depends on how much gasoline demand is replaced by the EV tax credit (D_T^g), the increase in the ethanol blend rate determining the change of the slope of the demand curves, and the quantity of gasoline at the equilibrium (Q_{M+T}^g).

4.3 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 sum of discounted consumer and producer surpluses subject to policy constraints of corn ethanol only mandate or with cellulosic ethanol mandate, with various technological and material balance constraints. The market equilibrium is achieved for the transportation, electricity, and agriculture sectors when demand equals supply. The technological constraints of the transportation sector describe that the fuel economy of the vehicle determines the fuel consumption to meet the VKT traveling demand. In the transportation sector, the material balance is defined as traveling demand met by the capacity of driving mileage supplied by vehicles in stock.

We specify the consumers' utility of drivers as part of the social welfare with consumer surplus derived from the aggregated demand for VKT minus the ownership costs of the vehicle. The ownership costs include not only the economic costs of vehicle prices, fuel costs, and maintenance costs but also the behavioral inconvenience costs. We capture the heterogeneity of

consumers' behavior in daily driving and the value of time. We further mimic the random utility framework by including the stochastic error terms to represent the idiosyncratic preferences.

4.3.1 Transportation Sector

We construct a dynamic transportation model that endogenously solves vehicle kilometers traveled (VKT) demand, fuel consumption, and vehicle adoptions. The heterogeneous driving demands are specified by downward sloping linear demand functions of vehicle kilometers traveled (VKT) for twenty electricity market regions and three driving demand groups based on the annual VKT from National Household Travel Survey (Federal Highway Administration 2017) and driving cost from Alternative Fuel Data Center (AFDC 2019). We consider a representative vehicle fleet that takes 99% of the total US light-duty vehicle stock (in Table B.1)²⁵ based on the vehicle stock distribution by fuel types, driving demand groups, vehicle ages, and states in 2016. Specifically, in the light-duty fleet, we include vehicles of five different powertrains: conventional vehicle (CV), flexible-fuel vehicle (FFV), hybrid gasoline vehicle (HBV), plug-in hybrid vehicle (PHEV), and battery electric vehicle (BEV). We represent the US transportation demand with ten representative consumers considering the stochasticity in behavior of daily driving demand, the value of time, and idiosyncratic preferences for consumers in three driving demand groups, and four charging modes in addition to public charging, with ownership of vehicle aging up to 24 years, across 20 regions in the US.

We address intangible disutility costs of range limitation, waiting, and detour associated with ownership of alternative powertrain vehicles. Range limitation cost quantifies the cost of the alternative modes of transportation if BEV runs out of battery. Waiting cost is the total valuation

²⁵ We don't model the vehicle choice submodules of diesel vehicle fleet as it is dominated by the conventional diesel vehicle without much diversification by alternative fuels.

of time spent inside the public charging stations while waiting for charging. Detour cost is measured by the value of time spent on the road to find the nearest station. An idiosyncratic preference for each vehicle powertrain is added and calibrated 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 B and Chapter 3.

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

4.3.2 Electricity Sector

We also include the supply and demand of the electricity at the regional market level, 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 aggregates 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 latest

eGRID data (EPA 2016). The additional electricity demand due to the increasing electric vehicle shifts the aggregate demand outward. The endogenous solutions of market equilibrium of electricity prices determine the electricity sources and also the electricity prices of driving EV. We estimate the cost of establishing the charging portals of both L2 and fast-charging by multiplying the estimates of a single outlet from DOE (2015) with the numbers of portals required for stations, assuming each station on average having three portals. We assume the station and portals increases at a rate of 2% annually, according to the AEO outlook (EIA 2019a).

4.3.3 Agricultural Sector

The agricultural sector endogenously determines the quantities of row crops, biomass feedstock, biofuels, and fossil fuels and their prices to meet the market demand. It incorporates domestic agricultural and fuel markets in the US and trade of 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).

4.3.4 Welfare Analysis

To analyze the social welfare effects of the policy incentives for decarbonization, we assess the changes 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, compared to the baseline 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. But because gasoline and diesel fuel supply are proportionally produced by crude oil as zero-profit owners, the fuel producer surplus equals crude oil producer surplus. 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).

4.3.5 GHG Estimation

Unlike EPA and NHTSA overlook the upstream emission only considering 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 over the vehicle kilometer traveled (VKT) under each scenario. We examine the cumulative emissions of each scenario from 2016 to 2040 and the GHG emission in 2040. Finally, we calculate the abatement cost of the policy strategy by dividing the change of economic surplus over the cumulative GHG mitigation compared to the baseline scenario.

4.3.6 Scenarios

We first investigate three potential policy scenarios that promote electrification in the transportation sector over the 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 electricity. 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 sales of internal combustion engines starting 2020 in addition to scenario (2).

We then analyze the above three scenarios under the extended cellulosic biofuel mandate to achieve 61 billion liters of cellulosic biofuel production by 2030 as mandated by the Renewable Fuel Standard (RFS) and define them as scenarios (4) to (6). We assume that cellulosic ethanol production grows linearly from 0.87 billion liters in 2016 to 61 billion liters in 2040, while annual corn ethanol levels remain constant at 56 billion liters.

4.4 Results

We validate the model by comparing simulated outcomes with observed data in the fuel and vehicle sectors under scenario (1) over the 2016-2019 period. We find that the four-year average of fuel consumption and production in the US and the rest of the world generally deviate by less than 2% from observed data (Table B2 in Appendix B.4). The fuel prices on average deviate by 12% from the observation. The vehicle stocks are 9% less than the observed levels. The deviations of the simulated outcomes of the updated BEPAM from their observed actual values over the 2016–2019 period are generally within a 10% tolerance used in previous studies applying BEPAM (Chen et al. 2020; Hudiburg et al. 2016; Oliver and Khanna 2017b).

4.4.1 Effect of Policy Interaction on Fuel Incentives

The numerical results of implicit price incentives for biofuel policy for gasoline, diesel, and ethanol are provided in Table 4.1. We find that implicit subsidy on ethanol production increases from $\$0.33 \text{ L}^{-1}$ of baseline scenario (1) to $\$0.39 \text{ L}^{-1}$ when adding the EV tax credit in scenario (2), and implicit tax also increases from $\$0.04 \text{ L}^{-1}$ to $\$0.06 \text{ L}^{-1}$ in 2040. The gasoline and diesel are subject to the same amount of implicit tax as the ethanol blend mandate is defined by the sum of gasoline and diesel (as we discussed in Chapter 2). The price incentive (or implicit subsidy) increases to bridge the gap between the lower overall ethanol demand (from the displaced E10 and slow-growing E85 demand) and the production cost of the mandated levels of ethanol. The addition of the CV ban to the EV tax credit, however, reduces the implicit subsidy to $\$0.31 \text{ L}^{-1}$ when the market demand for E85 is pushed by the low E10 consumption due to the same volumetric target (same as illustrated in Figure 4.1), whereas the implicit taxes on petroleum fuels remain the same²⁶.

The scenarios (4) to (6) with cellulosic ethanol mandate increase the implicit subsidies and taxes because the stringent ethanol blend mandate doubles the blend mandates with 61 billion liters of cellulosic ethanol mandated in 2040. The addition of EV tax credit still increases the implicit subsidies from $\$0.38 \text{ L}^{-1}$ to 0.56 L^{-1} and also implicit taxes from $\$0.10 \text{ L}^{-1}$ to $\$0.18 \text{ L}^{-1}$. The CV ban reduces the implicit tax and subsidy relative to scenario (5) for the same reason that the expanded E85 market demand reduces the incentives needed as we find in scenario (3).

²⁶ The implicit tax is the multiplication of increased blend rate and dropping shadow price of the policy constraints (also equals to ethanol subsidy).

4.4.2 Effect of Electrification Incentives

EIA predicted that in 2040 the VKT demand will be 23% above the 2016 level; the prices of BEVs will be 11% cheaper; and vehicles of all types will be more efficient (details are provided in Appendix A.1 and A.2). The outcomes of vehicle choices, energy consumption, and vehicles kilometer traveled (VKT) in 2040 are presented in Table 4.2 for policy scenarios under study. By 2040, the total vehicle stock expands to 298 million (as shown in Table 4.2) and is diversified with alternative-fuel vehicles. The total market shares of HBV and PHEV increase to 18%, and the BEVs stock rises to 4 million by 2040. The electrified VKT contributed by both BEVs and PHEVs rises to 10%, whereas the ethanol blend of the VKT remains at 10%. The efficient and diversified vehicle fleet reduces the consumption of E10 in 2040 by 11% compared to the baseline scenario that reversely pushes the E85 consumption and FFV adoption to maintain the 56 billion liters of corn ethanol consumption. The detour distances for E85 and charging stations decline as the infrastructure slowly diffuses across the country with an annual increase rate of 2%, which needs less price incentive for the E85 users to offset the inconvenience cost so that E85 price is higher than the 2016 level. The increasing driving demand raises the E10 price above the 2016 level, despite the fact that the vehicles are efficient and E10 are displaced by other fuel types.

In case of extending tax credits of \$7,500 and \$2,500 for BEV and PHEV to 2040 in scenario (2), stocks of BEVs and PHEVs are further enlarged to 46 million and 51 million and together account for 32% of the total vehicle fleet. They contribute to a 36% of the VKT electrified but only reduce 15% of total energy consumption compared to scenario (1). We find E85 consumption increases by 12 billion liters compared to baseline policy scenario (1) to meet the 56 billion liters of ethanol mandate when 74 billion liters reduction in E10 consumption is

substituted by the 29 billion increase of gasoline-equivalent liters of electricity. The EV tax credit lowers the E85 price due to the increased implicit subsidy received in 2040, as discussed in 4.4.1 that the lower E85 price induces 4 million more FFV adoptions.

The aggressive policy restriction of CV bans together with EV tax credit over the 2016-2040 period raises the overall ownership costs of EVs that marginally reduce both the total light-duty VKT and total vehicle stocks that enhance the fuel efficiency to 24 km per liter. 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 to 108 million, followed by the FFV stock of 84 million and BEV stock of 72 million. E10 consumption drops to 127 billion liters, but E85 increases to 46 billion liters. The electricity consumption increases to 68 billion gasoline-equivalent liters, whereas diesel consumption remains unchanged as an implicit tax does not change on both diesel and gasoline (Table 4.1). Altogether, they contribute to a reduction of 148 billion liters of energy consumption (-22%) compared to the baseline scenario (1). The extent of energy savings is lower than the drops in CV stock. It is due to the fact that reduced implicit subsidy for ethanol and constant taxes on petroleum fuels due to the restrictive CV ban deter energy saving and GHG mitigation.

4.4.3 Effect of Cellulosic Ethanol Mandate

The implementation of Corn + Cellulosic Ethanol Mandate increases the volumetric target of cellulosic ethanol linearly to the goal of 61 billion liters over the 2016-2040 period in addition to the extant production capacity of 56 billion liters of corn ethanol, and it thus doubles the ethanol share for light-duty VKT to 18% by 2040 (Table 4.2). The stringent ethanol policy induces 50 million FFV stock and 90 billion liters of E85 consumption in 2040 (Table 4.2). The total energy consumption reduces by 1%, contributed mainly by reduced E10 and diesel consumption, but is

then offset by the 68 billion liters of increased E85 consumption compared to the baseline scenario (1). The E85 price decreases by \$0.02 per liter, whereas the E10 price increases by \$0.05 per liter compared to the baseline scenario (2).

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 increases in FFV stock by 40 million and BEV stock by 48 million are greater than the sum of the increases from EV tax credit (scenario 2) and from cellulosic ethanol mandate (scenario 4) alone. It is because EV tax credit contracts the demand for motor fuels that reversely increases the ethanol blend rate 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 cellulosic ethanol mandate increases the BEVs stock by 5 million compared to scenario (3), whereas PHEV is replaced by FFV stock. FFVs and BEVs are complementary in taking the market share of the vehicle stock and replacing the E10 fuels. The cellulosic ethanol mandate increases E85 consumption by 66 billion liters and replaces 49 billion liters of E10 fuel use compared to the scenario (3). The total energy consumption reversely increases by 5 billion liters compared to the counterpart without cellulosic blend mandate in scenario (3). The reduced implicit subsidy for ethanol raises the E85 price, but E85 consumption is still pushed by the blend mandate to meet the volumetric target of ethanol.

4.4.4 GHG Intensity of Vehicle

The greenhouse gas (GHG) emissions per mile of five vehicle types under different policy scenarios are displayed in Figure 4.2²⁷. Under the baseline policy scenario (1) in Figure 4.2, the CV has the highest emission intensity, followed by FFV with 26% less emission due to the consumption of E85 that has lower carbon intensity. HBV and PHEV with higher fuel efficiency show a 30% and 67% less emission than CV, whereas BEV has zero-emission intensity as the electricity for transportation is 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 E85 consumption. The joint imposition of EV tax credit and CV ban of scenario (3) raises the emission 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 when FFV becomes the second cheapest vehicle option substituting for CV and still heavily consumes E10. The carbon intensities of HBV, PHEV, and BEV relatively remain the same.

Lastly, we find that the Cellulosic Ethanol Mandate in 2040 cuts the emission intensity of all vehicles. The carbon intensities of FFVs are 60%-67% lower than those of the CV and driven by the greater consumption of E85. The emission intensities of all other vehicles in scenario (4) to (6) reduce by 3% universally in 2040 relative to no cellulosic ethanol mandate counterparts in scenario (1) to (3). It is because the higher E10 prices speed up the adoption of alternative fuel vehicles that raise the average fuel efficiency, and the faster retirement of the old CVs also reduces the carbon intensity. The CV ban together with the EV tax credit in scenario (6), raises the carbon intensity of CV by 15% and that of FFV by 12% compared to scenario (4) without

²⁷ We use the same unit of gram per mile as EPA uses for GHG emission standard

any EV incentive. It is due to the same reason that the remaining CVs in stock are aged and inefficient, and FFVs are the second-best options on the road using primarily E10.

4.4.5 Total GHG Emission

We calculate the GHG emissions of transportation, electricity, and agriculture sectors, as shown in Table 4.3. In 2040, the transportation and electricity sectors account for 47% and 50% of the total emissions, and the share of cumulative GHG emissions by both the transportation and electricity sectors are the same at 48%. 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 use that leads to a total net decrease of 6% of the GHG emissions compared to the baseline scenario (1). The cumulative emission reduction caused by the EV tax is only 2%. The lower cumulative reduction percentage compared to the last-year reduction in 2040 shows the highest fuel efficiency of the fleet and the highest potential of GHG reduction achieved 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 over 2016-2040 period.

The imposition of the cellulosic policy in scenarios (4)-(6) lowers both the 2040 GHG emissions and the cumulative emissions over 2016-2040 compared to that of the counterpart scenarios (1)-(3) without cellulosic ethanol mandate. The cumulative emissions from agricultural sectors reduce by 13%-14%, but the absolute contribution is relative small. The Cellulosic Ethanol Mandate alone in scenario (4) outperforms the EV tax credit in scenario (2) in cumulative emission reduction. The cumulative GHG emissions over the 2016-2040 period is additive with the joint implementation of the cellulosic ethanol mandate and the EV tax credit in achieving a 5% reduction in, adding from the emission reduction achieved by the EV tax credit

and cellulosic ethanol mandate alone. 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 by itself in scenario (4).

4.4.6 Welfare Analysis

We find that the EV tax credit will lead to an overall \$125 billion economic loss over the 2016-2040 period relative to the baseline scenario of no-EV tax credit 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' surplus of driving BEV and PHEV but reducing those of the CV and HBV. The higher implicit subsidies and taxes discussed in section 4.4.1 reduce the consumer benefit of diesel by \$72 billion. The electricity market benefits by \$95 billion (1%) as both power consumption and prices rise for transportation purposes, increasing the producers' surplus and reducing the consumer surplus in the electricity market. The government revenue from fuel taxes falls by \$62 billion (-5%) due to less petroleum fuel consumption and is further exacerbated by \$369 billion of EV tax credit associated with the EV purchase. The expense of EV tax credit is greater than the economic gain from the transportation fuel sector and electricity sector. As the cumulative GHG emission reduces by 2,334 million Mg CO₂ (-2%), the abatement cost of CO₂ with the tax credit for EV is \$54 per MgCO₂. It is close to the widely accepted value of the social cost of carbon at \$50 per MgCO₂.

The additional CV ban in scenario (3) forces drivers to buy more expensive alternative fuel vehicles, leading to an overall net economic loss of \$607 billion compared to the baseline policy scenario. The declining CV stocks lead to a drastic loss of \$44,518 billion (-30%) in the consumer surplus of CV but enhance those of all other alternative fuel vehicles that offset the loss with a net gain of \$117 billion (0.1%) for light-duty vehicles compared to the baseline

scenario (1). The welfare gain for the light-duty consumers is lower than the scenario (2) without the CV bans due to the expensive vehicle costs. The electricity sector further enhances the economic benefit by \$202 billion. The government revenue loss is exacerbated by the reduced fuel tax revenue of \$145 billion and the increased requirement for the vehicle tax credit by \$678 billion. Implementing the CV ban together with EV tax credit doubles the abatement cost to \$111 per Mg CO₂ as the economic loss grows faster than the GHG reduction.

