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Decarbonizing Transportation using Market-Based Low-Carbon Fuel Incentives

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Decarbonizing Transportation using Market-Based Low-Carbon Fuel Incentives

By

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DISSERTATION

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Abstract

Decarbonizing the transportation sector, which is the largest contributor to U.S. greenhouse gas (GHG) emissions, requires a transition away from fossil fuels to renewables like biofuels and electricity. An increasing number of policies have been enacted to incentivize the use of renewable fuels. The U.S. Renewable Fuel Standard, California Low Carbon Fuel Standard, and Oregon Clean Fuels Program are in the vanguard of such policies in the United States. California and Oregon's policies are examples of a carbon intensity standard, a tool that has become increasingly popular among U.S. policymakers. This dissertation explores the past, present, and future of these policies. The first chapter begins with the present, addressing an important challenge of achieving efficient outcomes currently faced by policy stakeholders: pass-through of policy costs and incentives to fuel prices. Findings suggest that compliance costs are fully passed through, and biofuel incentives are fully passed through in some regions and less than fully passed through in others. The second chapter looks ahead to the end of the decade, forecasting a range of compliance outcomes under California's LCFS through 2030. Annual compliance requires that by 2030, the state's transportation sector must achieve a 20 percent carbon intensity reduction below 2010 levels. Achieving the target will require the majority of diesel demand to be supplied with biomass-based diesel unless electric vehicle adoption grows substantially. Finally, lessons from the last decade are drawn in the third and final chapter, exploring trends in the three standing carbon intensity standards in California, Oregon, and British Columbia utilizing publicly available historical data.

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Contents

Introduction

Decarbonization of the U.S. and global economies requires a transition away from fossil fuels to renewables, especially in the transportation sector – the largest contributor to U.S. greenhouse gas (GHG) emissions.[1] The environmental costs associated with the production and combustion of petroleum fuels have not been internalized by producers and consumers, respectively, prompting government intervention. Federal and state governments have increasingly looked to market-based environmental policies to reach their decarbonization goals, often by enacting credit trading schemes for markets to meet an annual standard. This dissertation studies the most prominent of such U.S. public policies that incentivize displacement of petroleum fuels with renewable and low carbon transportation fuels.

The Renewable Fuel Standard (RFS) is the largest program to support renewable fuels in the U.S., requiring a variety of biofuels to be blended in the national fuel supply. The RFS is criticized for being technology biased, as it specifies how much of which biofuels must be used to reach its emissions reduction goals. State and other federal governments now increasingly look to carbon intensity standards in the transportation sector, which provide a technology-neutral policy option. The largest of such policies is California's Low Carbon Fuel Standard (LCFS), which sets a carbon intensity standard for the state's transportation fuel supply.

This dissertation explores the past, present, and future of low-carbon fuel incentive programs. Chapter 1 begins with the present, addressing an important ongoing challenge associated with these policies – namely incomplete pass-through of incentives and costs to fuel prices. Chapter 2 looks ahead a decade, forecasting a range of compliance outcomes for California's LCFS

[1] In 2019, the transportation sector accounted for 30 percent of all GHG emissions in the U.S. according to the Environmental Protection Agency: https://www.epa.gov/greenvehicles/fast-facts-transportation-greenhouse-gas-emissions.

through 2030. Finally, lessons from the last decade are drawn in Chapter 3, exploring trends in the three standing carbon intensity policies worldwide using publicly available historical data.

Chapter 1 provides an empirical analysis of credit revenue pass-through. Specifically, time series techniques are used to estimate the extent to which implicit taxes and subsidies generated from the RFS, LCFS, and CFP are passed through to a variety of diesel fuel prices. In a second-best policy framework, an efficient RFS and LCFS achieve their respective GHG targets while minimizing compliance costs. If fuel blenders have market power, they have the incentive to drive up compliance costs, leading to an inefficient outcome. The findings from Chapter 3 suggest that obligated parties completely pass through their implicit taxes from the RFS, LCFS, and CFP to wholesale diesel prices. They suggest incomplete pass through, on the other hand, of biodiesel subsidies to rack blended diesel prices.

The RFS, LCFS, and other carbon intensity standards all tout an attractive feature: revenue neutrality. These policies are revenue neutral to the transportation system because the implicit tax revenue generated from obligated parties purchasing compliance credits is used to lower the price of alternative fuels, effectively subsidizing them. Market imperfections, however, may restrict how much of the credit revenue is being fully passed through to consumers in the form of lower prices for alternative fuels.

Chapter 2 assesses if and how California is likely to achieve the 20 percent CI reduction target by 2030 set forth by their LCFS. Using a Vector Error Correction (VEC) model, LCFS credit demand is projected through 2030 under business-as-usual uncertainty. The model is trained using 30 years of historical trends in gasoline and diesel demand, vehicle miles travelled, oil prices, and other economic indicators. Several policy scenarios are simulated and evaluated against a baseline scenario, which extrapolates current trends. Biomass-based diesel, the marginal fuel for LCFS compliance, makes up between about 60 and 80 percent of finished diesel in 2030 in the baseline scenario, reflecting a substantial increase from current levels.

Under most alternative policy scenarios, and especially in the case of rapid electric vehicle deployment, compliance is met with significantly less biomass-based diesel.

The first two chapters analyze the LCFS and CFP, which are a relatively new policy instruments used to reduce transportation emissions reductions. As more and more states continue to adopt similar carbon intensity (CI) standards, it is imperative to understand similar existing programs have performed, however comprehensive analyses on them are relatively scant.[2] Aiming to fill that gap, the final chapter, Chapter 3, reviews the three standing carbon intensity standards in California, Oregon, and British Columbia using publicly available data and information.

British Columbia was the first jurisdiction to implement a CI standard in 2010, followed shortly after by California in 2011, and later followed by Oregon in 2016. California's program is the largest given the state's voluminous population and fuel demand. Low CI scores associated with avoided emissions have brought about staggering growth in the use diesel alternatives such as biodiesel, renewable diesel, and biogas in the three jurisdictions. In California, diesel alternatives generated the majority of LCFS credits, generating nearly two billion dollars in revenue in 2020 alone, a third of the total. Since diesel are so critical to compliance, this dissertation pays special attention to that side of the transportation sector and seeks to impart an understanding of how diesel markets and alternative fuel policies interact.

[2] Washington enacted a Clean Fuel Standard to begin in 2023; Brazil implemented a transportation fuel carbon intensity standard called RenovaBio (which applies only to renewable liquid fuels); Colorado, New Mexico, and New York are considering developing LCFS-like programs; and Canada will finalize their federal carbon intensity standard regulation in spring 2022.

Chapter 1. Pass-Through of Policy Costs and Incentives to Fuel Prices.

Renewable and low carbon fuels are becoming an important part of decarbonization strategies worldwide. Several policies have been, or are being planned to be, implemented in the United States. There are three policies, one federal and two state, that lead this effort. The U.S. Renewable Fuel Standard (RFS) requires certain percentages of gasoline and diesel be displaced by renewable fuels each year. California's Low Carbon Fuel Standard (LCFS) and Oregon's Clean Fuels Program (CFP) set targets to reduce the CI of transportation energy in their states. The RFS, LCFS, and CFP all rely on systems of tradeable credits for compliance which prompt implicit tax-subsidy schemes in fuel markets. Firms pay a penalty on their petroleum products and the revenue is transferred to alternative fuel producers effectively in the form of a subsidy. The efficacy and efficiency of these policies hinge on the implicit taxes and subsidies propagating through fuel supply chains.

This paper studies pass through across two dimensions in the diesel sector: implicit taxes placed on petroleum diesel and implicit subsidies awarded to biodiesel. Implicit taxes and subsidies from the RFS stack with those from the LCFS and CFP in California and Oregon, respectively, and therefore are evaluated both separately and together. There are three points in fuel supply chains where pass through is relevant, this paper studies two of them: the wholesale market to blenders and blenders to retailers. This paper does not investigate pass through from retailers to consumers, which must also be complete to achieve efficacy of the policies. The pass through of biodiesel subsidies to retail prices of blended diesel is an important area for future research, especially given evidence of incomplete pass through of ethanol RIN subsidies to E85 retail prices in the literature (Lade & Bushnell, 2019; Li & Stock, 2019).

U.S. crude oil refiners and petroleum importers are required to purchase Renewable Identification Numbers (RINs), the compliance credits in the RFS, for each gallon of gasoline and diesel supplied, which act as an implicit tax. California and Oregon refiners and importers face a similar obligation under the LCFS and CFP, respectively, namely deficits that are generated for each gallon of gasoline and diesel consumed in-state. The total tax payments reflect the cost of compliance of the policies. There are robust markets for RINs, LCFS, and CFP credits and the market price, along with the stringency of the policies, determine the level of the taxes and therefore the cost of compliance.

Fuel blenders purchase biofuels with a RIN attached to it. Once the fuel is blended, the RIN is separated from the fuel and can be sold on the RIN market. The value of the RIN then, acts as an implicit subsidy on the biofuel. If blenders have market power in selling RINs, they have the incentive to drive up RIN prices, which in turn, raises compliance costs for refiners and consumers. How much of the RIN tax that is passed through by refiners will determine the incidence of the increased RIN prices resulting from the incomplete pass through of the RIN subsidy. The same relationship between the tax and subsidy is present in the LCFS and CFP. This paper is the first to analyze RIN pass through on both sides of the tax-subsidy mechanism, the first to examine pass through of biodiesel subsidies, and the first to consider either the LCFS or CFP.

Indeed, most studies to date on pass-through for implicit taxes and subsidies for fuels have focused on the federal RFS and the gasoline industry, with much less focus on state policies and the diesel industry. Diesel fuels accounted for 27 percent of total transportation energy in 2020.[3] Biomass-based diesel (BBD) earns the lion's share of credits in California's LCFS and a growing proportion in Oregon's CFP, making diesel an important piece of the transition to lower carbon fuels. Furthermore, pass-through results from the gasoline industry may not hold for the diesel industry because of differences in costs, production, storage, and blending constraints, demand and supply elasticities, and market structure.

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[3] See EIA: https://www.eia.gov/energyexplained/diesel-fuel/use-of-diesel.php.

The first contribution of this paper is estimating the extent to which the RIN tax, the LCFS diesel tax, and the CFP diesel tax have been passed through to wholesale diesel prices since 2015. To estimate pass through of the RIN tax, I take the approach used in Knittel et al. (2017) which exploits the fact that wholesale diesel and jet fuel prices only differ in their RIN obligation. Their sample covers 2013-2015, whereas mine covers 2015-2021, therefore providing a larger and more recent sample to leverage. I find that refiners, on average, fully passed through the cost of their RIN obligations to wholesale diesel prices over the last six years.

The issue of RIN pass through has been of particular interest recently. RFS compliance costs reached an all-time high in 2021, strengthening the already substantial concern of potential harm on consumers and the refining industry, especially amidst a global pandemic. Senator Pat Toomey and his senate colleagues sent a letter to the Environmental Protection Agency (EPA) – the administrator of the RFS – asking them to waive or reduce the 2020 volume requirements to mitigate the unduly burden placed on consumers and refiners via RFS compliance costs.[4] EPA responded in kind, reducing the 2020 mandate retroactively in 2021.[5]

Still, some in the refining industry have argued that the RFS has made it harder to produce gasoline and diesel domestically, according to a recent article in Reuters.[6] Refiners have indeed seen much larger RFS bills this year; one Pennsylvania refinery had a $350 million RIN obligation in the first three months of 2021, 500% higher than their total 2019 of $58 million.[7] In 2021, refiners paid an implicit tax upwards of 20 cents per gallon of gasoline and diesel. Smaller refiners have been granted exemptions by EPA for their RIN obligations for several years. However, prior work suggests that smaller refineries have been able to pass through the cost of their RIN obligations at the same rate as large refineries (Burkhardt, 2019). This also comes at a

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[4] See https://www.toomey.senate.gov/newsroom/press-releases/toomey-and-colleagues-urge-epa-to-waive-biofuel-blending-requirements.
[5] See https://asmith.ucdavis.edu/news/biofuel-policy-explained for a discussion of the
[6] The Reuters article can be found here: https://www.reuters.com/business/energy/us-oil-refiners-bet-farm-biden-will-back-them-biofuels-2021-11-11/.
[7] See https://www.afpm.org/newsroom/blog/rins-disappear-2021-rfs-compliance-could-hit-30-billion.

time when gasoline and diesel prices have both reached their highest levels since 2014. The Biden administration has announced that the Department of Energy will release 50 million barrels of oil from the Strategic Petroleum Reserve to combat the high fuel prices. As of November 2021, the average retail price of diesel is $3.72/gallon and gasoline, $3.49/gallon.[8]

The unprecedented growth in RIN prices due to the soybean boom in 2020 and 2021 mentioned above raises speculation as to whether that period is driving any result of incomplete pass through. However, I present results where that period is dropped from the sample and find lower rates of pass through, not higher, especially in San Francisco. In fact, the striking increase in compliance costs during that period were largely passed through in most U.S. regions.

Refiners in California and Oregon face an additional cost due to deficit obligations under the LCFS and CFP, respectively. In California, the additional cost is double for diesel; the implicit tax associated with their deficits were also upwards of 20 cents per gallon of diesel under the LCFS. In this paper, I find that refiners have passed through little to none of the LCFS tax to wholesale diesel prices. However, I find that the LCFS tax has been fully passed through to rack prices by blenders, which suggest that refiners have exercised their ability to trade their deficit obligations downstream. This suggests that LCFS compliance costs are borne by retailers and/or consumers. Due to data limitations, I am unable to estimate the pass through of the implicit CFP tax.

The second contribution of this paper is estimating the extent to which implicit subsidies from the RFS, LCFS, and CFP are passed through to rack prices of blended diesel. Pass through of RIN subsidies to biodiesel has been acknowledged but sidestepped in previous work due to data limitations and the unknown interactions of the RFS and the Blender's Tax Credit (BTC). The BTC awards blenders a $1 tax credit against their federal liability for every gallon of

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[8] Average retail petroleum prices can be found at https://www.eia.gov/dnav/pet/pet_pri_gnd_dcus_nus_w.htm.

biodiesel blended in the U.S. and it is realized in addition to the RIN, and the LCFS credit or CFP credit in California and Oregon, respectively. The BTC was implemented in 2005 and expired four times since, but retroactively reinstated each time. When expired, blenders and biodiesel producers formed contracts to share the expected future credit and had potentially unknown impacts on the blenders' margins and RIN prices. However, with straightforward assumptions about the BTC, I can identify the pass through of RIN subsidies to blended diesel prices.

This subsidy pass-through analysis undertaken here is most like Pouliot et al. (2017) in the existing literature, which studies pass through of ethanol RIN subsidies to blended gasoline prices at racks across country. They find incomplete pass through in some regions and attribute it to lack of salience about how the subsidies impacted profit margins. I extend their empirical framework to estimate the pass through of RIN, LCFS, and CFP subsidies to blended biodiesel prices at fuel terminals in eight U.S. cities. I utilize daily pricing data from the Oil Price Information Service (OPIS) and Bloomberg on rack prices and spot prices of diesel, biodiesel, RINs, and LCFS and CFP credits to calculate daily profit margins for blenders. If a subsidy is fully passed through, blenders' profit margins should move one-for-one with changes in said subsidy.

There are significant heterogeneities in the pass through of biodiesel subsidies across space, time, and policy. RIN subsidy pass-through is complete in the Midwest, incomplete on the West Coast, Gulf Coast, and East Coast. These results are somewhat consistent with Pouliot et al., (2017); they find incomplete pass-through only in the eastern U.S. Price spreads in the west coast were too volatile to provide reliable estimates. This was due to an extreme event at the end of their sample in 2015 — the Exxon Mobil refinery explosion in California. My sample follows the explosion and accounts for the LCFS, allowing for more precise estimates of pass through on the West Coast. The finding that pass through is still incomplete on the East Coast may suggest that incomplete RIN subsidy pass through stems from a mechanism other than lack of salience. As with pass through of the RIN tax, pass through of the RIN subsidy is less complete when dropping the time period with the shock to RIN prices.

LCFS subsidies exhibited significantly less variation over my sample, making it difficult to recover precise estimates of pass through. However, I find that, on average none, of the LCFS subsidy is passed through to rack prices of blended diesel in California urban centers. In smaller California cities, complete pass through of the LCFS subsidy pass cannot be ruled out. After the LCFS subsidy grew to significant levels, pass through was lower, indicating lack of salience wouldn't explain the results of incomplete pass through. LCFS subsidy pass through is lower for blends with higher biodiesel content, which is consistent with market power in higher blends (Pouliot et al., 2020). CFP subsidy pass through is estimated even less precisely but the findings resemble a similar pattern as the LCFS.

Taken together, the results outlined above can be summarized as follows. The RFS largely operates as intended in the diesel sector, however, findings are consistent with local market power in fuel blending on the coasts. With incomplete pass through of RIN subsidies in some markets and complete pass through of the tax, it may be that blenders are raising RFS compliance costs for consumers. California and Oregon exhibit less than complete RIN subsidy and LCFS subsidy pass through, which suggest blenders exercise local market power. On average, only 68 percent and 66 percent of the combined subsidies are passed through in California and Oregon, respectively.

The remainder of the paper is structured as follows. Section 1.1 provides background information and institutional context on the RFS, LCFS, CFP, and the. Section 1.2 describes markets for diesel and biomass-based diesel. Section 1.3 describes the data used to execute the empirical strategy. Section 1.4 describes the empirical strategy for and presents results from estimating pass through of the implicit taxes from the RFS, LCFS, and CFP. Section 1.5 describes the empirical strategy for and presents results from estimating pass through of the implicit subsidies from the RFS, LCFS, and CFP. Section 1.6 concludes and discusses policy implications of the findings.

1.1 Policy Background

1.1.1 The U.S. Renewable Fuel Standard

The RFS was enacted in the 2005 Energy Policy Act and was revised and expanded as part of the Energy Independence and Security Act of 2007, sometimes referred to as RFS2. The RFS is administered by the U.S. Environmental Protection Agency (EPA) and specifies a fraction of U.S. petroleum transportation fuel consumption that must be displaced by renewable fuels. Using projections of gasoline and diesel consumption from the Energy Information Administration (EIA), the mandate is communicated as a volume of renewable fuels for the upcoming two years. These volumetric mandates are called Renewable Volume Obligations (RVOs).

RVOs are set separately each for conventional (D6), advanced (D5), BBD (D4), and cellulosic (D3) categories. Refiners or fuel importers, the obligated parties under the RVO, can either produce biofuels or purchase credits, called Renewable (fuel) Identification Numbers (RINs), generated from the production of renewable fuels. Each refiner must retire (submit to EPA) a certain number of each type of RIN each year for each gallon of gasoline or diesel that they sell. For example, in 2018, for every 100 gallons of gasoline or diesel sold, refineries had to retire a total of 10.67 RINs, including at least 2.37 advanced biofuel (D5) RINs, 1.74 biodiesel (D4) RINs, and 0.16 cellulosic (D3 or D7) RINs. The remaining 8.14 RINs that must be retired can be of any category, but typically come from corn ethanol (D6) RINs and BBD (D4) RINs. Corn ethanol is the lowest-cost renewable fuel, however the E10 blendwall forces the market to use the next lowest-cost option, BBD, for much of the conventional RVO.

Since refiners must purchase RINs for every gallon of gasoline and diesel they sell, RINs act as a tax that is used to subsidize renewable fuels. The magnitude of the taxes and subsidies depend on the economics of the underlying fuel markets. Since each category relies on different types of renewable fuels, each type of RIN has its own market price. Generally, the market price for each type of RIN reflects the expected cost of supplying the marginal gallon of the relevant renewable fuel needed to meet the RVO, relative to the cost of gasoline or diesel. Since advanced and cellulosic biofuels are much more expensive than conventional biofuels, the market price for their RINs are relatively expensive. Since BBD has been used to satisfy the conventional (D6) RVO, the market price for D6 RINs have converged to the market price for D4 RINs.

RINs can be traded freely before being retired for annual compliance, and 20 percent of RINs generated in one year can be banked compliance in the next year. In an efficient RIN market, these features cause future expectations around fuel markets and policy to influence RIN prices. Lade et al., (2018) show that RIN prices follow a random walk and respond quickly to EPA announcements that change expectations around future compliance.

The point of policy incidence is at the fuel terminal for the RFS. The fuel terminal is the midpoint in the supply chain of RINs. Renewable fuel producers generate RINs with every gallon of renewable fuel they supply. When RINs are generated, they are "attached" to the renewable fuel, meaning that whoever purchases that fuel receive the RIN certificate with the purchase. Terminals purchase the renewable fuels with the attached RINs and blends the renewable fuel with petroleum, which separates the RIN from the fuel. When the RIN is separated, it can be traded freely. When blenders separate RINs, they sell them to refiners who must retire RINs to EPA for compliance. Since blenders can sell RINs once separated, they are willing to pay a premium for renewable fuels. Figure 1 shows the movement of fuel and RINs through the supply chain in the context of diesel.

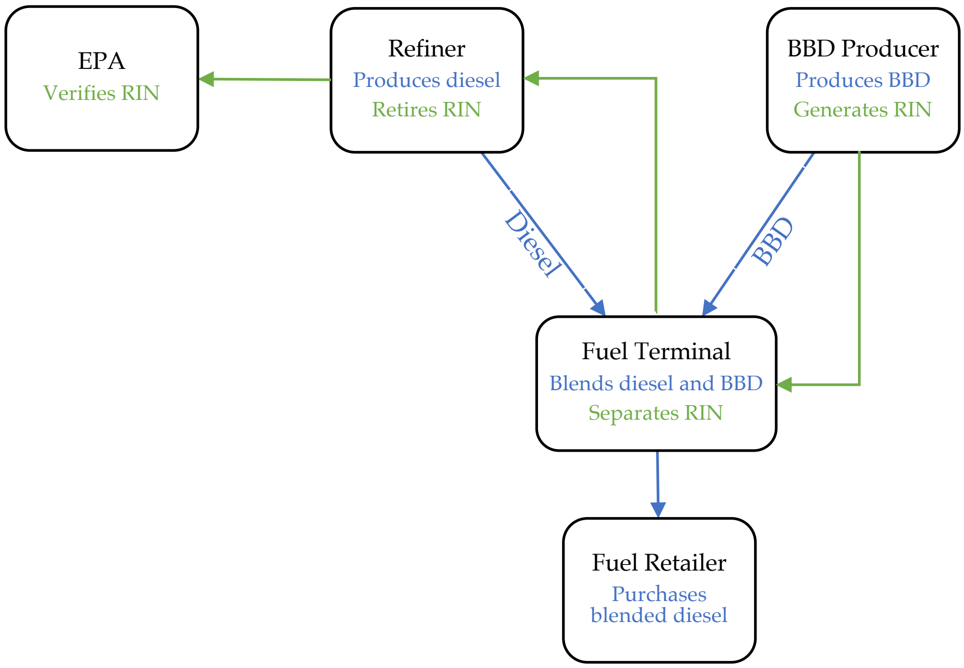

Figure 1: Supply Chain of Fuel and RINs

RINs can be generated by domestic BBD producers, foreign BBD producers, and domestic BBD importers. The majority of biodiesel consumed in the U.S. is produced domestically. In 2016, nearly a quarter of biodiesel was imported, however in recent years imports fell below an eighth of total consumption – 10 percent in 2020. Almost no RINs generated from U.S. biodiesel consumption are awarded to foreign producers. The majority of renewable diesel used in the U.S. comes from abroad, although domestic production is on the rise. The share of U.S. renewable diesel consumption from domestic production has nearly doubled from 2013 (27 percent) to 2020 (55 percent). Unlike biodiesel, virtually all RINs generated from foreign renewable diesel producers go to the foreign producer rather than the importer.

1.1.2 California's Low Carbon Fuel Standard

The LCFS was approved by the California Air Resources Board (CARB) in 2009. CARB then implemented the LCFS in 2011, amended it in 2013, re-adopted it in 2015, and extended it in 2019 to set targets through 2030. The LCFS was designed to lower the carbon intensity (CI) of transportation fuel in the state. To that end, CARB specifies an annual CI standard, measured in grams of CO2 equivalent per megajoule (gCO2e/MJ) of energy, that the California transportation fuel pool must satisfy. Currently, CARB has specified that the CI of transportation energy must reach a 20 percent reduction below 2010 levels by 2030. Beginning in 2020, this entails the CI declining 1.25 percent annually.

The LCFS relies on a system of tradeable credits for compliance like the RFS, but with important differences. Fuels with a CI score above the standard generate deficits and fuels with a CI score below the standard generate credits. Compliance requires that every deficit be met with a credit. The supply chain of LCFS credits can follow a similar path as RINs described in Figure 1, but aren't restricted to it like RINs are. Refiners and importers are the obligated parties who generate deficits; however, the obligation can be traded to other entities, for example from refiners to blenders.[9] Similarly, alternative fuel producers generate LCFS credits but that status may also be transferred downstream and the fuel mustn't be sold with the credit "attached."

Each year petroleum and other higher-CI fuels generate more deficits per gallon each year as the standard tightens. Similarly, alternative fuels generate less and less credits each year, unless producers can demonstrate a lower CI. This dynamic is intended to incentivize innovation in reducing the CI of fuels. Alternative fuel producers must demonstrate the lifecycle CI of their fuel via third-party verification. Producers apply for "pathways" which track the lifecycle carbon intensity of fuels from well to wheel. When a fuel pathway application is approved, their fuel earns the CI score associated with the pathway.

LCFS credits can be banked freely out to 2030 and are fully fungible, so credits generated from any type of fuel can be used to cover deficits generated from any type of fuel. As of 2021 Q1, approximately 7.86 million credits sit in the LCFS credit bank. The LCFS uses a Cost Containment Mechanism (CCM) that effectively sets a credit price ceiling of $200/MT in 2016

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[9] See § 95483(a)(2) of 2020 California LCFS regulation which can be found at https://ww2.arb.ca.gov/sites/default/files/2020-07/2020_lcfs_fro_oal-approved_unofficial_06302020.pdf

dollars, tied to inflation thereafter. LCFS credits were trading between $20/MT and $100/MT in early years of the program but hovered near the ceiling between 2018 and 2020, before falling due to issues with the COVID-19 pandemic and expectations around expanding renewable diesel capacity (Mazzone et al., 2021).

A range of alternative fuels generate LCFS credits. Figure 2 depicts the annual percentages of energy (bottom) and credits (top) coming from each alternative fuel type since the LCFS began in 2011. Ethanol made up the majority of both energy and credits among alternative fuel sources in the earlier years of the program. A much larger percentage of credits now come from biomass-based diesel, electricity, and biogas. Large credit contributions from electricity and biogas have come more from utilization of lower CI pathways over time rather than significant increases in volume. Growth in renewable diesel crediting has come from substantial increases in blending in the state.

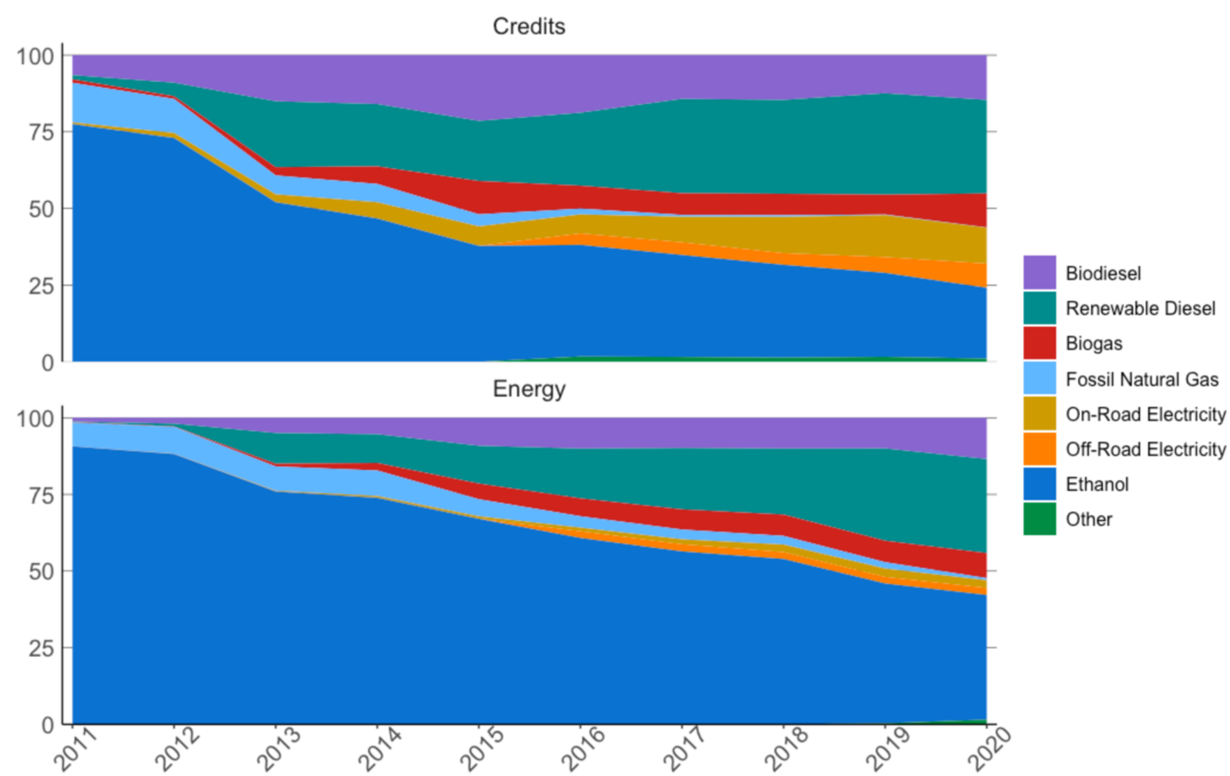

Figure 2. Share of Alternative Fuel Energy and Credit Shares by Fuel Type

Since 2011, there have been approximately 3.5 billion gallons of finished diesel consumed in California each year. However, the portion made up of biomass-based diesel has grown from approximately 0.3 to 24 percent over the decade. The 855.4 million gallons of biomass-based diesel consumed in the state has been produced from a variety of feedstocks, including vegetable oils, waste oils, and animal fats. Soybean oil is by far the most prominent feedstock for biomass-based diesel in the U.S. but is rarely used in California due to its relatively high CI – which is in large part due to its adverse effects on land use, captured by the indirect land use change (ILUC) score. The vast majority of biodiesel consumed in California is produced from corn oil and used cooking oil. The volume-weighted average reported CI of all biodiesel is shown later in Figure 5, along with the average CI score of SME-specific biodiesel. This paper is concerned with the LCFS insofar as the costs it places on petroleum diesel and incentives provided to biodiesel, but a more detailed description of the policy and the other fuel types can be found in Mazzone et al., 2021.

1.1.3 Oregon's Clean Fuels Program

The CFP sets an annual CI standard, similar to the LCFS, and was implemented in 2016 by Oregon's Department of Environmental Quality (DEQ). It specifies a 10 percent reduction in the state's transportation fuel CI by 2025 from 2015 levels. A recent executive order laid out an extension of the CFP target 20 percent reduction by 2030 and 25 percent by 2035 but is yet to be formalized in the regulation. Although they go by different names, Oregon's CFP is very similar to California's LCFS and is in large part designed after it. The CFP accepts certified LCFS pathways, adjusted for differences in transportation.

Figure 3 shows the percentage of energy and credits from each fuel type and shows a much more static picture than the LCFS. Ethanol and biomass-based diesel make up the majority of both alternative fuel energy and CFP credits. Biodiesel has contributed over a quarter of both alternative fuel energy and credits over the lifetime of the program. Unlike California, biodiesel is still blended more than renewable diesel in Oregon. The majority of biodiesel consumed in

Oregon is produced from canola oil and used cooking oil. Canola oil pathways are generally associated with higher CI scores than corn oil, which is why the average CI score of biodiesel is higher in Oregon than California.

CFP credits are also fungible and freely banked, with 709.5k CFP credits in the bank as of 2021 Q1. CFP credit prices have been generally lower than but have followed a similar path as LCFS credit prices, since trading began in 2017. CFP credits started trading around \$50/MT, rose to \$100/MT in 2019, peaked around \$170/MT, and settled around \$130/MT in 2021. The CFP also has an effective price ceiling of \$200/MT indexed to 2016 dollars, but market prices haven't neared it yet. For more information on Oregon's CFP, I refer the reader to Witcover & Murphy (2019) and Mazzone et al. (2021).