The cellulosic ethanol mandate reduces the overall economic surpluses by \$417 billion (-0.1%). The stringent biofuel policy raises the E10 and diesel prices thus lower the economic benefits 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 economic benefits for EVs and FFV drivers reduce the net welfare loss by 478 billion (-0.1%). It is greater than the sum of welfare gains from the agricultural sector for ethanol production (\$53 billion), the electricity sector for synergic electrification (\$1 billion), and government revenue for imported ethanol (\$7 billion). The cumulative GHG emission of 2,945 Million Mg CO₂ (-3%) is higher than that with EV Tax credit in scenario (2), but the high economic cost leads to an abatement cost of \$142 per Mg CO₂.

The cellulosic ethanol mandate, together with the EV tax credit, worsens the total economic benefit by \$668 billion (-0.3%) compared to the baseline policy scenario (1). It is greater than the sum of economic welfare losses of the individually implemented EV tax credit in scenario (2) and cellulosic ethanol mandate in scenario (4). Combining EV tax credit and the cellulosic ethanol mandate creates 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. Though the light-duty consumers benefit from the EV tax credit increases by \$237 billion, the

diesel fuel users bear the loss of \$606 billion, leading to a net of \$370 billion loss in the transportation sector. The higher implicit tax due to the addition of the EV tax credit discussed in section 4.4.1 aggravates the welfare loss for diesel consumers compared to scenario (4) without the EV tax credit. The synergistic welfare effects of jointly implemented cellulosic ethanol mandate and the EV tax credit on government revenue (\$462 billion of welfare loss) and electricity market (\$98 billion of welfare gain) are more than the sum of the welfare effects of the separate policy impact of cellulosic ethanol mandate (scenario 4) and EV tax credit (scenario 2). The cumulative GHG emission reduction of the policy interaction at 5,425 Million Mg (-5%) is also more than the sum of the reduction of the single implementation of the EV tax credit and cellulosic ethanol mandate. The abatement cost reduces to \$123 per Mg CO₂, 13% lower than the level of cellulosic ethanol alone (\$142 per Mg CO₂) but higher than that of the EV tax credit alone (\$54 per Mg CO₂). It is mainly driven by the welfare cost of light-duty consumers who lose the economic welfare by the cellulosic ethanol mandate but still benefit from the EV tax credit.

The addition of the CV ban to the EV tax credit and the cellulosic ethanol mandate deteriorates the total economic loss by \$1,022 billion but enhances the cumulative GHG mitigation to 8,143 Mg CO₂, compared to the baseline scenario (1). Though the results are less than the sum of welfare effects of the separately implemented cellulosic ethanol mandate and CV ban in scenarios (3) and (4), the impacts are higher than either two individual scenarios. The abatement cost is \$126 per Mg CO₂, which is 11% lower than that of the cellulosic scenario (\$142 per Mg CO₂), but higher than that of CV ban only (\$111 per Mg CO₂) in scenario (3). The joint implementation of cellulosic ethanol mandate and electrification incentives for the EV tax credit and CV ban can be more efficient in reducing GHG emissions at a lower cost, due to the

compounded effects of the lower EV prices, more expensive vehicle choices under CV ban, and the fuel prices on the consumers surplus.

4.5 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 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 the policy. The numerical results show that the EV tax credit combined with the ethanol blend mandate enlarge the price incentives for ethanol and petroleum fuels. However, the aggressive electrification policies of the CV ban and EV tax credit reduces the implicit subsidy for E85 fuel.

The numerical simulations show the EV tax credit alone and scenario with both the EV tax credit and CV ban diversify the vehicle fleet with 34% and 53% of electrified VKT, 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 to

diversify vehicle adoptions by raising the blend rate and cutting the E10 demand. The aggressive CV ban also helps boost flex-fuel vehicle sales complementarily with EV.

The cellulosic ethanol mandate helps to lower the carbon intensity of FFV from being the second-highest emission-intensive vehicle to as much as PHEV by raising the ethanol blend. Overall, the cellulosic ethanol mandate mitigates the cumulative GHG emissions by 3% compared to the counterparts without the cellulosic ethanol mandate, contributed by transportation and agricultural sectors. The synergy between cellulosic ethanol mandate and EV tax credit as well as CV bans leads to additive mitigation in GHG emissions.

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. The welfare cost of the cellulosic ethanol mandate is still more expensive than the extended EV tax credit despite more government investment required for the increased EV adoption. The interaction between the cellulosic ethanol mandate and the electrification policy incentives leads to a compounded effect on consumer surplus from the lower EV prices, CV ban, and the ambiguous fuel prices affected by the interactions of the policies.

We find that the abatement cost of the EV tax credit (\$54 per MgCO_2) is comparable to the social cost of carbon. The scenario of the CV ban and EV tax credit doubles the abatement cost relative to the scenario with EV tax credit alone. The cellulosic ethanol mandate increases the abatement cost to \$142 MgCO_2 , mainly born by the fuel consumers. The synergy created by the cellulosic ethanol mandate and EV tax credit, and even with the CV ban reversely reduces the abatement cost to \$123 per MgCO_2 and \$126 per MgCO_2 due to the benefit of the enhanced consumers surplus from the EV tax credit.

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 policies displace E10 and emission by raising E10 prices. Our findings should also provide normative evidence to policymakers to extend the blend rate requirement to 2040 for the cellulosic mandate. Our approach provides the first estimation of the implication of the biofuel mandate implementation amid the trend of electrification and assesses the distributional welfare effect considering the consumers' utility obtained from vehicle ownership with behavioral considerations.

Tables and Figures

Table 4.1 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
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

Table 4.2 Effect of policy scenarios on the 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 (90%)	221 (74%)	166 (56%)	5 (2%)	191 (64%)	130 (43%)	4 (2%)
FFV	20 (8%)	21 (7%)	25 (8%)	84 (28%)	50 (17%)	61 (20%)	111 (37%)
HBV	4 (2%)	20 (7%)	11 (4%)	29 (10%)	17 (6%)	9 (3%)	21 (7%)
PHEV	0 (0%)	32 (11%)	51 (17%)	108 (36%)	35 (12%)	47 (16%)	83 (28%)
BEV	0 (0%)	4 (1%)	46 (15%)	72 (24%)	5 (2%)	52 (17%)	77 (26%)
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

Table 4.2 Effect of policy scenarios on the transportation sector in 2040 (Cont.)

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)							
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)							
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 4.3 GHG emissions in 2040 and cumulative GHG emissions

	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 4.4 Effect of policy scenarios 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
<i>Agricultural sector</i>	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
<i>Transportation fuel sector</i>	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
<i>Electricity sector</i>	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
<i>Government revenue</i>	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 MgCO₂)		54	111	142	123	126

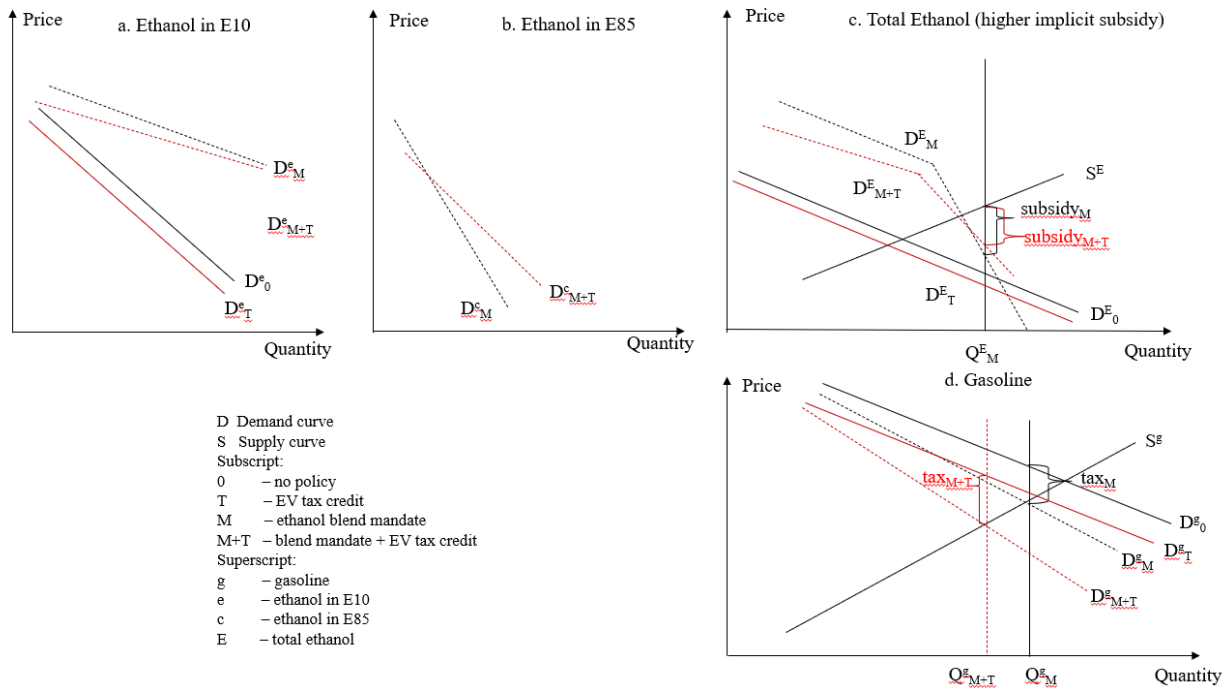


Figure 4.1 Policy implication of joint implementation of biofuel policy and EV tax credit

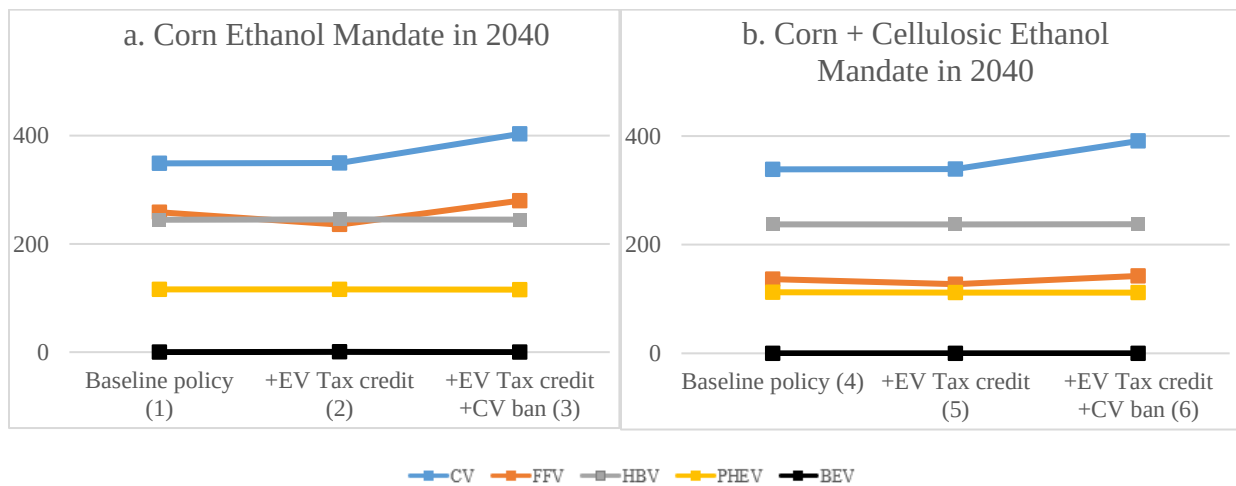


Figure 4.2 The carbon intensity of vehicle mileage under each scenario (g CO₂ per mile)

CHAPTER 5: CONCLUSION

The overriding theme of the three papers included in this dissertation is the decarbonization strategies of US transportation by displacing the consumption of petroleum fuels, including increasing the blends of low-carbon biofuels and promoting alternative fuel vehicles. This dissertation aims at threefold targets: (1) addressing the impact of policy designs of Renewable Fuel Standard on the fuel markets, (2) examining the behavioral and technological determinants of electric vehicles, and (3) analyzing the synergic/agnostic effects of the policy interaction between biofuel blend mandates and EV incentives.

In particular, in Chapter 2, I study the disincentives created by the design of the RFS and accompanying policies, specifically the nested structure, joint-base blend rate, biodiesel tax credit, and cellulosic waiver credit in creating a blend wall and I analyze its welfare and GHG implications. I apply a multi-market partial equilibrium model integrating the fuel distribution system from the wholesale producers to the consumers and incorporate the policy features in the model to reflect the existing policy designs. The results show analytically and numerically that the discretionary policy and flexibility in compliance reduce the incentives for selling a higher blend of corn and cellulosic ethanol and lead to an overall blend wall problem. The findings include: (1) the blend rate mandate with the joint base of gasoline and diesel leads to an implicit tax on diesel consumers and an implicit subsidy on gasoline-ethanol consumers; (2) the nested feature results in biodiesel over-production when its elasticity-weighted marginal production cost is relatively low; (3) the provision of a biodiesel tax credit and cellulosic waiver credit increases the competitiveness of biodiesel. They all raise the retail price of higher ethanol blend (E85) higher than the energy-equivalent price of motor fuel (E10). The flexibility of compliance

increases social welfare and GHG savings marginally. The RFS reduces the welfare of ethanol fuel producers, benefits biodiesel producers, and delays the displacement of gasoline.

Chapter 3 analyzes behavioral, technological, and economic determinants in electric vehicle adoptions and examines the market uncertainties that affect the decarbonization of transportation in the US over the 2016-2030 period. We construct and integrate a vehicle choice model into a dynamic, open-economy, multi-market optimization model (BEPAM) of US transportation, electricity, and agriculture sectors to endogenously determine the vehicle mix and fuel consumptions amid the hype of electrified vehicle fleet with a welfare-economic framework. We find that the range limitation cost and detour cost reduce the BEV adoption without home or work charging and in regions with sparse public charging stations. The waiting cost further deters the BEV purchase in regions with the low availability of fast charging. The detour cost, however, induces more FFV adoptions in the Midwest region, where new consumers can afford the detour costs of E85 fuels. Finally, the randomized preference representing the passion for the particular technology raises the BEV adoption to only 16 million in 2030 when the majority still prefers conventional vehicles over the EV in the US. The market acceptance of battery electric vehicles relies on the changes in vehicle prices, fuel market, charging availability, and policy incentives. The federal tax credit benefits the economic welfare of light-duty consumers and the diesel consumers and electricity sector, although the BEV adoption is low; however, the financial support required for the government usually offsets the benefit for light-duty consumers. The optimistic scenarios with better charging deployment and EV price reduction requiring significant government support for EV tax credits still lead to a net welfare loss. Moreover, the benefit from GHG mitigation is less responsive than the electrification of the

vehicle fleet to the market uncertainties due to the increased GHG emissions from the electricity sector.

The last chapter examines the economic and environmental implications of the portfolio of policy strategies, combining the stringent cellulosic ethanol mandate with EV tax credit and conventional vehicle ban over the 2016-2040 period. We first analytically show that the interaction between the ethanol blend mandate and the electrification incentives leads to ambiguous changes in the implicit price incentives for E85, E10, and diesel from the blend mandate. The direction of price change depends on the extent to which both E10 being substituted by the EV tax credit and E85 increased to meet the volumetric mandate, as well as the blend rate. The numerical simulations show that the cellulosic ethanol mandate synergizes with the EV tax credit to diversify vehicle adoptions by raising the blend rate and cutting the E10 demand. The aggressive CV ban even prioritizes the flex-fuel vehicle as one of the top vehicle choices. The synergy between cellulosic ethanol mandate and EV tax credit as well as CV bans reduces the FFV carbon intensity and additively mitigates the GHG emissions. The cellulosic ethanol mandate leads to greater net welfare loss than the EV tax credit alone due to high fuel prices. But the joint implementation of both policies reduces abatement costs lower than the cellulosic ethanol mandate alone. Our analysis shows that the cellulosic biofuel mandate has the potential to reduce energy consumption, reduce GHG emissions, complement other climate policies and would, therefore, warrant policy support.

The research described here provides many policy implications given the advanced understanding of the biofuel blend mandate, especially the Renewable Fuel Standard, as well as the incentives for electrifications and their interactive policy implications on the fuel mix, vehicle mix in the US. The unintended market failure of the design features of the Renewable

Fuel Standard suggests the need to shift towards a non-nested structure with a separate fossil fuel base in order to eliminate the blend wall and to create demand for cellulosic ethanol, which has significantly greater potential to reduce the GHG intensity of fuel than biodiesel. The second paper implies that electrification of the vehicle fleet is restricted by behavioral, technological, and economic factors and could only be maintained by EV tax credit, though its GHG mitigation is limited. The third paper indicates that the electrification incentives and blending biofuel policy complementarily reduce energy consumption and emission by synergistically raising the E10 price and reducing economic surplus and GHG mitigation. Our approach does provide the first estimation of the implication of the biofuel mandate amid the trend of electrification and assess the distributional welfare effects considering the consumers' utility obtained by vehicle choices associated with behavioral considerations.

There are many pathways of further research that could be undertaken with the modeling framework developed in this dissertation utilizing the broad and flexible. First, the stylized model of the policy analysis framework of Renewable Fuel Standard could be extended to include the trade effect with the rest of the world. The model also can easily be extended to include the differentiated demand for E10 and E85 fuels, considering the heterogeneous preference towards different fuel types. The vehicle choice model incorporated with the dynamic partial-equilibrium model in chapters 3 and 4 could also be expanded to include the spatial variation in ethanol markets and ethanol fuel prices to differentiate the regional effect instead of the uniform effect nationally. Also, it is of interest to differentiate the sources of electricity that serve the transportation on the margin of the market equilibrium in each electricity market region. By doing so, the dynamics of electrification of the vehicle fleet subject to the risks of the electricity demand and supply shocks could be further studied across regions.