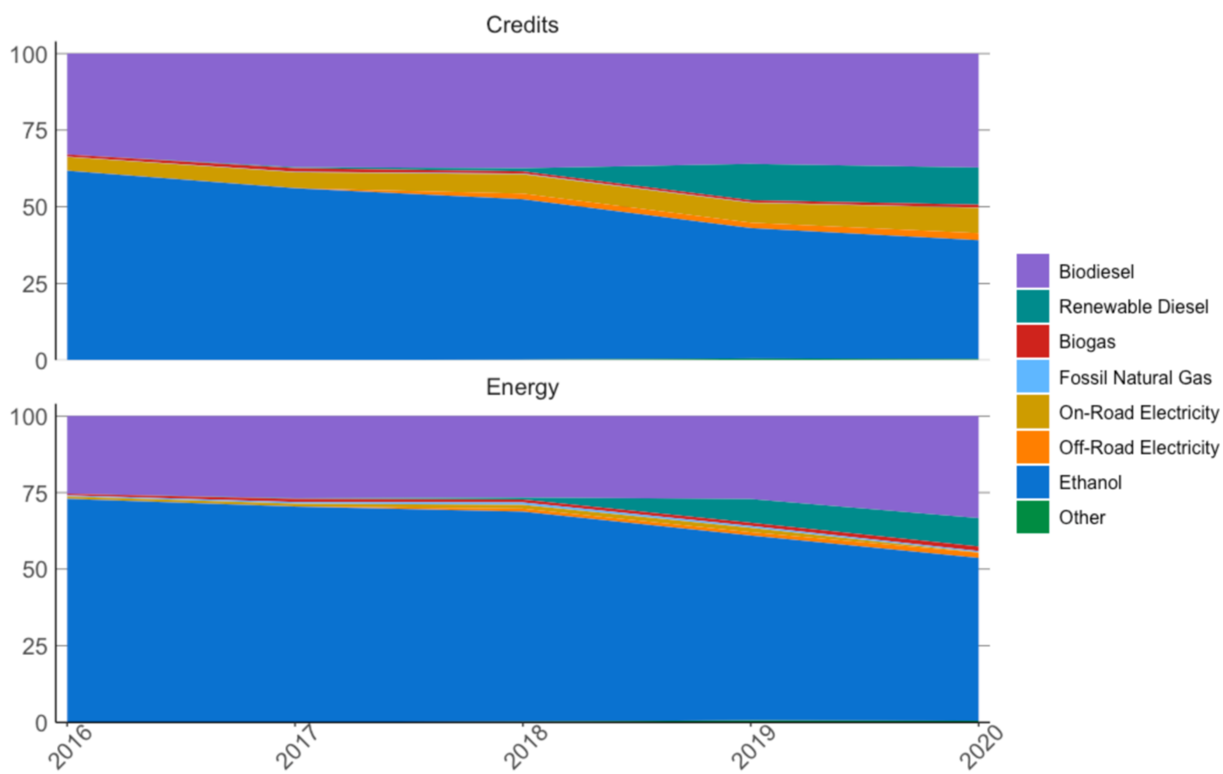

Figure 3. Alternative Fuel Energy and CFP Credit Shares

1.1.4 Blender's Tax Credit

The biodiesel Blender's Tax Credit (BTC) was implemented in 2005 and issues blenders of biomass-based diesel a credit of $1 per gallon against their U.S. federal tax liability. The BTC was the first major policy promoting BBD in the U.S. Like the RFS, the BTC has fallen subject to considerable political uncertainty, which has rippled through the BBD market in ways important to answering the research questions at hand. Congress allowed the BTC to expire four times since its implementation, at the end of 2009, 2011, 2013, and 2016.

The BTC was in place in 2016, taken away in 2017, retroactively reinstated for 2017, taken away again in 2018 and most of 2019, the retroactively reinstated again in December 2019 for both 2018 and 2019, and then extended for 5 years thereafter. Blenders and BBD producers formed contracts in response to the expiration of the BTC, agreeing to share the credit if and when reinstated. Often, suppliers and blenders would bear equal risk with a 50/50 split of the expected $1 future revenue stream (Irwin 2017). The way the BTC is shared will matter when analyzing the pass through of RIN prices since they are stacked. The handling of the BTC is discussed further in Section 1.5.

1.2 Diesel Fuels and their Supply Chains

In 2020, 56.17 billion gallons of ULSD were consumed by the US transportation sector. In California, the comparable figure is 2.73 billion gallons, or 5 percent of total U.S. consumption. Oregon's market is much smaller, consuming 672.52 million gallons, or 1.2 percent of total U.S. consumption in 2020. For context, 117.71 billion gallons of motor gasoline were used in the same year. [10] Diesel is refined from crude oil like gasoline. Diesel fuels, with few exceptions, are consumed by commercial consumers like heavy duty trucks. Diesel products are often available

[10] U.S. ultra-low sulfur diesel and gasoline consumption was collected from EIA prime supplier sales data, which can be accessed at https://www.eia.gov/dnav/pet/pet_cons_prim_dcu_nus_m.htm. California and Oregon numbers are collected from the quarterly summaries released by CARB and DEQ, respectively.

at most retail fuel stations that offer gasoline. However, they are also distributed to commercial sites, card stations, and other outlets. The average U.S. retail price of diesel was $2.55/gallon in 2020, and $3.38/gallon in California.

Federal and state environmental policies, described in Section 1.1, have supported the transition to diesel fuels made from biomass due to their lighter carbon footprint. BBD encompasses two types of fuels: biodiesel and renewable diesel. Both fuels are produced from largely the same sources– soybean oil, corn oil, canola oil, used cooking oil (UCO), and tallow. Figure 4 plots biodiesel (top) and renewable diesel (bottom) consumption in California, Oregon, and the rest of the U.S. Around 2 billion gallons of biodiesel were consumed nationwide in 2020, 266.5 million gallons in California, and 68.4 million gallons in Oregon. California accounted for around 13 percent of U.S. biodiesel consumption, but over half of U.S. renewable diesel consumption. Renewable diesel has become more popular because it can overcome blending restrictions faced by biodiesel. The market for renewable diesel is young but is expected to grow substantially in the next five years according to plans for new capacity to be built. According to the Energy Information Administration (EIA), total U.S. production capacity of renewable diesel will reach over 5 billion gallons by 2024 if all announced and proposed projects are seen through.[11] Under business-as-usual conditions, LCFS compliance could require biomass-based diesel to reach between 60 and 80 percent of finished diesel (Bushnell et al., 2020).

[11] See https://www.eia.gov/todayinenergy/detail.php?id=48916 for more information on the announcements for planned renewable diesel capacity proposed to become operational by 2025.

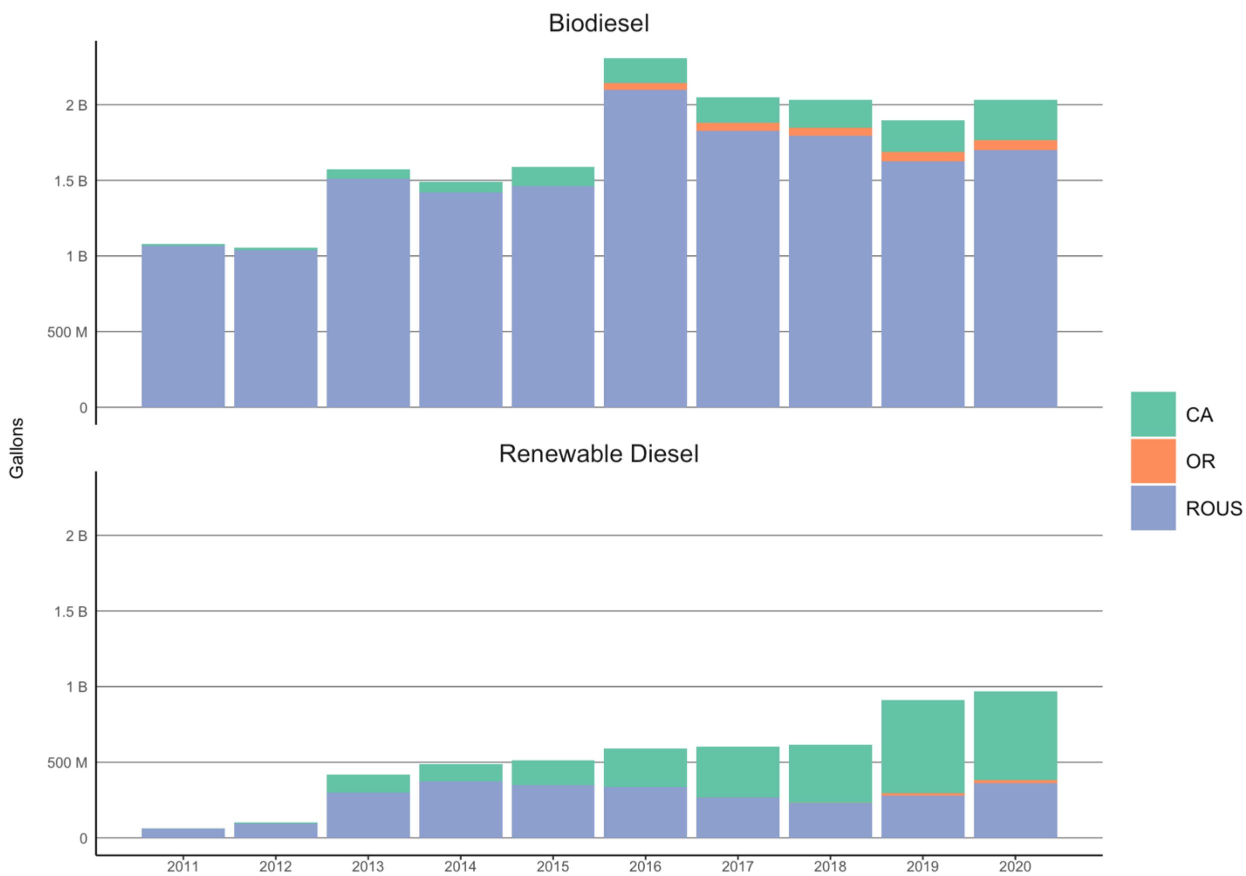

Figure 4. U.S. Biomass-Based Diesel Consumption by Region

SME biodiesel has been the mainstay BBD in the U.S. but biodiesel made from waste oils like UCO have grown in popularity because they account for avoided emissions, providing them favorable CI ratings in policies like the LCFS. UCO producers currently face a relatively inelastic supply curve, alerting that UCO may be close to being "tapped out."[12] This will likely lead to soybean oil being the primary source of BBD coming from most of the new capacity (Mazzone et al., 2021).

[12] See https://www.reuters.com/business/energy/used-cooking-oil-renewable-fuels-feedstock-nearly-tapped-out-us-valero-2021-04-22/.

1.2.1 *Labeling, Storage, and Distribution of Diesel Fuels*

Biodiesel faces similar blending restrictions as ethanol. Blending restrictions are put in place for several reasons. Most importantly, higher concentrations of biodiesel can adversely affect diesel engines and void manufacturer warranties. Labeling, distribution, and storage regulations differ by the percentage of the finished fuel that contains BBD. These differences are important to how diesel fuels are transacted at rack terminals.

1.2.1.1 *Labeling*

All BBD sold in the U.S. must comply with Federal Trade Commission (FTC) fuel rating regulations. Although renewable diesel in a drop in substitute to diesel and biodiesel is not, they are treated equivalently under FTC labeling requirements. BBD blends containing no more than 5 percent BBD are exempt, and the percentage of BBD is not required to be specified. A diesel blend containing up to 5 percent biodiesel (renewable diesel) is referred to as B5 (R5). Similarly, a diesel blend containing between 6 and 20 percent biodiesel (renewable diesel) by volume is labeled B20 (R20). Diesel blends containing more than 20 percent biodiesel (renewable diesel) by volume must be labeled according to the exact amount of biodiesel (renewable diesel) i.e., above 40 percent must be labelled B40 (R40), 50 percent must be labelled B50 (R50), and so on (ECFR :: 16 CFR Part 306). State labeling requirements can be slightly more stringent. For example, labels for diesel blends above 5 percent biodiesel by volume must state "THIS FUEL CONTAINS BIODIESEL. CHECK THE OWNER'S MANUAL OR WITH YOUR ENGINE MANUFACTURER BEFORE USING" in California.[13]

1.2.1.2 *Storage*

EPA allows B20 to be stored in underground storage tanks (USTs) in the U.S. [14] In California, UST regulations were stricter – only allowing B5 – until 2019, when the California Water Board

[13] See https://www.cdfa.ca.gov/dms/notices/petroleum/2018/P-18-02.pdf.

[14] See https://www.epa.gov/ust/emerging-fuels-and-underground-storage-tanks-usts.

amended their regulation to allow 20 percent biodiesel by volume, matching federal requirements.[15] Prior to the 2019 amendment, annual industry-, state-wide consumption of finished diesel never surpassed 5 percent biodiesel by volume. In 2020, biodiesel accounted for 7.5 percent of finished diesel in California.

1.2.1.3 Distribution

Petroleum gasoline and diesel are distributed from refineries to terminals, typically via pipeline. There are two types of terminals: bulk terminals and local terminals. Bulk terminals are in the six major bulk markets for diesel: New York Harbor, Chicago, Group 3 (Great Plains states), the Gulf Coast, West Coast, and Pacific Northwest (PNW). Local fuel prices are set according to a basis relative to a bulk market price. Fuel coming into bulk markets can either be sold to retailers at bulk terminals or redistributed to local terminals. Pipeline systems run from bulk markets to local terminals. Three of the bulk petroleum markets are also bulk biodiesel markets; New York Harbor, Chicago, and the Gulf coast bulk markets trade soy methyl ester (SME) B100. These are the only bulk market prices available for biodiesel. There are no bulk markets for renewable diesel at the time of writing.

Biodiesel, except for B5, can't be distributed through existing pipeline systems because pipelines that distribute diesel are also used for jet fuel, which can't be mixed with FAME. It is transported from producers to terminals by truck, rail, or barge. USTs and other storage infrastructure have been installed at terminals to allow blending of BBD with petroleum diesel to take place. Rack sellers can purchase bulk petroleum diesel and BBD and blend them, then sell the blended fuel to retailers at the rack. Retailers, or rack buyers, can also purchase bulk petroleum diesel and BBD above the rack and store and blend the fuels at the retail station.

[15] https://www.biodiesel.org/news-resources/biodiesel-news/2019/08/07/California-Approves-B20-Biodiesel-in-Underground-Storage-Tanks

1.3 Data Description

1.3.1 Calculating implicit taxes and subsidies

The RFS requires all refiners to retire a bundle of RINs, consisting of a certain number of each "D" category, for each gallon of gasoline and diesel sold. The RIN obligations for each category are determined according to the percentage standard set out in EPA's annual RFS rulemaking.[16] The cost of purchasing the RIN bundle acts as an implicit tax per gallon of gasoline and diesel. Since the RFS mandate is nested, the RIN tax per gallon of ULSD is:

$$R_t^u = P_t^{D3}V_t^{D3} + P_t^{D4}V_t^{D4} + P_t^{D5}(V_t^{D5} - V_t^{D3} - V_t^{D4}) + P_t^{D6}(V_t^{D6} - V_t^{D5}) \tag{1}$$

where V_t^x is the percentage standard for RIN category x and P_t^x is the RIN price. Daily spot prices for D3, D4, D5, and D6 RINs are collected from a Bloomberg Terminal. The Bloomberg data has missing observations for D3 and D5 RIN prices in 2021, so the implicit RIN tax is calculated using only the D4 and D6 obligations, which account for most of the total RIN tax. Results in later sections are robust to ignoring the D3 and D5 obligations in earlier years.

The blender's ability to sell D4 RINs acts as an implicit subsidy for the act of blending biodiesel. The EPA assigns an equivalence value (EV) to each alternative fuel that specifies the energy content of that fuel relative to ethanol. Biodiesel's EV is 1.5, so each earns 1.5 D4 RINs. Therefore, the RIN subsidy for blend k, with δ^k percent biodiesel, on day t is:

$$R_t^k = D4\ RIN\ Price_t \times \delta^k \times 1.5 \tag{2}$$

Unlike the RIN tax, the LCFS and CFP taxes for ULSD is specific to diesel and reflects the cost of purchasing enough credits to cover the deficits generated from one gallon of ULSD. The prices of LCFS and CFP credits are measured in USD per metric ton (MT) of CO2 equivalent (CO2e)

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[16] RFS annual rulemakings can be found at https://www.epa.gov/renewable-fuel-standard-program/regulations-and-volume-standards-renewable-fuel-standards.

and the number of deficits generated per gallon of ULSD are determined according to the CI score of ULSD relative to the diesel CI standard and the energy density (ED) of ULSD, which are program specific. CARB assigns an ED of is 134.47 MJ/gallon to ULSD in the LCFS. I calculate the LCFS tax as:

$$L_t^u = -Credit\ Price_t * (CI_t^s - CI_t^u) * ED^u * 10^{-6} \tag{3}$$

where CI_t^s is the diesel standard, CI_t^u are the reference CI scores of ULSD, ED^u is the energy density of ULSD, and 10^{-6} translates gCO2e into metric tons of CO2e. Daily average spot prices of LCFS and CFP credits are purchased from the Oil Price Information Service (OPIS) covering January 1st, 2013, to July 31st, 2021. Annual CI standards, reference CI scores, and EDs are taken from the LCFS and CFP regulations.[17]

In 2021, for example, petroleum diesel has a reference CI score of 100.5 gCO2e/MJ and the diesel standard is 91.7 gCO2e/MJ, and the energy density of diesel is 134.47 MJ/gallon. Therefore, refiners accrue $(100.5 - 91.7) * 134.47 * 10^{-6} = .0011836$ MT of deficits per gallon of diesel they supply to the CA transportation sector.

As I will show in Section 1.4, blenders both pay the tax on the ULSD and receive the subsidy on the biodiesel, so they realize a net subsidy. The LCFS net subsidy is:

$$L_t^k = \delta^k * Credit\ Price_t * \left(CI_t^s - CI_t^b\right) * ED^b * 10^{-6} - (1 - \delta^k)L_t^u \tag{4}$$

[17] More details on the credit generating equation used to calculate implicit taxes and subsidies for the LCFS can be found in § 95486 of the LCFS regulation. See https://ww2.arb.ca.gov/sites/default/files/2020-07/2020_lcfs_fro_oal-approved_unofficial_06302020.pdf.

Where CI_t^s is the diesel standard in the LCFS or CFP; CI_t^b and CI_t^u are the average reported CI scores for SME biodiesel and ULSD, respectively; ED^b and ED^u are the energy densities of biodiesel and ULSD, respectively.

The CI scores used for ULSD in calculations above are the diesel reference scores in the LCFS and CFP, listed in the respective regulations. The CI scores used for biodiesel in calculations above is the volume-weighted average CI score of SME biodiesel, which is solved using quarterly LCFS credit generation data and the credit-generating equation.[18] Data from CARB's quarterly summaries spans 2011-2021 Q1 and DEQ's quarterly summaries from 2016-2021 Q1. Figure 5 plots the diesel standards, diesel reference scores, and average reported biodiesel CI scores for California and Oregon. Figure 5 shows that the diesel standard is tighter in California and reference CI scores for diesel have been about the same. The average reported CI of all biodiesel in California is lower than Oregon's because canola oil is the primary feedstock in Oregon, which has a relatively high CI score. SME biodiesel was about 20 gCO2e/MJ higher than the biodiesel average in 2020.

[18] It isn't possible to calculate average CI scores by feedstock in the Oregon CFP because the number of credits generated by feedstock is not reported by DEQ. Therefore, we assume the CI of a feedstock/fuel combination is the same in the Oregon CFP as it is in the California LCFS. This is a reasonable assumption since both jurisdictions use the same lifecycle emissions calculation method (GREET) and share many of the same pathways.

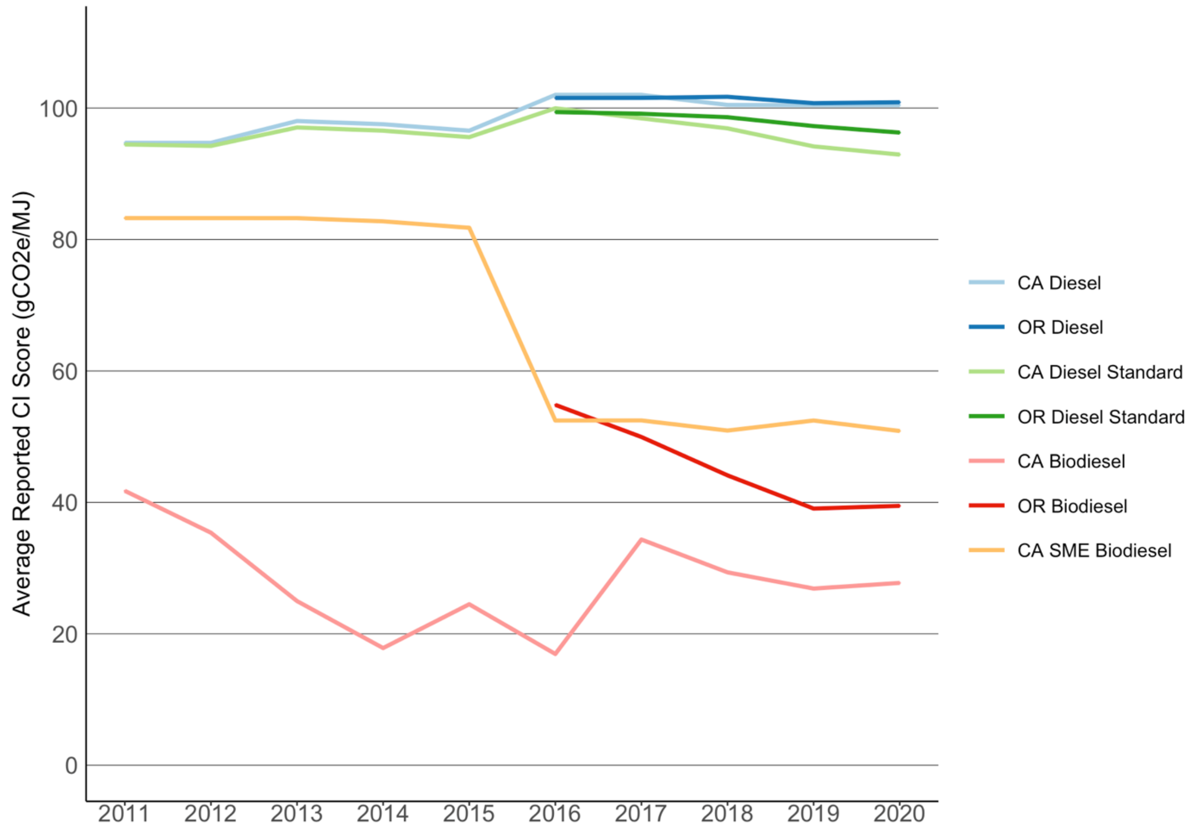

Figure 5. Average Reported Carbon Intensity Score of Diesel Fuels in California and Oregon

Figure 6 plots the sample of ULSD taxes and biodiesel subsidies from the RFS, LCFS, and CFP. The RIN tax for ULSD reached an all-time high in 2021, coming in over 20 cents/gal due to the sharp increase in D4 and D6 RIN prices brought on by the soybean boom. The LCFS tax, coincidentally, now sits around 20 cents/gal also. Oregon's CFP tax is currently much smaller, still below 10 cents/gal. The RIN subsidy has also reached an all-time high in 2021 of $3/gal. The LCFS and CFP subsidies have remained less than $1/gal in 2021.

Figure 6 introduces five time periods of interest, which I refer to as: Low LCFS Price (1/2015-12/2015), Mid LCFS Price (1/2016-3/2018), High LCFS Price (4/2018-2/2020), COVID Shock (3/2020-5/2020), and RIN Price Shock (6/2020-7/2021). LCFS credit prices rose significantly for the first time in the Mid LCFS Price period and sat around $1/gal less than the RIN subsidy. The stark jump in the tax in the beginning of 2016 is attributable to CARB's modeling change that resulted in a lower CI for SME biodiesel (Figure 5). LCFS credit prices varied widely in this period (Figure A- 1), ranging between around \$50/MT to \$150/MT. On average, the LCFS subsidy for SME biodiesel was its highest in High LCFS Price period and surpassed the value of the RIN subsidy.

The COVID Shock period is short and is used to control for weirdness occurring from the impact of COVID-19 impacts on fuel prices. The RIN Price Shock period describes the shock to D4 RIN prices brought on by increased demand for soybeans in China, causing soybean (and therefore, soybean oil) prices to rise drastically. The soybean boom of 2020/2021 had an appreciable impact on both the RIN subsidy and tax. The RIN subsidy leapt to \$3/gal in 2021 and the tax to 20 cents/gal, both doubling their previous highs (excluding outliers).

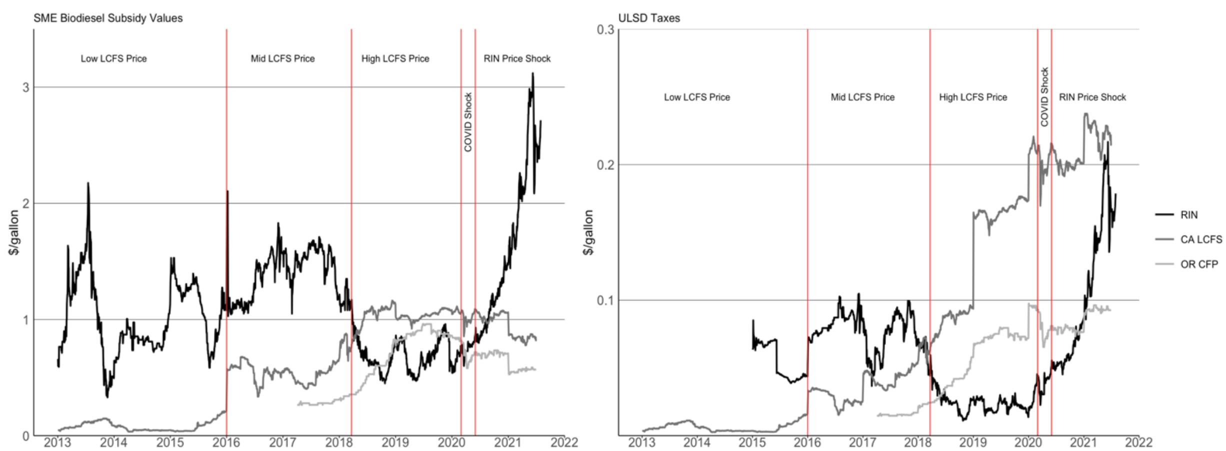

Figure 6. Implicit Taxes and Subsidies

1.3.2 Spot Prices

For both the tax and subsidy pass through analyses, I utilize daily spot prices for ULSD, jet fuel, and biodiesel (B100) in the major U.S. spot markets purchased from OPIS. I obtained spot prices for ultra-low sulfur diesel (ULSD) and jet fuel from the following markets: Los Angeles, San Francisco, Pacific Northwest, Gulf Coast, Group 3, and New York Harbor Barge. Three of those spot markets – Chicago, NY Harbor, and Gulf Coast – also post spot prices for soy methyl ester (SME) B100. Spot markets only exist for SME B100 because, as mentioned in Section 1.1.1, soybean oil makes up the majority of biodiesel used in the U.S. for RFS compliance. The sample includes observations from each spot market covering business days from 1/1/ 2015 to 7/31/ 2021.

Table 1 summarizes the sample of spot prices. ULSD spot prices range from $1.63/gal (Los Angeles) to $1.75/gal (PNW) on average over the entire sample. Jet fuel spot prices are slightly lower than ULSD, ranging between $1.57/gal (Los Angeles) and $1.68/gal (PNW) on average. SME B100 spot prices are almost twice as large as ULSD on average. Section 1.4 shows that ULSD prices exceed the jet fuel price by the amount of the RIN tax on ULSD, on average. Section 1.5 shows that B100 prices exceed ULSD prices by the amount of the RIN subsidy for B100.

Table 1. Average ULSD and B100 Spot

	Avg. Spot Price ($/gal)		
Spot Market	**ULSD**	**Jet Fuel**	**B100**
Chicago	1.66	1.65	3.21
Group 3	1.66	1.62	-
Gulf Coast	1.63	1.57	3.14
Los Angeles	1.71	1.66	-
NY Harbor Barge	1.68	1.62	3.20
Pacific Northwest	1.75	1.68	-
San Francisco	1.71	1.65	-

1.3.3 *Rack Prices*

For our analysis we purchased several types of pricing data from OPIS. This data includes supplier-level, daily prices paid for blended diesel fuels at rack terminals in six cities: Los Angeles, CA; San Francisco, CA; Bakersfield, CA; Stockton, CA; Portland, OR; Eugene, OR;

Wood River, IL; Trenton, NJ; Dallas, TX; St. Louis, MO. Rack prices are differentiated by the blend level and feedstock type. Biodiesel is assigned one of three feedstock types in the OPIS data: soy methyl ester (SME), yellow grease methyl ester (YGME), and a mix of multiple feedstocks (MULT). To make the analysis internally consistent, I only utilize rack prices for SME biodiesel blends, since B100 spot prices are only available for SME-based biodiesel (Section 1.3.2).

Suppliers enter and exit the sample in all cities. For this reason, I aggregate to city-blend averages, instead of using the supplier-level data. I only include suppliers with consistent pricing over at least a one-year period. Therefore, the unit of observation when studying rack margins is a city-blend-day. This process is done separately for branded and unbranded products. For each rack market, the number of suppliers is listed in Table A- 2.

As shown in Figure 6 the implicit taxes and subsidies have varied significantly over the sample. Rack spreads also vary over time, and across markets and blends. Additionally, different cities have different blend offerings (Table A- 2). Table 2 summarizes the sample of rack spreads in the subsamples outlined in Figure 6 and the full sample. A general trend is that rack margins are negative for many blends and inversely correlated with the percentage of biodiesel in the blend. They are also lower in subsamples where the RIN subsidy is higher. This reflects the fact that RIN subsidies are being fully passed through at the rack, because suppliers can sell more RINs for a higher blend, and therefore, can accept a lower price. In California and Oregon, this trend does not always hold, and margins are generally much higher than the rest of the country. Higher margins in California and Oregon are consistent with incomplete pass through of LCFS and CFP credits. The pass through of RIN, LCFS credit, and CFP credit subsidies is discussed in detail in Section 1.5.

Table 2. Blended Biodiesel Rack Margin and Policy Incentive Summary Statistics

Subsidies/Taxes from Policies		Low LCFS 1/15-12/15	Mid LCFS 1/16-3/18	High LCFS 4/18-2/20	COVID Shock 3/20-5/20	RIN Shock 6/20-7/21	Full Sample
CA LCFS Subsidy		0.09	0.56	1.04	1.01	0.95	0.71
CA LCFS Tax		0.01	0.04	0.14	0.2	0.21	0.10
OR CFP Subsidy		-	0.29	0.74	0.69	0.64	0.61
OR CFP Tax		-	0.02	0.06	0.08	0.08	0.06
D4 RIN Subsidy		1.12	1.40	0.68	0.76	1.59	1.15
Unbranded Rack Spreads							
Rack City	**Blend**						
Trenton	B2	0.03	0.01	0.06	0.04	0.02	0.03
	B5	0	-0.04	0.03	0	-0.06	-0.02
	B10	-0.08	-0.14	-	-	-0.22	-0.14
	B20	-0.21	-0.34	-	-	-0.52	-0.34
	B99	-1.22	-1.78	-	-1.80	-2.44	-1.83
Dallas Metro	B0-5	-	0.08	0.06	0.06	0.09	0.07
	B5	0.01	0	0.03	-0.01	-0.04	0
	B20	-	-	-0.04	-0.24	-0.4	-0.2
	B99	-	-1.61	-0.65	-1.53	-2.44	-1.45
Wood River	B2	0.07	0.02	0.04	0.04	0.03	0.04
	B5	0.05	-0.02	0.02	0.01	-0.06	0
	B20	-0.04	-0.24	-0.04	-0.2	-0.42	-0.18
	B50	-0.18	-0.63	-0.11	-0.53	-1.07	-0.52
St. Louis	B0-5	-	0.05	0.06	-	-	0.05
	B2	0.07	0.02	0.04	0.05	0.02	0.04
	B5	0.05	-0.02	0.03	0.02	-0.05	0
	B11	0.01	-0.11	0	-0.09	-0.2	-0.07
	B20	-0.04	-0.24	-0.03	-0.19	-0.41	-0.18
	B50	-	-0.57	-0.11	-0.53	-1.07	-0.51
Eugene	B5	-0.01	-0.03	0.06	0.04	0	0.01
	B20	0.2	0.04	0.11	-0.04	-0.21	0.04
Portland	B5	-0.03	-0.04	0.04	0.01	-0.03	-0.01
	B10	0.05	-0.04	0.02	-0.06	-0.14	-0.03
	B20	-0.04	-0.17	0.04	-0.26	-0.47	-0.15
	B50	-0.35	-0.63	-0.25	-0.7	-1.06	-0.56
Bakersfield	B20	-	-0.31	-0.16	-	-	-
Los Angeles	B0-5	0.06	0.06	0.16	0.19	0.08	-0.21
	B100	0.82	0.36	1.4	0.58	0.52	0.1
San Francisco	B1	0.35	0.37	0.48	0.45	0.34	0.81
	B5	0.39	0.38	0.53	0.47	0.36	-
	B20	0.49	0.42	0.71	0.53	0.43	0.41
	B50	0.43	0.2	0.77	0.34	0.27	0.44
	B100	0.83	0.34	1.37	0.53	0.51	0.54
Stockton	B0-5	-	-	0.19	0.08	-0.01	0.44
	B5	-	0.62	0.63	-	-	0.79
	B10	-	-	0.06	-0.1	-0.29	0.08
	B100	-	0.33	1.12	-	-	0.62

Notes: $/gal. Subsidies measured per gallon of SME B100; taxes measured per gallon of ULSD. Branded spread summary stats are listed in the Appendix. B0-5 is for blends up to B5 but identified, assumed to be B0 since subsidies are unlikely to be collected for these blends.

1.4 Diesel Tax Pass Through

Refiners and petroleum importers are the obligated parties are the obligated parties in each policy, meaning they must purchase RINs and LCFS credits proportional to their output which act as implicit taxes. Refiners sell ULSD in the major spot markets, meaning the implicit tax created from their RIN obligation will be embedded in spot market prices to the extent refiners pass through the cost. In this section, I test whether obligated parties fully pass through the implicit taxes created by the RFS and LCFS in spot market transactions. I extend the methodology developed in Knittel et al. (2017) analyzing spreads between ULSD and jet fuel spot prices.

ULSD and jet fuel are nearly identical products, so their prices tend to move together.[19] Figure A- 2 shows daily ULSD and jet fuel spot prices since 2015 in the major spot markets. The only substantive difference between the two is their policy treatment: ULSD has a RIN obligation and generates LCFS/CFP deficits in California and Oregon, whereas jet fuel does not. Other federal and state taxes may differ between the two fuels but are assessed below the rack, so those differences won't be captured in the spot prices. Additionally, spreads are calculated within spot markets, so transportation costs will not differ between ULSD and jet fuel. The spread between ULSD and jet fuel may capture fluctuations other than changes in the RIN tax, but I assume that any differences are constant over time. This provides a clean setting where one of two identical products are treated.

Figure 7 plots the daily spreads between ULSD and jet fuel prices along with the RIN tax, and where applicable, the LCFS/CFP tax. The RIN tax is calculated according to (1) and the LCFS/CFP taxes are calculated according to (3). The Gulf Coast and NY Harbor have the most efficient spot markets for ULSD and jet fuel; in those markets it is easy to see that the spread

[19] ULSD and jet fuel consist primarily of kerosene; however, ULSD has lower sulfur content, primarily due to EPA regulations, and contains added lubricants. Jet fuel is more similar no. 1 diesel than no. 2 diesel, which is used for transportation fuel.

tends to equal the RIN tax, suggesting the tax is fully passed through. Group 3 exhibits a similar pattern, but the spread is much noisier. Spreads in California and the Pacific Northwest are also very noisy, however Figure 7 clearly shows that the spreads generally follow the RIN tax while seemingly unaffected by LCFS and CFP taxes. If the LCFS and CFP taxes were fully passed through, we would see that the sum of the LCFS (CFP) tax and the RIN tax would equal the ULSD-jet spread in California (PNW).

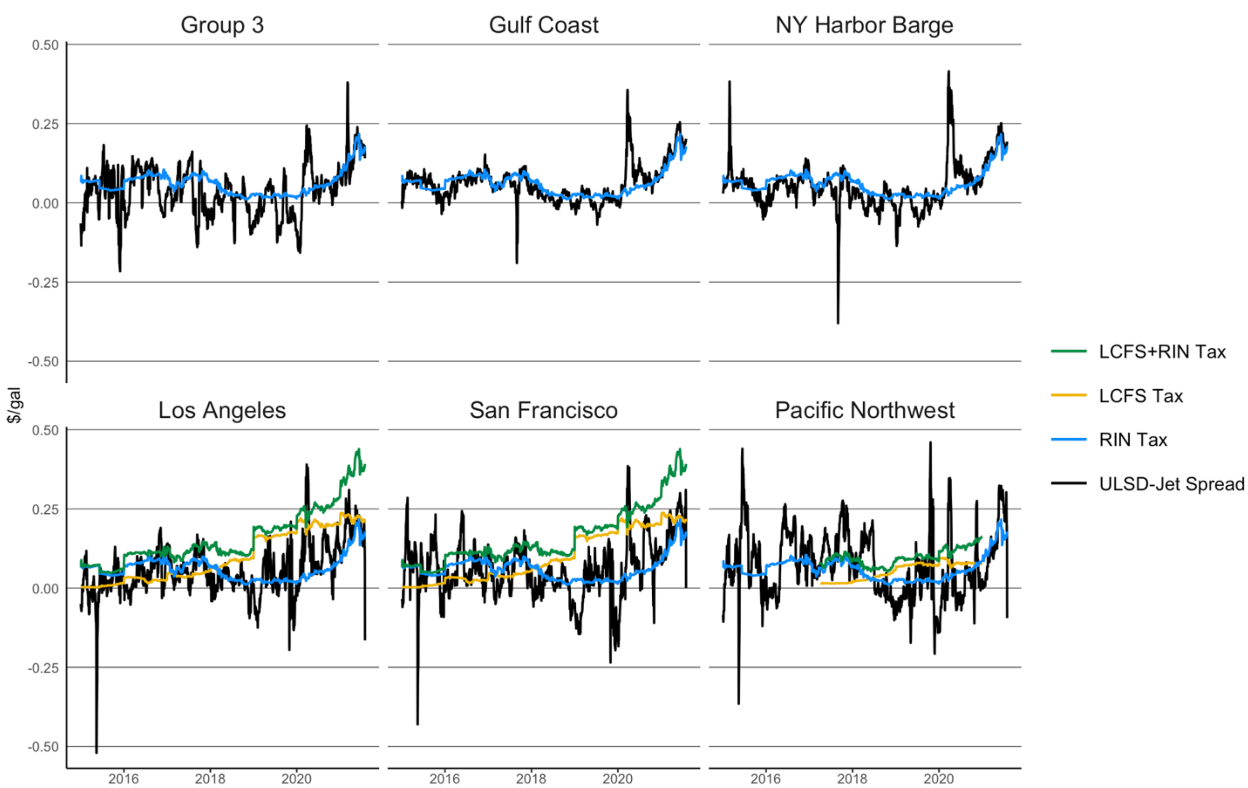

Figure 7. ULSD-Jet Spreads and Implicit ULSD Taxes. The LCFS tax in Los Angeles and San Francisco are from the CA LCFS and the LCFS tax in the Pacific Northwest is from the OR CFP tax.

To test whether the RIN tax and LCFS/CFP taxes are pass-through to ULS spot prices, I estimate the following model:

$$S_{it} = \alpha_i + \sum_{d=0}^{D-1} \theta_d^R \Delta R_{t-d}^u + \theta_D^R R_{t-D}^u + \sum_{d=0}^{D-1} \theta_d^L \Delta L_{t-d}^u + \theta_D^L L_{t-D}^u + \boldsymbol{\Theta X}_t + e_{it} \tag{5}$$

Where s_{it} is the ULSD-jet spread in spot market i on day t, Δ is the first-difference operator, R^u and L^u are the RIN and LCFS taxes, respectively, for ULSD; α_i are spot market fixed effects; $\boldsymbol{X}_t$ is a vector of seasonal and other controls; and e_{it} is the idiosyncratic error term. I impose θ=0 in cities not subject to the LCFS or CFP. In line with Knittel et al. (2017), $\boldsymbol{X}_t$ includes the first four harmonic frequencies to control for seasonality. Specifically, I include the following eight control variables in all subsequent regression models.

$$SEASON_t = \sum_{k=1}^{4} v_c \cos\left(\frac{2\pi tk}{366}\right) + \sum_{k=1}^{4} v_s \sin\left(\frac{2\pi tk}{366}\right) \quad (6)$$

Where t corresponds to the day of the year. $\boldsymbol{X}_t$ also includes a dummy variable for the COVID-19 pandemic (dates according to the COVID Shock period in Table 2), when applicable. The coefficients of interest in (5) are the long-run pass-through coefficients θ_D, where a coefficient equal to zero corresponds to none of the tax being passed through and a coefficient equal to one corresponds to the tax being fully passed through in the long run. Results are presented in Figure 8. Using the full sample, long-run pass through of the RIN tax is complete in some markets and more than complete in others. However, when dropping the RIN Price Shock Period (6/20-7/21), pass-through in the Gulf Coast and NY Harbor are tightly estimated around full pass through. Dropping this period diminishes the signal in San Francisco and PNW even more, making it difficult to make conclusions about RIN tax pass-through in those regions.

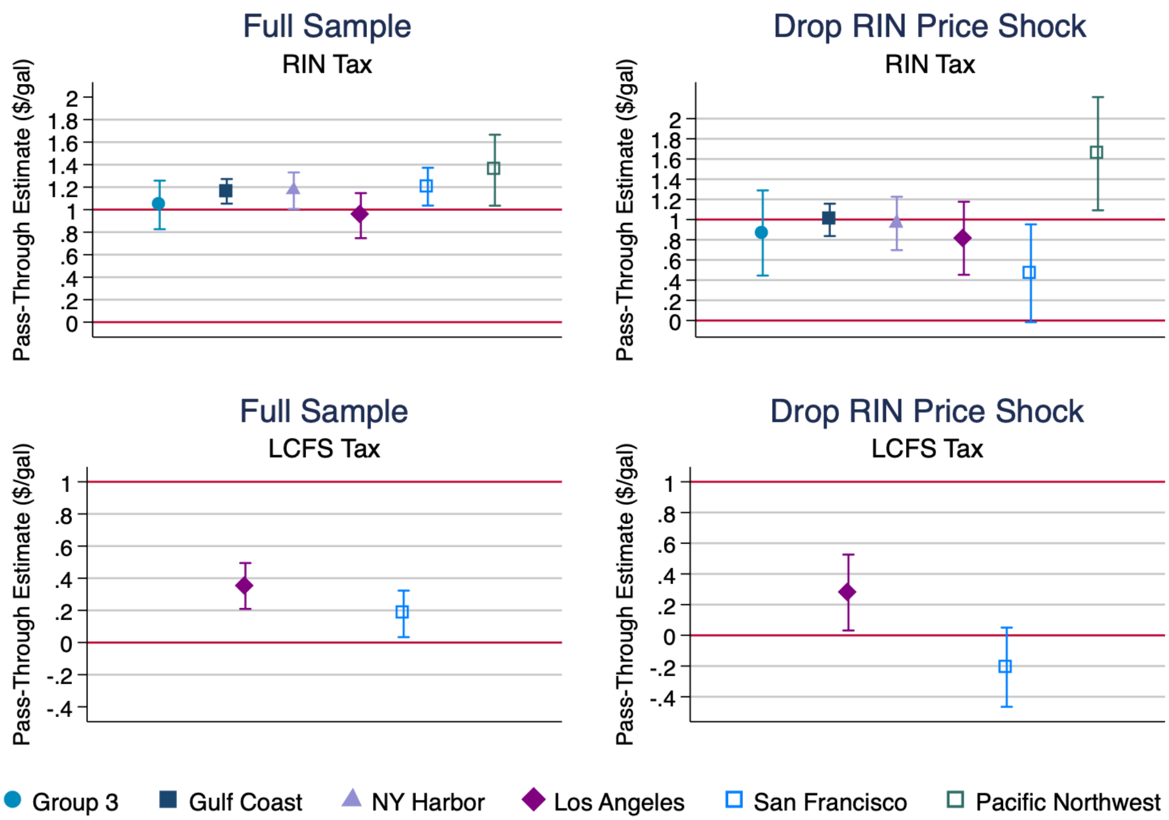

Figure 8. Pass-Through of Implicit ULSD Taxes to Spot Prices. Point estimates and 95% confidence intervals are plotted. The dependent variable is the ULSD-jet spread. There are 10 lags of the both the RIN tax variable and the LCFS tax variable. A dummy variable for the COVID Shock Period, which is March 2020 through June 2020. Standard errors are clustered at the month-year level. The results in the first column use data in the interval January 2015 through July 2021, results in the second column are restricted to January 2015 through June 2020.

The bottom panels of Figure 8 present estimates of the LCFS tax pass-through in Los Angeles and San Francisco, which shows that little to none of the LCFS tax is passed through to ULSD spot prices in California. Using the full sample, a $1/gal increase in the LCFS tax results in a 37 cents/gal increase in the spot price in Los Angeles on average, 16 cents/gal in San Francisco. When dropping the RIN Price Shock Period, which is the preferred specification because spreads are volatile in that period, the coefficients for Los Angeles and San Francisco fall to 0.28 and -0.2, respectively, and pass through is statistically indistinguishable from zero in San Francisco. The 95 percent confidence interval in Los Angeles is [0.03, 0.53] when dropping the RIN Price Shock Period. These results suggest that much of the LCFS tax is not passed through to spot prices but does not suggest that refiners are eating the cost. In the remainder of this section, I present evidence that LCFS deficit obligations are transferred downstream to blenders, and they completely pass through the LCFS tax to rack prices. As described in Section 1.1.2, obligated parties under the LCFS are allowed to transfer their status as the deficit generator to another entity if agreed upon by both parties. If deficit obligations are transferred to a different point in the supply chain, the tax will be priced in at the new point. Additionally, in some cases, refineries also own blending operations which would lead to the same results – the LCFS tax being passed through at the rack rather than the spot market.

Blenders may agree to fulfill the deficit obligation as they already trade credits. If refiners exercise this option, blenders will incur the LCFS deficit obligation and pass through the tax to the rack price. There is no rack price for pure ULSD in the OPIS rack pricing data. However, there are rack prices for B0-5 – ULSD that may contain up to 5 percent biodiesel by volume but doesn't earn credits because the amount of biodiesel is unidentifiable. This is essentially ULSD sold at the rack. I calculate the margin at the rack for B0-5 in city i on day t using the previous day's nearest spot price of ULSD.

$$m_{it}^{u} = p_t^{B0-5} - p_{t-1}^{u} \tag{7}$$

Figure 9 plots the daily rack margins, calculated according to (7), for both branded and unbranded ULSD in Los Angeles – the only city in California or Oregon with consistent reporting of B0-5 rack prices. Prior to April 2020, unbranded ULSD rack prices were higher than the spot price by the amount of the LCFS tax on average. The branded ULSD rack margin is less noisy than its unbranded counterpart but is slightly marked-up above the amount of the LCFS tax. This is consistent with the fact that branded rack buyers are limited to purchasing diesel that is of their brand and may therefore exhibit a higher willingness to pay than unbranded buyers who have more options (Pouliot et al., 2020).

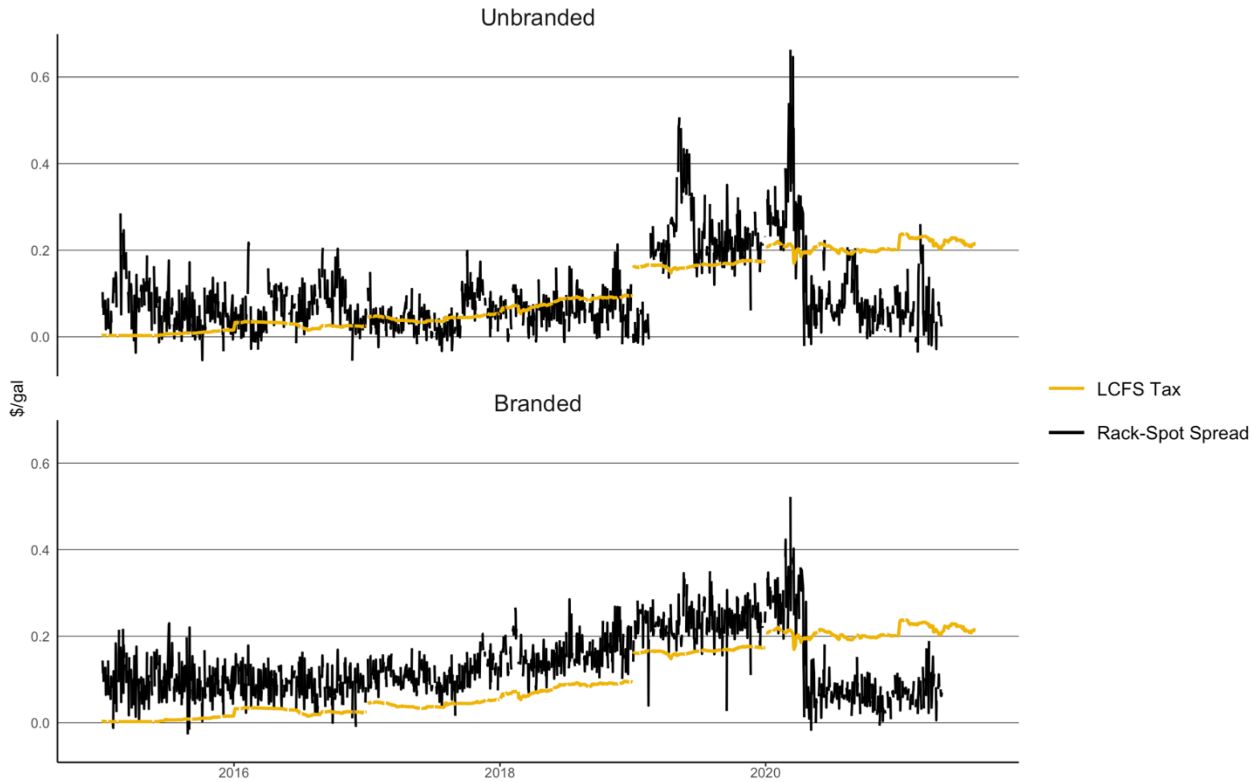

Figure 9. ULSD Rack Margins in Los Angeles, CA.

The level of the LCFS tax shifts upward at the start of each year with the annual decline in the diesel CI standard, and the reference diesel CI score often changes annually. The standard has been laid out in advance and changes to reference CI scores are specified by CARB and are not determined in any way by rack margins; therefore, they act as exogenous shifters in this setting. The most striking rise in the tax was on January 1st, 2019. The CI reference score for ULSD fell only slightly from 100.48 to 100.45 in 2019, the diesel CI standard fell from 96.91 to 94.17. The standard decreasing by nearly three full points, coupled with a record-high market price for LCFS credits, led to an average LCFS tax that was, on average, 6.72 cents/gallon higher in January 2019 than December 2018. In the same two-month period, the rack margin for branded ULSD was 6.13 cents/gallon higher in 2019. Rack margins for unbranded ULSD also responded to the change in the tax but later, around mid-March of 2019. It is unclear why the response was delayed, and it only occurred in that year.

Furthermore, the following regression model is used to estimate the long-run pass through of the LCFS tax to ULSD rack margins, as calculated in (7):

$$m_{it}^{u} = \sum_{d=0}^{D-1} \beta_d^L \Delta L_{t-d}^{u} + \beta_D^L L_{t-D}^{u} + \Theta \boldsymbol{X}_t + \epsilon_{it} \tag{8}$$

Results from this model are presented in Table 3. I estimate (8) for both branded and unbranded rack ULSD spreads, yielding pass-through coefficients of 0.24 and 0.4, respectively. However, this result is heavily driven by the downward shock to rack ULSD spreads beginning in mid-April 2020, likely due to the COVID-19 pandemic. Therefore, columns 3 and 4 of Table 3 presents results from the preferred specification, which includes a dummy variable for observations after April 15th, 2020. This set of results present evidence that refiners transfer their LCFS deficit obligation downstream and is consistent with complete pass through of the LCFS tax at racks in California.

Table 3. Long-Run Pass-Through of Implicit LCFS Tax to Rack Spread

	Branded (1)	Unbranded (2)	Branded (3)	Unbranded (4)
L_{t-10}^{u}	0.24**	0.40***	0.93***	1.00***
	(0.12)	(0.13)	(0.03)	(0.13)
$1[t > 4/15/2020]$			-0.20***	-0.17***
			(0.01)	(0.02)
Constant	0.11***	0.06***	0.08***	0.03***
	(0.01)	(0.01)	(0.00)	(0.01)
Observations	927	921	927	921
R-squared	0.15	0.21	0.72	0.50

Notes: The dependent variable is the rack B0-5 spread. Standard errors are clustered at the month-year level. * Statistically significant at the 10% level, ** Statistically significant at the 5% level, *** Significant at the 1% level.

Table 3 also shows the significant and persistent impact that the COVID-19 pandemic had on ULSD rack margins, which were around 20 cents lower on average following mid-March of 2020 than their long-run average since 2015. Evident from Figure 9, since the pandemic started in spring 2020, rack sellers were either unable to continue to pass through the full cost of the LCFS tax at the rack or they were able to pass their obligation even further downstream. The rack pricing data for Portland and Eugene do not include B0-5, so this exercise can't be done for Oregon and the CFP. However, given the similarities between the Oregon and California programs, and the results from Figure 7 and Figure 8, it is plausible that CFP obligated parties act in similar fashion.

There are three important findings that emerge from the analysis in this section. First, the RIN tax appears to be fully passed through to ULSD spot prices, consistent with previous studies (Burkhardt, 2019; Knittel et al., 2017). ULSD-jet spreads are noisy in most of the major spot markets except for the Gulf Coast, where the long-run pass through coefficient θ_D^R equals 1.00, and its 95 percent confidence interval is [.84, 1.16]. This implies that refiners have still been able to recoup the cost of RFS compliance, even as RIN prices have reached all-time highs.

Second, little to none of the implicit tax from LCFS deficit obligations is passed through to ULSD spot prices because refiners shift the obligation downstream to blenders. However, Figure 8 shows that, in Los Angeles especially, some of the LCFS tax is passed through to the spot price of ULSD. This could occur because some refiners keep the obligation and others don't, and the coefficients represent an average of This result, qualitatively, raises interesting questions. How do these agreements work? Does this occur because refiners have more bargaining power than blenders? These questions are outside the scope of this paper but present further research opportunities.

Third, blenders have passed through the full LCFS tax to rack buyers for both branded and unbranded ULSD. Together, these findings suggest that *the tax side* of these policies operate as intended. That is, raising the price of petroleum for blenders and, ultimately, consumers. Complete pass through of the taxes is necessary but not sufficient to conclude that the policies operate effectively and efficiently.

1.5 Biodiesel Subsidy Pass-Through

Section 1.4 presented an empirical framework for estimating pass through of taxes implicitly levied on ULSD through RIN and LCFS deficit obligations and found they are fully passed through to diesel prices. This raises the price of the petroleum product so that blenders and, if passed through to retail prices, consumers demand less of it. This suggests effectiveness of one prong of the two-pronged approach of these policies. The implicit taxes have made petroleum more expensive, but have the implicit subsidies made the alternatives cheaper? In this section, I shift focus to the second prong; pass through of biodiesel subsidies from the RFS, LCFS, and CFP is estimated.

Racks provide an ideal setting to study pass through because the marginal cost of producing the blended fuel is observed daily. The marginal revenue for the blender is the rack price and the marginal cost is the wet cost of the component fuels. The wet cost is the sum of the petroleum and biofuel costs associated with one gallon of blended fuel. Spot prices are a good measure of the true marginal cost because they reflect the cost of replacing a gallon of fuel on a given day. I use the previous day's spot price when calculating the wet cost because that is the information available to rack participants on the day of the transaction. Let j denote the city of the rack market, t denote days, and k denote the diesel blend. The wet cost is then

$$w_{jt}^{k} = \delta^{k} p_{j,t-1}^{b} + \left(1-\delta^{k}\right) p_{j,t-1}^{u} \tag{9}$$

The wet cost is denoted by j, but the spot prices are not unique to the city of the terminal. I map each city in the rack pricing data to its nearest spot market, displayed in Table A- 1. Each rack city has a robust spot market for ULSD in close proximity, but only three of them also post spot prices of B100: Chicago, NY Harbor, and Gulf Coast. In California and Oregon, I use the NY Harbor B100 spot price to calculate the wet cost because it is often used as a basis for spot gallons on the west coast.[20] Only SME biodiesel is sold in B100 spot markets, so the analysis is restricted to that feedstock. The blender's margin for SME biodiesel blend k is

$$m_{jt}^{k} = p_{jt}^{k} - w_{jt}^{k} \tag{10}$$

The rack margin for B20, for example, would be the rack price of B20 minus 0.2 times the spot price of B100 and 0.8 times the spot price of ULSD. If the value of the RIN subsidy is fully passed through at the rack, the margin will move one-for-one with changes in the negative of the RIN value. The same goes for the LCFS and CFP credit subsidies. I employ a Cumulative Dynamic Multiplier (CDM) model to estimate both the short- and long-run pass through of RFS, LCFS, and CFP incentives. Specifically, I estimate the following model:

$$m_{it}^{k} = \alpha_i + \sum_{d=0}^{D-1} \beta_d^R \Delta R_{t-d}^{k} + \beta_D^R R_{t-D}^{k} + \sum_{d=0}^{D-1} \beta_d^L \Delta L_{t-d}^{k} + \beta_D^L L_{t-D}^{k} + \Theta \boldsymbol{X}_t + \varepsilon_{it}^{k} \tag{11}$$

Where Δ is the first-difference operator, α_i are city fixed effects, and ε_{it}^{k} is the idiosyncratic error term. I impose β^L=0 in cities not subject to the LCFS or CFP. R^k and L^k are the RIN and LCFS subsidies, respectively, for blend k. Both the rack margins and subsidies are measured in \$/gal, so the long-run coefficients can be interpreted such that a \$1\gal increase in the RIN subsidy results in the rack margin decreasing by \$$\beta_D^R$/gal. Similarly, for the LCFS and CFP, a \$1/gal increase in the LCFS or CFP net subsidy results in the rack margin decreasing by \$$\beta_D^L$/gal. Since RIN and LCFS incentives stack in California and Oregon, the additive incentives will be salient

[20] This is based on anecdotal evidence and conversations with businesses that sell fuel into California. However, results are robust to using any of the three spot markets. From another data source, there is a spot price of biodiesel on the west coast, but it captures an average price over several feedstocks. It may be that the NY Harbor price plus a transportation cost is a better approximation of the cost of blending a gallon of SME biodiesel in California or Oregon, than the ambiguous west coast price. The results, however, are also robust to using that price as the SME biodiesel cost component.

to rack market participants. Therefore, I also estimate the following model to explore pass through of the total incentives in California and Oregon.

$$m_{it}^{k} = \alpha_i + \sum_{d=0}^{D-1} \beta_d \Delta(R_{t-d}^{k} + L_{t-d}^{k}) + \beta_D (R_{t-D}^{k} + L_{t-D}^{k}) + \mathbf{\Theta X}_t + u_{it}^{k} \quad (12)$$

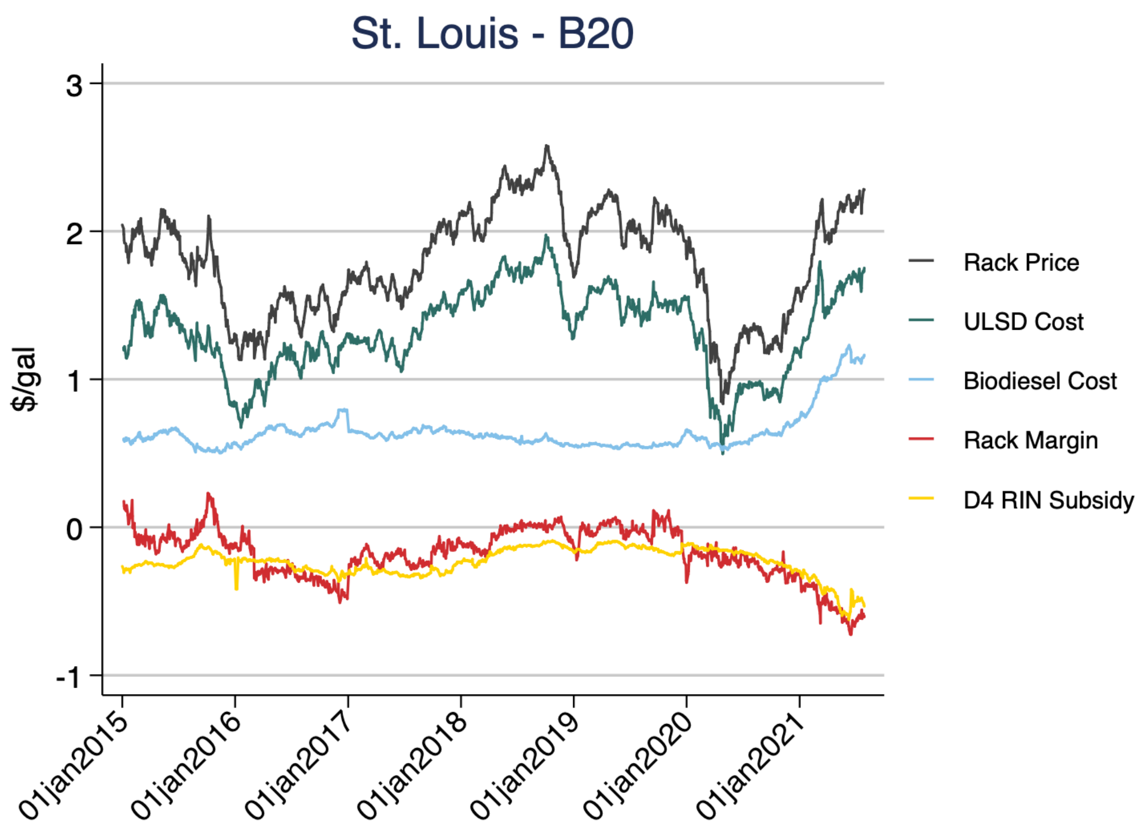

Figure 10. Prices, Costs, and RIN Subsidy for B20 in St. Louis.

One important confounding factor is the Blender's Tax Credit (BTC), which acts as an additional implicit subsidy for biodiesel realized by the rack seller. The nature and timeline of the BTC is described in Section 1.1.4. As mentioned, within the sample used in this paper, the BTC was in place some years and retroactively reinstated in others. In years that it wasn't in place, the market formed expectations around the likelihood it would be retroactively reinstated which led to risk-sharing contracts between rack sellers and buyers. These year-to-year changes directly affect the observed margin in (10) and may be correlated with RIN prices.

To see this, consider a scenario where the BTC is taken away and the market forms expectations around its reinstatement, and the biodiesel producer and the blender form a 50/50 sharing contract. If the biodiesel producer passes through the full value, their spot price will fall by 50 cents/gal of B100. In this case, the observed margin of the blender rises by $\delta^k \times 50$ cents/gal. The blender still receives $\delta^k \times 50$ cents/gal from their half of the BTC, so the RIN price will remain unchanged. This relationship would severely bias the estimates of the β coefficients if between year variation in rack margins and the RIN subsidy is used. Since the level of the adjustment of the margin is directly proportional to the blend level δ^k, I include blend-by-year dummy variables to account for changes to the BTC. This means that implied subsidy pass through is identified from within-year and within-blend variation in rack margins.

The identification strategy outlined above requires additional assumptions about how the BTC affects margins and RIN prices. The first assumption I make is that blenders and biodiesel producers expect the tax credit to be reinstated with probability one throughout each year that it's not in place. The other assumption is that sharing contracts are 50/50 split throughout the year. If either are violated, the resulting impacts on margins will be attributed to the RIN subsidy. These assumptions seem reasonable since the tax credit had already been retroactively reinstated three times prior to the beginning of my sample, in 2010, 2012, and 2014.

Similarly, I assume that pass-through of the BTC to biodiesel spot prices is complete in years when the BTC expired. Irwin (2017), looking at a sample of biodiesel prices from Iowa plants in the months before and after the BTC expired (including 2016/2017), suggests that it hadn't been passed through in previous years. In the example above, if none of the BTC was passed through to biodiesel spot prices, we would see no change to the biodiesel cost and the observed margin, and an increase in the D4 RIN subsidy. In my sample, however, biodiesel spot prices and rack margins do appear to respond to the BTC expiration in 2017, and the RIN subsidy remains constant (Figure 10). Similarly, in 2020 when the BTC was reinstated, observed rack margins fell, consistent with the retroactive BTC being completely passed through. The RIN subsidy fell at the same time, but likely reflects the decline in ULSD prices rather than the BTC.

In addition to the confounding effects of the BTC outlined above, anticipation of changes to the BTC may create similar issues. The spot price of B100 rose starkly at the end of 2016, which may have resulted from blenders purchasing and blending excess biodiesel before the tax credit expired. A similar but more modest pattern emerged at the end of 2019 prior to the 2020 reinstatement. Therefore, I also include blend-specific dummy variables for these two anticipation periods for robustness. Results are not sensitive to the inclusion of these variables. Outside of the anticipation periods, I assume nothing about the BTC is changing within years.

Like jet fuel, blended biodiesel (when the percentage of biodiesel content is small, which is the case in my sample) is nearly a perfectly substitute to petroleum diesel. Therefore, since the RIN tax is fully passed through to ULSD prices, B100 (net the BTC) and ULSD prices should only differ by their net RIN obligation, which is 1.5 D4 RINs, if the subsidy is fully passed through at the wholesale level (Knittel et al., 2017). Figure 11 plots the B100-ULSD spread in Chicago, Gulf Coast, and New York Harbor Barge and the D4 RIN price multiplied by 1.5. The two series are nearly identical outside of the years with the BTC in place, which is to be expected. Figure 11 also highlights the fact that SME biodiesel is the marginal fuel for compliance in the D4 category, meaning that D4 RIN prices should reflect the marginal cost of D4 compliance.