REFERENCES

- 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].
- Allcott, H., and N. Wozny. 2014. "Gasoline Prices, Fuel Economy, and the Energy Paradox." *Review of Economics and Statistics* 96(5).
- 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].
- Anderson, S.T., I.W.H. Parry, J.M. Sallee, and C. Fischer. 2011. "Automobile Fuel Economy Standards: Impacts, Efficiency, and Alternatives." *Review of Environmental Economics and Policy* 5(1):89–108. Available at: <https://academic.oup.com/reep/article-lookup/doi/10.1093/reep/req021> [Accessed August 14, 2017].
- Ashkrof, P., G. Homem de Almeida Correia, and B. van Arem. 2020. "Analysis of the effect of charging needs on battery electric vehicle drivers' route choice behaviour: A case study in the Netherlands." *Transportation Research Part D: Transport and Environment* 78:102206.
- Axsen, J., J. Bailey, and M.A. Castro. 2015. "Preference and lifestyle heterogeneity among potential plug-in electric vehicle buyers." *Energy Economics* 50:190–201. Available at: <https://linkinghub.elsevier.com/retrieve/pii/S0140988315001553> [Accessed March 15, 2021].
- Babae, S., A.S. Nagpure, and J.F. Decarolis. 2014. "How much do electric drive vehicles matter to future U.S. emissions?" *Environ Sci Technol* 48(3):1382–1390.
- 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].
- Baik, Y., R. Hertzke, H. Patrick, and S. Knupfer. 2019. "Making electric vehicles profitable." *McKinsey*. Available at: <https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/making-electric-vehicles-profitable> [Accessed January 22, 2020].
- 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."
- BloombergNEF. 2019. "A Behind the Scenes Take on Lithium-ion Battery Prices." Available at: <https://about.bnef.com/blog/behind-scenes-take-lithium-ion-battery-prices/> [Accessed January 22, 2020].
- Bonges, H.A., and A.C. Lusk. 2016. "Addressing electric vehicle (EV) sales and range anxiety through parking layout, policy and regulation." *Transportation Research Part A: Policy and Practice* 83:63–73.
- Bradley, M., and A. Daly. 1994. "Use of the logit scaling approach to test for rank-order and fatigue effects in stated preference data." KluwerAcademic Publishers.
- 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].
- Busse, M.R., C.R. Knittel, and F. Zettelmeyer. 2013. “Are consumers myopic? Evidence from new and used car purchases.” *American Economic Review* 103(1):220–256.
- 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*.
- 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, X., H. Huang, M. Khanna, and H. Önal. 2014. “Alternative transportation fuel standards: Welfare effects and climate benefits.” *Journal of Environmental Economics and Management* 67(3):241–257. Available at: <http://www.sciencedirect.com/science/article/pii/S0095069613001277> [Accessed November 30, 2016].
- Coppess, J., and S. Irwin. 2017. “The Other General Waiver: RFS and Severe Economic Harm.” *farmdoc daily* (7):187((7):187). Available at: <http://farmdocdaily.illinois.edu/2017/10/general-waiver-rfs-and-severe-economic-harm.html> [Accessed October 25, 2017].
- 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].
- Cui, J., H. Lapan, G. Moschini, and J. Cooper. 2011. “Welfare Impacts of Alternative Biofuel and Energy Policies.” *American Journal of Agricultural Economics* 93(5):1235–1256.
- Davis, S.C., and R.G. Boundy. 2018. “Transportation Energy Data Book: Edition 37.”
- DOE. 2021a. “Alternative Fueling Station Locator.” Available at: <https://afdc.energy.gov/stations/#/find/nearest>.
- 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.”
- DOE. 2021b. “Gross Domestic Product and Vehicle Miles Traveled Declined in 2020.” Available at: <https://www.energy.gov/eere/vehicles/articles/fotw-1181-april-12-2021-gross-domestic-product-and-vehicle-miles-traveled> [Accessed April 20, 2021].
- 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](https://www.transportation.gov/sites/dot.gov/files/docs/2015%20Revised%20Value%20of%20Travel%20Time%20Guidance.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. 2019a. “Annual Energy Outlook 2019 with projections to 2050.” Available at: <https://www.eia.gov/outlooks/aeo/> [Accessed May 23, 2019].
- EIA. 2014. “Gasoline prices tend to have little effect on demand for car travel.” Available at: <https://www.eia.gov/todayinenergy/detail.php?id=19191>.

- 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].
- EIA. 2019b. “Monthly Energy Review.” Available at: <https://www.eia.gov/totalenergy/data/monthly/index.php> [Accessed March 30, 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. 2018a. “Highlights of the Automotive Trends Report.” Available at: <https://www.epa.gov/automotive-trends/highlights-automotive-trends-report> [Accessed August 17, 2019].
- EPA. 2010. “Regulation of Fuels and Fuel Additives: Changes to Renewable Fuel Standard Program; Final Rule.” Available at: <https://www.govinfo.gov/content/pkg/FR-2010-03-26/pdf/2010-3851.pdf> [Accessed April 26, 2021].
- EPA. 2015. “Renewable Fuel Standard Program: Standards for 2014, 2015, and 2016 and Biomass-Based Diesel Volume for 2017.” *Federal Register*. Available at: <https://www.federalregister.gov/documents/2015/06/10/2015-13956/renewable-fuel-standard-program-standards-for-2014-2015-and-2016-and-biomass-based-diesel-volume-for> [Accessed April 26, 2021].
- EPA. 2018b. “Renewable Fuel Standard Program: Standards for 2019 and BiomassBased Diesel Volume for 2020.” Available at: www.regulations.gov. [Accessed December 5, 2018].
- 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].
- Ferguson, M., M. Mohamed, C.D. Higgins, E. Abotalebi, and P. Kanaroglou. 2018. “How open are Canadian households to electric vehicles? A national latent class choice analysis with willingness-to-pay and metropolitan characterization.” *Transportation Research Part D: Transport and Environment* 58:208–224. Available at: <https://linkinghub.elsevier.com/retrieve/pii/S1361920916306058> [Accessed March 10, 2021].
- Gartner. 2020. “2020 Hype Cycle for Connected and Smart Mobility.” Available at: <https://www.sae.org/news/2020/09/2020-hype-cycle-for-connected-vehicles-and-smart-mobility#:~:text=2020 Hype Cycle for Connected and Smart Mobility&text=Gartner Inc.’s annual Hype,automated driving and new mobility.&text=The hard work of commercializing m.>
- 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.
- de Gorter, H., and D.R. Just. 2009. “The Economics of a Blend Mandate for Biofuels.” *American Journal of Agricultural Economics* 91(3):738–750.
- Greene, D.L. 2001. *TAFV Alternative Fuels and Vehicles Choice Model Documentation*.

- Available at: papers://a0cac570-6072-44e1-9d44-cdd15f758707/Paper/p352.
- Hidrué, M.K., G.R. Parsons, W. Kempton, and M.P. Gardner. 2011. "Willingness to pay for electric vehicles and their attributes." *Resource and Energy Economics* 33(3):686–705. Available at: <https://linkinghub.elsevier.com/retrieve/pii/S0928765511000200> [Accessed December 14, 2020].
- 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].
- Hu, L., J. Dong, and Z. Lin. 2019. "Modeling charging behavior of battery electric vehicle drivers: A cumulative prospect theory based approach." *Transportation Research Part C: Emerging Technologies* 102:474–489.
- Huang, H., M. Khanna, H. Önal, and X. Chen. 2013. "Stacking low carbon policies on the renewable fuels standard: Economic and greenhouse gas implications." *Energy Policy* 56:5–15.
- 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].
- Hughes, J.E., C.R. Knittel, and D. Sperling. 2008. "Evidence of a shift in the short-run price elasticity of gasoline demand." *Energy Journal* 29(1):113–134. Available at: www.iaee.org/en/publications/ejarticle.aspx?id=2243 [Accessed April 19, 2021].
- Irwin, S. 2013. "Estimating the Biodiesel Supply Curve." *farmdoc daily*. Available at: <https://farmdocdaily.illinois.edu/2013/10/estimating-biodiesel-supply-curve.html> [Accessed December 3, 2018].
- Irwin, S., K. McCormack, and J. Stock. 2020. "The Price of Biodiesel RINs and Economic Fundamentals." *American Journal of Agricultural Economics* 102(3):734–752.
- Johnson, C., and M. Melendez. 2007. "E85 Retail Business Case: When and Why to Sell E85." Available at: <https://www.afdc.energy.gov/pdfs/41590.pdf> [Accessed October 31, 2018].
- Kannan, R., N. Strachan, S. Pye, G. Anandarajah, and N. Balta-Ozkan. 2007. "UK Markal Model Documentation." Available at: www.ucl.ac.uk/energy-models/models/uk-markal.
- 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].
- Knittel, C.R., B.S. Meiselman, J.H. Stock, D. Burkholder, B. Hengst, and M. Shelby. 2017. "The Pass-Through of RIN Prices to Wholesale and Retail Fuels under the Renewable Fuel Standard." *Journal of the Association of Environmental and Resource Economists* 4(4):1081–1119. Available at: https://scholar.harvard.edu/files/stock/files/pass-through_of_rin_prices_1.pdf [Accessed May 20, 2017].
- Korting, C., and D.R. Just. 2017. "Demystifying RINs: A partial equilibrium model of U.S. biofuel markets." *Energy Economics* 64:353–362. Available at: http://ac.els-cdn.com/S014098831730110X/1-s2.0-S014098831730110X-main.pdf?_tid=99fbd74c-8127-11e7-83a0-00000aacb360&acdnat=1502739455_1d42d52e68773bc7a47a80cd8988a22b [Accessed August 14, 2017].
- Korting, C., D.R. Just, and H. De Gorter. 2019. "Who Will Pay for Increasing Biofuel

- Mandates ? Incidence of the Renewable Fuel Standards Given a Binding Blend Wall.” *American Journal of Agricultural Economics* (c):1–15.
- Krupa, J.S., D.M. Rizzo, M.J. Eppstein, D. Brad Lanute, D.E. Gaalema, K. Lakkaraju, and C.E. Warrender. 2014. “Analysis of a consumer survey on plug-in hybrid electric vehicles.” *Transportation Research Part A: Policy and Practice* 64:14–31.
- Kubendran, K.R. 2016. *Integration of vehicle consumer choice in energy system models and its implications for climate policy analysis*. University of California, Davis.
- Lade, G.E., and J. Bushnell. 2019. “Fuel Subsidy Pass-Through and Market Structure: Evidence from the Renewable Fuel Standard.” Available at: <http://www.card.iastate.edu/products/publications/pdf/16wp570.pdf> [Accessed May 22, 2017].
- Lapan, H., and G. Moschini. 2012. “Second-best biofuel policies and the welfare effects of quantity mandates and subsidies.” *Journal of Environmental Economics and Management* 63(2):224–241. Available at: <http://linkinghub.elsevier.com/retrieve/pii/S0095069611001240> [Accessed October 26, 2016].
- Leard, B., J. Linn, V. McConnell, and W. Raich. 2015. “Fuel Costs, Economic Activity, and the Rebound Effect for Heavy-Duty Trucks.”
- Lévay, P.Z., Y. Drossinos, and C. Thiel. 2017. “The effect of fiscal incentives on market penetration of electric vehicles: A pairwise comparison of total cost of ownership.” *Energy Policy* 105:524–533. Available at: <https://www.sciencedirect.com/science/article/pii/S0301421517301404> [Accessed August 8, 2018].
- Levin, L., M.S. Lewis, and F.A. Wolak. 2017. “High frequency evidence on the demand for gasoline.” *American Economic Journal: Economic Policy* 9(3):314–347.
- Li, J. 2019. “Compatibility and Investment in the U.S. Electric Vehicle Market.” Available at: <https://www.eenews.net/stories/1060042082> [Accessed May 20, 2019].
- Li, J., and J.H. Stock. 2018. “Cost pass-through to higher ethanol blends at the pump: Evidence from Minnesota gas station data.” *Journal of Environmental Economics and Management*. Available at: <https://www.sciencedirect.com/science/article/pii/S0095069617305508> [Accessed November 20, 2018].
- Li, S., L. Tong, J. Xing, and Y. Zhou. 2017. “The Market for Electric Vehicles: Indirect Network Effects and Policy Design.” *Journal of the Association of Environmental and Resource Economists* 4(1):89–133. Available at: <https://www.journals.uchicago.edu/doi/10.1086/689702> [Accessed June 11, 2018].
- Lin, Z. 2014. “Optimizing and Diversifying Electric Vehicle Driving Range for U.S. Drivers.” *S. Drivers. Transportation Science* 48(4):635–650. Available at: <http://pubsonline.informs.orghttp://www.informs.org> [Accessed March 8, 2020].
- Lin, Z., J. Dong, C. Liu, and D.L. Greene. 2012. “PHEV Energy Use Estimation: Validating the Gamma Distribution for Representing the Random Daily Driving Distance.” *Transportation Research Record* 2287:37–43. Available at: <https://www.ornl.gov/publication/phev-energy-use-estimation-validating-gamma-distribution-representing-random-daily-0> [Accessed September 16, 2020].
- 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://trjournalonline.trb.org/doi/pdf/10.3141/2252-07> [Accessed

- March 30, 2018].
- Liu, W. 2014. "Modeling gasoline demand in the United States: A flexible semiparametric approach." *Energy Economics* 45:244–253.
- Luchansky, M.S., and J. Monks. 2009. "Supply and demand elasticities in the U.S. ethanol fuel market." *Energy Economics* 31(3):403–410.
- 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, M. Bevione, S. Carrara, O.Y. Edelenbosch, J. Emmerling, C. Guivarch, P. Karkatsoulis, I. Keppo, V. Krey, Z. Lin, E.Ó. Broin, L. Paroussos, H. Pettifor, K. Ramea, K. Riahi, F. Sano, B. Solano Rodriguez, and D.P. Van Vuuren. 2018. "Interaction of consumer preferences and climate policies in the global transition to low-carbon vehicles." *Nature Energy*. Available at: <https://doi.org/10.1038/s41560-018-0195-z> [Accessed July 18, 2018].
- McCullum, 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].
- Meyer, S., and W. Thompson. 2012. "How Do Biofuel Use Mandates Cause Uncertainty? United States Environmental Protection Agency Cellulosic Waiver Options." *Applied Economic Perspectives and Policy* 00:1–17. Available at: <http://aepp.oxfordjournals.org/> [Accessed April 27, 2021].
- Miao, R., D.A. Hennessy, and B.A. Babcock. 2012. "Investment in cellulosic biofuel refineries: do waivable biofuel mandates matter?" *American Journal of Agricultural Economics* 94(3):750–762. Available at: <https://academic.oup.com/ajae/article-abstract/94/3/750/54227> [Accessed June 19, 2019].
- Miller, J. 2020. "Electric car costs to remain higher than traditional engines." *Financial Times*. Available at: <https://www.ft.com/content/a7e58ce7-4fab-424a-b1fa-f833ce948cb7> [Accessed March 16, 2021].
- Mohamed, M., C. Higgins, M. Ferguson, and P. Kanaroglou. 2016. "Identifying and characterizing potential electric vehicle adopters in Canada: A two-stage modelling approach." *Transport Policy* 52:100–112. Available at: <http://dx.doi.org/10.1016/j.tranpol.2016.07.006> [Accessed March 10, 2021].
- Moschini, G., H. Lapan, and H. Kim. 2017. "The Renewable Fuel Standard in Competitive Equilibrium: Market and Welfare Effects." *American Journal of Agricultural Economics* 99(5):1117–1142. Available at:

- <http://academic.oup.com/ajae/article/doi/10.1093/ajae/aax041/4103044/The-Renewable-Fuel-Standard-in-Competitive> [Accessed September 12, 2017].
- Muehlegger, E., and D.S. Rapson. 2018. “Subsidizing Low- and Middle-Income Adoption of Electric Vehicles: Quasi-Experimental Evidence from California.” Available at: <https://www.nber.org/papers/w25359> [Accessed August 22, 2021].
- Needell, Z.A., J. McNERney, M.T. Chang, and J.E. Trancik. 2016. “Potential for widespread electrification of personal vehicle travel in the United States.” *Nature Energy* 1(9):16112. Available at: www.nature.com/natureenergy [Accessed November 12, 2019].
- Noori, M., and O. Tatari. 2016. “Development of an agent-based model for regional market penetration projections of electric vehicles in the United States.” *Energy* 96:215–230.
- 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].
- NREL. 2021. “Alternative Fuel Stations API.” *Developer Network*. Available at: <https://developer.nrel.gov/docs/transportation/alt-fuel-stations-v1/> [Accessed April 20, 2021].
- Okada, T., T. Tamaki, and S. Managi. 2019. “Effect of environmental awareness on purchase intention and satisfaction pertaining to electric vehicles in Japan.” *Transportation Research Part D: Transport and Environment* 67:503–513.
- 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.
- Plotkin, S., M. Singh, P. Patterson, J. Ward, F. Wood, F. Woof, N. Kydes, J. Holte, J. Moore, G. Miller, S. Das, D. Greene, A. Rousseau, P. Sharer, and S. Pagerit. 2009. “Multi-Path Transportation Futures Study: Vehicle Characterization and Scenario Analyses Energy Systems Division.” Available at: <https://publications.anl.gov/anlpubs/2009/11/65560.pdf> [Accessed July 8, 2019].
- 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].
- Roberts, M.C. 2008. "E85 and fuel efficiency: An empirical analysis of 2007 EPA test data." *Energy Policy* 36(3):1233–1235. Available at: <https://linkinghub.elsevier.com/retrieve/pii/S030142150700496X> [Accessed June 10, 2020].
- 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].
- Sallee, J.M., S.E. West, and W. Fan. 2016. "Do consumers recognize the value of fuel economy? Evidence from used car prices and gasoline price fluctuations." *Journal of Public Economics* 135:61–73. Available at: <https://linkinghub.elsevier.com/retrieve/pii/S0047272716000049>.
- Schuitema, G., J. Anable, S. Skippon, and N. Kinnear. 2013. "The role of instrumental, hedonic and symbolic attributes in the intention to adopt electric vehicles." *Transportation Research Part A journal* 48(2013):39–49. Available at: <http://dx.doi.org/10.1016/j.tra.2012.10.004>.
- 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].
- Sen, B., M. Noori, and O. Tatari. 2017. "Will Corporate Average Fuel Economy (CAFE) Standard help? Modeling CAFE's impact on market share of electric vehicles." *Energy Policy* 109:279–287. Available at: <https://linkinghub.elsevier.com/retrieve/pii/S0301421517304391>.
- Sexton, S.E., and A.L. Sexton. 2013. "Conspicuous conservation: The Prius halo and willingness to pay for environmental bona fides." Available at: <http://dx.doi.org/10.1016/j.jeem.2013.11.004>.
- Souloupoulos, N. 2017. "When Will Electric Vehicles be Cheaper than Conventional Vehicles?" Available at: https://data.bloomberglp.com/bnef/sites/14/2017/06/BNEF_2017_04_12_EV-Price-Parity-Report.pdf [Accessed April 14, 2020].
- Springel, K. 2020. "Network Externality and Subsidy Structure in Two-Sided Markets: Evidence from Electric Vehicle Incentives." *American Economic Journal: Economic Policy* In press. Available at: <https://sites.google.com/site/springelkatalin/research> [Accessed May 20, 2019].
- Stephens, T.S., Rebacca Levinson, Aaron Brooker, ChangZheng Liu, Zhenhong Lin, and Alicia Birky. 2017. "Comparison of Vehicle Choice Models." Available at: <https://publications.anl.gov/anlpubs/2017/12/140846.pdf> [Accessed November 2, 2020].
- 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].
- The White House. 2021. "FACT SHEET: President Biden Sets 2030 Greenhouse Gas Pollution Reduction Target Aimed at Creating Good-Paying Union Jobs and Securing U.S. Leadership on Clean Energy Technologies." Available at: <https://www.whitehouse.gov/briefings->
- 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/aep/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. Perkins. 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*.
- U.S. EPA, and NHTSA. 2018. “The Safer Affordable Fuel-Efficient (SAFE) Vehicles Rule for Model Years 2021–2026 Passenger Cars and Light Trucks.”
- 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. 2015. “Cellulosic Biofuel Standard Guidance (EPA-420-B-15-027).” Available at: <https://nepis.epa.gov/Exe/ZyPDF.cgi?Dockkey=P100M2F6.pdf> [Accessed December 6, 2018].
- US EPA. 2016. “Lifecycle Greenhouse Gas Emissions for Select Pathways (kg CO₂e per mmBtu).” (July):6–7. Available at: <https://www.epa.gov/sites/production/files/2016-07/documents/select-ghg-results-table-v1.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].
- Wang, S., F. Zhao, Z. Liu, and H. Hao. 2018. “Impacts of a super credit policy on electric vehicle penetration and compliance with China’s Corporate Average Fuel Consumption regulation.” *Energy* 155:746–762. Available at: <https://linkinghub.elsevier.com/retrieve/pii/S0360544218308624>.
- Watkiss, P., and T. Downing. 2008. “The social cost of carbon: Valuation estimates and their use in UK policy.” *Integr. Assess* 8.
- Williams, J.H., A. DeBenedictis, R. Ghanadan, A. Mahone, J. Moore, W.R. Morrow, S. Price, and M.S. Torn. 2012. “The technology path to deep greenhouse gas emissions cuts by 2050: The pivotal role of electricity.” *Science* 335(6064):53–59. Available at: <https://science.sciencemag.org/content/335/6064/53> [Accessed March 24, 2021].
- Winebrake, J.J., E.H. Green, B. Comer, C. Li, S. Froman, and M. Shelby. 2015. “Fuel price elasticities in the U.S. combination trucking sector.” *Transportation Research Part D*

- 38:166–177. Available at: <http://dx.doi.org/10.1016/j.trd.2015.04.006> [Accessed March 30, 2019].
- Xie, F., and Z. Lin. 2017. “Market-driven automotive industry compliance with fuel economy and greenhouse gas standards: Analysis based on consumer choice.” *Energy Policy* 108:299–311. Available at: <https://linkinghub.elsevier.com/retrieve/pii/S0301421517303518>.
- Yang, C., S. Yeh, S. Zakerinia, K. Ramea, and D. McCollum. 2015. “Achieving California’s 80% greenhouse gas reduction target in 2050: technology, policy and scenario analysis using ca-times energy economic systems model.” *Energy Policy* 77:118–130.
- Yang, Y., E. Yao, Z. Yang, and R. Zhang. 2016. “Modeling the charging and route choice behavior of BEV drivers.” *Transportation Research Part C: Emerging Technologies* 65:190–204. Available at: <https://linkinghub.elsevier.com/retrieve/pii/S0968090X15003319> [Accessed April 14, 2020].
- 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. “Behavioral, Technological and Economic Determinants of Electric Vehicle Adoption in the United States.”

APPENDIX A Supplementary Material For Chapter 2

A.1. Legislative support about the E85 expectation

The Energy Independent Security Act (Title II) Subtitle C- Sec. 244 Renewable Fuel Infrastructure Grants aimed to “maximize the availability and use of renewable fuel blends, and that will ensure that renewable fuel blends are available across the country”, where renewable fuel blends are defined as gasoline blend that contains not less than 11 percent, and not more than 85 percent renewable fuel. The earlier version of the EISA (H.R. 6 Senate version) required the “Secretary of Transportation to develop and implement an action plan so that alternative fuel vehicles (including E85 vehicles) represent at least 50% of new vehicle sales by 2015. [Sec. 520]”. They jointly support the policy vision in expanding the high ethanol blend.

The revised RFS policy in 2010 [EPA–HQ–OAR–2005–0161; FRL–9112–3] claimed on page 14760 (EPA 2010) that “ To get beyond the blend wall and consume more than 14-15 billion gallons of ethanol, we are going to need to see an increase in the number of FFVs on the road, the number of E85 retailers, and the FFV E85 refueling frequency”. On page 14758, the “Need for Additional E85 Retail Facilities” estimated the E85 retail facilities needed to enable the ethanol consumption in E85 to be “approximately 1,520 facilities each year from 2010 through 2022”.

The regulation of 2013 RFS [EPA–HQ–OAR–2012–0546; FRL–9834–5] estimated that the requirement for E85 consumption was 2.1 billion gallons on page 49821 section C to comply with the Total Renewable Fuel Standard and expected that “...consumption of E85, and perhaps blends with other concentrations of ethanol, will grow over time”.

The RFS standards for 2014- 2016 [EPA–HQ–OAR–2012–0546; FRL–9834–5] stated that “...if all of the additional volumes were ethanol, the US would need to consume volumes of E85 far higher, in our estimation, than the market is capable of supplying: in 2015 the required volume of E85 would need to be about 6.4 billion gallons, while in 2016 it would need to be about 9.2 billion gallons.” in page 33116 with the assumptions in footnote 38 “In general when discussing efforts to increase the use of ethanol beyond the blend wall we focus on the volume of E85 that is consumed”. The expectation for E85 is supported on page 33118 that “...E85 and biodiesel will dominate efforts to increase the use of renewable fuel”.

The 2017 RFS standard [EPA–HQ–OAR–2016–0004; FRL–9946–90– OAR] examined the limitation in E85 supply expansion and estimated that “under highly favorable conditions related to growth in the number of E85 retail stations, retail pricing, and consumer response to that pricing, it is possible that E85 volumes as high as 400 million gallons.

A large body of literature also highlights the role of high-ethanol gasoline blends required to meet the required ethanol blend and estimate the market demand and supply (Pouliot and Babcock 2014; Pouliot, Liao and Babcock 2018; Johnson and Melendez 2007).

A.2. The Lagrangian Framework and First-order Conditions

The Lagrangian framework is established as follows. The shadow prices of the explicit RINs generation constraint show the market price of the RINs, at which the blenders and obligated parties traded the RIN credits. The shadow prices of the constraints (such as $P_E^w, P_g^w, P_d^{rt}, P_{D3}, P_{D4}, P_{D6}, \lambda_{D3}, \lambda_{D4}, \lambda_R$) reflect the marginal increase in the welfare with respect to the variables described by the constraints, which are the market-mediated prices. The shadow prices are positive when the constraints are binding.

$$\begin{aligned}
\mathcal{L} = & \int_0^{\gamma_{E10} q_{E10} + \gamma_{E85} q_{E85}} D_{gf}(\cdot) dq_{gf} + \int_0^{q_b + q_d} D_{df}(\cdot) dq_{df} - \int_0^{q_e} S_e(\cdot) dq_e - \int_0^{q_c} S_c(\cdot) dq_c - \\
& \int_0^{q_b} S_b(\cdot) dq_b - P_{g0} q_d - P_{d0} q_d - w_{gf} q_{gf} - w_{df} q_{df} + t_B q_b - P_{cw} q_{cw} + P_E^w (q_e + q_c - \\
& 0.1 q_{E10} - 0.74 q_{E85}) + P_g^w (q_g - 0.9 q_{E10} - 0.26 q_{E85}) + P_{gf}^r (q_{E10} + q_{E85} - q_{gf}) + \\
& P_d^w (q_b + q_d - q_{df}) + P_{D3} (q_c - q_{D3}) + P_{D4} (q_b - q_{D4}) + P_{D6} (q_e - q_{D6}) + \lambda_{D3} [q_{D3} + q_{cw} - \\
& \theta_{D3} (q_g + q_d)] + \lambda_{D4} [q_{D4} - \theta_{D4} (q_g + q_d)] + \lambda_R [q_{D3} + q_{D4} + q_{D6} - \theta_R (q_g + q_d)] \quad (A.1)
\end{aligned}$$

First-order conditions using Karush Kuhn-Tucker (KKT) theorem for each variable are listed for the interest of each stakeholder. The first-order conditions satisfy the complementary slackness condition that only when the variables are interior solutions would the equality hold.

A.2.1 Fuel Producers

$$\frac{\partial \mathcal{L}}{\partial q_e} = S_e(q_e) - P_{D6} - P_E^w \geq 0 \text{ or } (S_e(q_e) - P_{D6} - P_E^w) \times q_e = 0 \quad (A.2)$$

Every gge of corn ethanol is subsidized with the D6 RIN credit at P_{D6} per gge and reduce the corn ethanol production cost from $S_e(\cdot)$ to the wholesale price at P_E to blenders. The wholesale ethanol price is endogenously determined, represented as $P_E = S_e(\cdot) - P_{D6}$.

$$\frac{\partial \mathcal{L}}{\partial q_c} = S_c(q_c) - P_{D3} - P_E^w \geq 0 \text{ or } (S_c(q_c) - P_{D3} - P_E^w) \times q_c = 0 \quad (A.3)$$

Similarly, cellulosic ethanol is subsidized by D3 RIN at P_{D3} per gge, which lowers the wholesale price of the cellulosic ethanol to the same level at P_E as corn ethanol. It is because we assume cellulosic ethanol is a perfect substitute for corn ethanol that blenders are indifferent to the source of ethanol. Only when the cellulosic ethanol is fully subsidized with P_{D3} that lowers the price of ethanol would it incentivize the cellulosic ethanol production, as $P_E = S_c(q_c) - P_{D3}$.

$$\frac{\partial \mathcal{L}}{\partial q_b} = S_b(q_b) - P_{D4} - t_B - P_d^w \geq 0 \text{ or } (S_b(q_b) - P_{D4} - t_B - P_d^w) \times q_b = 0 \quad (A.4)$$

The biomass-based diesel is subsidized at P_{D4} in addition to the tax credit, the blenders face the wholesale biodiesel at the price of P_d . We assume that biodiesel is a perfect substitute for petroleum diesel that has the same wholesale price as petroleum diesel, which is $P_d = S_b(q_b) - P_{D4} - t_B$.

$$\frac{\partial \mathcal{L}}{\partial q_g} = P_{g0} + \lambda_{D3}\theta_{D3} + \lambda_{D4}\theta_{D4} + \lambda_R\theta_R - P_g^w \geq 0$$

$$\text{or } (P_{g0} + \lambda_c\theta_c + \lambda_b\theta_b + \lambda_r\theta_r - P_g^w) \times q_g = 0 \quad (\text{A.5})$$

Due to the joint compliance bases applied three nested RFS blend mandates, the gasoline gets implicit tax from each of the mandates. The wholesale price is raised to P_g . We note that the shadow price of the RFS mandate can also be reinterpreted in the form of the RIN prices in section 2.3.3.1. $P_g = P_{g0} + \lambda_{D3}\theta_{D3} + \lambda_{D4}\theta_{D4} + \lambda_R\theta_R$.

$$\frac{\partial \mathcal{L}}{\partial q_d} = P_{d0} + \lambda_c\theta_c + \lambda_b\theta_b + \lambda_r\theta_r - P_d \geq 0 \text{ or } (P_{d0} + \lambda_c\theta_c + \lambda_b\theta_b + \lambda_r\theta_r - P_d) \times q_d = 0 \quad (\text{A.6})$$

Similarly, the joint-base scenario implicitly taxes the diesel at the same rate for each gallon equivalent of diesel. We assume the blenders are indifferent between two substitutable diesel products of petroleum diesel and biomass-based diesel. The wholesale prices of the two are the same: $P_d = P_{d0} + \lambda_{D3}\theta_{D3} + \lambda_{D4}\theta_{D4} + \lambda_R\theta_R$.

$$\frac{\partial \mathcal{L}}{\partial q_{cw}} = P_{cw} - \lambda_c \geq 0 \text{ or } (P_{cw} - \lambda_c) \times q_{cw} = 0 \quad (\text{A.7})$$

The compliance cost of the cellulosic waiver credit is P_{cw} , which is announced by EPA before every compliance year. However, only if the P_{cw} equals to λ_c that the waiver credit cost

equal to the incentive of using the cellulosic waiver to comply with cellulosic biofuel mandate should be the obligated party purchase the cellulosic waiver, which $P_{cw} = \lambda_c$.

A.2.2 Blenders

$$\frac{\partial \mathcal{L}}{\partial q_{E10}} = 0.1P_E^w + 0.9P_g^w + w_{gf} - P_{gf}^r \geq 0 \text{ or } (0.1P_E^w + 0.9P_g^w + w_{gf} - P_{gf}^r) \times q_{E10} = 0 \quad (\text{A.8})$$

A blender produces a lower ethanol blend product with an upper limit of blend rate at 10% or E10. The production cost is the proportionate marginal cost of blending ethanol and gasoline plus the marginal blending cost. The retail price at the station gate per gge of E10 is at P_{gf} from the demand curve. By plugging in the wholesale prices of gasoline and ethanol from the FOCs of fuel producers from the previous section, we get the retail price of E10 at the gge basis. $p_{E10}^r = \frac{1}{\gamma_{E10}} \left[(0.9S_g(q_g) + 0.1 \frac{S_e(q_e)q_e + S_c(q_c)q_c}{q_e + q_c} + w_{gf}) - 0.1 \frac{P_{D6}q_e + P_{D3}q_c}{q_e + q_c} + 0.9(\lambda_{D3}\theta_{D3} + \lambda_{D4}\theta_{D4} + \lambda_R\theta_R) \right]$. We note that the wholesale ethanol price can be expressed as when two wholesale ethanol are perfectly substitutable $p_E^w = \frac{S_e(\cdot)q_e + S_c(\cdot)q_c}{q_e + q_c} - \frac{P_{D6}q_e + P_{D3}q_c}{q_e + q_c}$.

$$\frac{\partial \mathcal{L}}{\partial q_{E85}} = 0.74P_E^w + 0.26P_g^w + w_{gf} - P_{gf}^r \geq 0 \text{ or } (0.74P_E^w + 0.26P_g^w + w_{gf} - P_{gf}^r) \times q_{E85} = 0 \quad (\text{A.9})$$

Likewise, the production cost of E85 is volume-weighted ethanol and gasoline wholesale prices plus the blending cost. The retail price is also at P_{gf} , the same with E10 when E85 consumption shares the same demand curve. By plugging in the rack prices from the FOCs of fuel producers, we get the retail price of E85 at the energy equivalent basis.

$$p_{E85}^r = \frac{1}{\gamma_{E85}} \left[\left(0.26S_g(q_g) + 0.74 \frac{S_e(q_e)q_e + S_c(q_c)q_c}{q_e + q_c} + w_{gf} \right) - 0.74 \frac{P_{D6}q_e + P_{D3}q_c}{q_e + q_c} + 0.26(\lambda_{D3}\theta_{D3} + \lambda_{D4}\theta_{D4} + \lambda_R\theta_R) \right]$$

A.2.3 Consumers

$$\frac{\partial \mathcal{L}}{\partial q_{dgf}} = D_{gf}(\cdot) - P_{gf}^r \geq 0 \text{ or } (D_{gf}(\cdot) - P_{gf}^r) \times q_{dg} = 0 \quad (\text{A.10})$$

According to the aggregated demand curves for gasoline blended fuel of E10 and E85, the retail prices of these two types are identical determined by the demand function $D_{gf}(\cdot)$: $P_{gf}^r = D_{gf}(\cdot)$.

$$\frac{\partial \mathcal{L}}{\partial q_{df}} = D_{df}(\cdot) - p_{df}^w - w_{df} \geq 0 \text{ or } (D_{df}(\cdot) - p_{df}^w - w_{df}) \times q_{df} = 0 \quad (\text{A.11})$$

The consumer has another demand curve for blended diesel. The consumer price of blended diesel is the wholesale diesel price plus the blending cost of petroleum diesel and biomass-based diesel, where $p_{df}^{rt} = D_{df}(\cdot) = p_d^w + w_{df}$. The wholesale price of both biodiesel and petroleum diesel is assumed perfectly substitutable, so the wholesale blended diesel can be written as the volumetric weighted price of marginal production cost of biodiesel and petroleum diesel net the weighted incentives, represented as $p_d^w = \frac{S_b(\cdot)q_b + S_d(\cdot)q_d}{q_b + q_d} - \frac{q_b(1.5p_{D4} + t_B) - q_d\tau}{q_b + q_d}$.