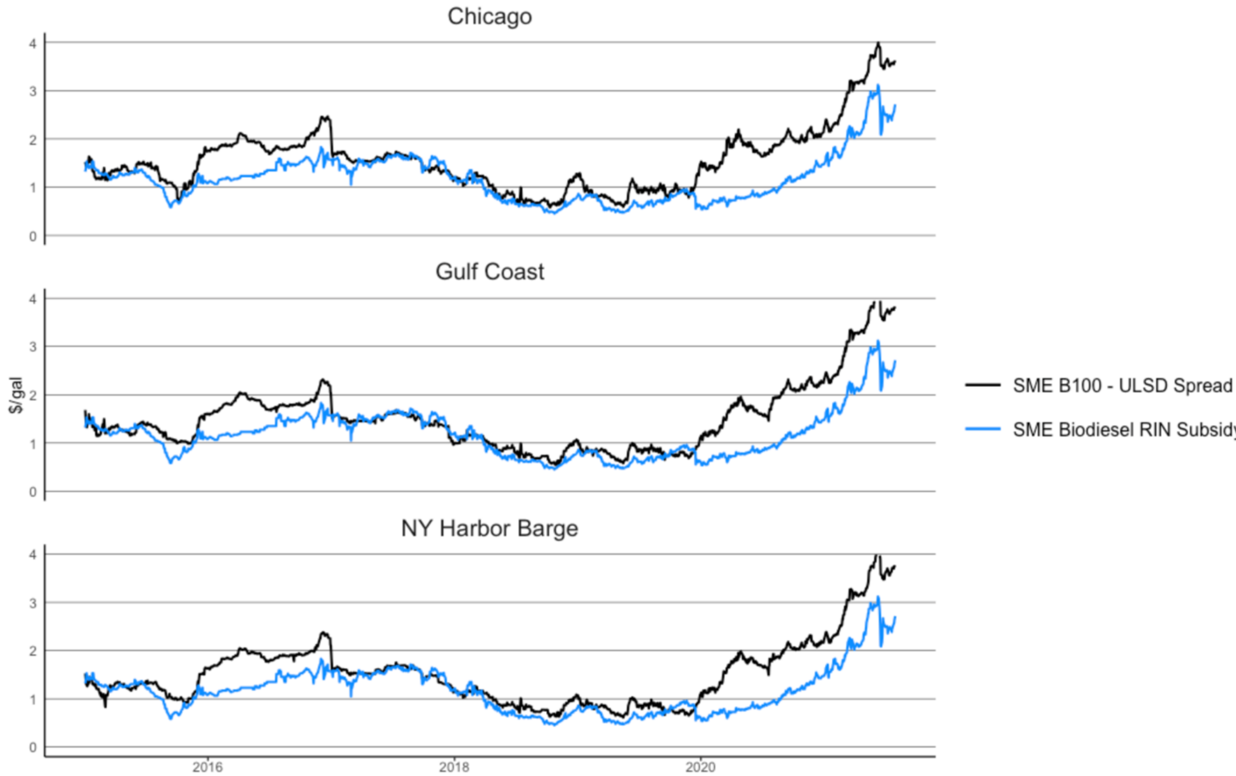

Figure 11. SME Biodiesel - ULSD Spread

Identification in (11) and (12) relies on the assumption that input costs, namely ULSD and B100 spot prices, are fully passed through to rack prices. If this is assumption is invalid, estimates of pass through of RIN subsidies will be biased since input costs are correlated with RIN prices (Figure 11). Incomplete pass through of B100 prices, for example, could be attributed to incomplete pass-through of RIN subsidies. Therefore, I relax this assumption by augmenting (11) to allow input cost pass through to differ from one; I regress unbranded rack prices on the RHS variables in (11) and input costs. I perform this separately for wet costs and biodiesel and ULSD separately, shown in (13) and (14), respectively.

$$p_{it}^{k} = \alpha_i + \sum_{d=0}^{D-1} \beta_d^R \Delta R_{t-d}^k + \beta_D^R R_{t-D}^k + \sum_{d=0}^{D-1} \beta_d^L \Delta L_{t-d}^k + \beta_D^L L_{t-D}^k \tag{13}$$

$$+\sum_{d=0}^{D-1}\gamma_d^w \Delta w_{t-d}^k + \gamma_D^w w_{t-D}^k + \mathbf{\Theta X}_t + \varepsilon_{it}^k$$

$$p_{it}^k = \alpha_i + \sum_{d=0}^{D-1}\beta_d^R \Delta R_{t-d}^k + \beta_D^R R_{t-D}^k + \sum_{d=0}^{D-1}\beta_d^L \Delta L_{t-d}^k + \beta_D^L L_{t-D}^k$$
$$+\sum_{d=0}^{D-1}\gamma_d^b \Delta b_{t-d}^k + \gamma_D^b b_{t-D}^k + \sum_{d=0}^{D-1}\gamma_d^u \Delta u_{t-d}^k + \gamma_D^u u_{t-D}^k + \mathbf{\Theta X}_t + \varepsilon_{it}^k \tag{14}$$

Results from the unrestricted models in (13) and (14) support complete pass through of input prices in all regions and are presented in Figure A- 1. For the remainder of this section, results are reported only for the restricted model outlined in (11), since subsidy pass through estimates are robust to inclusion of input costs as controls.

1.5.1 RIN Subsidy Pass Through

Table 4 presents estimates of short- and long-run RIN subsidy pass through for California, Oregon, and the rest of the U.S. (ROUS) – which consists of Dallas, Trenton, St. Louis, and Wood River. The first three columns utilize the full sample, while the last three drop observations in the RIN Shock Period outlined in Section 1.3.1. The long-run coefficients suggest regional heterogeneity of RIN subsidy pass through; using the full sample, only around 60 cents/gal are passed through on the West Coast compared to 95 cents/gal in ROUS. When dropping the RIN Shock Period, ROUS RIN subsidy pass-through falls to 77 cents/gallon. Sensitivity of results to inclusion of the RIN Shock Period are discussed later in this section.

Short-run estimates in California and Oregon are imprecise and not statistically different from zero. Columns 3 and 6 show that it takes more than one week for the cumulative pass through of the RIN subsidy to reach its long-run average in ROUS. Only 34 cents/gal are passed through one day after a shock to the RIN price, 21 cents/gal when dropping the RIN Price Shock Period.

Table 4. RIN Subsidy Pass Through Dynamics

	Full Sample			Drop RIN Shock (6/20-7/21)		
	CA	OR	ROUS	CA	OR	ROUS
	(1)	(2)	(3)	(4)	(5)	(6)
ΔR_t^k	0.02	0.26	0.27***	0.01	0.13	0.11
	(0.10)	(0.17)	(0.10)	(0.10)	(0.29)	(0.12)
ΔR_{t-1}^k	0.07	0.36**	0.34***	0.07	0.30	0.21**
	(0.10)	(0.17)	(0.06)	(0.10)	(0.27)	(0.08)
ΔR_{t-2}^k	0.08	0.33*	0.36***	0.10	0.62**	0.30***
	(0.11)	(0.19)	(0.05)	(0.11)	(0.27)	(0.08)
ΔR_{t-3}^k	0.11	0.37**	0.41***	0.11	0.42	0.29***
	(0.11)	(0.18)	(0.06)	(0.11)	(0.36)	(0.07)
ΔR_{t-4}^k	-0.03	0.40***	0.46***	-0.04	0.27	0.19
	(0.15)	(0.14)	(0.14)	(0.15)	(0.30)	(0.20)
ΔR_{t-5}^k	0.01	0.43**	0.66***	0.02	0.24	0.47***
	(0.16)	(0.20)	(0.09)	(0.17)	(0.40)	(0.11)
ΔR_{t-6}^k	0.09	0.43***	0.66***	0.11	0.37	0.53***
	(0.15)	(0.16)	(0.07)	(0.15)	(0.32)	(0.09)
ΔR_{t-7}^k	0.17	0.43**	0.66***	0.17	0.51	0.55***
	(0.14)	(0.20)	(0.07)	(0.15)	(0.31)	(0.09)
ΔR_{t-8}^k	0.19	0.53***	0.78***	0.19	0.33	0.67***
	(0.15)	(0.14)	(0.11)	(0.16)	(0.25)	(0.16)
ΔR_{t-9}^k	0.23	0.35**	0.77***	0.25	0.23	0.64***
	(0.15)	(0.15)	(0.07)	(0.15)	(0.28)	(0.09)
$\boldsymbol{R_{t-10}^k}$	**0.58*** **	**0.62*** **	**0.95*** **	**0.57*** **	**0.22**	**0.77*** **
	(0.11)	**(0.11)**	**(0.05)**	**(0.11)**	**(0.30)**	**(0.07)**
Constant	-0.79	0.14	0.03	-0.63	1.46	-0.05
	(0.64)	(0.62)	(0.21)	(0.63)	(1.72)	(0.25)
Observations	5,681	3,358	19,162	5,258	2,434	15,275
R-squared	0.90	0.94	0.98	0.89	0.86	0.98

Notes: The dependent variable is the rack margin. Standard errors are clustered at the month-year level. * Statistically significant at the 10% level, ** Statistically significant at the 5% level, *** Significant at the 1% level.

Table 4 highlights some of the regional heterogeneity in pass through of biodiesel RIN subsidies, however, heterogeneity is present within the ROUS as well. Figure 12 presents point estimates and 95 percent confidence intervals of long-run pass through of the RIN subsidy for each region in the sample. Regions are presented in ascending order of long-run pass through rates using the full sample. Rates in California and Oregon are the lowest nationwide at about 60 cents/gal on average. In the ROUS, average pass-through rates are 0.8, 0.95, and 1.07 in the

East Coast, Gulf Coast, and Midwest, respectively; however, the 95 percent confidence intervals include 1 (complete pass through) for all three regions. The estimates in Figure 12 are robust to controlling for both 5 lags and 30 lags, except for California. In California, confidence intervals for the long-run RIN subsidy pass through fall to [0.22, 0.61] and [0.25, 0.67] for the full sample and dropping the RIN Price Shock period, respectively, when increasing the number of lags to 30 days. In both cases, the point estimates fall below 0.5, suggesting less than half of the RIN subsidy has been passed through in California. Despite the quantitative differences in results between the two specifications, the qualitative conclusions remain: the RIN subsidy pass through has only been partially passed through in the state.

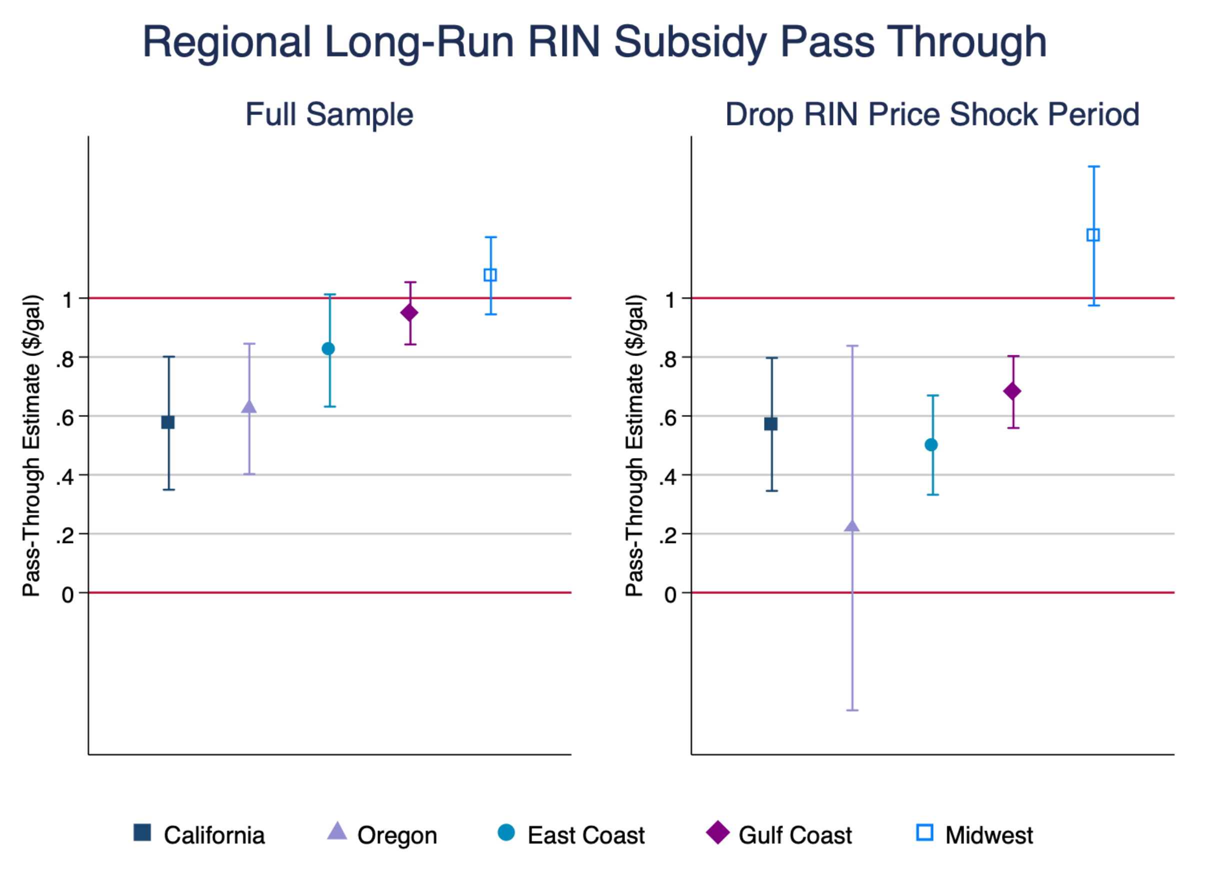

Figure 12. Regional Long-Run Pass Through of SME Biodiesel RIN Subsidies. Standard errors are clustered at the month-year level. Shapes are point estimates and bars are 95 percent confidence intervals.

Long-run RIN subsidy pass through results are qualitatively different when ignoring the RIN Price Shock Period and the ordering of regions changes. Pass through in Oregon becomes very imprecise since CFP prices begin in 2017, leaving a small sample once dropping the period from the analysis. The lowest levels of RIN subsidy pass through levels now occur in the East Coast, where only half is passed through on average and the upper bound of the 95 percent confidence interval lies below three quarters of complete pass through. Using the restricted sample, pass through in the Gulf Coast is 67 cents/gal on average and the confidence interval no longer includes complete pass through. Incomplete pass through in the Gulf Coast is economically significant, as previous studies have consistently found complete pass through of implicit gasoline taxes and ethanol subsidies from the RFS (Burkhardt, 2019; Knittel et al., 2017; Pouliot et al., 2020).

One concern regarding the results from the Gulf and East Coast is the effect of the Colonial pipeline shutdown in May of 2021 in response to ransomware attack.[21] The Colonial pipeline runs from Texas to New Jersey supplies a substantial amount of fuel to both Dallas and Trenton. The pipeline shutdown on May 7th, 2021, and continued operation on May 13th, 2021. Estimates for the two cities served by the pipeline aren't sensitive to the inclusion of a blend-specific dummy for the month of March in 2021, therefore I don't control for the event moving forward and differences between the results from the full sample and dropping the RIN Price Shock period shouldn't be attributed to the shutdown.

Another concern about the results presented in Table 4 and Figure 12 is that blend offerings vary across regions (Table A- 2), which raises the question of whether or not I am attributing differences in pass through among blends to regional differences. The portfolio of biodiesel blends exhibits similar characteristics to ethanol, in that there are lower-percentage blends that are commonly used by retail consumers around the U.S. and higher blends that are only used in

[21] Information regarding the Colonial pipeline shutdown

certain types of engines and have limited availability nationwide. Previous literature is mixed in its findings regarding high- vs low-blend RIN pass through. A body of work has demonstrated lower pass-through rates of RIN subsidies for E85, gasoline with 85 percent ethanol, than the more common blend with less ethanol content, E10 (Knittel et al., 2017; Li & Stock, 2019; Pouliot et al., 2020). This work generally finds E85 pass through is incomplete. However, more recent work has found that it had been completely passed through (Lade & Bushnell, 2019).

To test for heterogeneity in the pass through of RIN subsidies across blends, I estimate (11) separately for each blend in each region.[22] The long-run coefficients from those regressions are depicted in Figure 13, showing that long-run RIN subsidy pass through is generally consistent across blends within each region. When point estimates differ in a meaningful way, one of them tends to be much more imprecise than the other. Generally, lower blends are estimated less precisely because variation in the subsidy is smaller in magnitude than for higher blends. Most notably, B5 estimates are much less precise than other blends in most regions.

[22] Results from Oregon are omitted from the blend-level analysis because they are very imprecise and therefore not informative.

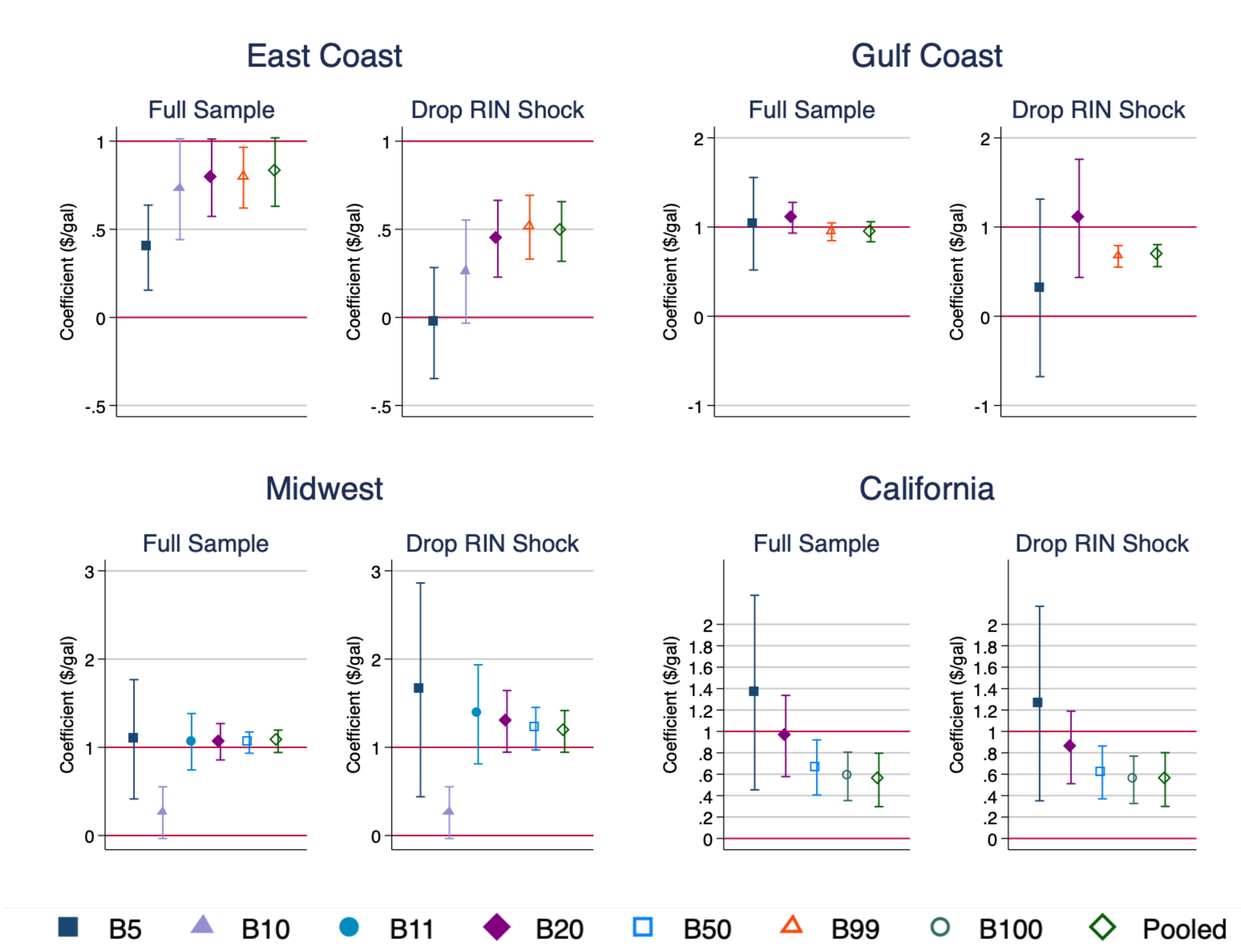

Figure 13. RIN Subsidy Pass Through by Blend. The estimates for California are from San Francisco. Note the difference in scales for each region. Oregon is omitted because estimates are extremely imprecise and not informative, especially when using the smaller sample when the RIN Price Shock period is dropped. Standard errors are clustered at the year-month level.

In the East Coast, however, the results for B5 are qualitatively different. This could result from the fact that markets for B5 are fundamentally different in some cases (see Section 1.2). It could also be that some B5 is blended above the rack. The PNW, for example, has a spot market for B5, so the subsidy there would be passed through to the spot price rather than the rack price and this action could arise in other regions. In California, the pattern is similar, however only blends above B20 have 95 percent confidence intervals that exclude complete pass through. Additionally, although imprecise, pass-through point estimates tend to be lower for higher blends. This is discussed further in conjunction with LCFS subsidies in Section 1.5.2.

The RIN subsidy pass through results exhibit some consistencies with previous findings in the literature studying pass through of RIN subsidies to blended gasoline and some important differences. The finding of complete pass through in the Midwest and incomplete pass through on the East Coast is generally consistent with Pouliot et al. (2017). However, the cities used in my sample differ from theirs for each region, and their finding are sensitive to looking at branded and unbranded products, and only unbranded fuels are available here. Comparing the East Coast results here – which are for Trenton, NJ – to their results from Newark, NJ for unbranded E10, I find lower rates of pass through, especially when dropping the RIN Price Shock period.

Like mine, their sample includes a period with a significant upward shock to RIN prices – the first eight months of 2013 – that has a significant impact on estimates of pass through. In that period, D6 RIN prices rose from under 10 cents/gal to over $1/gal and was the first time RINs represented a substantial portion of gasoline margins. They argue that much of the findings of incomplete pass through are driven by the market learning how D6 RIN prices affected rack margins.

Figure 12 suggest a different story. The soybean boom that began in 2020 put substantial upward pressure on biodiesel prices, and therefore, D4 RIN prices. RIN subsidies for biodiesel surpassed $3/gal in 2021, more than tripling since 2020, and nearly double its all-time high (excluding outliers). Blenders adjusted quickly to this, fully passing through the subsidy as it grew exponentially. This is visually clear in Figure 16, and suggests the RIN subsidy is salient to market participants. In fact, only when excluding the RIN Price Shock period can I reject complete pass through in the Gulf and East Coast. Although reaching record highs, the RIN subsidy was still meaningful prior to the RIN Price Shock period it represented around half the price of B100 for much of the time. Pass through of the RIN subsidy was lower prior to the RIN Price Shock period, so the salience argument doesn't explain the finding of incomplete pass through of the RIN subsidy in this paper.

1.5.2 LCFS and RFS Incentive Pass Through in California

In this section, pass-through of the LCFS subsidy to rack margins for biodiesel are considered. An important difference relative to RIN subsidies, LCFS subsidies exhibits less daily variation, which introduces a lack of statistical power, especially in the short run. Generally, however, the results presented in this section will suggest that LCFS subsidies is not fully passed through in the California rack markets in my sample. Table 5 presents short- and long-run estimates from the unrestricted and restricted models in (11) and (12), respectively. Columns 1 and 2 show that all short-run coefficients are statistically insignificant when the LCFS and RIN subsidies are included separately in the model. The coefficients in column 3, however, are statistically significant and suggest 70 cents/gal of the combined subsidy is passed through in the long-run, and it takes over a week to reach the long-run rate of pass through. The restricted model is more parsimonious, but the combined subsidy may better explain variation in rack margins since they are stacked, and blenders are total policy revenue is what's salient to the blender.

Table 5. Subsidy Pass-Through Dynamics in California

	Unrestricted Model		Restricted
	$X_t^k = R_t^k$	$X_t^k = L_t^k$	$X_t^k = R_t^k + L_t^k$
	(1)	(2)	(3)
ΔX_t^k	0.02	0.29	0.14
	(0.10)	(0.43)	(0.09)
ΔX_{t-1}^k	0.07	0.30	0.20**
	(0.10)	(0.31)	(0.10)
ΔX_{t-2}^k	0.08	0.02	0.16
	(0.11)	(0.34)	(0.11)
ΔX_{t-3}^k	0.11	-0.07	0.16
	(0.11)	(0.33)	(0.10)
ΔX_{t-4}^k	-0.03	0.23	0.18
	(0.15)	(0.32)	(0.12)
ΔX_{t-5}^k	0.01	0.29	0.24*
	(0.16)	(0.35)	(0.12)
ΔX_{t-6}^k	0.09	0.05	0.25*
	(0.15)	(0.34)	(0.13)
ΔX_{t-7}^k	0.17	0.02	0.29**
	(0.14)	(0.32)	(0.13)

ΔX_{t-8}^k	0.19	0.34	0.34**
	(0.15)	(0.31)	(0.15)
ΔX_{t-9}^k	0.23	0.46	0.40***
	(0.15)	(0.29)	(0.14)
$\boldsymbol{X_{t-10}^k}$	0.58***	-0.02	**0.68*** **
	(0.11)	(0.26)	**(0.12)**
Constant	-0.79	-0.79	-0.99
	(0.64)	(0.64)	(0.66)
Observations	5,681	5,681	5,681
R-squared	0.90	0.90	0.89

Notes: Columns 1 and 2 are estimated from the same regression model. All California cities and blends are included, see Table A- 2. The dependent variable is the rack margin. Standard errors are clustered at the month-year level. * Statistically significant at the 10% level, ** Statistically significant at the 5% level, *** Significant at the 1% level.

Long-run pass through of the individual and combined subsidies exhibits heterogeneity within in California. Table 6 shows that pass through is lower in larger cities in the sample (Los Angeles and San Francisco) and higher in the smaller cities (Bakersfield and Stockton). The RIN subsidy is fully passed through in the smaller cities on average, and 60 cents/gal of the LCFS subsidy is passed through on average, but the 95 percent confidence interval includes both zero and one. The 95 percent confidence interval for the combined subsidy in the smaller cities is [0.87, 1.74].

The majority of operational biodiesel production capacity is in Los Angeles, San Diego, and San Francisco (Brown, 2020). Los Angeles and San Francisco also both have major spot market hubs for ULSD. Therefore, the remainder of this section will focus on those larger cities. Only half the RIN subsidy is passed through in the urban markets on average and pass through of the LCFS subsidy is not statistically different from zero. The confidence intervals for R_t^k, L_t^k, and $R_t^k + L_t^k$ are [0.28, 0.77], [-.056, 0.57], and [0.37, 0.82], respectively. Therefore, complete pass through is rejected for all three variables.

Table 6. Long-Run Subsidy Pass-Through in California

	Large Cities		Small Cities	
	(1)	(2)	(3)	(4)

R_t^k	0.54***		1.10***	
	(0.12)		(0.18)	
L_t^k	0.02		0.61**	
	(0.29)		(0.29)	
$R_t^k + L_t^k$		0.61***		1.30***
		(0.11)		(0.21)
Constant	0.09	0.01	0.05	-1.96
	(0.66)	(0.65)	(1.89)	(1.88)
Observations	4,604	4,604	1,077	1,077
R-squared	0.94	0.93	0.89	0.88

Notes: The dependent variable is the rack margin. Standard errors are clustered at the month-year level. * Statistically significant at the 10% level, ** Statistically significant at the 5% level, *** Significant at the 1% level.

The results of the LCFS subsidy analysis discussed thus far have been averages over the full sample. So, for example, it could be that those estimates reflect an average of incomplete pass through in earlier years due to a lack of salience but pass through becomes complete later in the sample as the market better understands how LCFS credits affect margins (Pouliot et al., 2020). Also, the LCFS subsidies for biodiesel have risen from an average of 9 cents/gal in 2015 to over $1/gal since 2018, so it may have been easier to hide changes in the subsidy when levels were so low. To explore the aforementioned questions, I estimate (11) and (12), keeping observations in Los Angeles and San Francisco, for each subsample defined in Table 2. I present those results in Figure 14.

The first observation is the downward shift in the rates of pass through from the Low LCFS Price period to the Mid LCFS Price period. Pass through of the RIN subsidy, on average, is close to one in the Low LCFS Price period and falls to nearly a quarter in the next period. There isn't much signal in the LCFS subsidy during the Low LCFS Price period, but the point estimate is also close to one. In the Mid LCFS Price period, pass through of the LCFS subsidy falls to 0.06 but the 95 percent confidence interval includes up to half. Since the LCFS subsidy estimates are so imprecise in the Low LCFS Price period, I'm not able to confidently rule out the salience argument, but the near-zero point estimates in later periods, and confidence intervals with upper bounds around a half, suggest that a change in salience is unlikely to be the driver of the finding of incomplete pass through of the LCFS subsidy when utilizing the full sample.

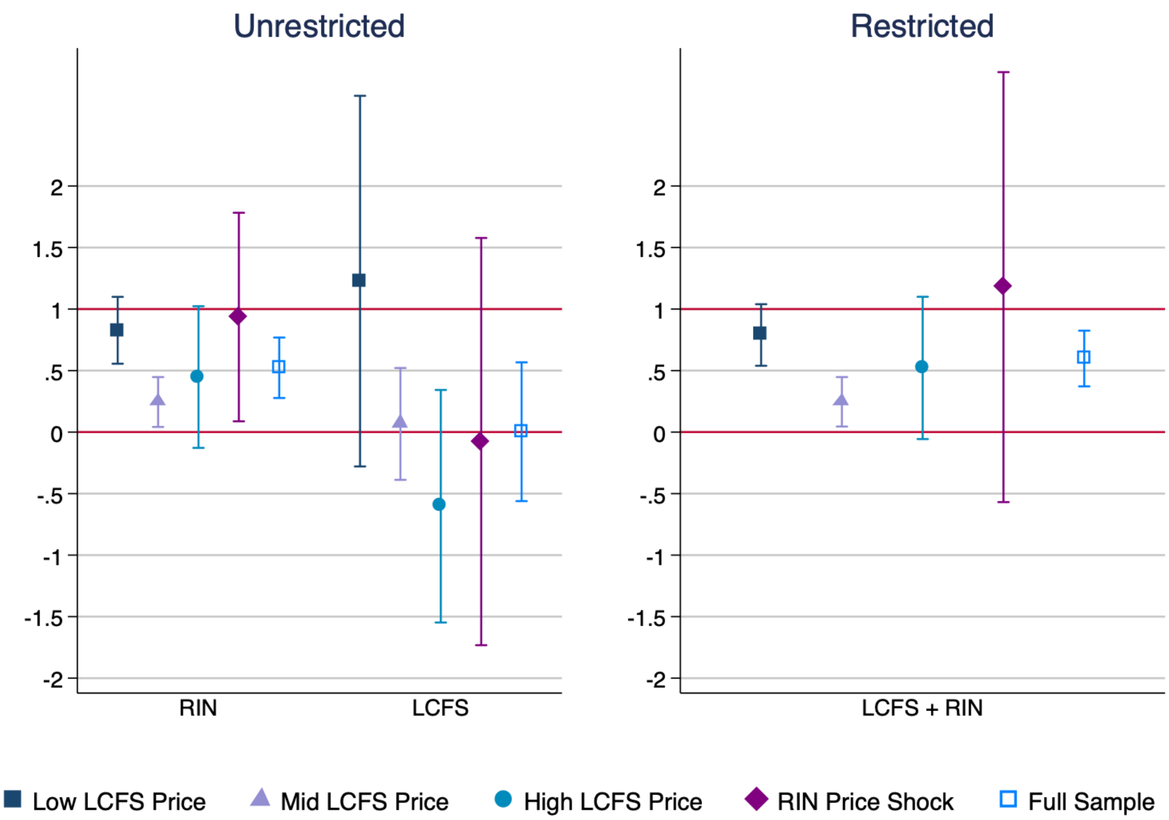

Figure 14. Long-Run Pass-Through of Implicit Subsidies in California by Sub-sample. Results are shown for Los Angeles and San Francisco only. Standard errors are clustered at the year-month level.

Results from the restricted model resemble RIN pass through from the unrestricted model, which is to be expected as there is more variation in RIN subsidies than LCFS subsidies over most of the sample. These RIN subsidy pass-through estimates are put into context with other cities in the sample in Figure A-4, which shows that RIN subsidy pass through, apart from the East Coast, was complete or near complete in all subsamples.

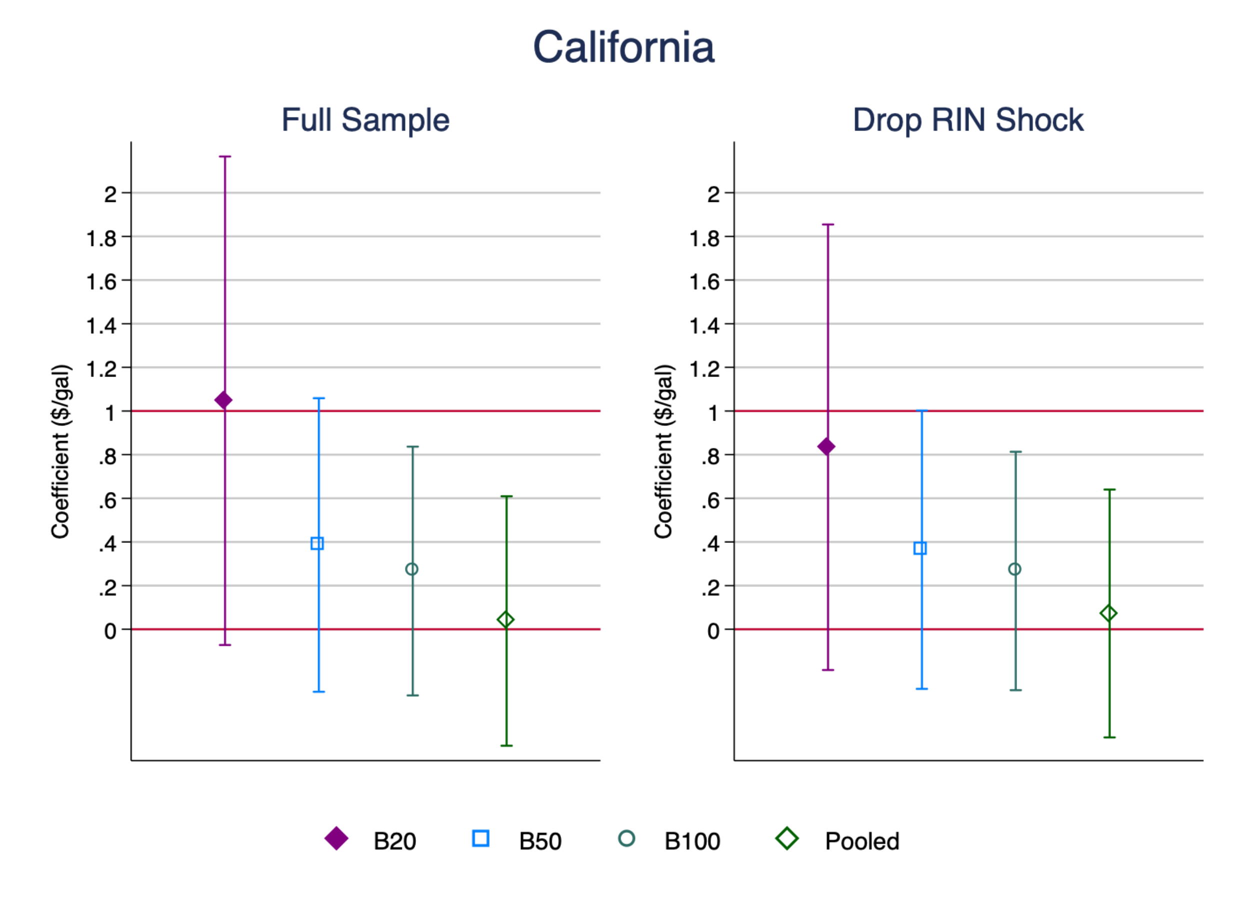

Figure 15. LCFS Subsidy Pass Through by Blend. The estimates for California are from San Francisco. B5 is not depicted because confidence intervals are too wide.

Figure 13 showed some RIN subsidy pass-through heterogeneity across blends in California. Figure 15 paints a similar picture for the LCFS subsidy; B20 is the only blend with a confidence interval including complete pass through and point estimates decrease with the share of ULSD in the blend. This result, combined with Figure 13, is consistent with blenders having greater market power in the higher blends, especially above B20.

The lack of pass-through of the LCFS subsidy can be easily visualized. The bottom panel of Figure 16 plots rack margins for B100 in Los Angeles, along with the LCFS subsidy, the RIN subsidy, and the combined subsidy. It is important to reemphasize that west coast margins are calculated using the B100 spot price in NY Harbor Barge and therefore neglect transportation and other costs, which will inflate the observed margins above true levels by an unknown amount. I assume these costs are constant over time but don't speculate as to their level. With that assumption, I plot the same thing but shifting margins down to better visualize co-movement with the subsidies in the top panel of Figure 16. At first glance, it appears that the rack margin follows the combined subsidy well (which would indicate complete pass through), especially in early 2016 when the LCFS credit price rose. That's not the case, however, because the BTC was put back in place in 2016, and, under the assumptions laid out earlier in this section, blenders received an additional 50 cents/gal of B100 from the BTC. This, coincidentally, coincided with the LCFS subsidy increasing by about 50 cents/gal of B100 due to the modeling change by CARB. In subsequent years, rack margins generally followed movements in the RIN subsidy, but not the LCFS or combined subsidies. I use Los Angeles B100 as an illustrative example in Figure 16; however, the picture looks similar in San Francisco and other blends.

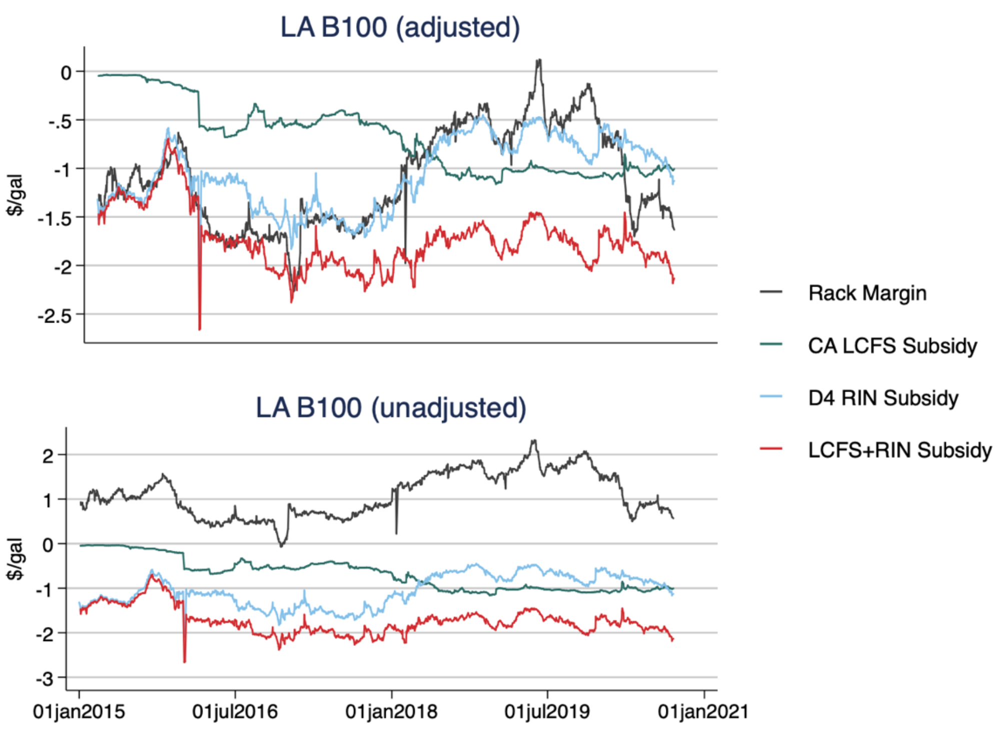

Figure 16. Rack Margins in Los Angeles. In the adjusted panel (top), I subtract the observed rack margin by $2.2/gal in order to better visualize co-movement with implicit subsidies. Margins in LA are calculated using B100 spot prices from NY Harbor Barge, so in practice they will be lower because of transportation and other costs. I assume these additional costs are constant over time.

Pass through of the LCFS subsidy to blended biodiesel prices is not statistically different from zero, and in the preferred specification, pass through is 0.02 on average. There are a few important limitations that could significantly impact the results presented above. First is, again, the lack of a clear understanding how the BTC affected the relationship between RIN subsidies and rack margins, and whether the effect is different for California relative to other U.S. regions. Second is the absence of a California-specific spot price of SME B100. If the assumption that the spot price, or the blender's marginal cost, of SME B100 is equal to a NY Harbor Barge basis plus a constant transportation cost is violated, the estimates of LCFS subsidy pass through will be biased if California-specific costs are correlated with the LCFS subsidy. Specifically, if transportation costs exhibit a positive relationship with the LCFS subsidy, I will systematically underestimate the rate it is passed through. With the data available at the time of writing, the prevalence of that relationship is untestable. Lastly, margins for diesel blended with SME biodiesel are volatile and data availability limit the analysis to SME biodiesel only, which is rarely used in California.

The advantage of focusing on SME biodiesel, however, is that its CI has been relatively constant over time (aside from the 2016 modeling change, Figure 5). Yet, if the CI of SME biodiesel used in California changes significantly within any given year, it will have two direct effects on the models used to estimate subsidy pass through, (11) and (12). The first is that the true spot price of SME B100 in California will likely move inversely with the CI, which will violate the assumption that the California spot price equals the NY Harbor spot price plus a constant. The second is that the implicit subsidy calculation in (4) will be inaccurate.

Take a simplified example. Suppose blenders start purchasing biodiesel with a lower CI and a higher price mid-year and nothing else changes. The observed margin in (10) will not change because I don't observe the true California spot price. Since the number of credits per gallon would not change. The subsidy calculated in (4) would only change if the decreasing CI is associated with an increase in the LCFS credit price, which would attenuate the estimates of

LCFS subsidy pass through. However, it's unlikely CI scores of SME biodiesel are changing meaningfully within years in my sample.

Accurate, high-frequency biodiesel, as well as renewable diesel, pricing data for feedstocks and localities would allow researchers to study pass through using prices for fuels that reflect a much more significant market share of the biomass-based diesel consumed in the state. Additional data on the CI of fuels in the rack pricing data would allow for more accurate calculations of the implicit LCFS subsidies they receive, instead of assuming the volume-weighted average CI score for the listed feedstock. Quantity data would also be particularly useful in the LCFS analysis given how thin the market for SME biodiesel is in California. Many of the rack prices in my sample for California may come from transactions with relatively small quantities of fuel and may not be fully representative of the entire market.

1.5.3 CFP and RFS Incentive Pass Through in Oregon

Credit market data for the CFP is only available since 2017 and there hasn't been much variation in credit prices. Additionally, spot prices in the PNW and Oregon rack margins are very volatile. This makes identifying pass through of the CFP subsidy difficult and results presented here are imprecise. Table 7 presents the short- and long-run estimates from (11) and (12), using the Oregon cities in the sample. All estimates of CFP pass through are statistically insignificant. Like California, short-run estimates of the combined subsidy are measured more precisely than either of the individual subsidies.

Table 7. Pass-Through Dynamics in Oregon

	Unrestricted		Restricted
	$X_t^k = R_t^k$ (1)	$X_t^k = L_t^k$ (2)	$X_t^k = R_t^k + L_t^k$ (3)
ΔX_t^k	0.26	1.30	0.31**
	(0.17)	(0.93)	(0.15)
ΔX_{t-1}^k	0.36**	0.80	0.38**
	(0.17)	(0.75)	(0.16)

ΔX_{t-2}^{k}	0.33*	0.92	0.37**
	(0.19)	(0.80)	(0.16)
ΔX_{t-3}^{k}	0.37**	0.31	0.37**
	(0.18)	(0.80)	(0.16)
ΔX_{t-4}^{k}	0.40***	1.20	0.44***
	(0.14)	(0.73)	(0.12)
ΔX_{t-5}^{k}	0.43**	0.77	0.44**
	(0.20)	(0.73)	(0.18)
ΔX_{t-6}^{k}	0.43***	1.45*	0.51***
	(0.16)	(0.77)	(0.15)
ΔX_{t-7}^{k}	0.43**	1.31*	0.47**
	(0.20)	(0.77)	(0.19)
ΔX_{t-8}^{k}	0.53***	1.01	0.54***
	(0.14)	(0.70)	(0.12)
ΔX_{t-9}^{k}	0.35**	0.45	0.38***
	(0.15)	(0.62)	(0.14)
$\boldsymbol{X_{t-10}^{k}}$	0.62***	0.19	0.66***
	(0.11)	(0.35)	(0.10)
Constant	0.14	0.14	0.40
	(0.62)	(0.62)	(0.59)
Observations	3,358	3,358	3,358
R-squared	0.94	0.94	0.93

Notes: Columns 1 and 2 are estimated from the same regression model. All Oregon cities and blends are included, see Table A- 2. The dependent variable is the rack margin. Standard errors are clustered at the month-year level. * Statistically significant at the 10% level, ** Statistically significant at the 5% level, *** Significant at the 1% level.

Also, like California, pass-through is spatially heterogeneous in Oregon. Table 8 presents long-run estimates from (11) and (12) for Portland and Eugene separately. It shows that pass through of the RIN, CFP, and combined subsidies is higher in Eugene on average. Although imprecise, the results here suggest a similar pattern to California and the LCFS, complete pass through of the CFP in the smaller city, on average, relative to the urban center. Meaningful analysis in Oregon is also hindered by data availability and price volatility.

Table 8. Long-Run Pass-Through of Implicit Subsidies in Oregon

	Portland		Eugene	
	(1)	(2)	(3)	(4)

R_t^k	0.61***		0.75***	
	(0.10)		(0.19)	
L_t^k	0.13		1.02*	
	(0.37)		(0.57)	
$R_t^k + L_t^k$		0.65***		0.75***
		(0.10)		(0.19)
Constant	-0.17	0.11	0.65	0.98
	(0.64)	(0.62)	(0.79)	(0.60)
Observations	2,239	2,239	1,119	1,119
R-squared	0.96	0.96	0.82	0.82

Notes: The dependent variable is the rack margin. Standard errors are clustered at the month-year level. * Statistically significant at the 10% level, ** Statistically significant at the 5% level, *** Significant at the 1% level.

1.6 Conclusion

An important contribution of this paper is utilizing institutional details and context to build an understanding of how the stacked costs and incentives from multiple market-based environmental policies propagate through the supply chain of fuels. This paper provides a framework to evaluate tax and subsidy pass through in the diesel sector, which is nontrivial, especially relative to the gasoline sector, due to the intermittent nature of the Blender's Tax Credit (BTC).

Although a similar tax-subsidy scheme is used, pass through of the LCFS and CFP taxes and subsidies can't be evaluated in the same way as the RFS, due to nuanced policy differences. Section 1.4 showed that applying the same framework to the LCFS leads to the wrong conclusion about tax pass through. Estimating pass through of the LCFS tax at the wholesale level will suggest that it isn't passed through, when in fact it is being passed through downstream at the rack level. This finding also informs the analysis on LCFS subsidy pass through, as it suggests that blenders hold both credits and deficits, creating a net subsidy rather than a gross subsidy. Not accounting for the tax will overstate the amount of the actual subsidy realized by the blender.

Pass through of the RIN tax is found to be complete in all major spot markets on average, except for San Francisco. Pass through of the RIN subsidy is complete in the Midwest, incomplete in the East Coast, West Coast, and Gulf Coast. The findings of incomplete RIN subsidy pass through in my sample, which includes data from the last six years, suggest that lack of salience may not be the explanation. Additionally, incomplete pass through of the RIN subsidy in the Gulf Coast differs from findings in the blended gasoline sector (Pouliot et al., 2020).

In California, RIN taxes and LCFS taxes are fully passed through to wholesale prices and rack prices, respectively, with the exception of the tax in San Francisco. Pass through of both the RIN subsidy and LCFS subsidy is incomplete. I find that 68 percent of the combined subsidy is passed through to rack prices in California in the long-run on average. Pass through of LCFS subsidies is lower for higher biodiesel blends, which is consistent with blenders having market power in higher blends. However, there are significantly more blending facilities in Los Angeles than San Francisco, yet pass through estimates of the RIN, LCFS, and combined subsidy for B100 in the two cities are nearly identical, which is surprising.[23] I can rule out lack of salience as the cause of incomplete pass through of both subsidies in California because that would require that all costs be passed through at the same rate (Pouliot et al., 2020), which is inconsistent with results from the unrestricted models discussed in Figure A-3.

CFP tax pass through is not studied here due to lack of data. Spot prices for diesel are especially volatile in the Pacific Northwest, which creates noisy margins in Oregon. At the same time, CFP biodiesel subsidies lack variation, therefore estimates of pass through are very imprecise in Oregon. With that caveat, CFP pass through is incomplete on average and resembles similarities to the LCFS.

[23] B100 is the only blend used in both cities. Information on blending facilities can be found here: http://www.edf.org/content/biodiesel-california.

Together, the results presented in this paper point to some inefficiencies in the RFS, LCFS, and CFP. The primary contribution of this paper was providing the first set of estimates of pass through of LCFS implicit taxes and subsidies. There is strong evidence that much of the credit value is held by fuel blenders. Explanations for their ability to capture rents from LCFS credits are unclear and requires further research and better data. However, some explanations are ruled out, such as salience. Accurate cost estimates of biodiesel in California and Oregon would greatly assist researchers study pass through of the policies' costs and incentives. Additionally, feedstock-specific costs would allow for more accurate calculations of implicit subsidies and for the study of pass-through using feedstocks with much larger market shares. Lastly, better cost data on renewable diesel would lead to a more valuable study of LCFS subsidy pass through as it has become much more widely used than biodiesel in the state.

1.A Appendix

1.A.1 Supplemental Figures

Figure A- 1. Spot Price of CA LCFS and OR CFP Credits.

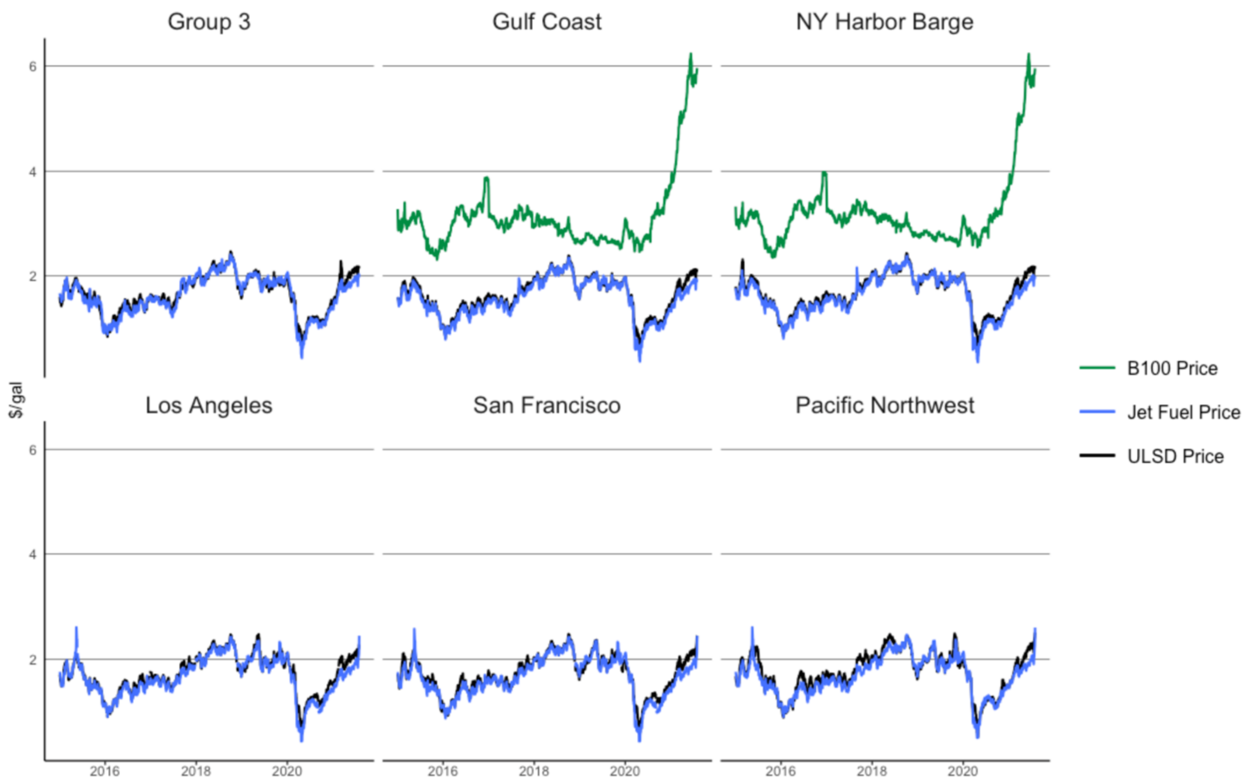

Figure A- 2. Spot Prices

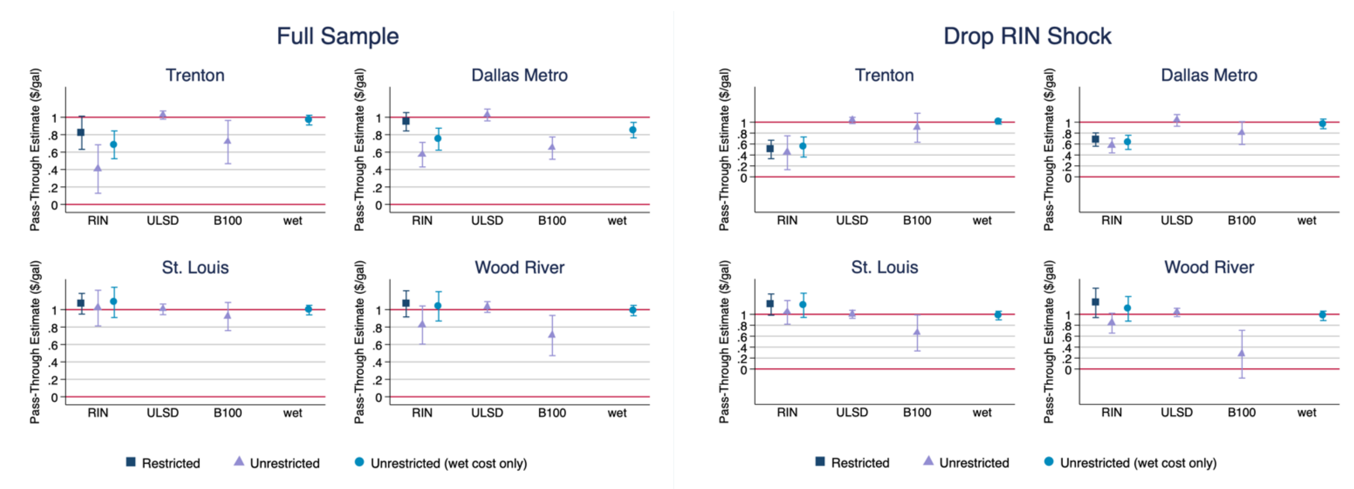

Figure A-3. Input Cost and Subsidy Pass Through

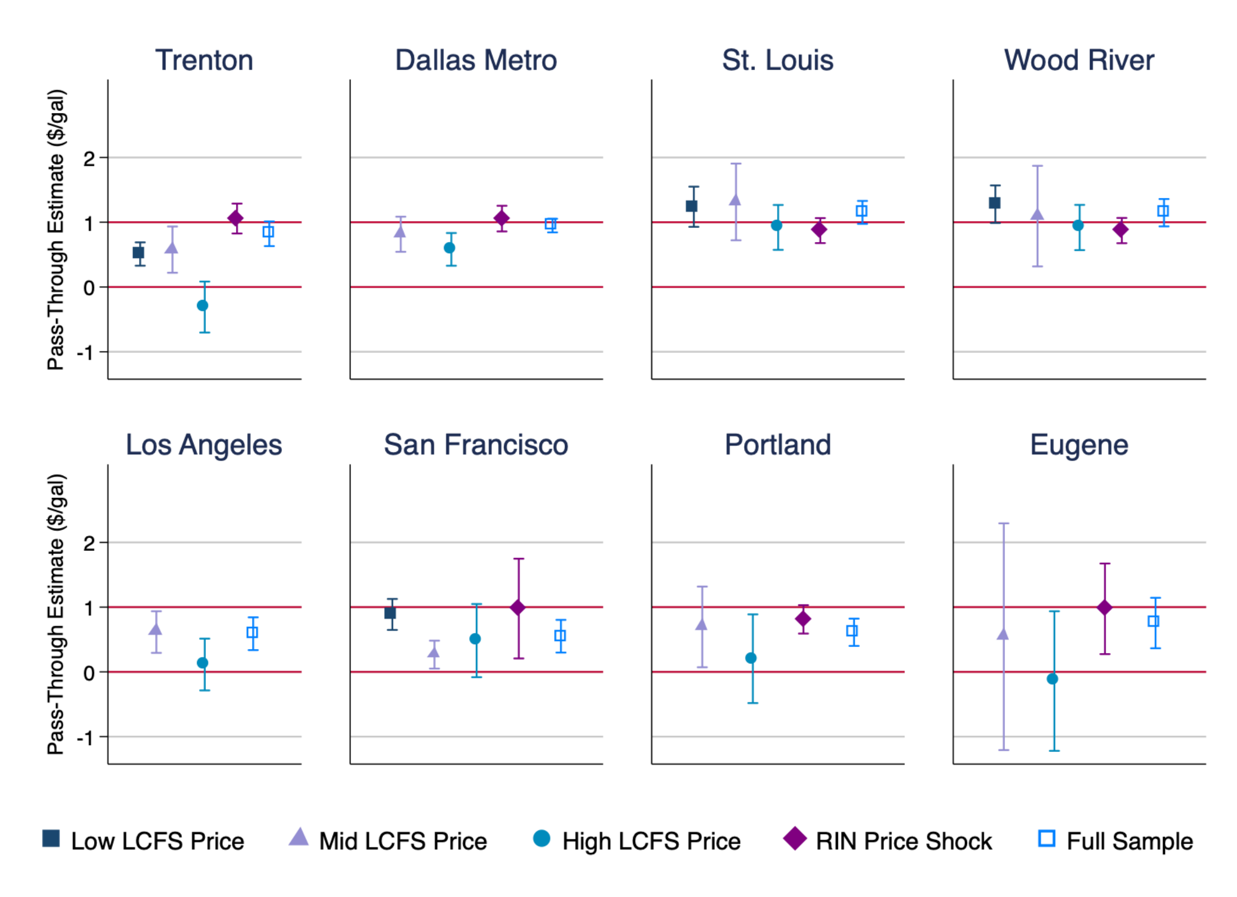

Figure A-4. Long-Run Pass Through if RIN Subsidies by Subsample and City.

1.A.2 Supplemental Tables

Table A- 1. List of Rack Cities and Nearby Spot Markets

Rack City	State	Region	ULSD Spot Market	B100 Spot Market
Trenton	NJ	East Coast	NY Harbor Barge	NY Harbor Barge
Dallas Metro	TX	Gulf	Gulf Coast	Gulf Coast
Wood River	IL	Midwest	Chicago	Chicago
St. Louis	MO	Midwest	Group 3	Chicago
Eugene	OR	Pacific Northwest	Pacific Northwest	NY Harbor Barge
Portland	OR	Pacific Northwest	Pacific Northwest	NY Harbor Barge
Bakersfield	CA	West Coast	Los Angeles	NY Harbor Barge

Rack City	State	Region	ULSD Spot Market	B100 Spot Market
Los Angeles	CA	West Coast	Los Angeles	NY Harbor Barge
San Francisco	CA	West Coast	San Francisco	NY Harbor Barge
Stockton	CA	West Coast	San Francisco	NY Harbor Barge

Table A- 2. Rack Suppliers and Available Blends

		Available Blends	
Rack City	**# of Suppliers**	**Unbranded**	**Branded**
Trenton	4	B2, B5, B10, B20, B99	B2, B5, B10, B20, B99
Dallas Metro	15	B5, B20, B99	B5
Wood River	4	B2, B5, B20, B50	B5
St. Louis	3	B2, B5, B11, B20, B50	B5
Eugene	13	B5, B20	B5
Portland	15	B5, B10, B20, B50	B5
Bakersfield	3	B20	B20
Los Angeles	5	B100	N/A
San Francisco	7	B1, B5, B20, B50, B100	N/A
Stockton	8	B5, B10, B20, B100	B100

Table A- 3. RIN Tax Pass Through Dynamics

	Full Sample			Drop RIN Shock (6/20-7/21)		
	CA	PNW	ROUS	CA	PNW	ROUS
	(1)	(2)	(3)	(4)	(5)	(6)
ΔR_t^u	0.80*	-1.11*	1.44***	-0.02	-0.66	1.09**
	(0.46)	(0.66)	(0.36)	(0.52)	(1.04)	(0.44)
ΔR_{t-1}^u	0.90**	-0.83	1.32***	0.04	-0.94	1.05***
	(0.36)	(0.52)	(0.28)	(0.46)	(0.91)	(0.35)
ΔR_{t-2}^u	0.70*	-1.15	1.22***	-0.21	-1.64	0.89***
	(0.40)	(0.69)	(0.25)	(0.45)	(1.07)	(0.32)
ΔR_{t-3}^u	0.69*	-1.50**	1.04***	-0.40	-2.06*	0.54

	(0.39)	(0.73)	(0.24)	(0.43)	(1.06)	(0.34)
ΔR^{u}_{t-4}	0.68	-1.45**	1.03***	-0.42	-2.09**	0.51
	(0.45)	(0.70)	(0.25)	(0.53)	(0.85)	(0.39)
ΔR^{u}_{t-5}	0.73	-1.36*	1.08***	-0.48	-2.24**	0.60*
	(0.50)	(0.68)	(0.22)	(0.56)	(1.00)	(0.33)
ΔR^{u}_{t-6}	0.86*	-1.44**	1.10***	-0.34	-2.30**	0.46
	(0.48)	(0.65)	(0.25)	(0.59)	(1.03)	(0.39)
ΔR^{u}_{t-7}	0.65	-1.16*	1.01***	-0.57	-2.26**	0.38
	(0.45)	(0.65)	(0.26)	(0.62)	(0.96)	(0.48)
ΔR^{u}_{t-8}	0.76	-1.19	0.88***	-0.67	-2.53**	0.29
	(0.55)	(0.76)	(0.27)	(0.69)	(1.00)	(0.47)
ΔR^{u}_{t-9}	0.95*	-1.59**	0.96***	-0.35	-2.44***	0.41
	(0.57)	(0.68)	(0.25)	(0.66)	(0.89)	(0.38)
$\boldsymbol{R^{u}_{t-10}}$	**1.23*** **	**1.35*** **	**1.12*** **	**0.72*** **	**1.65*** **	**0.94*** **
	(0.11)	**(0.16)**	**(0.07)**	**(0.17)**	**(0.28)**	**(0.12)**
Constant	-0.02**	-0.01	-0.04***	-0.01	-0.02	-0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Observations	3,260	1,630	4,890	2,674	1,337	4,011
R-squared	0.42	0.39	0.59	0.32	0.39	0.48

Notes: The dependent variable is the ULSD-Jet wholesale spread. Standard errors are clustered at the month-year level. * Statistically significant at the 10% level, ** Statistically significant at the 5% level, *** Significant at the 1% level.

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Chapter 2. Uncertainty, Innovation, and Infrastructure Credits: Outlook for the Low Carbon Fuel Standard through 2030.

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State and local policy makers in the U.S. and beyond are looking to Low Carbon Fuel Standards (LCFS) as a policy instrument for reducing GHG emissions in the transportation sector. California implemented its LCFS in 2011, setting a target of a ten percent reduction in carbon intensity (CI) values for transport fuels used in the state by 2030 from 2011 levels, as part of its climate policy. The target has since been updated to a 20 percent reduction below 2011 levels by 2030. Oregon fully implemented its LCFS, the Clean Fuels Program (CFP), in 2016, seeking to reduce CI values of Oregon transportation fuels by ten percent from 2015 to 2025.[24] [25] Washington State failed in several legislative attempts to pass a LCFS that proposed a ten percent reduction over a ten-year period, most recently in 2019.[26] Also in Washington State, Puget Sound Air Quality Agency is considering a regional clean fuel standard to contribute to its 2030 GHG emissions goals.[27] Other jurisdictions with, developing, or considering an LCFS-like program include British Columbia (in effect since 2011), Canada and Brazil (under development), and Colorado (initial feasibility analysis).[28]

While the LCFS regulation is now moving forward, its history is not without controversy. There have been legal challenges linked to the way it differentiates fuels originating in different locations. There have also been extensive debates about the life cycle calculations used to establish the carbon intensities of different fuels used for compliance, particularly aspects linked to the indirect land use effects caused by biofuels. More recently, opponents have pointed to increasing costs of compliance and raised concerns about both the efficiency of the regulation and its potential impact on fuel prices. Such concerns contributed to the rejection of the LCFS mechanism in some states.

Partly in response to concerns over compliance costs, and partly in an effort to spur more innovation, new dimensions have continued to be added to the LCFS. In California, regulators have allowed the expansion of "book-and-claim," an accounting mechanism that allows certain specialized fuels, particularly bio-methane sourced from dairy digesters to be physically consumed in one state but still allowed to generate LCFS credits in another. In another departure from the original design, the LCFS will also now award credits for investment in

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[24] See https://www.oregon.gov/deq/aq/programs/Pages/Clean-Fuels.aspx for more information on the Oregon CFP.

[25] See, also, https://escholarship.org/uc/item/0ct4m7gs.

[26] See https://washingtonstatewire.com/whats-next-for-a-low-carbon-fuel-standard/.