A.2.4 RINs Traded

Nested

Non-nested

$$\frac{\partial \mathcal{L}}{\partial q_{D3}} = \lambda_{D3} + \lambda_R - P_{D3} \geq 0 \quad \frac{\partial \mathcal{L}}{\partial q_{D3}} = \lambda_{D3} - P_{D3} \geq 0$$

$$\frac{\partial \mathcal{L}}{\partial q_{D4}} = \lambda_{D4} + \lambda_R - P_{D4} \geq 0 \quad \frac{\partial \mathcal{L}}{\partial q_{D4}} = \lambda_{D4} - P_{D4} \geq 0$$

$$\frac{\partial \mathcal{L}}{\partial q_{D6}} = \lambda_R - P_{D6} \geq 0 \quad \frac{\partial \mathcal{L}}{\partial q_{D6}} = \lambda_R - P_{D6} \geq 0$$

The prices of the RIN credits are determined by the capacity of biofuel production and also the RFS mandate. The nested structure counts D3 and D4 RINs towards the total renewable fuel

standard that D3 RIN price is equal to the sum of shadow prices of cellulosic mandate and that of total renewable fuel mandate. Similarly, the D4 RIN price is the sum of shadow prices of the biodiesel mandate and the total renewable mandate. It indicates that under the nested structure, the price of the advanced fuel is higher than the conventional fuel $P_{D3} > P_{D6}$ and $P_{D4} > P_{D6}$.

However, under the non-nested structure, the shadow prices of each separate mandate are equal to its corresponding RIN prices.

A.3. Proofs for Propositions

Table A.1 lists the comparison of RFS between the joint fossil fuel base and the separate fossil fuel base. The joint-base structure applies the blend rates to both gasoline and diesel to obtain the volumetric biofuels. The separate-base structure, however, applies the blend rate only to the counterpart fossil fuel to get the biofuel volumes: biodiesel rate applies to petroleum diesel; cellulosic and corn ethanol rates apply to gasoline.

Table A1. The comparison of non-nested structure between joint base and separate base.

	Non-nested with joint fossil fuel base	Non-nested with separate fossil fuel base
Cellulosic biofuel (D3)	$q_{D3} \geq \theta_{D3} (q_g + q_d)$	$q_{D3} \geq \theta_{D3} q_g;$
Biomass-based diesel (D4)	$q_{D4} \geq \theta_{D4} (q_g + q_d)$	$q_{D4} \geq \theta_{D4} q_d;$
Conventional biofuel (D6)	$q_{D6} \geq \theta_{D6} (q_g + q_d)$	$q_{D6} \geq \theta_{D6} q_g$

The revenue-neutral conditions for joint-base and separate-base have one common ground that the tax revenue gained from the fossil fuels would all return back to the biofuel producers in the form of subsidy under the assumption of perfectly competitive market condition and the revenue-neutral condition for the blend rate mandate. The separate-base scenario has a revenue-neutral condition of $P_{D6}q_e + P_{D3}q_c + P_{D4}q_b = (\lambda_{D3}\theta_{D3} + \lambda_{D6}\theta_{D6})q_g + \lambda_{D4}\theta_{D4}q_d$ (A.12). By moving the taxes of the above condition from right to left and rearrange it, we have $P_{D6}q_e +$

$P_{D3}q_c - (\lambda_{D3}\theta_{D3} + \lambda_{D6}\theta_{D6})q_g + P_{D4}q_b - \lambda_{D4}\theta_{D4}q_d = 0$. We replace the $\tau_g = \lambda_{D3}\theta_{D3} + \lambda_{D6}\theta_{D6}$ and $\tau_d = \lambda_{D4}\theta_{D4}$ as well as $\kappa = \frac{P_{D6}q_e + P_{D3}q_c}{q_e + q_c}$ into the above equation, and have

$$[\kappa(q_e + q_c) - \tau_g q_g] + [P_{D4}q_b - \tau_d q_d] = 0.$$

The joint-base scenarios (non-nested, nested without waiver, and nested with waiver) have a similar revenue-neutral condition of $P_{D6}q_e + P_{D3}q_c + P_{D4}q_b = (\lambda_{D3}\theta_{D3} + \lambda_{D4}\theta_{D4} + \lambda_R\theta_R)(q_g + q_d)$. The left-hand sides are the same as where the total RIN credits biofuels obtained. The only differences are on the right-hand side where the tax from fossil fuels. Following the same steps, we unify the above revenue-neutral conditions of two bases into:

$$[\kappa(q_e + q_c) - \tau_g q_g] + [P_{D4}q_b - \tau_d q_d] = 0 \quad (\text{A.13})$$

where the first bracket is the net policy instruments for mixed gasoline fuel between E10 and E85 ($\kappa(q_e + q_c) - \tau_g q_g$) and the second one is the net policy instruments for mixed diesel fuel, where κ is the per gallon ethanol subsidy, and τ_g and τ_d are the implicit taxes on gasoline and diesel derived from policy scenarios.

A.3.1 Proof of Proposition 1 for Separate-Base with Non-nested Structure

Before the blend wall occurs, which is the overall ethanol blend in the gasoline less than 10% blending limit, or $(q_e + q_c)/q_g = \theta_{D3} + \theta_{D6} < \frac{1}{9}$, there is no incentive to induce E85 consumption, and the E10 fuel does not reach 10% ethanol. We name it EX for the lower ethanol blended fuel with blend rate (denote as x%) lower than 10%.

The non-nested on separate-base scenario leads to implicit taxes for gasoline as $\tau_g = \lambda_{D3}\theta_{D3} + \lambda_{D6}\theta_{D6}$ and for diesel as $\tau_d = \lambda_{D4}\theta_{D4}$ with shadow prices listed in Table 3. We then take the second term of revenue-neutral equation A.13 and plug the τ_d back, $\tau_d q_d = \lambda_{D4}\theta_{D4}q_d =$

$P_{D4}q_b$, which leads the second term $[P_{D4}q_b - \tau_d q_d] = 0$. This proves a net zero incentive for blended diesel from biodiesel mandate with petroleum diesel only on the application base.

The first term in revenue-neutral condition (equation A.13) is thus equal to zero when $[\kappa(q_e + q_c) - \tau_g q_g] = 0$ and $\tau_g/\kappa = (q_e + q_c)/q_g$. When below the blend rate $\frac{q_e + q_c}{q_g} = \frac{x\%}{1-x\%} = \tau_g/\kappa < \frac{1}{9}$, we have $\kappa > 9\tau_g$. With this condition, the policy instrument on E85 is proven to be a net subsidy of $0.74\kappa - 0.26\tau_g > 6.4\tau_g > 0$ even though it is not produced. As E85 consumption is zero, the revenue-neutral condition holds for EX fuel that the subsidy ethanol passes to EX is offset by the implicit tax gasoline passed to EX.

A.3.2 Proof for Proposition 1 for Joint-Base with Non-nested and Nested structure:

The joint-base scenarios with both non-nested and nested structures have the same proofs for proposition 1. The joint base of gasoline and diesel for the RFS mandate leads to an identical implicit tax on gasoline and diesel where $\tau_g = \tau_d = \tau = \lambda_{D3}\theta_{D3} + \lambda_{D4}\theta_{D4} + \lambda_{D6}\theta_{D6}$. The revenue-neutral equation still holds with $[\kappa(q_e + q_c) - \tau q_g] + [P_{D4}q_b - \tau q_d] = 0$.

To address the magnitude of cross-subsidization for retail products, we need to find the relative scale of the ethanol subsidy κ with respect to fossil fuel tax τ . We first expand the τq_g by plugging the $\tau = \lambda_{D3}\theta_{D3} + \lambda_{D4}\theta_{D4} + \lambda_{D6}\theta_{D6}$ equation and reorganizing it using κ and D4 RIN price.

$$\begin{aligned}\tau q_g &= (\lambda_{D3}\theta_{D3} + \lambda_{D4}\theta_{D4} + \lambda_{D6}\theta_{D6})q_g = \frac{(\lambda_{D3}q_c + \lambda_{D6}q_e)q_g}{q_g + q_d} + \lambda_{D4}\theta_{D4}q_g \\ &= (P_{D3}q_c + P_{D6}q_e)\frac{q_g}{q_g + q_d} + P_{D4}\frac{q_b}{q_g + q_d}q_g = \kappa\frac{(q_c + q_e)q_g}{q_g + q_d} + P_{D4}\frac{q_b}{q_g + q_d}q_g\end{aligned}$$

$$= \kappa(q_e + q_c) - \kappa(q_e + q_c) \frac{q_d}{q_g + q_d} + q_b P_{D4} \frac{q_g}{q_g + q_d}$$

$$\text{Thus, } \tau q_g = \kappa(q_e + q_c) - \frac{q_g q_d}{q_g + q_d} \left(\frac{q_e + q_c}{q_g} \kappa - \frac{q_b}{q_d} P_{D4} \right) \quad (\text{A.14})$$

Equation A.14 indicate that only if $\frac{q_e + q_c}{q_g} \kappa > \frac{q_b}{q_d} P_{D4}$, would we have $\tau q_g < \kappa(q_e + q_c)$

that implies that EX get a subsidy of $x\% \kappa - (1 - x\%) \tau > 0$ when $\kappa > \frac{q_g}{q_e + q_c} \tau = \frac{1 - x\%}{x\%} \tau$. The

positive subsidy of EX of the first term in A12 indicates a negative tax on blended diesel for the second term in A12, where $P_{D4} q_b - \tau q_d < 0$. Overall, the above argument proves that the joint-base scenarios of either non-nested or nested below the blend wall of 10% will lead to the same results that EX is subsidized ($\kappa(q_e + q_c) - \tau q_g > 0$) and blended diesel is taxed ($\frac{P_{D4} q_b - q_d \tau}{q_b + q_d} < 0$), when E85 consumption is zero.

The precondition of $\frac{q_e + q_c}{q_g} \kappa > \frac{q_b}{q_d} P_{D4}$ will hold if both $\frac{q_e + q_c}{q_g} > \frac{q_b}{q_d}$ and $\kappa > P_{D4}$ stand. This is being said, the overall ethanol blend should be higher than the biodiesel blend; and weighted ethanol RIN prices should be higher than biodiesel RIN price. The RIN prices are affected by the factors of marginal costs of production, RFS mandate stringency, and blend percentage. The higher weighted ethanol RIN prices could be higher than biodiesel RIN price $\frac{P_{D6} q_e + P_{D3} q_c}{q_e + q_c} > P_{D4}$ in cases when (1) $P_{D6} \geq P_{D4}$ if corn ethanol target is more ambitious than biodiesel as of current market condition while ethanol RIN price of $\frac{P_{D6} q_e + P_{D3} q_c}{q_e + q_c}$ is dominated by corn ethanol RIN price P_{D6} ; or (2) $P_{D3} > P_{D4}$ if cellulosic ethanol is subject to a higher production cost than biodiesel as of current market condition while cellulosic ethanol RIN price leads the $\kappa = \frac{P_{D6} q_e + P_{D3} q_c}{q_e + q_c}$; or (3) $P_{D3} > P_{D4}$ and $P_{D6} \geq P_{D4}$ when both conditions (1) and (2) hold when either the high marginal cost or stringent biofuel mandate lead to higher ethanol RIN prices than biodiesel RIN price.

The current market condition of producing bioethanol and biodiesel with respect to the corresponding RFS mandates of 15 billion gallons of corn ethanol, 331 million gallons of cellulosic ethanol, and 2 billion gallons of biodiesel indicates a higher implicit subsidy κ for ethanol than the subsidy for biodiesel P_{D4} ($\kappa > P_{D4}$). Considering the higher mandate for corn ethanol relative to biodiesel, also the greater marginal costs of producing cellulosic ethanol than the rest of fuels, the weighted RIN price per gallon of ethanol should be higher than biodiesel (D4) RIN price. Therefore, we get $\frac{q_e + q_c}{q_g} \kappa > \frac{q_b}{q_d} P_{D4}$ by multiplying the price incentive κ and P_{D4} on two sides. This leads to a negative value for the second term of τq_g in the equation above and $\tau q_g < \kappa(q_e + q_c)$ or $\kappa > \frac{q_g}{q_e + q_c} \tau$. This implies a subsidy for E10 when $[\kappa(q_e + q_c) - \tau q_g] > 0$.

A.3.3 Proof for Proposition 2 for Separate-Base with Non-nested Structure at or above the Blend wall

With a marginal increase in the ethanol blend rate over blend wall, the policy effect on biodiesel and blended diesel is unchanged as the same argument for A2.1. Therefore, the blended diesel has zero net effect from the RFS policy even if the blend wall emerges. But when at $\theta_{D3} + \theta_{D6} = (q_e + q_c)/q_g \geq 1/9$, both E10 and E85 are also required to be consumed and have interior solutions. The cross-subsidization between ethanol and gasoline is zero under the non-nested with separate-base with $[\kappa(q_e + q_c) - \tau_g q_g] = 0$ and $\frac{\tau_g}{\kappa} \geq 1/9$. This leads to a negative policy incentive for E10 as net tax with $0.1\kappa - 0.9\tau_g < 0$ and net E85 subsidy with $0.74\kappa - 0.26\tau_g > 0$.

A.3.4 Proof for Proposition 2 for Joint-Base with Non-nested and Nested Structure:

Using the same argument as in A2.2, if the joint-base structure (including both non-nested and nested structures) has $\kappa > P_{D4}$ and biofuel ethanol blend is higher than the biodiesel blend $\frac{q_e + q_c}{q_g} > \frac{q_b}{q_d}$, the generic policy instruments on E10 and E85 is a subsidy ($\kappa(q_e + q_c) - \tau q_g > 0$). At the margin of hitting the blend wall $\theta_{D3} + \theta_{D6} = (q_e + q_c)/q_g = 1/9$, $\kappa(q_e + q_c) - \tau q_g > 0$ then turns into $0.1\kappa - 0.9\tau_g > 0$ that shows E10 has a net subsidy from RFS. Furthermore, the blend of E85 is higher than the E10 that secures a net subsidy for E85 too. Overall, the policy effect of RFS on E85 and E10 are net subsidies $0.74\kappa - 0.26\tau_g > 0.1\kappa - 0.9\tau_g > 0$, where E85 will get a higher subsidy than E10. But the blended diesel is taxed with $P_{D4}q_b - \tau q_d < 0$ to hold the revenue-neutral condition.

A.3.5 Proof of Proposition 3, 4, and 5

The blenders change their fuel choice for compliance under the nested structure is mainly due to the total blending cost. Unlike Korting's analysis, the net profit the blenders earn is zero under the perfectly competitive market condition with a free-entry blender industry. The total revenue generated from selling the blended products net the blending cost ($TR = (P_{gf} - w_{gf})q_f + (P_{df} - w_{df})q_{df}$) evens out the total cost of purchasing the fuel from the refiners and biofuel producers net the tax credit. The zero-profit condition holds for the blenders where $\Pi = TR - TC = 0$. Therefore, the blenders adjust the fuel choice bundles in order to minimize fuel costs.

$$TC = P_E(q_e + q_c) + P_d(q_b + q_d) + P_g q_g. \quad (A.15)$$

We further reorganize the first term of the equation A.15 on the right into

$(S_e(\cdot) - P_{D6})q_e + (S_c(\cdot) - P_{D3})q_c$, with $P_E = \frac{(S_e(\cdot) - P_{D6})q_e + (S_c(\cdot) - P_{D3})q_c}{q_e + q_c}$ jointly expressed by corn

and cellulosic ethanol from the equations i and ii Table 2.3. Similarly, the second term of

equation A.15 is extended into $(S_d(q_d) + \lambda_{D3}\theta_{D3} + \lambda_{D4}\theta_{D4} + \lambda_R\theta_R)q_d + (S_b(q_b) - P_{D4} -$

$t_B)q_b$ with equation A.4 and A.6; The third term is expanded into $S_g(\cdot) + \lambda_{D3}\theta_{D3} + \lambda_{D4}\theta_{D4} +$

$\lambda_R\theta_R)q_g$ with equation A.5. The above total cost is thus expanded into:

$$TC = S_c(\cdot)q_c + S_e(\cdot)q_e + S_b(\cdot)q_b + S_g(\cdot)q_g + S_d(\cdot)q_d - P_{D3}q_c - P_{D6}q_e - P_{D4}q_b + (\lambda_{D3}\theta_{D3} + \lambda_{D4}\theta_{D4} + \lambda_R\theta_R)(q_d + q_g) - t_Bq_b \quad (A.16)$$

From the nested structure $q_{D3} \geq \theta_c(q_g + q_d)$; $q_{D4} \geq \theta_b(q_g + q_d)$; $q_{D3} + q_{D4} + q_{D6} \geq \theta_r(q_g + q_d)$ and $\lambda_{D3} + \lambda_R = P_{D3}$, $\lambda_{D4} + \lambda_R = P_{D4}$, $\lambda_R = P_{D6}$, the sixth to eighth term can be reorganized as:

$$P_{D3}q_c = (\lambda_{D3} + \lambda_R)q_{D3} = (\lambda_{D3} + \lambda_R)\theta_{D3}(q_g + q_d)$$

$$P_{D6}q_e = \lambda_R q_{D6} = \lambda_R(\theta_R - \theta_{D3} - \theta_{D4})(q_g + q_d)$$

$$P_{D4}q_b = (\lambda_{D4} + \lambda_R)q_{D4} = (\lambda_{D4} + \lambda_R)\theta_{D4}(q_g + q_d)$$

The summation of the above equation on both sides $P_{D3}q_c + P_{D6}q_e + P_{D4}q_b = (\lambda_{D3} + \lambda_R)\theta_{D3}(q_g + q_d) + \lambda_R(\theta_R - \theta_{D3} - \theta_{D4})(q_g + q_d) + (\lambda_{D4} + \lambda_R)\theta_{D4}(q_g + q_d) = (\lambda_{D3}\theta_{D3} + \lambda_{D4}\theta_{D4} + \lambda_R\theta_R)(q_d + q_g)$. This reduces the TC to be $S_c(q_c)q_c + S_e(q_e)q_e + S_b(q_b)q_b + S_g(q_g)q_g + S_d(q_d)q_d - t_Bq_b$. Without loss of generality, TC will end up with the same formula. The hypothesis of the condition under which a blender use strategic biodiesel

overage is when the marginal change is driven by $d(TC) < 0$ that $d(TC) = d(S_c(q_c)q_c + S_e(q_e)q_e + S_b(q_b)q_b + S_g(q_g)q_g + S_d(q_d)q_d - t_B q_b) < 0$.