[27] See https://www.pscleanair.org/528/Clean-Fuel-Standard/.

[28] For information on Colorado, see https://ngtnews.com/colorado-looks-into-establishingcarbon-fuel-standard.

infrastructure related to EV charging facilities and hydrogen fueling station. This decoupling of credit generation from fuel consumed within the state could affect both the long run credit price and its transmission through to various types of fuels. However, such effects will arise only if sufficient infrastructure credits are generated to alter the long-run marginal options for compliance.

In this paper, we assess if and how California is likely to achieve the proposed 20 percent reduction in CI values by 2030, and the likely impact of infrastructure credits on this compliance outlook. We follow a general methodology similar to that used in Borenstein et al. 2019 for the California cap-and-trade program. We apply time-series econometric methods to account for uncertainty in demand under business-as-usual (BAU) as indicated by historical data on a range of key variables. We begin by projecting a distribution of demand for fuel and vehicle miles under BAU economic and policy uncertainty, which we define as continuation of the trends and correlations since 1987. We then transform those projections into a distribution of LCFS net deficits for the entire period from 2019 through 2030, assuming a steady drawdown of the currently accumulated credit "bank."

The distribution of net deficits illustrates a range of possibilities of demand for LCFS credits based on historical trends. Next, we generate LCFS credit supply scenarios that consider a variety of assumptions about inputs, technology, and the efficacy of complementary policies. By interacting projections of demand and various supply scenarios for LCFS credits, we can characterize the equilibrium number of credits generated under varying policy conditions and, furthermore, illustrate the changes in the fuel mix that would be necessary to achieve compliance.

For sources of credits generation not yet prevalent in the policy, we use ARB figures based on the modeling it used in its scoping plan. These sources include the potential role of a new category for credit generation, ZEV infrastructure capacity credits.[29] Credit supply scenarios also cover certain state goals, showing sensitivity of results to, for example, meeting the Governor's goals for battery electric vehicles in the light duty sector by 2030. State policies impacting the demand side such as vehicle efficiency standards and target reductions in vehicle miles traveled, are not explicitly modeled, although the modeled uncertainty in BAU takes account of past trends in these variables and allows for considerable variability. Targeted scenario modeling of demand side policies and additional supply side policies is a possible area for future research.

The remainder of this paper is organized as follows. Section 2.1 describes the background of the California LCFS, discussing the history of the policy, recent trends, and the economic mechanisms through which CI standards influence markets. In Section 2.2, we describe our data and econometric model used to forecast BAU demand for LCFS credits and discuss the projected outcomes. In Section 2.3, we characterize a variety of scenarios regarding LCFS credit supply and assess annual compliance in each. Finally, in Section 2.4, we conclude by discussing the implications of our analysis and highlight opportunities for future research.

2.1 Background: California's Low Carbon Fuel Standard

The California Low Carbon Fuel Standard was initially implemented in 2011, amended in 2013, re-adopted in 2015, and extended in 2019 to set targets through 2030. The LCFS sets a carbon intensity (CI) standard percentage reduction from the petroleum-based reference fuel that decreases each year. Implementation involves classifying all fuel volumes into a fuel pool defined by the reference fuel used or displaced and setting a nominal CI standard for each fuel pool. The reference fuels are diesel, E10 gasoline, and, from 2019 forward, jet fuel. The LCFS falls within a general regulatory framework known as intensity standards. It regulates the

[29] ARB credit generation assumptions from the scoping plan modeling include that a variety of state targets will be met, and an LCFS credit price of approximately $125/MTCO2e.

carbon intensity (e.g., gCO2e per megajoule) of transportation fuels, rather than the total amount of CO2 released through fuels.

As with all intensity standard mechanisms, the LCFS implicitly subsidizes the sales of fuels that are cleaner – that is, lower in carbon intensity – than the standard, and pays for the subsidy through charges imposed on fuel that is 'dirtier' than the standard (CI rating above the standard). Sales of individual fuels rated at a CI below the standard generate credits, and fuels rated at a CI above the standard generate deficits, in amounts proportionate to volumes. The LCFS requires annual compliance by regulated entities; all incurred deficits must be met by credits generated by production of low-carbon fuels or purchased from a credit market. The units of LCFS credits are dollars per metric ton of CO2e. LCFS credits can be banked without limit, allowing overcompliance under less stringent standards to help cover increased obligations as the standard grows more stringent, and they are fungible – meaning credits generated in any fuel pool are treated equivalently.

One of the attractions of policies like the LCFS to the policy community is that these subsidies and charges work to partially offset each other and dilute the pass-through of the implied carbon cost to retail fuel prices. This 'feature' of the LCFS has also been criticized by environmental economists, who note that the dilution of the carbon cost works to encourage more fuel consumption than would arise under alternative instruments such as a carbon tax.[30] In an extreme case, the subsidy of 'cleaner' fuel could spur consumption growth to the point where the quantity of fuel that is consumed overwhelms the reduction in the carbon intensity of the fuel and carbon emissions can increase. This extreme case is unlikely as it would require extremely price-elastic fuel demand. However, the overall point that, relative to other regulations, the LCFS can encourage consumption of fuels has continued to raise concerns in some circles.

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[30] See Holland, Hughes, and Knittel (2009).

CARB set annual standards for the CI of fuels in both the diesel and gasoline pools. These annual mandates are shown in the appendix in Table A-6. LCFS credits are awarded to fuels with a reported CI rating below the standard and deficits to those above the standard. The number of credits per unit of fuel depends on the CI rating of that fuel. The LCFS is energy based and thus the number of credits per unit of fuel also depends on factors regarding the energy output of the fuel.[31]

2.1.1 LCFS and Infrastructure Credits

Early policy development and academic research on the LCFS focused on its characteristic as an intensity standard targeting the marginal costs of fuels. As described above, per unit costs of cleaner fuels would be reduced through the subsidy effect and the costs of dirtier fuels would reflect the cost of acquiring credits. Recent revisions to the LCFS program have increased the role of alternative forms of compliance, in particular, the ability of firms to generate credits through the installation of infrastructure, rather than the production of fuel.

Fueling infrastructure credits are limited to zero tailpipe emission vehicles (ZEVs), hydrogen fuel cell vehicles and battery electric vehicles. LCFS infrastructure credits can be generated based on potential fuel flow from unused operational capacity for publicly accessible hydrogen fueling stations and DC fast chargers. ZEV infrastructure credits are capped at 5% of the prior quarter's deficit generation – 2.5% for hydrogen fueling and 2.5% for DC fast charging equipment. Applications for ZEV infrastructure credits are open through 2025 and are valid for 15 years in the case of hydrogen infrastructure, and 5 years in the case of DC fast charging infrastructure.

On one level, the addition of infrastructure credits represents a major departure from the original design of the LCFS as it does not directly subsidize the consumption of a low carbon

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[31] See Holland, Hughes, and Knittel (2009) for more information regarding energy based LCFS relative to other types of LCFS.

fuel. Rather, the credits subsidize a fixed cost of providing network infrastructure that may encourage adoption of EVs, the technology which may in turn use a low carbon fuel. In the same way, however, the infrastructure credit can reduce the very effect that LCFS critics have focused on as the central flaw in the regulations design: the encouragement of low, but still non-zero carbon fuel. While infrastructure credits may spur vehicle adoption, their effect on expanding driving miles would be second order.

At the same time, if the amount of infrastructure credits awarded through the program were significant enough to ease compliance, these credits can have the effect of lowering the overall LCFS credit price, and therefore reduce even the diluted carbon price effect on end-use fuel prices. The magnitude of any price-suppression effect would depend upon both the quantity of infrastructure credits and the slope of the LCFS compliance cost curve.

2.1.2 Cost Containment

Initially, there were no formal limits on how high LCFS credit prices could rise, although legal challenges to the regulation effectively delayed implementation, freezing the standard from 2013 through 2015, and effectively limited demand for credits and their pass-through to fuel prices. However, as the lawsuits were resolved in favor of continued implementation of the LCFS and the standard declined steadily in the last several years (with the exception of a court-ruled hiatus for the diesel pool standard in 2017-2018, which resumed its trajectory in 2019), credit prices have risen steadily and raised increasing concerns about the cost of the regulation.[32] In its 2015 re-adoption rule, the ARB introduced the credit clearance market, which is a cost-containment mechanism that would in theory limit price increases under some scenarios.

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[32] Historical LCFS credit prices can be accessed via the Data Dashboard at the ARB website: https://ww3.arb.ca.gov/fuels/lcfs/dashboard/dashboard.htm.

Entities in need of LCFS credits for purposes of immediate compliance can purchase credits in the credit clearance market at a price no higher than the prescribed maximum of $200 per ton in 2016 and adjusted for inflation thereafter (currently $216 per ton). If these entities are unable to purchase sufficient credits in this market to reach compliance, then they may carry over their deficits to future periods. Carryover deficits grow by 5% per year, meaning that firms pay an 'interest' penalty for deferring compliance. However, firms that hold credits are not required to sell in the credit clearance market, and they would not do so if they believed that they be able to sell their credits at a higher price in the future. Thus, the credit clearance market provides only a soft cap. However, ARB is currently proposing to impose a hard price cap of $200 per ton in 2016 dollars for LCFS credit transactions. To help facilitate compliance under this cap, it proposes a mechanism to 'borrow credits' from future residential electric vehicle charging. Under this mechanism, obligated entities could use credits expected to be generated in 2026-2030 to meet unmet annual deficit obligations in 2020 – 2025.

These cost-containment mechanisms are suited for dealing with a transient disruption in clean fuel supply or some other cause of a short-term supply-demand imbalance of LCFS credits. Because of the requirement that borrowed credits be restored with interest, it will not be effective at containing costs in an environment of chronic, long-term credit supply demand imbalance. The future prospects of the regulation are therefore linked to the potential supply and demand balance through the next 11 years of the program. A circumstance where compliance is only feasible through high cost fuels or sharp reductions in fuel consumption would push credit prices above the maximum credit price for the credit clearance market. One objective of this paper is to assess the potential likelihood of such an outcome. In 2019, ARB is proposing amendments that would backstop this cost containment mechanism, enforcing additional borrowing of future credit generation from residential electricity charging for electric vehicles at the maximum credit price, with a rolling payback schedule enforced on utilities that will borrow the credits, up to a cumulative total of 10 million borrowed credits.

2.2 Data and Methodology

This section outlines data and methods used to project business-as-usual (BAU) for LCFS credit and deficit generation to 2030. In this paper we use the term business-as-usual (BAU) frequently, and take it to mean, regarding LCFS credit demand, the continuation of historical trends through the compliance period. For LCFS credit supply, BAU refers to a continuation of current alternative fuel mix trends to 2030. Therefore, the uncertainty in the projections stems from the estimation of BAU demand, which against an assumed steady state of supply, yields a distribution of net deficits accumulate over the period 2019 to 2030, on which we base subsequent analysis.

2.2.1 Model of BAU Demand

We are interested forecasting demand for fuel and vehicle miles under BAU economic conditions. Demand for fuel and vehicle miles are highly dependent on other economic variables. Demand for both fuel and vehicle miles will be influenced by general economic activity and oil prices. In a booming economy, consumers travel more and purchase more fuel. Our aim is to fit an econometric model that characterizes past trends in key credit demand variables such as fuel consumption and key input prices for the gasoline and diesel fuel "pools," namely oil price and soybean prices, vehicle miles traveled, and an indicator of the state economy.[33] The estimates from that model are then used to simulate relationships moving forward to project potential credit demand.

Let $X_t = (X_{1t}, X_{2t}, \ldots, X_{6t})'$ denote the vector composed of the six variables included in our model used to characterize the BAU environment, where t is at the quarterly level. The six components of X_t are

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[33] The list includes soybean prices to capture trends in commodity prices. It may also improve the model's ability to project trends in use of biomass-based diesel within the diesel pool.

X_{1t} = California Reformulated Gasoline Consumption

X_{2t} = California Diesel Fuel Consumption

X_{3t} = U.S. Soybean Prices

X_{4t} = California Vehicle Miles Traveled (VMT)

X_{5t} = Brent Oil Price

X_{6t} = California Gross State Product (GSP)

Define $Y_{it} = ln(X_{it})$ for $i = 1, \ldots, 6$ and $Y\_t = (Y_{1t}, Y_{2t}, \ldots, Y_{6t})'$. We fit a cointegrated vector error correction (VEC) model to Y_{it}. Cointegration allows the variables to have one or more stable long-run relationships. We specify three cointegration relationships:

$$Y_{1t} = \beta_{10} + \beta_{11} Y_{4t} + \beta_{12} Y_{5t} + \beta_{13} Y_{6t} + z_{1t} \tag{15}$$

$$Y_{1t} = \beta_{10} + \beta_{11} Y_{4t} + \beta_{12} Y_{5t} + \beta_{13} Y_{6t} + z_{1t} \tag{16}$$

$$Y_{3t} = \beta_{30} \qquad + \beta_{32} Y_{5t} \qquad + z_{3t} \tag{17}$$

The first equation represents the demand for gasoline and the second represents the demand for diesel. The third equation implies that soybean and crude oil prices are tied together in the long run. We impose zero coefficients on VMT and GSP in the third equation because we have no rationale for these California variables to be tied to the soybean price.[34] The z_{it} terms represent the deviations from the cointegration relationship, also known as the error-correction terms.

The VEC model to estimate the interrelationships among the six credit demand variables is:

[34] The purpose of this third equation is to model the marginal cost of producing biomass-based diesel, which can then be used to model LCFS credit price under the assumption that biomass-based diesel is the marginal compliance fuel. We do not conduct that analysis in this paper; we defer it to future research.

$$\Delta Y_t = \alpha z_{t-1} + \Sigma_{j=1}^{p-1} \Gamma_j \Delta Y_{t-j} + \Sigma_{k=1}^{4} \omega_k s_k + \varepsilon_t \qquad (18)$$

where Δ is the first-difference operator, s_k are seasonal indicators for the quarter of the year, $p = 4$ so that three quarterly lags of Y_t are included in the model, and ε_t is a vector of idiosyncratic disturbances. The 6×3 matrix α represents how the six variables respond to deviations from the cointegration relationship. Combining (15)-(17) with (18), we can write the model as:

$$\Delta Y_t = \alpha\beta_0 + \alpha\beta' Y_{t-1} + \Sigma_{j=1}^{p-1} \Gamma_j \Delta Y_{t-j} + \Sigma_{k=1}^{4} \omega_k s_k + \varepsilon_t \qquad (19)$$

where

$$\beta = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ -\beta_{11} & -\beta_{21} & 0 \\ -\beta_{12} & -\beta_{22} & -\beta_{32} \\ -\beta_{13} & -\beta_{23} & 0 \end{bmatrix}$$

and $\beta_0 = (-\beta_{10}, -\beta_{20}, -\beta_{30})'$.

2.2.2 *Data*

We use data available from 1987 to 2018 for the six dependent variables to fit the VEC model. Because our data are measured at the quarterly level, we have a total of 124 observations for each variable.[35] California GSP was collected from the Bureau of Economic Analysis (BEA).[36] The

[35] All variables are measured at the quarterly level except CA GSP. The Bureau of Economic Analysis (BEA) reports quarterly data only since the year 2003. Therefore, we use annual data for CA GSP, which is available for the entire sample 1987-2018.

[36] Available at https://apps.bea.gov/regional/downloadzip.cfm

oil prices used in our model are Europe Brent spot prices FOB collected from the Energy Information Administration (EIA) at the monthly level and aggregated to quarterly averages.[37] We chose to use Brent oil prices rather than West Texas Intermediate (WTI) prices because Brent prices are more relevant to California markets. Historical vehicle miles traveled (VMT) on California highways are reported by the California Department of Transportation, CalTrans, at the monthly level.[38] On-highway VMT data are reported in the aggregate, and not divided into gasoline and diesel vehicles.[39] Our model also requires soybean prices, which we collect from the Agricultural Marketing Service (AMS) at the United States Department of Agriculture (USDA).[40] We aggregate monthly spot prices in Central Illinois to quarterly averages to be used in the model.

The main variables of interest in our model are gasoline and diesel consumption and VMT in California as we need to forecast BAU fuel demand in order to construct a distribution of LCFS deficits. We collect monthly prime supplier sales volumes for California reformulated gasoline (CaRFG) from the EIA.[41] This measure captures all finished gasoline that is consumed in

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[37] Historical Brent oil prices can be found at https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=PET&s=RBRTE&f=M.

[38] Available at http://www.dot.ca.gov/trafficops/census/mvmt.html

[39] We divide highway VMT by 0.56 to scale it up to an approximate total VMT. We use a factor of 0.56 because, when we compare on-highway VMT from Caltrans to total VMT from EMFAC, we find that on-highway VMT make up 56% of total VMT in CA on average. This re-scaling has no effect on the coefficient estimates or BAU projections from the VEC model described in the previous subsection because it is effectively just a change in units for one of the predictor variables. We re-scale the variable because later in our analysis when we estimate EV charging loads, we need to estimate VMT coming from EVs, which means we need total VMT rather than on-highway VMT.

[40] The soybean prices used in this study can be accessed by creating a custom report in the Market News Portal at https://www.ams.usda.gov/market-news/custom-reports and querying Central Illinois soybean under grains.

[41] The EIA classifies a prime supplier as "a firm that produces, imports, or transports selected petroleum products across State boundaries and local marketing areas, and sells the product to local distributors, local retailers, or end users."

California, including imports to the state. We assume all gasoline is consumed in the transportation sector.

Measuring diesel fuel consumption is more nuanced. The EIA reports monthly sales volumes for refiners at each step in the supply chain. We aggregate wholesale and retail sales volumes for No.2 distillate to construct a measure of consumption of No.2 distillate. According to data from the EIA, 99 percent of No.2 distillate is used for diesel fuel in California. Therefore we calculate sales volumes of CARB diesel, which is ultra-low sulfur diesel (ULSD) sold in California, as 99 percent of No.2 distillate sales. The diesel pool, however, comprises biomass-based diesel (BBD), which includes biodiesel and renewable diesel, as well as petroleum diesel. BBD demand was negligible prior to 2011, but has been increasing in the years since. Therefore, we construct the measure for diesel fuel consumption as the sum of BBD and ULSD. The EIA does not report sales of BBD, so we use volumes reported by CARB in the LCFS quarterly summary, since the years of substantial BBD demand occur in that time period.[42] We aggregate monthly CARB diesel sales from the EIA to quarterly totals and add quarterly volumes of BBD from CARB.

The LCFS regulates fuel used in the California transportation sector. Therefore, to accurately estimate the number of deficits generated from CARB diesel using our data, we need to measure the amount of diesel fuel consumed in California that is allocated to the transportation sector. Since 1992, approximately 70% of distillate consumed in California has been used on-highway in the transportation sector.[43] We therefore assume, in accordance with our definition of BAU, that 70% of all CARB diesel will be consumed in the transportation sector in each year over the 2019-2030 compliance period. We are unaware of information that would lead us to believe a divergence from this long term could occur and we don't consider altering this

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[42] The LCFS quarterly summary can be accessed at https://ww3.arb.ca.gov/fuels/lcfs/lrtqsummaries.htm

[43] Historical distillate sales in California by end-use sector can be accessed at https://www.eia.gov/dnav/pet/pet_cons_821usea_dcu_nus_a.htm

assumption in this study. Importantly, scaling diesel by a constant has no effect on the coefficient estimates in the VEC model that we use to generate our BAU simulations.

2.2.3 Coefficient Estimates from the VEC Model

The long-run coefficient estimates from the VEC cointegration model appear in Table 9. Collectively, the coefficient estimates presented here make up the $\hat{\beta}$matrix, therefore characterizing the long run, cointegrating relationships between the variables in our model using 1987-2018 data. The three columns in Table 9 correspond to the three cointegrating equations specified in (15), (16), and (17) and the rows to their long-run relationships with GSP, VMT, and the oil price.

Table 9. Long-Run Coefficient Estimates of the Co-Integrating Equations

	ln(**CaRFG**)	*ln*(**Diesel**)	*ln*(**SB Price**)
ln(**VMT**)	-0.360***	-0.539	0
	(0.0740)	(0.521)	(0)
ln(**Oil Price**)	0.0318	-0.359***	-0.250
	(0.0188)	(0.0875)	(0.247)
ln(**GSP**)	0.164***	1.024***	0
	(0.0449)	(0.316)	(0)
Constant	21.93	9.153	3.491
Observations	123	123	123

Standard errors in parentheses

*** $p<0.01$, ** $p<0.05$

In the first two equations (columns) of Table 9, gasoline and diesel demand in California, the coefficients on the oil price capture the price responsiveness of demand for each fuel. The elasticity for diesel is larger in magnitude and has the expected sign. The elasticity for gasoline, on the other hand, is positive but qualitatively small, and statistically insignificant at the 5% level. This may reflect fact that gasoline demand is very inelastic. The coefficients on GSP reflect the income effect. Gasoline and diesel fuel are normal goods and thus should be expected to be positively correlated with income in the state. The coefficient on VMT captures fuel economy improvements as more VMT per gallon implies fewer gallons. Because the VMT measure is not reported by vehicle type, implied fuel efficiency gains in each of the two fuel pools are not discernible. In the next section, we use the long-run coefficient estimates from Table 9, along with the short-run estimates located in the appendix in The estimates of the β and Γ matrices from the VEC model in (19) appear in Table A-4.

Table A-4, along with random shocks to project a range of forecasts for gasoline, diesel, and vehicle miles demand out to 2030.

2.2.4 BAU Demand Simulations

We use the coefficient estimates from the VEC model to predict the distribution for each variable through the compliance period, 2019-2030. Specifically, we simulate 1000 potential values for each variable in each quarter during the compliance period. To this end, we assume that the potential shocks ε_t that may occur in the compliance period have the same distribution as the shocks during our estimation sample period, 1987-2018. Using this assumption, we simulate potential future shocks by sampling randomly with replacement from the 1987-2018 shocks. For each random draw, we use the VEC model to generate a hypothetical path for the six variables. We repeat this exercise 1000 times to give us a distribution of potential paths.

Specifically, for each simulation $k = 1,2,\ldots,1000$, we generate hypothetical future values for the six variables by iterating on the following equation for t from 2019 through 2030:

$$\hat{Y}_{kt} = \hat{Y}_{k,t-1} + \hat{\alpha}\hat{\beta}_0 + \hat{\alpha}\hat{\beta}'\hat{Y}_{k,t-1} + \Sigma_{j=1}^{p-1}\hat{\Gamma}_j\Delta\hat{Y}_{k,t-j} + \Sigma_{k=1}^{4}\widehat{\omega}_k s_k + \hat{\varepsilon}_{kt}^{*} \tag{20}$$

where $\hat{\varepsilon}_{kt}^{*}$ is the k^{th} random draw from the estimation-sample residuals. For observations in the sample period, we use $Y_{kt} = Y_t$ and $\hat{\varepsilon}_{kt}^{*} = \hat{\varepsilon}_t$ which means that the simulation replicates observed data until the end of 2018 and then simulates a hypothetical path after 2018. We back out the projected levels of each variable for each simulation k as $\hat{X}_{ikt} = \exp(\hat{Y}_{ikt})$ for $i = 1,2,\ldots,6$.

The hypothetical paths for blended gasoline, diesel, and VMT, simulated using (20), are described in Figure 17 with the median draw from each year (solid line) and a 90% pointwise confidence interval (dashed lines).[44] In addition to those variables, we calculate the fuel economy of gasoline vehicles that is implied under BAU conditions. To do so, we multiply each VMT projection by the percent estimated in ARB's EMFAC model to come from gasoline-powered vehicles (approximately 90%).[45] Then we can express the average fuel economy, measured in miles per gallon (MPG), for gasoline vehicles by dividing gasoline VMT in each draw by the number of gallons of CaRFG. The implied fuel economy shown in Figure 17d highlights the range of efficiency gains considered in our simulations over the compliance period. This implied gasoline vehicle economy, derived from EMFAC percentages combined with our projections, is a fleet-wide average for gasoline powered vehicles only, and does not explicitly build in the recent California vehicle efficiency agreement with major automakers to reduce GHG emissions per mile for model years 2022 through 2026.[46]

For each variable in our VEC model, the level of future uncertainty grows as we move further into the future. In Figure 17a, 90% of the draws from our sample fall between 14 and 17 billion gallons of CaRFG being consumed in 2030 - a 12 percent increase and 13 percent decrease, respectively, from current levels. By similar calculations, the 90% confidence interval for consumption of diesel falls between a 10 percent reduction and 75 percent increase from current

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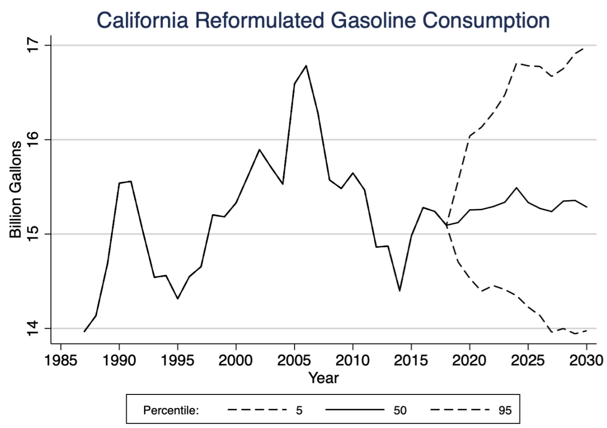
[44] Plots of GSP, oil prices, and soybean prices can be found in the appendix.

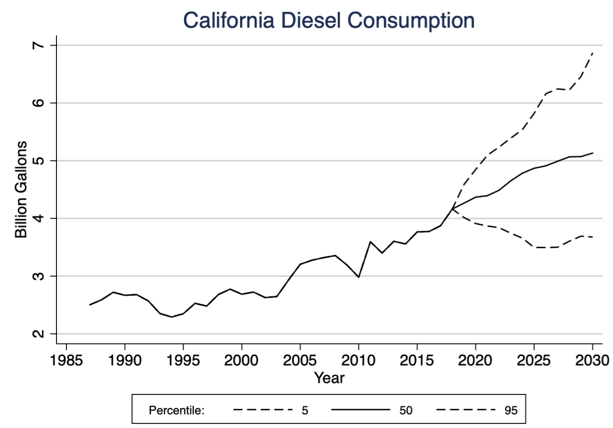
[45] Using data from ARB's EMFAC model, we find that gasoline-powered vehicles make up approximately 90% of California VMT and is projected to decline slowly over the next decade due to EV penetration. We use this projected percentage in each year to find VMT attributable to gasoline vehicles for each draw of our simulations.

[46] See https://www.reuters.com/article/us-autos-emissions/california-four-automakersdefy-trump-agree-to-tighten-emissions-rules-idUSKCN1UK1OD.

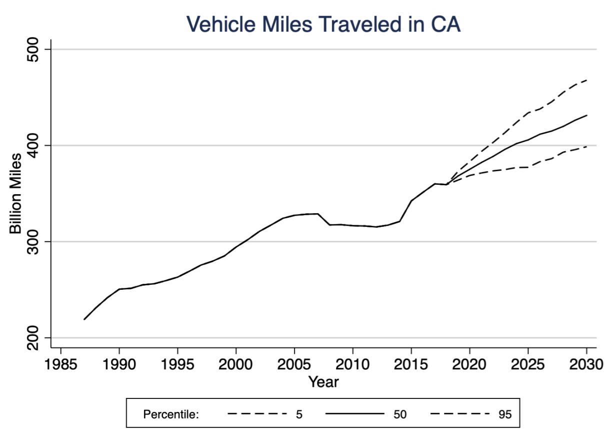
levels by 2030. The range of possibilities for diesel consumption is shown in Figure 17b. Lastly, VMT increases above current levels in 90% of the draws as shown in Figure 17c. VMT has been far less volatile than gasoline and diesel consumption in California and therefore we see a tighter range of uncertainty around future VMT projections.



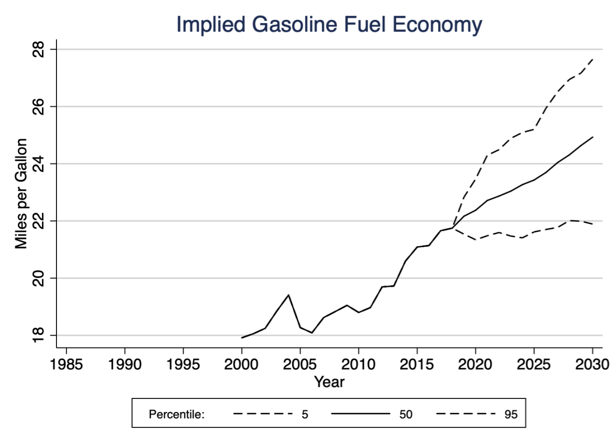
(a) **CaRFG**



(b) **Diesel**



(c) **VMT**



(d) **Implied MPG of Gasoline**

Figure 17. Demand Forecasts Under BAU Uncertainty

2.2.5 BAU Fuel Assumptions for Deficit Generation

Each gallon of CaRFG contains reformulated blendstock for oxygenate blending (CARBOB) and ethanol. Due to the "blend wall" for ethanol, CaRFG, as well as all reformulated gasoline in the U.S., is often referred to as E10. The average gallon of ethanol earns LCFS credits since the volume-weighted CI rating of ethanol used in the program falls below the standard. Therefore, each gallon of CaRFG consumed in California will generate both LCFS deficits and credits. We calculate total CARBOB consumption as 90 percent of CaRFG, with the remaining 10 percent being ethanol. Therefore, the BAU projection assumes that the E10 blend wall persists through 2030. Pursuant to our definition of BAU, currently observed BBD blend rate in the liquid diesel pool persists through 2030 as well. That is, we assume that 20 percent of liquid diesel fuel used in the transportation sector is BBD. The BAU projection extends the status quo assumption to fuel CI ratings over the compliance period. In the case of the biofuels, recent average volume-weighted CI ratings reported to the LCFS are used. These assumptions are summarized in Table 10.

Table 10. BAU Assumptions for Deficit-Generating Fuels

Gasoline Pool		
	Share of Total Fuel	**CI**
CARBOB	0.90	100.82
Ethanol	0.10	65
Diesel Pool		
	Share of Total Fuel	**CI**
CARB Diesel	0.8	100.45
Biodiesel	0.05	30
Renewable Diesel	0.15	34

The one area where BAU assumptions differ from the status quo is electric vehicles. We have to make an assumption regarding the penetration of electric vehicles to forecast credit generation from electricity as well as to forecast the level of fossil fuel displacement. EV penetration is difficult to predict and its trends have been evolving. For this reason, we use EMFAC projections of the share of all vehicles that are light-duty electric and heavy-duty electric.[47] EMFAC projects 1.3 million EVs on California roads by 2030. Table 11 shows how EMFAC

[47] See https://ww3.arb.ca.gov/msei/downloads/emfac2017_users_guide_final.pdf

projections translate into parameters that measure EV penetration in California now and in 2030; we follow the EMFAC rate of penetration in our BAU. Table 11 also shows our BAU assumptions regarding the CI rating of electricity. We use the current grid average CI rating and EERs reported by CARB. Policies in place to reduce the CI rating of the grid through increased use of renewables or accelerate penetration of EVs are not implemented in the BAU but considered in scenarios on the BAU and sensitivity analyses on results.

Table 11. BAU EV Assumptions by Vehicle Type

				2019 Share of Pop.:		**2030 Share of Pop.:**	
EV Type	**CI**	**EER**	**EER-Adj. CI**	**EVs**	**All Vehicles**	**EVs**	**All Vehicles**
LDV	81.49	3.5	23.28	0.95	0.007	0.7	0.025
HDV	81.49	5	16.30	0.05	0.001	0.3	0.01

In addition to the assumptions in Table 11, we assume in the BAU that future EVs will replace the average internal combustion engine vehicle (ICEV) on the light duty side but be driven 30 percent fewer miles, again taking the BAU stance of extending current conditions to 2030 (Davis, 2019). We have no information on how VMT for the heavy-duty sector may change with increasing EV penetration. While vehicles deployed may be well used, as currently the case, fleets and loads may also shift in unexpected ways. For this exercise, for simplicity, we apply the "30 percent fewer miles" assumption also to heavy-duty EVs and assess the displaced petroleum fuel all from the gasoline pool.[48] With these assumptions, we can project a quantity of kWhs of electricity that will be charged and project the resulting number of LCFS credits associated with the demand simulations. Since EVs are assumed to replace average fuel economy ICEVS, gasoline demand declines according to the share of EVs in the vehicle pool.

[48] These simplifying assumptions do not appreciably impact results given the low assumed HDV penetration levels during the period. At higher penetration levels, assumptions about and implementation of HDV fuel displacement could be important to volumes of biofuels required for compliance, and the treatment used here for simplicity would no longer suffice.

Specifically, we calculate the number of kWhs for light duty EVs according to the following equation:

$$kWh_t = s_t \times (0.7 \times X_{4t}) \times 0.32 \tag{21}$$

Where s_t the share of EVs to all vehicles in year t, X_{4t} is vehicle mile demand from the VEC model, and the 0.32 scale factor translates miles into kWhs.[49] Then, credits from electricity can be calculated by plugging in the number of kWhs into (32).