Note that the total differentiation of one typical term can be transferred in the form as below: $d(S(q) \times q) = dS(q) \times q + dq \times S(q) = \frac{S(q)}{q\eta} \times q \times dq + S(q) \times dq = (\frac{1}{\eta} + 1)S(q) \times dq$.

The above marginal change in the cost becomes

$$d TC = (\frac{1}{\eta_c} + 1) S_c(q_c) dq_c + (\frac{1}{\eta_e} + 1) S_e(q_e) dq_e + (\frac{1}{\eta_b} + 1) S_b(q_b) dq_b + (\frac{1}{\eta_g} + 1) S_g(q_g) dq_g + (\frac{1}{\eta_d} + 1) S_d(q_d) dq_d - t_B dq_b$$

We now need to provide the marginal condition for the blenders to choose biodiesel over other biofuels at the margin of the structural change. The total differentiation of the binding nested policy constraints are as follows: $dq_c = \theta_{D3} (dq_g + dq_d)$; $dq_e + dq_c + dq_b = \theta_R (dq_g + dq_d)$. We note that at the marginal of the biodiesel overage beyond the mandate level that leaves the biodiesel mandate slack, $dq_b \neq \theta_{D4} (dq_g + dq_d)$. This marginal overage enables us to use total differentiation to analyze the marginal change in the total fuel cost. By subtracting the marginal condition of the cellulosic ethanol mandate from the marginal condition of total renewable fuel mandate, we have $dq_e = (\theta_R - \theta_{D3})(dq_g + dq_d) - dq_b$. Plug it into the total differentiation cost, we have:

$$d TC = [(\frac{1}{\eta_b} + 1) S_b(q_b) - (\frac{1}{\eta_e} + 1) S_e(q_e)] dq_b + [(\frac{1}{\eta_e} + 1) S_e(q_e)(\theta_R - \theta_{D3}) + (\frac{1}{\eta_c} + 1) S_c(q_c)\theta_c](dq_g + dq_d) + (\frac{1}{\eta_g} + 1) S_g(q_g) dq_g + (\frac{1}{\eta_d} + 1) S_d(q_d) dq_d - t_B dq_b \quad (A.17)$$

Without the provision of the biodiesel tax credit, we note that the marginal increase in biodiesel $dq_b > 0$, or the biodiesel overproduction will affect the total cost change, regardless of the change in the joint base of petroleum fuel base, where $dq_g = dq_d = 0$. Only when the blenders lower the blending costs with the biodiesel overage that $[(\frac{1}{\eta_b} + 1) S_b(q_b) - (\frac{1}{\eta_e} + 1) S_e(q_e)] dq_b < 0$, where $(\frac{1}{\eta_b} + 1) S_b(q_b) < (\frac{1}{\eta_e} + 1) S_e(q_e)$ or $\frac{\frac{1}{\eta_b} + 1}{\frac{1}{\eta_e} + 1} < \frac{S_e(q_e)}{S_b(q_b)}$ would biodiesel be overproduced and be blended to reduce the total blending cost TC. This gives the proof for Proposition 3.

With additions of the cellulosic waiver, the nested policy structure with waiver becomes: $dq_c + dq_{cw} = \theta_{D3} (dq_g + dq_d)$; $dq_e + dq_c + dq_b = \theta_R (dq_g + dq_d)$. Note that the refiners purchase cellulosic waiver credit for compliance if necessary. The marginal change in the fuel mandate can be rewritten as $dq_b + dq_e = (\theta_R - \theta_{D3})(dq_g + dq_d) + dq_{cw}$ or $dq_b + dq_e = dq_{cw}$. The use of the waiver would require the extra production of biodiesel or corn ethanol to meet the total biofuel mandate.

$$\begin{aligned} dTC = & [(\frac{1}{\eta_b} + 1) S_b(q_b) - (\frac{1}{\eta_e} + 1) S_e(q_e)] dq_b + [(\frac{1}{\eta_e} + 1) S_e(q_e) - (\frac{1}{\eta_c} + 1) S_c(q_c)] dq_{cw} + [(\frac{1}{\eta_e} + 1) S_e(q_e) (\theta_R - \theta_{D3}) + (\frac{1}{\eta_c} + 1) S_c(q_c) \theta_c] (dq_g + dq_d) + (\frac{1}{\eta_g} + 1) S_g(q_g) dq_g + (\frac{1}{\eta_d} + 1) S_d(q_d) dq_d - t_B dq_b \end{aligned} \quad (A.18)$$

We consider two different conditions that the cellulosic waiver is used with the biodiesel.

(1) When corn ethanol does not hit the 15 billion gallons cap, under the nested structure, corn ethanol is substituted by biodiesel. The marginal condition of cellulosic waiver is when $dq_b + dq_e = dq_{cw}$. Every unit increase in cellulosic waiver purchased requires either biodiesel or corn

ethanol to backfill the waiver to meet the total renewable fuel mandate. The blenders choose to use biodiesel as a strategic overage when

$$dTC = [(\frac{1}{\eta_b} + 1)S_b(q_b) - (\frac{1}{\eta_e} + 1)S_e(q_e)]dq_b + [(\frac{1}{\eta_e} + 1)S_e(q_e) - (\frac{1}{\eta_c} + 1)S_c(q_c)]dq_{cw} < 0. \quad (A.19)$$

where the marginal change of the total cost indicates $(\frac{1}{\eta_b} + 1)S_b(q_b) < (\frac{1}{\eta_e} + 1)S_e(q_e) < (\frac{1}{\eta_c} + 1)S_c(q_c)$ and $dq_b > 0$ and $dq_{cw} > 0$.

(2) When corn ethanol hit the 15 billion gallons cap ($dq_e=0$), $dq_{cw} = dq_b > 0$, the biodiesel is used only for waiver substitutes. We have $dTC = [(\frac{1}{\eta_b} + 1)S_b(q_b) - (\frac{1}{\eta_c} + 1)S_c(q_c)]dq_b < 0$ and $(\frac{1}{\eta_b} + 1)S_b(q_b) < (\frac{1}{\eta_c} + 1)S_c(q_c)$. When corn ethanol reaches the 15 billion gallons cap, the biodiesel is used only for waiver substitutes. The marginal condition of using overproduced biodiesel results in a shorter form $(\frac{1}{\eta_b} + 1)S_b(q_b) < (\frac{1}{\eta_c} + 1)S_c(q_c)$. That is when the total cost of using biodiesel is less than using cellulosic ethanol. The condition is a subset of the conclusion from the previous condition when conventional fuel hits the 15 billion cap.

The above two sub-conditions can be generalized into $(\frac{1}{\eta_b} + 1)S_b(\cdot) < (\frac{1}{\eta_e} + 1)S_e(\cdot) < (\frac{1}{\eta_c} + 1)S_c(\cdot)$ when the cellulosic waiver is in use, which shows the proof of Proposition 4.

With the consideration of the biodiesel tax credit provision, the tax credit term in equation A.17 and A.18 indicate the blenders would further incentivize the blender to overuse biodiesel. It is because the marginal increase of biodiesel with any positive tax credit would reduce the total cost for blenders. Then the marginal conditions for the biodiesel to be overproduced of Propositions 3 and 4 still hold, but the upper bound condition for biodiesel to be overproduced is loosened as long as the marginal change in the total cost is negative in equations A.17 and A.18.

A.3.6 Proof of Proposition 6

At the blend wall, the policy constraint of the total renewable fuel target is binding, where $q_{D3} + q_{D6} + q_{D4} = \theta_R(q_g + q_d)$. We subtract the mandated quantity of the biodiesel $\theta_{D4}(q_g + q_d)$ from both sides of the total renewable fuel mandate, which indicates the total ethanol mandate from both conventional and cellulosic sources: $q_{D3} + q_{D6} + q_{D4} - \theta_{D4}(q_g + q_d) = (\theta_R - \theta_{D4})(q_g + q_d)$. Using E85 and E10 consumption to substitute this condition, we have the critical condition of E85 consumption at each level of the blend mandate:

$$0.1q_{E10} + 0.74q_{E85} + q_{D4} - \theta_{D4}(q_g + q_d) = (\theta_R - \theta_{D4})(0.9q_{E10} + 0.26q_{E85} + q_d)$$

$$q_{E85} = \frac{(0.9(\theta_R - \theta_{D4}) - 0.1)q_{E10} + (\theta_R - \theta_{D4})q_d - [q_{D4} - \theta_{D4}(q_g + q_d)]}{0.74 - 0.26(\theta_R - \theta_{D4})} \quad (A.20)$$

At the margin of confronting the blend wall, E10 saturates the markets and ethanol blend rises marginally beyond the 10% of E10, where the total ethanol blended is interpreted as $\theta_R - \theta_{D4} = 0.1q_g/[0.9(q_g + q_d)]$. We then take the total differentiation and have $dq_{E85} = -0.1dq_{E10} - dq_{D4}$. When the elasticity-weighted marginal cost of using biodiesel is lower than that of conventional biofuel $(\frac{1}{\eta_b} + 1)S_b(q_b) < (\frac{1}{\eta_e} + 1)S_e(q_e)$ from PROPOSITION 3 and 4, the D4 biodiesel RIN will be prioritized over other biofuels to meet the mandate and $dq_{D4} > 0$ where it substitutes the ethanol $0.1dq_{E10} = -dq_{D4}$, which leads the solution of q_{E85} remains zero where $dq_{E85} = 0$ with the marginal change to be zero.

We then discuss the extent to which biodiesel can affect E85 production when the overproduction is at present. At the margin where biodiesel overproduction is already used as a strategic compliance $q_{D4} - \theta_{D4}(q_g + q_d) > 0$, the blend rate now becomes $\theta_R - \theta_{D4} = (0.1q_{E10} + q_{D4} - \theta_{D4}(q_g + q_d))/(q_g + q_d)$. We still have this condition where $dq_{E85} =$

$-0.1dq_{E10} - dq_{D4}$. However, the biodiesel overage reaches its maximum ($dq_{D4} = 0$), until the elasticity weighted marginal cost at least equal or higher than that of ethanol ($\frac{1}{\eta_b} +$

1) $S_b(\cdot) \geq (\frac{1}{\eta_e} + 1) S_e(\cdot)$ and without the tax credit, discussed in propositions 3 and 4. Then, E85 production can be produced with $dq_{E85} > 0$ to overcome the blend wall and creates a 100% pass-through.

Table A2 Elasticity Values Used in the Study

	Elasticity	Range	Source
Gasoline fuel demand*	-0.03	-0.02 – -0.08	EIA 2014; Liu 2014; Levin, Lewis and Wolak 2017; Hughes, Knittel and Sperling 2008
Diesel fuel demand	-0.37	-0.07 – -0.43	Winebrake et al. 2015; Korting et al. 2019; Leard et al. 2015
Corn ethanol supply	0.8	0.22 – 5.01	Luchansky and Monks 2009; Cui et al. 2011
Biodiesel supply	2.1	1.5 – 2.5	Korting et al. 2019; Irwin 2013; Babcock, Agroicone, & Peng (2013)

* Several studies in the broader economics literature reach the common conclusion that price elasticity of the demand for gasoline in the United States is very low and has been declining over time (because of a reduction in the share of income spent on fuel), ranging from -0.02 to -0.08 after 2000. A similar trend is found for diesel in the literature.

Table A3 Notation

Variables	q_{E10} : Volume of E10, preblended gasohol (gge) q_{E85} : Volume of E85, higher blend (gge) q_{gf} : Volume of blended gasoline fuel from biomass-based diesel and petroleum diesel (gge) q_{df} : Volume of blended diesel fuel from biomass-based diesel and petroleum diesel (gge) q_e : Corn ethanol (gge) q_c : Cellulosic ethanol (gge) q_g : Gasoline (gge) q_d : Petroleum diesel (gge) q_b : Biomass-based diesel (gge) q_{cw} : Cellulosic waiver credit (gge) q_{DX} : Quantity of D-coded RINs (gge) p : price (\$ per gge) λ : Shadow price/ Lagrangian multiplier (\$ per gge)
Parameters	t_b : Tax credit of biomass-based diesel \$1per gge P_{cw} : the price of the waiver credit w : Blending cost (\$ per unit) θ : Blend rate mandate (%) η : Elasticity of inverse supply curve κ, τ : RFS policy instruments on ethanol and gasoline $\kappa = \frac{P_{D6}(\cdot)q_e + P_{D3}(\cdot)q_c}{q_e + q_c}$; $\tau = \lambda_{D3}\theta_{D3} + \lambda_{D4}\theta_{D4} + \lambda_R\theta_R$ if Joint-Base, $\tau_g = \lambda_{D3}\theta_{D3} + \lambda_{D6}\theta_{D6}$ and $\tau_d = \lambda_{D4}\theta_{D4}$ if RFS is on Separate-Base.

Table A4 The carbon intensity and energy density parameters for GHG estimation

	Emission intensity (kg CO ₂ per mmBtu)	Energy density (mmBtu per gge)	Emission factor (kg CO ₂ per gge)
Corn ethanol	85	0.115	9.8
Cellulosic ethanol	-29	0.114	-3.3
Biodiesel	57	0.114	6.5
Gasoline	98	0.115	11.3
Diesel	97	0.114	11.1

APPENDIX B Supplementary Material for Chapter 3 and Chapter 4

B.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 the 2017 National Household Travel Survey (as shown in Figure B1 and Figure B2). We roughly categorize the driving demand into three groups and demonstrate the annualized demand by using the data statistics from National Household Travel Survey (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.

Just as the demand for transportation in the BEPAM model (Chen et al. 2021), we establish aggregated VKT demand on national level and then disaggregate the total mileage of the US into 20 regions and three driving demand groups based on the distribution information from the 2017 NHTS.

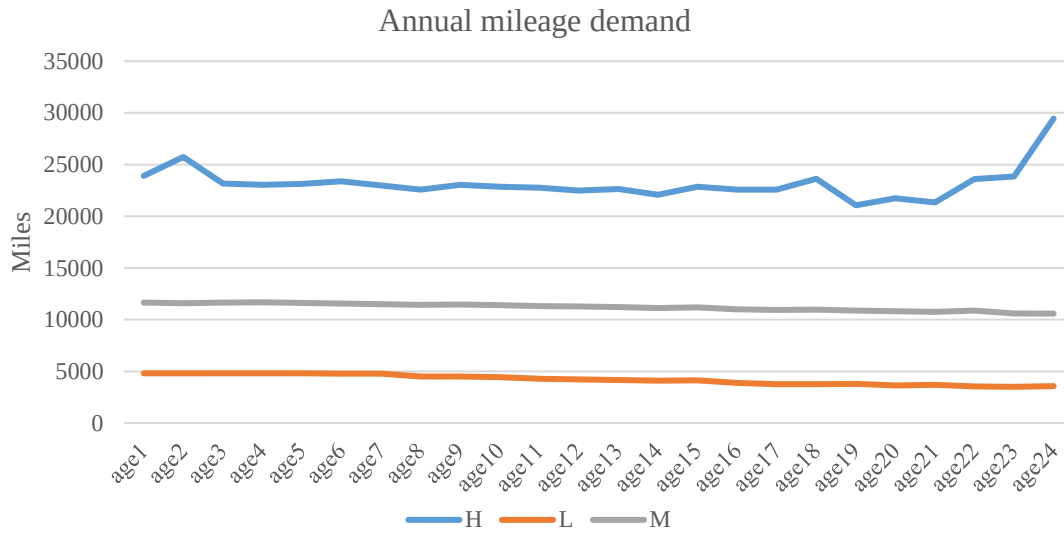


Figure B1 The annual mileage demand for each driving group across ages (NHTS, 2017)

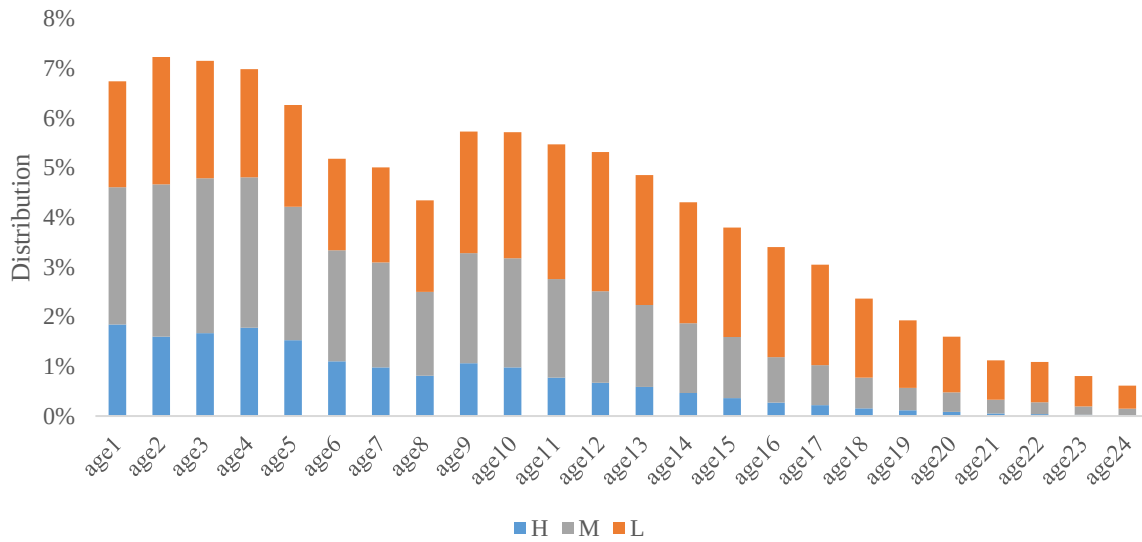


Figure B2 Vehicle count probability distribution in age and mileage group (NHTS, 2017)

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 the 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 and 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.

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 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 comply with Corporate Fuel Efficiency Standard (US Energy Information Administration 2019).

The vehicle stock dynamics are defined by equations B2 to B3 with the specification of the vehicle age, which allows us to update the age distribution of the vehicle stock at each year t . Equation B2 defines the number of new purchases of vehicle type i as the group of age 1 (denoted as $a1$) in year t . Equation B3 displays the turnover of the existing vehicle fleet (age a that is greater than 1) as 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 indicate the maximum amount of the mileage the fleet is capable of running, where m_{cap} is denoted as the maximum of annual mileage from NHTS discussed in Figure B2. 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.

$$N_{t,i,t}^i = V_{a1,t}^i \quad \forall i, t \quad (\text{B2})$$

$$V_{a,t}^i = V_{a-1,t-1}^i \times r_{a-1} - R_{a-1,t-1}^i \quad \forall i, a, 24 \geq a \geq a2, T \geq t \geq t2 \quad (\text{B3})$$

$$V_{a,t}^i \times m_{cap} \geq M_{a,t}^i \quad \forall i, a, t \quad (\text{B4})$$

Because vehicles are still drivable before reaching the extreme of the vehicle life span (age 24)²⁸, 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. 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.

B.2 Vehicle ownership cost

As shown in Figure B3, we take the average of the purchase price and fuel efficiency of the new vehicles from AEO weighted by the market share of each vehicle class from AEO 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 declining battery costs (BloombergNEF 2019). The fuel economies of all vehicle types are also projected to increase from 2016 to 2030. 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

²⁸ 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.

VMT driven by the PHEV are in charging-depleting mode. We apply this assumption to calculate the electrified mileage and electricity consumed by the PHEV.

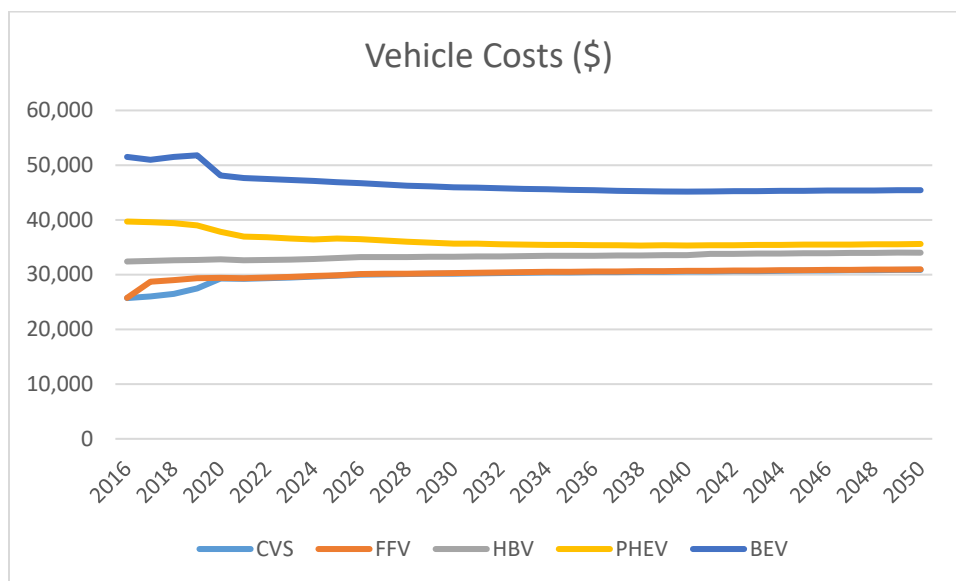


Figure B3 The vehicle purchase costs

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).

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 then apply

the factor of 0.7 to alter the compliance MPG to the actual non-experimental on-road MPG, according to the EPA (2016).

Table B1 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

B.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 could include costs of renting a car, car tolling service, or 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 \$20 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 demand distribution of vehicle miles traveled (VMT) established with the gamma distributions (Figure B4). Using the same Gamma distribution (Lin et al. 2012; Ramea et al. 2018), we generate the distribution of daily mileage driven and apply the mean and variance of the annual mileage driven obtained from National Travel Household Survey (2017) divided by 365 for three driving demand groups. The gamma distribution indicates that most of the daily trips are around the peak of the distribution, whereas the probability of driving higher mileage is relatively low. The caveat of doing so is not able to capture the difference in driving behaviors between workday and weekend.

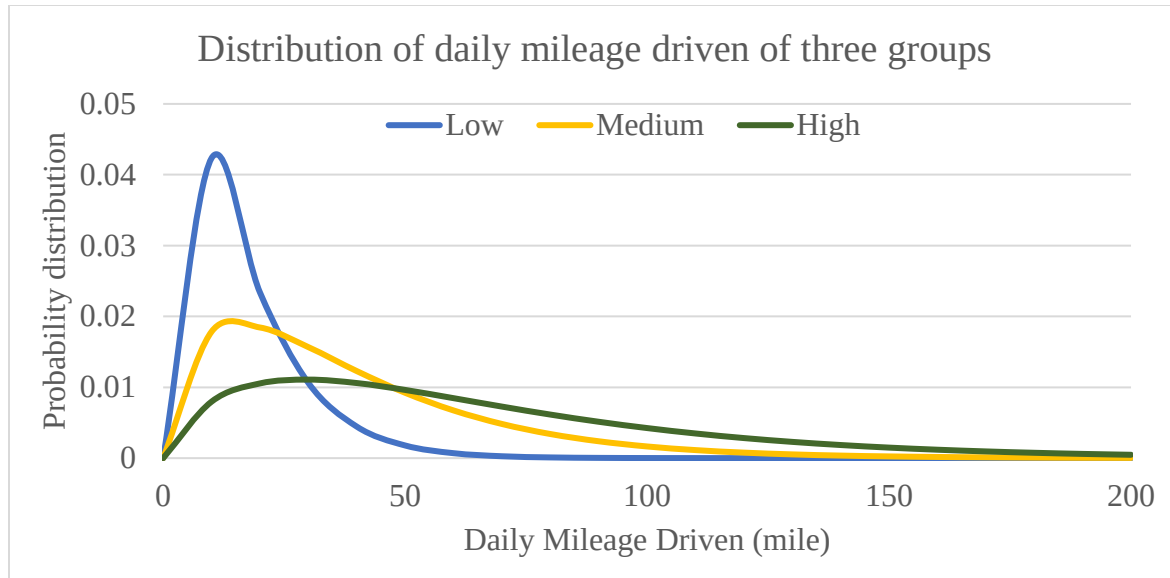


Figure B4 The Gamma distribution of the daily mileage driven

The effective mileage (eVMT) is defined as the sum of total mileage can be obtained from the available fixed charging (home and work if applied) and the public charging sources. The available charging portals (Q_{chrg}) depend on the options of charge modes chosen by the drivers and are endogenously solved by the model, in addition to 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 besides the public charging: Home and Work, Home only, Work only, and None of the 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. We assume the station and portals increases at a rate of 2% annually, according to the AEO outlook (EIA 2019a).

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

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

where T is the time spent at the charging place (8 hours 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 based on the AEO projection. We take the minimum mileage from charging availability and the range capacity to have a conservative estimation of the upper bound of the effective mileage. It determines the probability of driving demand exceeding the driving ability.

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 B3 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 (\$20 per day) times the total number of days where the demand of VMT exceeds the mileage capacity given the charging availability.

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

$$C_{range} = \sum_{day=1}^{365} 1(VMT_{day} > eVMT) \times \$20/day \quad (\$/veh)$$

B.2.2 Waiting cost

We define the waiting cost as the time spent in the stations waiting for the recharge, specifically for battery-electric vehicles. The valuation of the waiting cost 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. We quantify the number of visits to the public charging needed for the electric vehicle based on the total annual mileage demand (VMT) and the mileage range of the vehicle (R^{max}), as well as the probability ($P_{a,fix}$) 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 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 as the efficient mileage ($eVMT_{fix}$). The probability of exceeding the efficient mileage at the 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 using public charging is not related to the availability of the public charging portals.

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

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

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

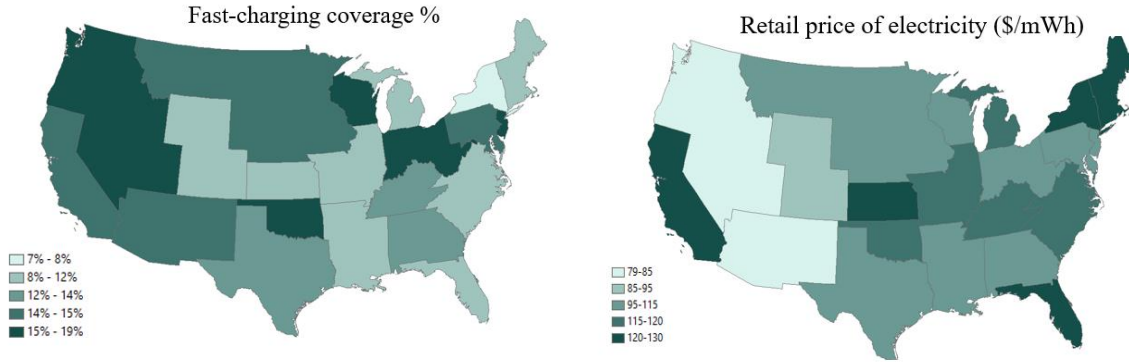


Figure B5 The DC fast-charging coverage and retail price of electricity across the US (Data sources: NREL)

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 most 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 time spent on the road, which is 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 et al. 2017) ten times for each VMT demand group, vehicle age, and each year from 2016 to 2040 to show the representative value of time across the US. We assume the plug-in hybrid vehicle (PHEV) owner has the 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.

B.2.3 Detour cost modeling

Pouliot and Babcock (2014) used the upward-sloped curves to show the increasing detour cost per gallon when the refueling stations sit farther away. It is the time cost 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 estimation.

$$C_{detour} = V_t \frac{VMT_v}{R^{max}} d_{detour} P_{a,fix} \frac{2 \times 1.3 \text{ Euclidean coefficient}}{32 \text{ mph}} = 0.082 \times V_t \frac{VMT_v}{R^{max}} d_{detour} P_{a,fix}$$

The detour cost is rewritten as the total amount of time running the detour distance monetized by the value of time, where the V_t is the value of the time; VMT is the total VMT consumption per year endogenously determined by the model; d_{detour} is the detour distance varying across states. $P_{a,fix}$ is the same probability of visit the public charging defined in B.2.2, which is defined by the probability of exceeding the efficient mileage at the fixed charging portal based on the daily driving behavior. 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 FFV (R^{max}) that increases over time and the value of time (V_t) to calculate the detour cost for FFV owners. We assume a representative car with a running speed of 32 miles per hour

and a fuel tank volume of 16.2 gallons, same 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.

$$C_{detour}^{E85} = 0.082 \times V_t \times \frac{VMT_{FFV}}{\gamma_{FFV} \times 16.2} \times d_{E85}$$

$$C_{detour}^{electricity} = 0.082 \times V_t \times \frac{VMT_{BEV}}{R^{max}} \times P_{a,fix} \times d_{charging}$$

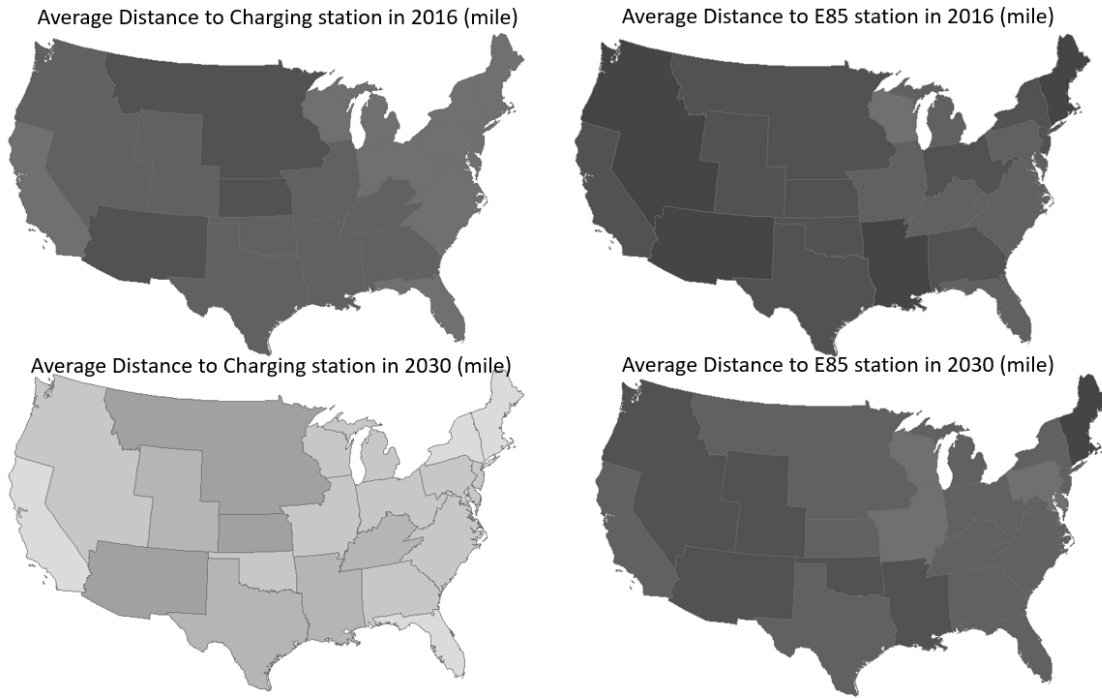


Figure B6 Reginal average mileage distance to the nearest station in the US in 2016 and 2030

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 E85 or charging stations. The dataset is available from the developer API request of NREL for the nearest

stations²⁹. The state-level detour distance is shown in Figure B6 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 vehicle, VMT demand group, and each year from 2016 to 2040 and divided by 2 to show the representative value of time across the US.

B.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 the 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 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 (as shown in the first row of Figure B7). 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.

²⁹ <https://developer.nrel.gov/docs/transportation/alt-fuel-stations-v1/>

We adjust the error terms by applying the alternative-specific constants and the scaling approach (across regions and the driving demand groups) that captures the average effect of all factors on the utility that are not included in the model by normalizing the heteroskedastic errors in different segments of the market (Train 2003). 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 in Figure B6).

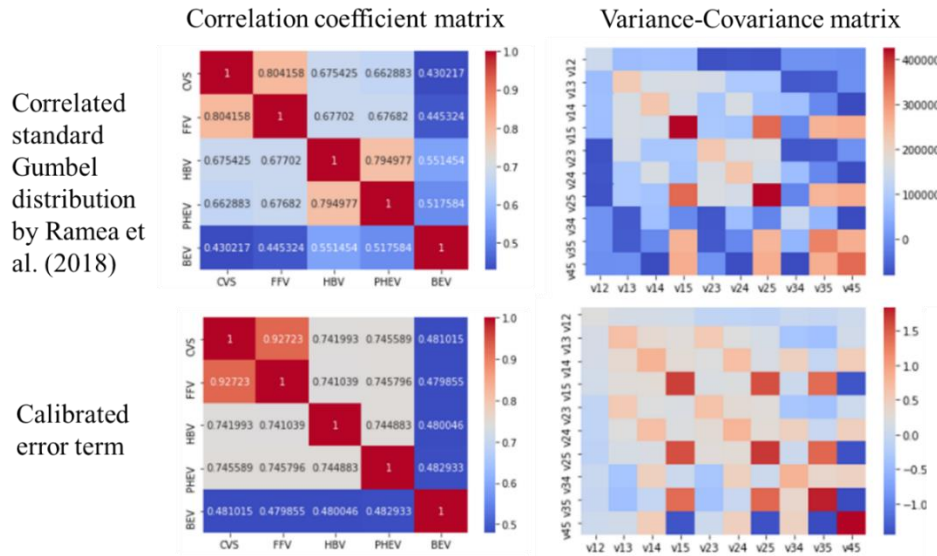


Figure B7 The heatmap of the correlation coefficient matrix and variance-covariance matrix compared to the nested error terms by Ramea et al. (2018)

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

($\text{InterestR}_{v,t,r}$). 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. The data of five keywords in 2020 is illustrated in Figure B7 as an example. These five sets of cross-sectional data, however, are not comparable between vehicle types 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 primarily concentrated in California; and searches for E85 cluster in the Midwest.