Using the parameters from Table 10 and Table 11, we translate the forecasts of fuel demand, after accounting for gasoline displacement from EVs, into forecasts of the deficit/credit balance over the compliance period subject to BAU conditions. Using the predictions of CaRFG and diesel demand, we calculate CARBOB and CARB diesel deficits in each state of the world represented by our simulations.[50] The distributions of deficits from each fuel are plotted in Figure 18. Figure 18a shows a distribution of CARBOB deficits centered around 290 MMT on average, or approximately 26 MMT per year. For context, the average is approximately 150 percent larger than the 10.3 MMT generated in 2018. The increase in deficits reflects the BAU demand projections as well as the increasing stringency of the standard to 2030: a gallon of fuel of a given CI rating generates more deficits in later years because a higher percentage CI reduction is required to meet the standard.

The total demand for LCFS credits plotted in Figure 19 is the sum of CARBOB and CARB diesel deficits, less the bank of system-wide credits accumulated since the beginning of the LCFS, reflecting CI rating reductions beyond required annual levels; the bank currently holds approximately 8.5 million metric tons (MMT) of credits. This distribution characterizes the number of LCFS credits that would need to be supplied to the market to cover aggregate deficits

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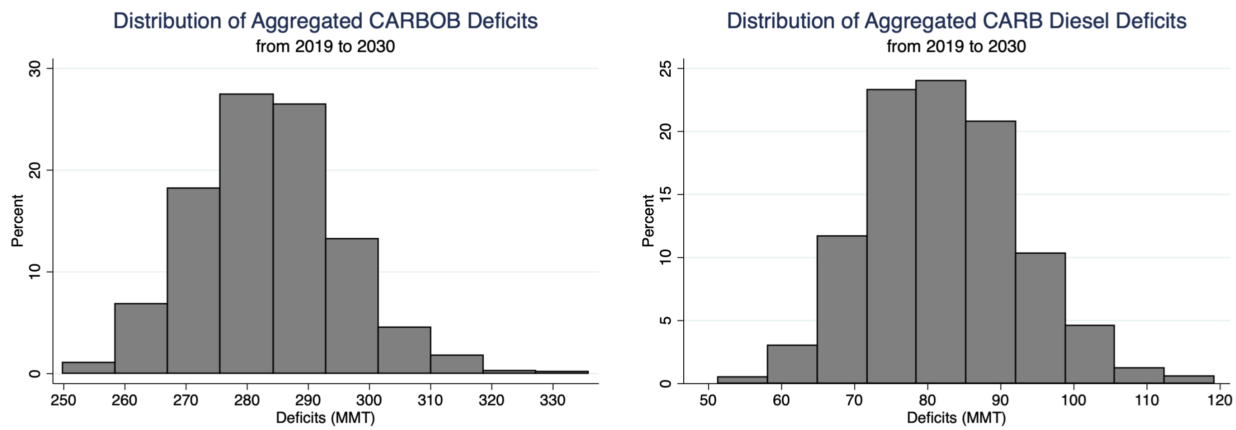
[49] The AFDC reports this: https://afdc.energy.gov/vehicles/electric_emissions_sources.html
[50] See (32) in the Appendix for more details.

expected to be generated under BAU conditions for the period 2019-2030. Note that our approach is high-level, examining aggregate net deficits for the compliance period, and abstracting away from annual compliance decisions and situations that could impact



(a) **CARBOB** (b) **CARB Diesel**

Figure 18. Projected Distribution of BAU Deficits by Fuel

year-to-year credit availability.

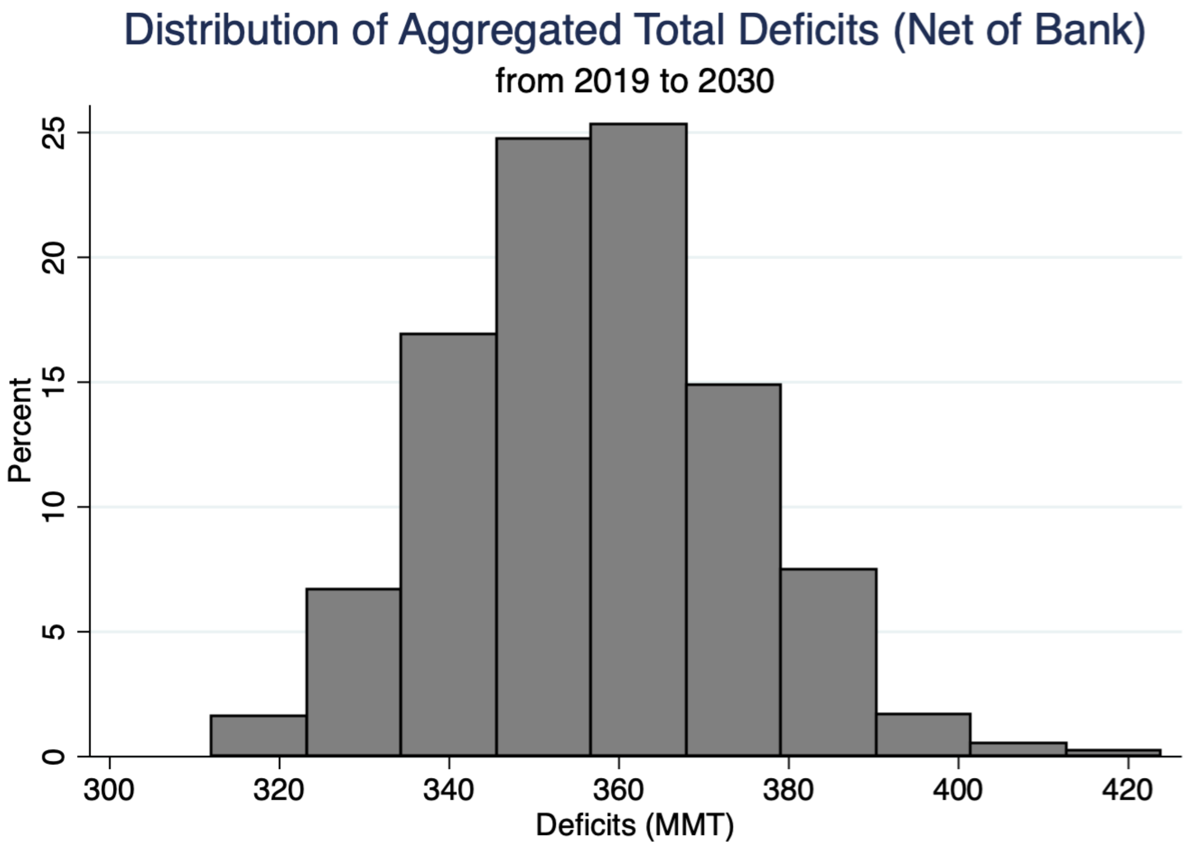


Figure 19. Projected Distribution of BAU LCFS Deficits

Until this point, we have described BAU forecasts for LCFS deficits and for credit generation from BBD, ethanol, and on-road electricity. However, there are other pathways to credit generation that must be considered before estimating a credit/deficit balance. As shown in Figure 20, BBD, ethanol, and on-road electricity make up 90 percent of the credits that were generated in 2018. For the remaining pathways, we simply that credit generation under BAU remains constant at 2018 levels. We will consider alternative credit-generating assumptions regarding these other pathways in the next section. The other pathways include renewable natural gas (RNG) - including from landfills and dairy, off-road electricity, projects such as carbon capture and sequestration (CCS) and innovative crude production, alternative jet fuel, and hydrogen. We use measures of different scenarios laid out by CARB in their illustrative compliance scenario calculator (ICS) to quantify these credits.

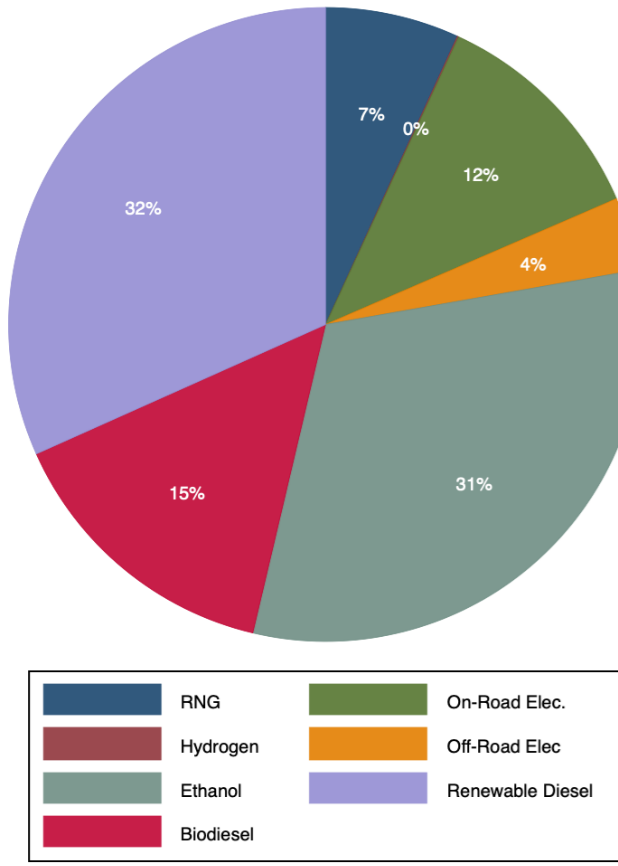


Figure 20. LCFS Credit Generation by Fuel Type, 2018.

We can now combine projected distributions of deficits and credits, some of the latter tied to the demand scenarios through blend levels and vehicle penetration rates, and others held constant at levels proscribed by CARB in its LCFS ICS, to illustrate the future compliance outlook through 2030 under BAU uncertainty. We present this in Figure 21 by taking slices of the distribution according to the percentile of net deficits remaining after BAU assumptions are applied. That is, we identify the percentile of each simulation according to the level of net deficits in that simulation and plot credits by each pathway in those simulations. Under the BAU, Figure 21 shows the scope of under-compliance in the LCFS. The under-compliance result under BAU assumptions is not a surprise, since LCFS targets were chosen to mandate substantial change in California's fuels mix, and the BAU freezes several key elements. It does, however, show magnitude of change required for compliance if past trends in fuel consumption and the state economy. On average across simulations, deficits are 163.61 MMT greater than credits over the entire compliance period. Figure 19 shows that the average number of deficits is about 360 MMT, indicating that our credit supply assumptions under a BAU would cover less than half the compliance requirements for the period 2019 to 2030.

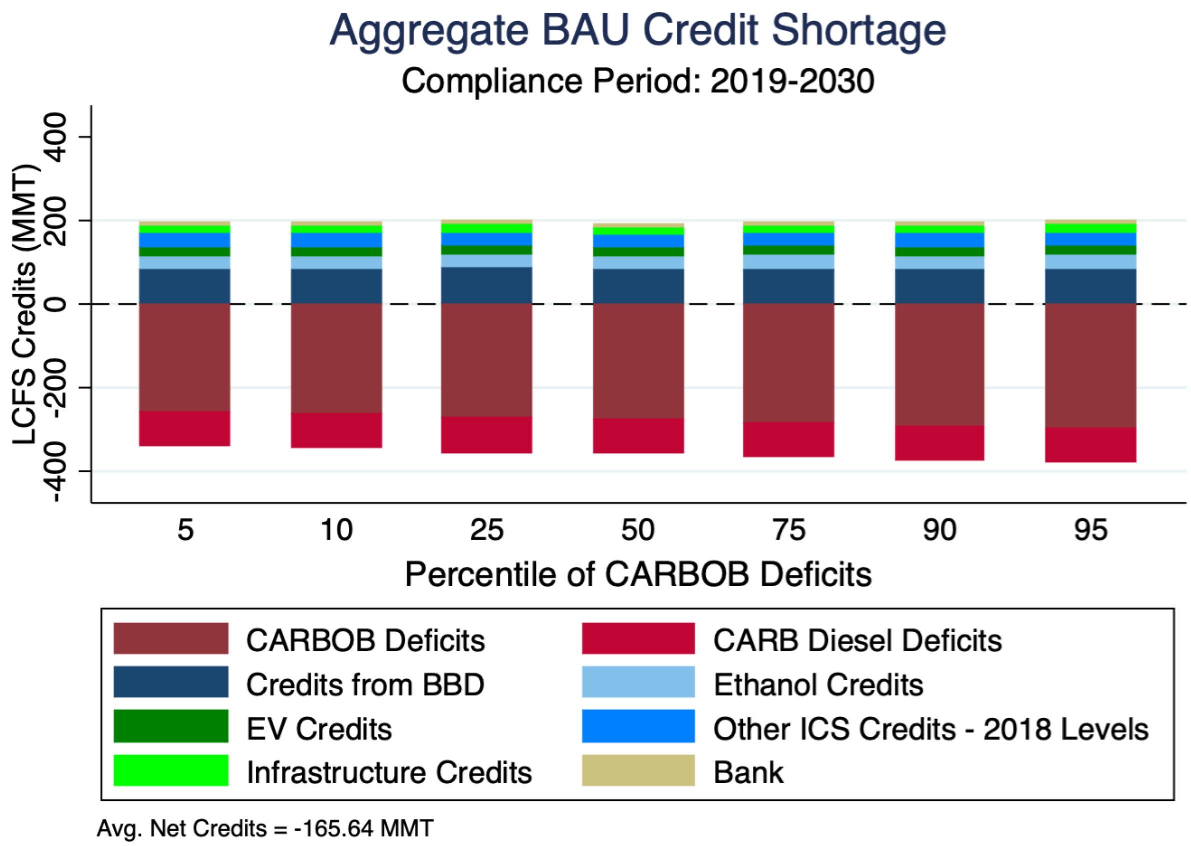


Figure 21. Projected LCFS Credit Generation under BAU. Other ICS credits reflect the number of credits from all other categories in CARB's illustrative compliance scenarios, assuming the volume of credits remains at 2018 levels. The Avg. Net Credits number is the average of credits minus deficits over all simulations.

The BAU case depicted in Figure 21 allows infrastructure credits to be generated at their maximum potential rate, which is 5% of the previous year's CARBOB deficits. It is readily apparent that infrastructure credits are much too small a source to make a meaningful difference in the net deficits, and that the burden of compliance will fall on other sources of credit generation.

2.3 Compliance Scenarios

Our projection of deficits under BAU uncertainty provides a range of possibilities of demand for LCFS credits. Next, we present compliance scenarios in which we overlay a range of possibilities for LCFS credit supply. We begin with a baseline scenario and then consider adjustments to each of the baseline assumptions.

Throughout, we make the assumption that biomass-based diesel will be the marginal fuel for compliance under the LCFS. This is the most likely case given past trends, and due to policy and capacity constraints inherent with other regulated pathways. Of current credit generators, the constraint from the ethanol blendwall is notable. Blends of ethanol up to E85 require a specialized vehicle not being prioritized for sales. E15, while allowable nationally, must go through an additional approval process for use within state.[51] Massive growth in newer technologies such as hydrogen, natural gas, or electric vehicles would require those technologies to be lower cost than the already mature renewable diesel. This may be possible, or additional credit generating opportunities may be opened up by regulatory amendments as in the past (e.g., recent expansion to book-and-claim for RNG use upstream in refineries), but these situations are too unknown or uncertain to be included here.

In the previous section, we presented a distribution of credit shortages assuming that BAU trends continue on both the demand and supply side. In this section we relax assumptions on the supply side and answer the question of how much BBD would be necessary to reach annual compliance under the LCFS. We take this approach to evaluating the difficulty of compliance because BBD is the marginal fuel for compliance. Therefore, we consider different assumptions regarding credit generation and assume the resulting net deficits must be satisfied by BBD credits. We assume a smooth drawdown of the existing credit bank going into the study period

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[51] See https://www.agri-pulse.com/articles/12295-market-demand-for-e15-looks-to-bemodest.

and require annual compliance through use of additional fuels, neither of which is imposed by the regulation. Our analysis is meant to illustrate difficulty of compliance.

2.3.1 Deriving Implied BBD Blend Rates Required for Compliance

Deficits from CARBOB and diesel demand in each draw arise directly from the VEC model, as described above, and require no additional assumptions. Net deficits from CARBOB are calculated as

$$ND_t^C \equiv D_t^C - elec_t^{on} - eth_t - infra_t - other_t - bank_t \tag{22}$$

where ND_t^C is equal to CARBOB deficits net of credits from on-road electricity, ethanol, infrastructure, the other sources from the ICS, and the bank. We assume the bank is allocated equally across the 11-year compliance period. Infrastructure credits are assumed to bind at the constraint; they are assumed to equal 5% of the prior quarter's CARBOB deficits in each quarter in each draw. The constraint is described in detail in the appendix.

The number of credits generated per gallon of ULSD and BBD for each year will depend on the reported CI of both fuels, as well as the diesel CI standard in each year. The CI standards for both gasoline and diesel are reported in the appendix in Table A-6. The next step requires additional notation. Define D_t as demand for diesel fuel in year t, B_t as BBD, U_t as ULSD, ND_t^C as net deficits from CARBOB, ψ_t^B as the number of credits earned per gallon of BBD, and ψ_t^U as the number of credits per gallon of ULSD. BBD is the sum of biodiesel and renewable diesel; $B_t \equiv BD_t + RD_t$ where BD_t is biodiesel and RD_t is renewable diesel. The reported CI for CARB diesel is currently 100.45 and is expected to remain there until 2030. Therefore, ψ_t^U is known for all t. Contrastingly, the future of reported CIs of BBD is uncertain and will depend on a few different factors.

The CI ratings of both biodiesel and renewable diesel are highly dependent on the feedstock. Waste oils and animal fats are rated as having relatively low life-cycle emissions and thus are rated with a very low CI. Used cooking oil (UCO) and tallow currently generate the lion's share of LCFS credits from BBD. However, it is plausible that UCO and tallow will experience supply shortages due to capacity constraints under a rapidly growing demand for BBD over the next decade. Soybean oil, on the other hand, is much more scalable and could more easily meet high demand for BBD. Soybean oil, however, has a considerably higher CI rating due to its impact on land use emissions, which would make lower credit generation from a given volume of BBD. Given the uncertainty around the CI ratings of BBD, we consider different assumptions around their time paths.

Conditional on the CI ratings used for BBD, the number of credits per gallon of BBD, ψ_t^B will be known and then we can solve the following system of two equations for the two unknowns, B_t and U_t for $t = 2019, \dots, 2030$.

$$D_t = B_t + U_t \tag{23}$$

$$ND_t^C = \psi_t^b B_t + \psi_t^U U_t \tag{24}$$

Using simple algebra, the quantities of B_t and U_t that satisfy the system of equations are:

$$U_t^* = \frac{D_t - \frac{ND_t^C}{\psi_t^B}}{1 - \frac{\psi_t^U}{\psi_t^B}} \tag{25}$$

$$B_t^* = \frac{D_t - \frac{ND_t^C}{\psi_t^U}}{1 - \frac{\psi_t^B}{\psi_t^U}} \tag{26}$$

Using (25) and (26), we can calculate the diesel pool blend rate that would be required for compliance under each of our scenarios accordingly:

$$BR_t^* = \frac{B_t^*}{B_t^* + U_t^*} \tag{27}$$

2.3.2 Scenario Assumptions

Certain elements of credit supply are tied to demand, whereas we assume others are independent of demand. We calculate the factors that depend on demand from output of the VEC model and the simulations. Ethanol volumes in each simulation, for example, are equal to 10 percent of gasoline demand so we calculate the volume of ethanol for each draw of the simulations.

For the factors that are separate from demand we run our simulation using different policy and supply scenarios to understand their impact. To characterize the relative influence of different assumptions, we evaluate each scenario against a baseline. In the baseline scenario, we assume all CI ratings remain at 2018 levels, infrastructure credits are maximized, and the other credit generating categories achieve the minimum values in the ICS. In Table 12 we summarize each scenario and its assumptions, relative to the BAU assumptions in the previous section and the baseline compliance scenario. In all scenarios, we assume that infrastructure credits are at the maximum allowable level of 5% of the previous year's CARBOB deficits.

The other credits we use from ARB's ICS are independent of our model of demand for LCFS credits. They are developed within the ARB modeling system, based on demand scenarios, and policy and credit pricing assumptions (of a steady level around $125) out to 2030.[52] To illustrate the magnitude in which these sources could affect BBD demand and LCFS compliance, we consider a scenario in which the maximum of each source across scenarios is realized. Specifically, we take the maximum number of credits across the ICS scenarios in each year for each pathway. This set of assumptions is A1 in Table 12. This characterizes a scenario with a higher credit profile for renewable natural gas and projects.

We consider a scenario in which the number of EVs rises sharply over the compliance period. In 2018, California Governor Jerry Brown announced a $2.5 billion plan with the objective of getting 1.5 million zero-emission vehicles (ZEV) on California roads by 2025 and 5 million by 2030.[53] This trajectory would be a stark deviation from any historical trends and would not be captured in our model of BAU fuel demand. Therefore, we consider a scenario in which 1.5 million EVs are on the road by 2025 and 5 million by 2030 at a constant rate. We refer to this set of assumptions as A2 in Table 12.

The CI rating of ethanol is also independent of demand. The future path of the CI value

Table 12. Summary of Compliance Scenario Assumptions

Label	Compliance Scenario	EV Population	Ethanol CI	BBD CI	ICS Credits
BAU	-	1.3M by 2030	65	32	2018 levels
A0	Baseline	1.3M by 2030	65	32	Min
A1	Max ICS Credits	1.3M by 2030	65	32	Max
A2	Jerry Brown's ZEV Goal	1.5M by 2025; 5M by 2030	65	32	Min

[52] We do not explicitly model credit price, but extrapolate from trends visible under historical credit pricing.

[53] See https://www.washingtonpost.com/national/california-gov-jerry-brown-unveils-25billion-plan-to-boost-electric-vehicles/2018/01/27/deed8cd8-039f-11e8-8acf-ad2991367d9dstory.html.

A3	Dec. Ethanol CI	1.3M by 2030	65 → 40	32	Min
A4	Inc. BBD CI	1.3M by 2030	65	32 → 50	Min

for ethanol will depend on technology development and adoption. CARB, in the ICS, assume a path for starch, sugar, and cellulosic ethanol in which the volume-weighted average CI rating of ethanol falls to 40 by 2030, a 38.5 percent reduction from the current level.[54] This CI reduction stems from assumed industry-wide adoption of CCS as well as increases in volumes of sugar ethanol in the near future and cellulosic ethanol toward the end of the decade. Therefore, we consider a scenario in which the ICS CI projections are realized. We refer to these set of assumptions as A3 in Table 12.

In addition to ethanol, the future path of the CI value for BBD is uncertain, as previously mentioned. We consider a scenario in which the volume-weighted average CI rating of BBD rises from its current level of approximately 32 to 50, a rating more commensurate with soybean oil feedstocks. This represents a future in which soybean oil makes up the majority of the BBD feedstock pool, to provide a bound of uncertainty in this parameter. This is assumption A4 in Table 12.

Beyond the four scenarios presented in this paper, we considered adjusting other assumptions in our analysis; none had a qualitatively different impact on the implied BBD blend rate results. For example, a scenario where a cleaner electricity grid is achieved, resulting in a grid-average CI reduction for electricity, as would occur as renewables' penetration continues, did not substantially impact results. Even with a zero CI rating for electricity over the compliance period had only small impacts on the implied BBD blend rate required for compliance. CI rating improvements for electricity are diluted relative to those for other fuels due to the relative efficiency of electricity, measured by the EER. Similarly, additional penetration of biogas with a

[54] The specific path for the ethanol CI rating assumed in the ICS can be found in Figure A-7 in the appendix.

substantial negative CI rating due to methane capture, into the natural gas used as a transport fuel did not have a large impact. Other potential scenarios that may be salient to LCFS compliance, such as expanded use of book-and-claim for low-CI rated electricity and biogas elsewhere in the production process, are left to future research.

2.3.3 Scenario Results

Here we present the output from four different compliance scenarios and discuss their differences from the baseline. In each scenario, we calculate the volume of CARB diesel, BBD, and the resulting implied blend rate of BBD in the diesel pool using (25), (26), and (27), respectively. Figure 22 shows the implied blend rate resulting from the baseline scenario and Figure 23 shows the blend rate under the alternative scenarios. For brevity, we present only the implied blend rates here, but the volumes of BBD and CARB diesel resulting from each scenario can be found in the appendix Figure A-6.

Because we force annual compliance, the annual quantities of BBD and ULSD, and the implied BBD blend rates, in the figures are conditional on compliance in the previous year. Due to the decreasing CI standards, shown in Table A-6, this characteristic has important implications for interpretation of our results; all else equal, BBD production shifted from one year to the next will earn fewer credits since the CI rating will be closer in magnitude to the standard, and the yet-to-be displaced diesel would earn more deficits as its CI rating falls farther above the standard. Therefore, if the path of any of the blend rates pictured in this section weren't met in early years, the implied blend rate required for compliance in later years would rise disproportionately more. In that sense, all of our scenarios depict a lower-bound of BBD implied blend rates needed for overall compliance over the eleven-year span. The annual compliance constraint also abstracts away from real-world optimization decisions on credit banking and deficit carryover. We did not model a proposed provision for credit borrowing.

Figure 22 shows that, under the baseline scenario, the median outcome calls for an increase in the BBD blend rate from the 2018 level of 17% to 70% in 2030. In nominal terms, given our demand projections, this outcome implies ramping up BBD consumption in the state to 3.5 billion gallons in 2030, nearly a 300% increase from current levels, and a reduction in CARB diesel consumption to 1.7 billion gallons in 2030, more than a 50% reduction below current levels.

Our median baseline scenario results in a BBD blend rate in diesel fuel similar to the high demand/low EV scenario in CARB's ICS, which is the highest among their four scenarios. Shown by the dashed lines in Figure 22, 90% of the blend rates from our simulations fall between 60 and 80 percent BBD in 2030. Next, we alter our baseline assumptions one by one and observe how the implied blend rate required for annual compliance changes.

Figure 23a shows that allowing for the largest number of credits from the other sources in the ICS (see discussion above for context on ARB's modeling assumptions in the ICS) in each year would result in a blend rate of 50% BBD, rather than 60, for the median draw from the simulations. Thus, the range of possibilities for the other pathways makes only a small difference to the BBD required to meet the standard. Thus, although pathways such as renewable natural gas, off-road electricity, CCS and innovative crude production at refineries, alternative jet fuel, and hydrogen receive significant attention in LCFS policy discussions, their influence on compliance scenarios is relatively minor, as considered in the ARB scoping plan modeling.

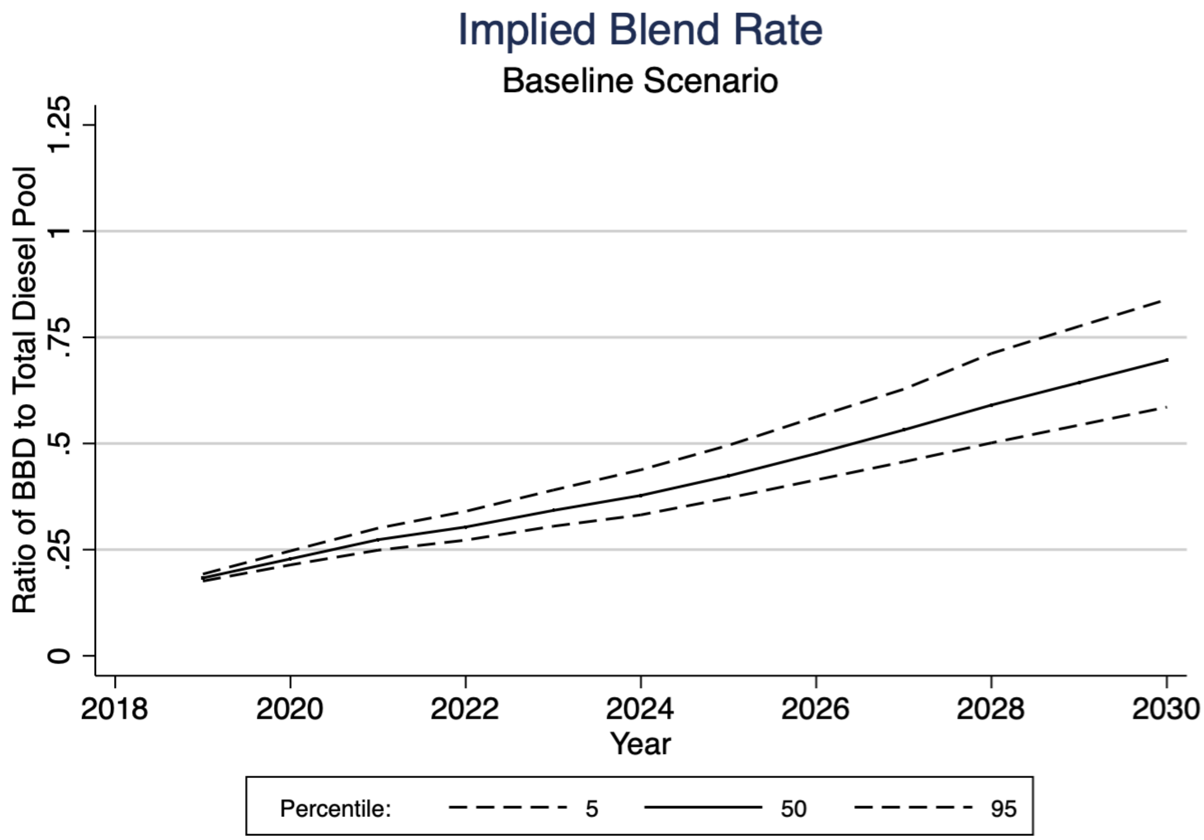
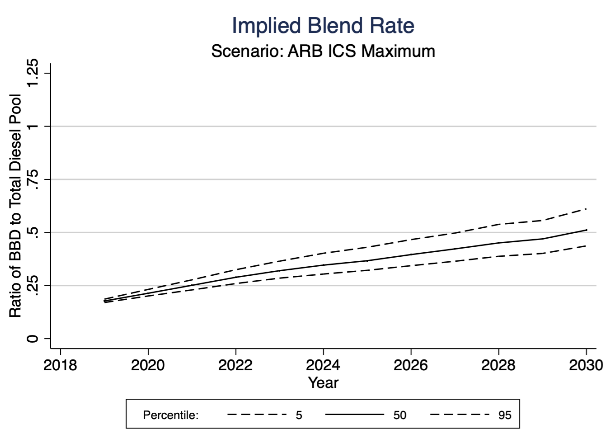
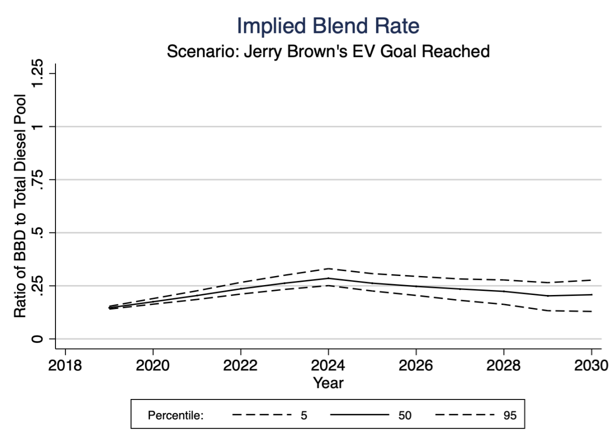


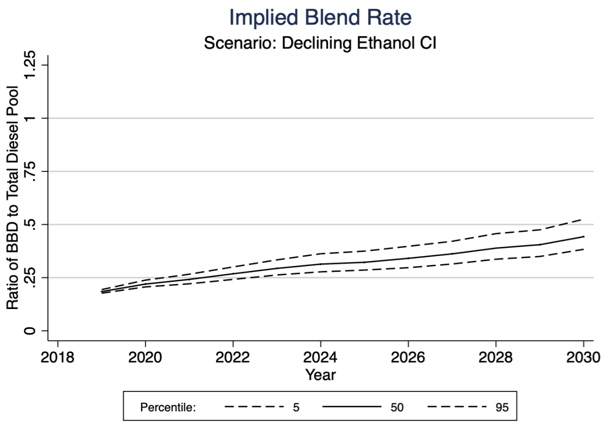
Figure 22. Projected Baseline Implied Blend Rate



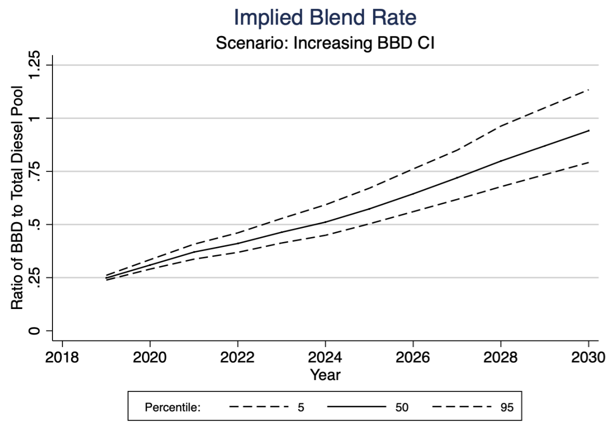
(a) **A1. ICS Maximum Credits**



(b) **A2. Jerry Brown's Goal Achieved**



(c) **A3. Declining Ethanol CI**



(d) **A4. Increasing BBD CI**

Figure 23. Projected Implied Blend Rates by Compliance Scenario

In contrast, rapid EV growth has the potential to reduce the blend rate below 25% in 2030, as shown in Figure 23b. This is by far the largest reduction from the baseline in any of our scenarios, and it is the only scenario that projects compliance without dramatic changes in the diesel pool. The median required BBD blend in 2030 is approximately 20%, and the 90% confidence interval ranges from 12% to 27%.