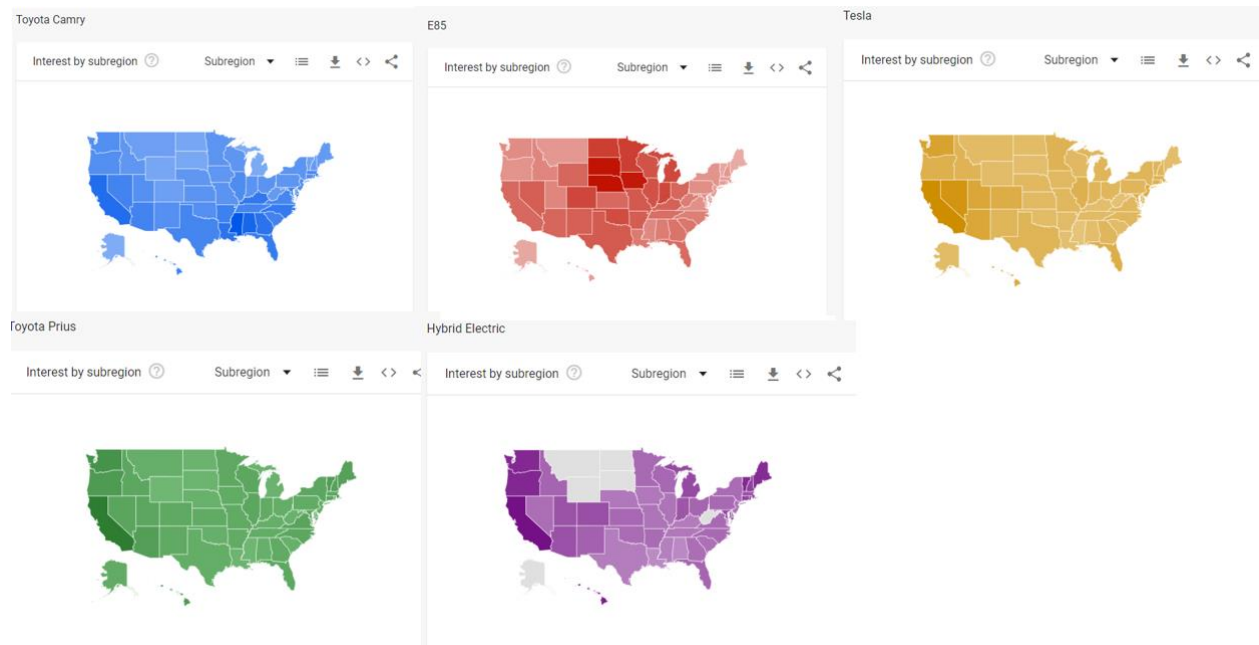


Figure B8 The normalized cross-sectional data of search interest for five keywords in 2020

Further, we adjust the mean of these error terms for each fuel type (a) to show the alternative-specific constants and the universal scalar (A) to validate the model from 2016 to 2040. The calibrated idiosyncratic preference follows the function: $\text{Idiosyncratic Preference}_{v,t,r,m} = A \times \text{InterestR}_{v,t} \times (\varepsilon_v + a)$. The systematic differentiation of preference across vehicle type, region,

and driving demand (Idiosyncratic Preference $_{v,t,r,m}$) would help identify the unobserved psychological preference (Train 2003) under the nested multinomial logit model framework. Figure B7 (second row) shows the correlation between the error terms and the variance-covariance matrix of the error difference terms. The histogram of the error terms after the adjustment are displayed in **Figure B9**.

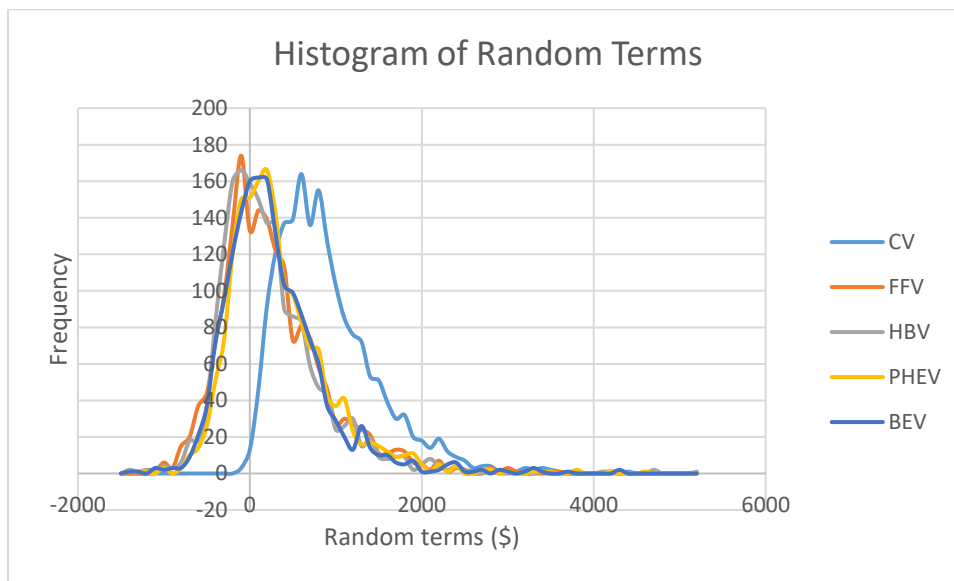


Figure B9 The histogram of the error terms for each vehicle type

B.4 Model validation

We validate the model 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 as -4, the same as Chen et al. (2020). The results compared to the observed price and quantity are shown in **Table B2**. We find the fuel consumption and production both in the US and the rest of the world generally deviate by less than 2%. The fuel prices are within a

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 a 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 conventional vehicles. The deviations of the simulated outcomes of the updated BEPAM 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 B2 Model validation from 2016 to 2019

Observed					Model outcome				Source	Average difference%
	2016	2017	2018	2019	2016	2017	2018	2019		
Fuel gallons (billion gallons)										
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%

B.5 Comparison between AEO modeling NEMS

We summarize the vehicle choice modeling structure and parameterized assumptions in Table B3 and compare them with AEO settings adopted by the National Energy Systematic Modeling maintained by the Energy Information Administration. We pivot on the AEO estimation because AEO forecast is widely used to inform federal agency decision-making and estimate the policy effect for Corporate Fuel Efficiency Standard and Safe and Affordable Fuel Efficiency standards (U.S. EPA 2012; U.S. EPA and NTHSA 2018).

The AEO estimation deploys a stepwise estimation that follows the reduced form of probability from the nested choice model. The three-stage bottom-up decisions first solve the fuel mix and fuel costs, and subsequently determines the subdivision share of the 15 alternative fuel vehicles, and finally aggregated them into five vehicle categories. The model applies the coefficient based on an analytical work of Greene (2001). The solutions of market shares are based on the linear utility functions that include only the observed vehicle attributes and fueling availability that may not reflect the nested features of different vehicle types. The total numbers of vehicle sales are determined by the Macro Activity Module and then multiply the market share to get the vehicle sales estimation for each vehicle type.

Based on the projected results from 2016 onward, we construct the benchmark scenario based on AEO estimated vehicle attributes, recharging availability. We weight the vehicle price data by the vehicle sales of each vehicle type from AEO to show the representativeness of the vehicles on sale each year. The projected prices increment the cost of the specification attributes and their cost trend, depending on the assumptions made for the technology development for each vehicle type (US Energy Information Administration 2019). Specifically, the battery electric vehicle undergoes a jump in the price as more costly 300-mile BEVs are projected to

take more than one-third share. However, as the battery cost reduces, the overall BEV price is declining. The range capacity of the battery-electric vehicle is also calculated by weighting the projected market share of three BEVs with 100-mile, 200-mile, and 300-mile of mileage capacity. The vehicle fuel economy of all vehicle types is also obtained from AEO with the market share weighted fuel economy. We use the recharging availability from AEO for 2016 and the 2% annual increase rate. AEO also projected the phasing-out schedule of the federal tax credit from 2016 and will gradually zero out the incentive by 2030 for BEV and PHEV, respectively (**Figure B10**).

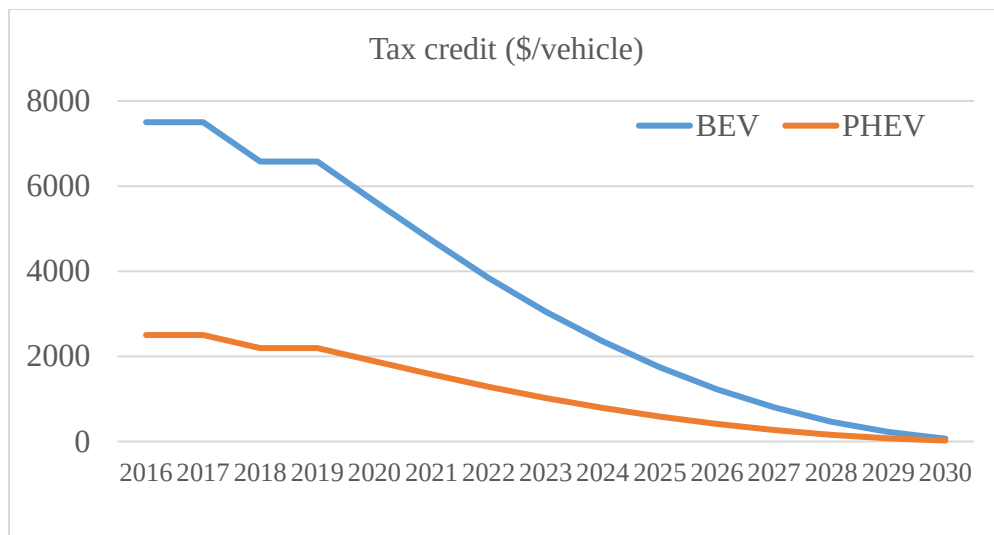


Figure B10 The projected schedule of federal tax credit phasing out by AEO

The difference of our model compared to AEO's setting is that the consumers simultaneously maximize the utility from driving the mileages net the economic costs of vehicle purchase cost, fuel cost, and maintenance cost. Moreover, the fuel costs vary not only by the fuel price but also by the mileage consumers choose to drive. The continuous solution for vehicle purchase bypasses the computational complexity in dealing with integer choices. In comparison, in AEO modeling, the consumers obtain the utility by applying the pre-determined utility function for

each vehicle type without flexibility in choosing mileage to run or volume of fuels to consume. The consumers' utility is not maximized when the option with the highest utility value only shares part of vehicle sales by applying the probability function of the logit model. Without considering the unobserved random term that indicates the consumers' idiosyncratic preferences, the probability obtained from above is biased without any economic meaning. We argue that it is necessary to consider the economic reasoning to estimate the consumers' choices in vehicle, fuels, and mileage driven.

Table B3 Comparison of Vehicle Choice Modeling and Assumption between AEO and BEPAM Simulation Model

	AEO NEMS	BEPAM
Vehicle Choice model		
Vehicle sales	Input from Macroeconomic Activity Module	Endogenous solved
Model	Three-stage logit	Social welfare optimization
Vehicle attributes considered	Vehicle price, maintenance, luggage space, battery replacement, acceleration, home refueling capacity, range, fuel availability	Vehicle price, maintenance, fuel efficiency, vehicle range, refueling capacity, fuel availability
Behavioral attributes	None	Heterogenous driving demand, four charging capacity, public charging, daily driving distribution, the value of time
Unobserved random term	None	Idiosyncratic preference from Nested Multinomial Logit Model (Bunch and Rocke, 2016)
Output	Market share	Vehicle purchase
Assumptions		
Vehicle types	2 classes, 14 fuel types, 16 model type, 9 regions	2 classes, 5 fuel type, 24 ages, 20 regions
Vehicle price	Incremental prices based on technology and fuel types	Sales-weighted price from AEO
Vehicle miles	Function of fuel cost, drivers, the employment rate	Endogenous solved by BEPAM
MPG	Estimated based on technology, cost, R&D, and model availability	Same as AEO for the new vehicle

Table B3 Comparison of Vehicle Choice Modeling and Assumption between AEO and BEPAM Simulation Model (Cont.)

Battery capacity	100 miles, 200 miles, 300 miles	Market shares weighted battery range from AEO
Fuel price	Input from macroeconomic activity module	Endogenous solved by BEPAM
Fuel availability	2% increase annually, varying across nine census regions	Same as AEO
Policy	RFS, Tax credit, CAFE standard, Low-Emission Vehicle Program	RFS, Tax credit, CAFE standard
GHG emission	EPA	EPA

B.6 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.

B.6.1 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 also boosts FFV purchases though 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.

B.6.2 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 B4). 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 B4 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)
<i>Vehicle Stock (million)</i>	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

Table B4 Effect of alternative biofuels mandate on transportation sector in 2030 (Cont.)

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.

B.6.3 GHG Intensity of Vehicle

The greenhouse gas (GHG) emissions per mile of five vehicle types under different policy scenarios are displayed in Figure B11. Under the baseline policy scenario (1), 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.

B.6.4 Total GHG Emission

We calculate the GHG emissions of transportation, electricity, and agriculture sectors, as shown in Table B5. In 2016, the transportation and electricity sectors accounted 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.

Table B5 GHG emissions of last year and cumulative GHG emissions in 2030

		<u>Corn Ethanol Mandate in 2030</u>			<u>Corn+Cellulosic Ethanol Mandate in 2030</u>		
	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%	

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 B5, however, have smaller effects with lower absolute changes in million Mg CO₂.

B.6.5 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 B6). 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 4.4.1 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 CO₂, the abatement cost of CO₂ with the tax credit for EV is negative at -\$49 per MgCO₂, 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 CO₂ 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 CO₂ 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 CO₂. 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 CO₂. 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 CO₂ of emission reduction upscales the abatement cost to \$274 per Mg CO₂.

Table B6 Effect of alternative biofuels mandate on social welfare over 2016-2030 (billion \$)

	<u>Corn Ethanol Mandate</u>			<u>Corn+Cellulosic Ethanol Mandate</u>		
	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
<i>Agricultural sector</i>	3,004	-2	-3	30	30	31
Agricultural consumers	2,111	1	2	-7	-9	-10
Agricultural producers	893	-3	-5	36	39	40
<i>Transportation fuel sector</i>	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
<i>Electricity sector</i>	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
<i>Government revenue</i>	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 MgCO₂)		-49	304	211	192	274

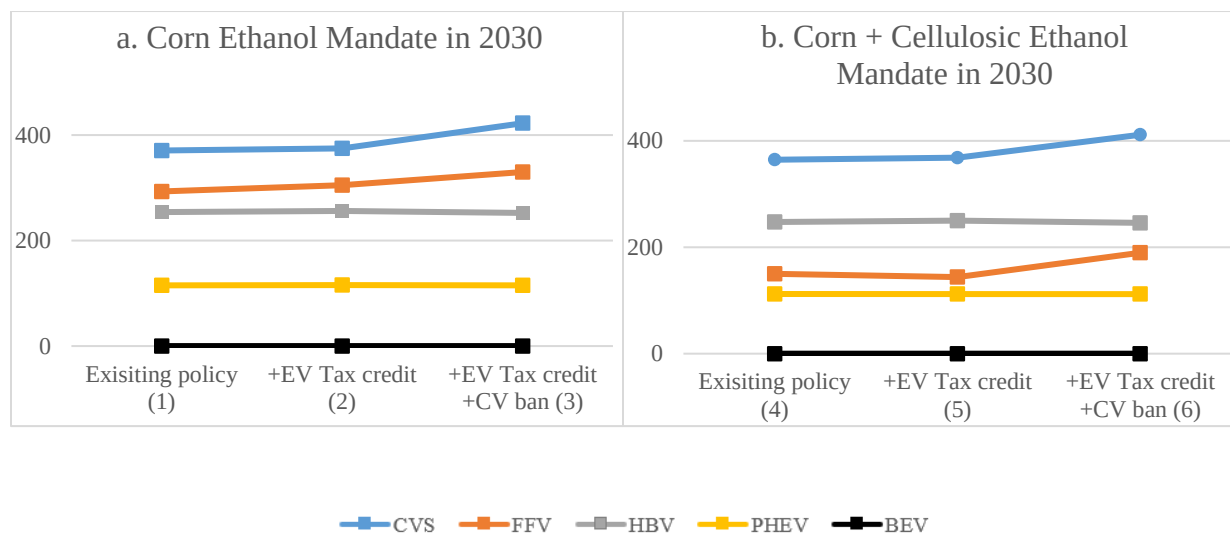


Figure B11 The carbon intensity of vehicle mileage under each scenario (g CO₂ per mile)