Scenarios A3 and A4 move the difficulty of compliance in opposite directions. A declining ethanol CI rating, due to CCS and increases in cellulosic and sugar ethanol volumes, would reduce the pressure on BBD production. Figure 23c shows that the median draw would have a BBD blend rate of approximately 45%, compared to 60% in the baseline. The lower bound of the 90% confidence interval is 37%, which is double the current BBD blend rate.

On the other hand, if the CI rating for BBD were to increase due to insufficient availability of low-CI feedstocks such as used cooking oil and a corresponding shift towards soybean oil, then the median BBD blend rate would need to rise to 90 percent in 2030 to achieve compliance, as shown in Figure 23d. The upper bound of the 90% confidence interval exceeds one, which means that compliance would not be achieved even if every on-road diesel gallon was 100% BBD. We have no reason to believe that one of A3 and A4 is more likely than the other. These two scenarios can be viewed as a widening of the baseline confidence interval to include possibilities that are both more optimistic and more pessimistic for compliance.[55]

2.4 Conclusion

The California LCFS sets out to achieve a 20% reduction in carbon intensity (CI) in the state's transportation sector below 2011 levels by 2030. Reaching the standard will require dramatic changes in the fuel mix in California, but the relative push needed from individual fuel sources is uncertain and will depend upon both demand and supply factors over the next decade. One of the most critical aspects of understanding compliance is future demand for fuel; the demand for LCFS credits will be explicitly tied to consumption of gasoline and diesel fuel in the state. Therefore, we estimate a distribution of fuel demand under business-as-usual (BAU) uncertainty, i.e. the continuation of historic trends, in order to estimate a distribution of demand for LCFS credits over the 2019-2030 compliance period. We estimate that gasoline and diesel will generate between 320 and 410 million metric tons (MMT) of deficits in the LCFS program over the eleven-year period. In 2018, a total of 11.2 MMT credits were generated. For context, if the lower-bound of the distribution of credit demand were realized, the market would need to supply 29 MMT credits per year on average, nearly a 170% increase from 2018 levels. State policies such as those targeting VMT and efficiency standards, represent a separate source of demand uncertainty, although the BAU uncertainty embraces a wide range of potential trajectories for each measure.

On the credit supply side, uncertainty surrounding compliance stems from the unknown future market penetration of alternatives to the internal combustion engine, such as electric vehicles, as well as uncertainty around adoption of technologies such as carbon capture and sequestration

[55] In the current LCFS structure, BBD credit generation beyond the on-road diesel pool is allowed for alternative jet fuel, of which a type derived in a similar manner to on-road RD is commercially available. We do not explicitly model use of RD in on-road or jet applications, or other credit generation possibilities in the program that could drive the implied BBD blend rate lower.

(CCS). We assume the marginal compliance fuel in the LCFS is biomass-based diesel (BBD) and we show that BBD's role in compliance could vary widely depending on, in addition to BAU demand conditions, the pace of EV adoption in the state. The adoption of CCS and other CI-reducing technologies and the market for feedstocks used to produce BBD also could have significant effects.

In our baseline scenario for credit generation, LCFS compliance would require that between 60% and 80% of the diesel pool be produced from biomass. Our baseline projections have the number of electric vehicles reaching 1.3 million by 2030, however if the number of electric vehicles increases more rapidly than what is captured under BAU conditions and reaches Jerry Brown's goal of 5 million vehicles by 2030, then LCFS compliance would require substantially less biomass-based diesel. Under this scenario, annual compliance could be achieved with between 10% and 25% biomass-based diesel in the diesel pool, which is commensurate with recent levels and could be achievable with an indexed $200 credit price through 2030.

Outside of rapid ZEV penetration, hitting 2030 targets with the $200 credit price may be much more difficult. For instance, a scenario in which CCS is widely adopted in ethanol plants would bring the median BBD blend rate down to approximately 45% BBD in 2030, rather than 60%. However, a 45% blend rate in 2030 under this scenario still results in nearly a 125% increase from current levels. Additionally, if increasing BBD production calls for an increasing level of higher-CI feedstocks, the implied blend rate required for compliance could increase above the baseline. If the volume-weighted average CI rating of BBD were to increase only to 50, the median draw requires nearly 100% of diesel to be biomass-based.

Since 2016, ARB has expanded credit generation opportunities in the program, and some opportunities are relatively new. The pathways as modeled in the ICS make little appreciable qualitative difference to results. This study provides a range of the magnitude of credit generation, under uncertainty, that such expanded opportunities would need to provide to appreciably change the compliance outlook from one more to one less reliant on cost containment mechanisms.

New mechanisms to allow firms to generate credits by building electric vehicle charging stations or hydrogen fueling stations have minor implications for overall compliance. This mechanism represents a major departure from the original design of the LCFS as it does not directly subsidize the consumption of a low carbon fuel. Rather, the credits subsidize a fixed cost of providing network infrastructure that may encourage adoption of EVs, the technology which may in turn use a low carbon fuel. In the same way, however, the infrastructure credits can reduce the very effect that LCFS critics have focused on as the central flaw in the regulations design: the encouragement of low, but still non-zero carbon fuel. Nonetheless, because the total quantity of infrastructure credits is restricted to be relatively small, their effect on potential compliance scenarios is small.

2.A Appendix

This appendix contains figures, tables, and equations that are referenced in the text and may be relevant to the reader.

2.A.1 Additional output from Simulations and the VEC Model

The estimates of the β and Γ matrices from the VEC model in (19) appear in Table A-4.

Table A-4. Short-Run Coefficient Estimates from VEC Model

	ΔY_{1t}	ΔY_{2t}	ΔY_{3t}	ΔY_{4t}	ΔY_{5t}	ΔY_{6t}
Panel A: Estimates of α Matrix						
$Y_{1,t-1}$	-0.0510	0.298	-0.00667	-0.451***	2.411**	-0.0763
	(0.0432)	(0.323)	(0.660)	(0.0736)	(0.990)	(0.102)
$Y_{2,t-1}$	-0.0144*	-0.0810	0.351***	-0.0287**	-0.397**	-0.0380*

	(0.00835)	(0.0625)	(0.128)	(0.0142)	(0.192)	(0.0198)
$Y_{3,t-1}$	0.000911	0.0604*	-0.161**	-0.0251***	0.220**	0.00565
	(0.00417)	(0.0312)	(0.0637)	(0.00710)	(0.0956)	(0.00989)
Panel B: Estimates of Γ Matrix						
$\Delta Y_{1,t-1}$	-0.275**	-0.0759	-0.129	0.600***	0.589	0.260
	(0.108)	(0.807)	(1.648)	(0.184)	(2.474)	(0.256)
$\Delta Y_{1,t-2}$	-0.0544	0.0761	0.400	0.572***	2.242	0.313
	(0.104)	(0.775)	(1.583)	(0.177)	(2.377)	(0.246)
$\Delta Y_{1,t-3}$	-0.0796	-0.286	-1.608	0.508***	-1.984	-0.365
	(0.0989)	(0.740)	(1.512)	(0.169)	(2.269)	(0.235)
$\Delta Y_{2,t-1}$	3.73e-05	-0.727***	-0.212	0.0279	0.00140	0.0619*
	(0.0146)	(0.109)	(0.223)	(0.0249)	(0.335)	(0.0347)
$\Delta Y_{2,t-2}$	0.00945	-0.440***	-0.00404	0.0434	0.155	0.0465
	(0.0160)	(0.119)	(0.244)	(0.0272)	(0.366)	(0.0379)
$\Delta Y_{2,t-3}$	0.00852	-0.115	-0.225	0.0307	0.184	0.0193
	(0.0132)	(0.0990)	(0.202)	(0.0226)	(0.303)	(0.0314)
$\Delta Y_{3,t-1}$	-0.00969	-0.0905*	0.433***	0.00728	0.0205	0.00417
	(0.00691)	(0.0517)	(0.106)	(0.0118)	(0.159)	(0.0164)
$\Delta Y_{3,t-2}$	-0.0171**	-0.00126	-0.0565	0.0178	0.166	-0.0261
	(0.00712)	(0.0533)	(0.109)	(0.0121)	(0.163)	(0.0169)
$\Delta Y_{3,t-3}$	0.00353	0.0540	-0.0261	0.0187	-0.280*	0.00215
	(0.00709)	(0.0531)	(0.108)	(0.0121)	(0.163)	(0.0168)
$\Delta Y_{4,t-1}$	0.0454	0.339	0.533	-0.374***	0.756	-0.0233
	(0.0482)	(0.361)	(0.737)	(0.0822)	(1.106)	(0.114)
$\Delta Y_{4,t-2}$	0.0492	0.741**	-0.639	-0.430***	0.263	-0.124
	(0.0490)	(0.366)	(0.748)	(0.0835)	(1.123)	(0.116)

	ΔY_{1t}	ΔY_{2t}	ΔY_{3t}	ΔY_{4t}	ΔY_{5t}	ΔY_{6t}
$\Delta Y_{4,t-3}$	0.0350	0.116	-0.854	-0.451***	-0.259	-0.0532
	(0.0483)	(0.362)	(0.738)	(0.0824)	(1.108)	(0.115)
$\Delta Y_{5,t-1}$	-0.00528	0.0308	-0.0714	-0.0117	0.227**	0.0236**
	(0.00439)	(0.0328)	(0.0670)	(0.00748)	(0.101)	(0.0104)
$\Delta Y_{5,t-2}$	0.0136***	0.0475	-0.0745	-0.00220	-0.0388	0.0111
	(0.00445)	(0.0333)	(0.0680)	(0.00759)	(0.102)	(0.0106)
$\Delta Y_{5,t-3}$	5.75e-06	0.00899	-0.0414	-0.00743	0.174	-0.00728

	(0.00461)	(0.0345)	(0.0705)	(0.00786)	(0.106)	(0.0109)
$\Delta Y_{6,t-1}$	-0.0764*	-0.162	0.653	-0.0152	-1.834*	-0.114
	(0.0460)	(0.345)	(0.704)	(0.0785)	(1.056)	(0.109)
$\Delta Y_{6,t-2}$	-0.00840	-0.214	-0.238	0.0405	0.263	0.0147
	(0.0463)	(0.346)	(0.707)	(0.0789)	(1.062)	(0.110)
$\Delta Y_{6,t-3}$	0.0281	0.258	1.375**	-0.00511	0.859	-0.0175
	(0.0434)	(0.325)	(0.664)	(0.0740)	(0.996)	(0.103)
Constant	-0.0152**	-0.0985**	-0.0270	-0.0525***	0.00160	-0.0105
	(0.00620)	(0.0464)	(0.0947)	(0.0106)	(0.142)	(0.0147)
Observations	123	123	123	123	123	123

Standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

In Table A-5 we summarize the distribution of demand forecasts coming out of the simulations over the compliance period. Total VMT, diesel, and gasoline demand forecasts are aggregated over the 2019-2030 timeframe for each draw.

Table A-5. Summary Statistics for Aggregate BAU Demand across Random Samples

Variables	N	Mean	SD	Min	Max
VMT (Billion mi.)	1000	14310.25	141.664	13734.2	14763.78
Diesel (Billion gal.)	1000	152.666	6.403	133.186	173.577
CaRFG (Billion gal.)	1000	669.158	6.889	649.944	696.943

2.A.2 LCFS Credit Implementation Details

In this subsection of the appendix, we provide details regarding how credits are generated under the LCFS. To illustrate how quantities of fuel translate into credits or deficits, we adopt the notation of the LCFS regulation and define the following terms.

- I is the set of credit-generating fuels.
- $XD \in \{gasoline, diesel\}$ represents the fuel being displaced.
- EER_i^{XD} the dimensionless Energy Economy Ratio (EER) of fuel i relative to gasoline or diesel. The EER is fuel and vehicle specific.
- ED_i is the energy density of fuel i.
- $CI_{standard,t}^{XD}$ is the CI requirement for fuel XD in the year of quarter t. The standard for each year is presented in Table A-6
- $CI_{reported,i,t}^{XD}$ is the EER-adjusted CI for fuel i, displacing fuel XD in quarter t.

- $E_{displaced,i,t}^{XD}$ is the total amount of *fuel energy* for fuel *XD* that is displaced by alternative fuel i in quarter t.
- E_it is the quantity of energy of fuel i in quarter t.
- Q_it is the quantity of fuel i used in quarter t.
- $C = 1 \times 10^{-6} \frac{MT}{gCO_2e}$ converts credits into metric tons.

Let $i \in I$ denote the fuel type (i.e., i= biodiesel, ethanol, electricity, etc.). LCFS credits or deficits for each fuel or blendstock for which a fuel reporting entity is the credit or deficit generator will be calculated according to the following equation in quarter t.

$$Credits_{i,t}^{XD}\,(MT) = \left(CI_{standard,t}^{XD} \& - CI_{reported,i,t}^{XD}\right) \times E_{displaced,i,t}^{XD} \times C \tag{28}$$

Where

$$CI_{reported,i,t}^{XD} = \frac{CI_{it}}{EER_i^{XD}} \tag{29}$$

And

$$E_{displaced,i,t}^{XD} = E_{it} \times EER_i^{XD} \tag{30}$$

And

$$E_{it} = ED_i \times Q_{it} \tag{31}$$

Substituting (29)-(31) into (28), we can then express credits as:

$$Credits_{it}^{XD}(MT) = \left(CI_{standard,t}^{XD} - \frac{CI_{it}}{EER_i^{XD}} \right) \times ED_i \times Q_{it} \times EER_i^{XD} \times C \tag{32}$$

Aggregating fuels and quarters over the compliance period, the total quantity of credits supplied over the compliance period will be

$$Aggregate\ LCFS\ Credits = \Sigma_{i \in I} \Sigma_{t=0}^{T} Credits_{it}^{XD} \tag{33}$$

In the calculations above, deficits are equivalent to negative credits. The compliance period is characterized by T, which for our purpose is the fourth quarter of 2030 and $t = 0$ corresponds to the first quarter of 2019.

Table A-6. LCFS Carbon Intensity Standards

Year	Gasoline Pool	Diesel Pool
2011	95.61	94.47
2012	95.37	94.24
2013	97.96	97.05
2014	97.96	97.05
2015	97.96	97.05
2016	96.5	99.97
2017	95.02	98.4
2018	93.55	96.91
2019	93.23	94.17
2020	91.98	92.92
2021	90.74	91.66
2022	89.5	90.41
2023	88.25	89.15
2024	87.01	87.89
2025	85.77	86.64
2026	84.52	85.38
2027	83.28	84.13
2028	82.04	82.87
2029	80.8	81.62
2030	79.55	80.36

2.A.3 Credit Generation and Infrastructure Investment

Owners of Fuel Supplying Equipment (FSE) generate Fast Charging Infrastructure (FCI) credits for investing in charging stations.

FSE owner i generates FCI credits according to:

$$Credits_{FCI}^{i}(MT) = \left(CI_{standard,t}^{XD} \times EER - CI_{FCI}\right) \times C_{elec} \times (Cap_{FCI}^{i} \times N \times UT - Elec_{disp}) \times C \quad (34)$$

where

- CI_{FCI} = CA average grid electricity CI from Lookup Table
- C_{elec} = conversion factor for electricity
- Cap_{FCI}^{i} = the (kWh/day) daily FCI charging capacity of FSE i.
- N = the number of days during the quarter
- UT = the `uptime multiplier' which is the fraction of time that the FSE is available for charging during the quarter.
- $Elec_{disp}$ = the quantity of electricity dispensed (kWh) during the quarter.
- EER is for PHEV or electricity/BEV relative to gasoline. Currently this $EER = 3.4$.

2.A.4 Cap on Infrastructure Credits

In this paper, we assume credits from infrastructure bind at the cap, which is described here.

The potential number of credits that can be generated from FCI charging infrastructure is

calculated as:

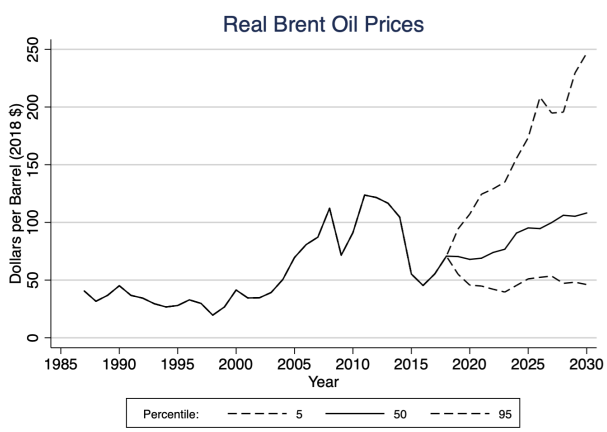
$$Credits_{FCI}^{potential}(MT) Credits_{FCI}^{prior\ qtr} \times \left(\frac{CAP_{FCI}^{approved}}{CAP_{FCI}^{operational}}\right) \quad (35)$$

Applications to generate credits are approved until

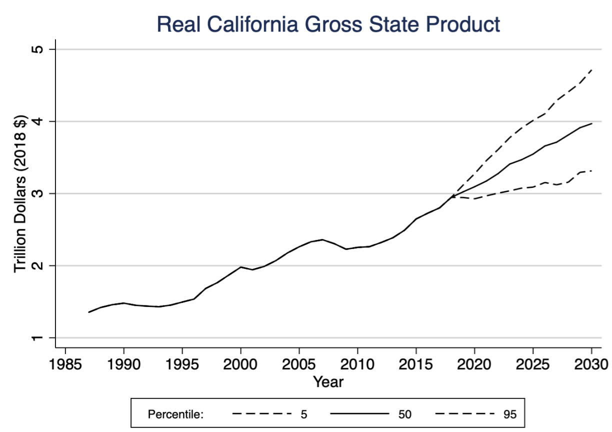
$$Credits_{FCI}^{potential} \geq 0.025 \times Deficits^{prior\ qtr} \tag{36}$$

2.A.5 Additional Figures

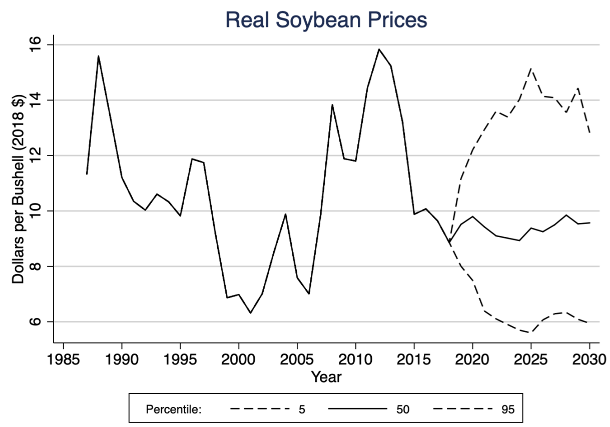
This subsection of the appendix contains figures referenced in the text. Figure A-5 shows projections for Brent oil prices, soybean prices, and CA GSP from the BAU simulations. Figure A-6 compiles a summary of the ULSD and BBD demand resulting in each compliance scenario, along with the corresponding diesel pool blend rate. Figure A-8 shows an aggregate credit/deficit balance under each compliance scenario, while holding the diesel pool blend rate at 20 percent. This illustrates how many credits would still need to be generated when each set of assumptions is assumed.



(a) **Brent Oil Price**

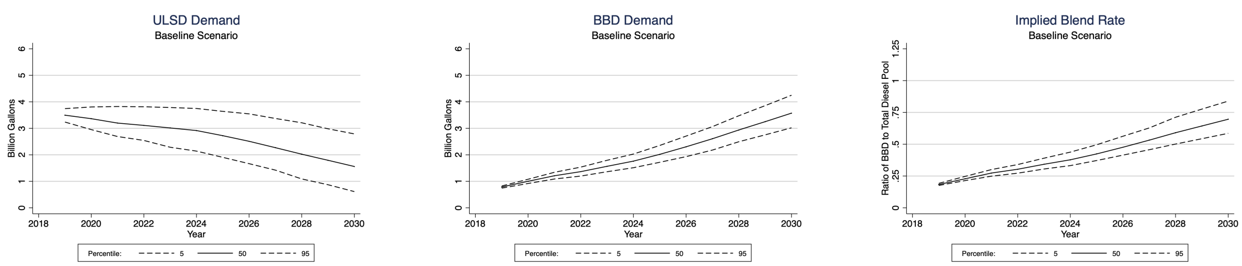


(b) **GSP**

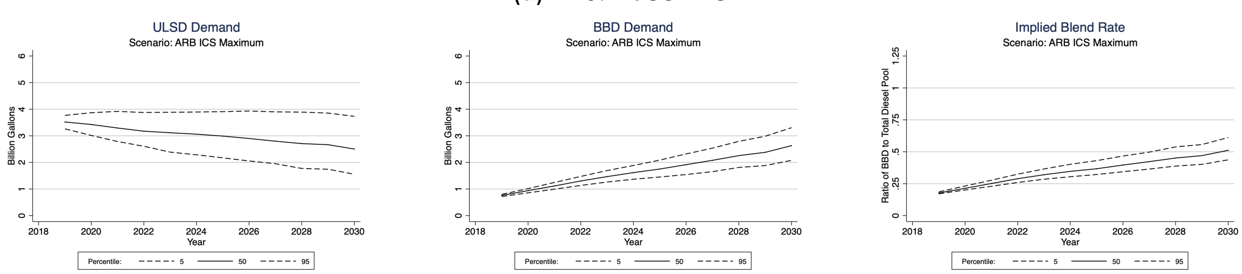


(c) **Soybean Prices**

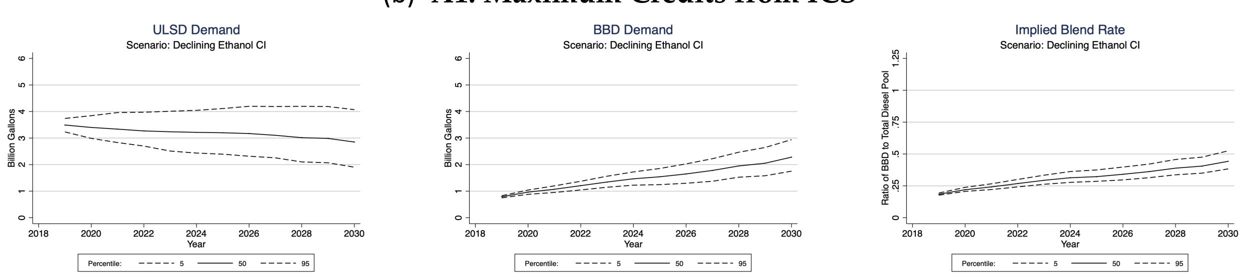
Figure A-5. Price Forecasts Under BAU Uncertainty



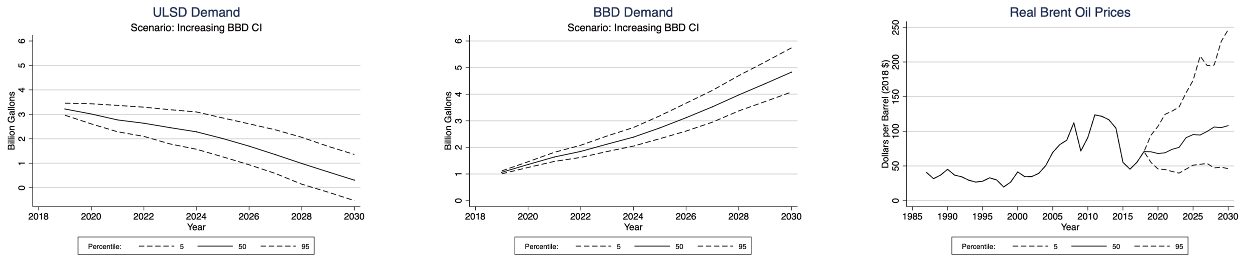
(a) **A0. Baseline**



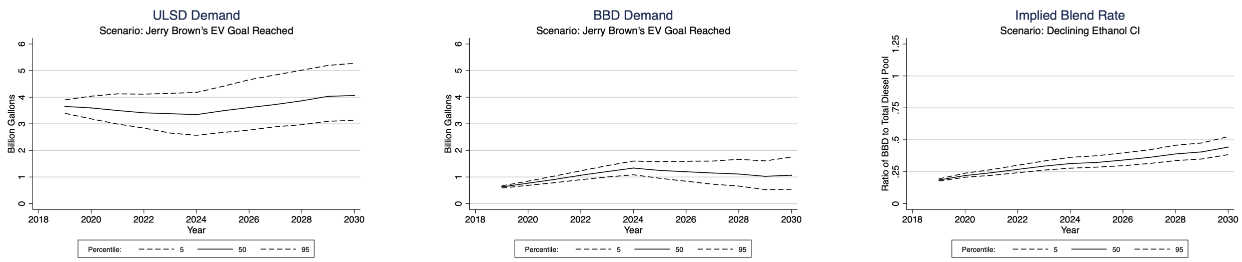
(b) **A1. Maximum Credits from ICS**



(c) **A2. Declining Ethanol CI**



(d) **A3. Increasing BBD CI**



(e) **A4. Jerry Brown's Goal Achieved**

Figure A-6. Summary of Diesel Pool by Compliance Scenario

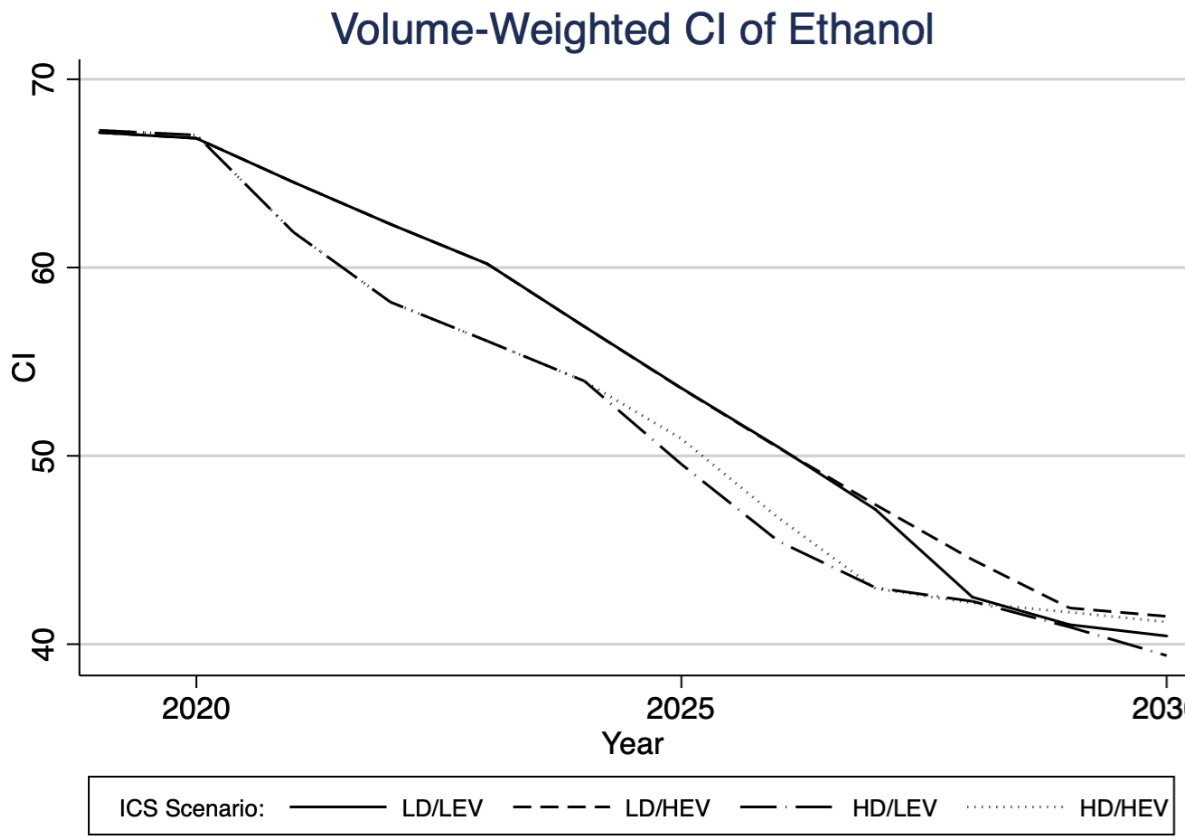
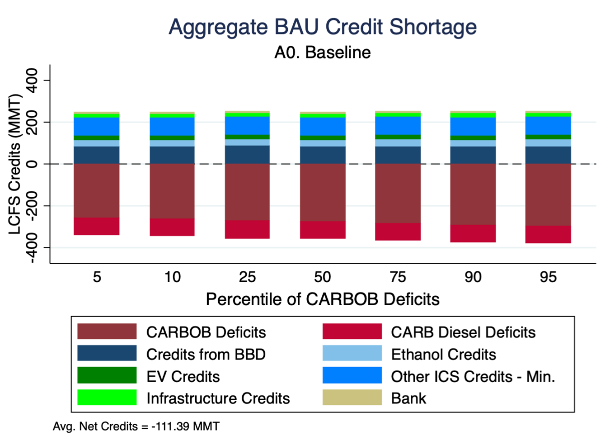
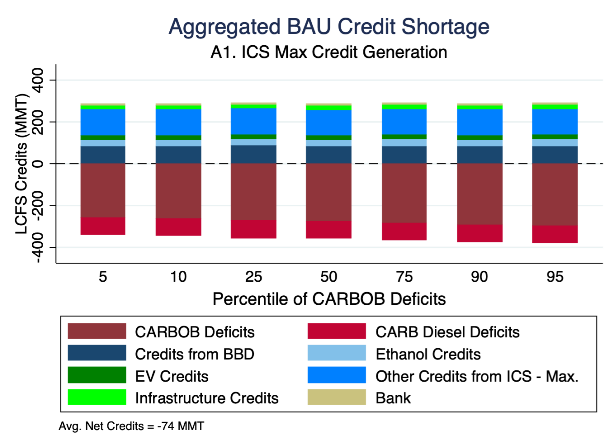


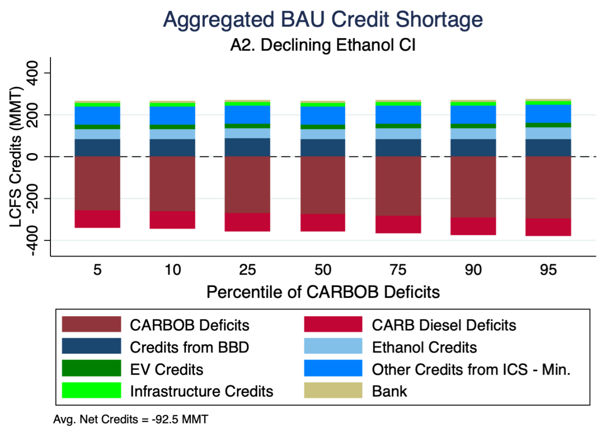
Figure A-7. Volume-Weighted CI of Ethanol from CARB's Illustrative Compliance Scenarios



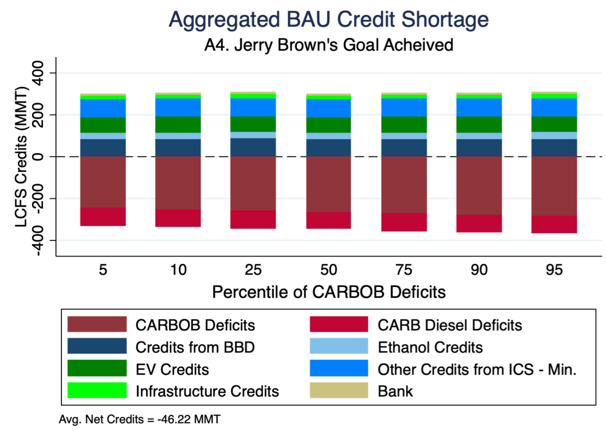
(a) **A0. Baseline**



(b) **A1. ICS Maximum Credits**



(c) **A2. Declining Ethanol CI**



(d) **A4. Jerry Brown's Goal Achieved**

Figure A-8. Summary of LCFS Credit Shortages by Compliance Scenario.

References

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Chapter 3. A Decade in Review: Low Carbon Fuel Standards in the U.S. & Canada, 2010-2020.

Co-Authors: Colin Murphy and Julie Witcover

A fuel carbon intensity (CI) standard aims to reduce transportation sector greenhouse gas (GHG) emissions by incentivizing innovation, technological development, and deployment of low-emission alternative fuels and vehicles. These programs set a performance standard that considers the full lifecycle impacts of fuel production and use while treating all transportation fuels similarly, allowing consumers and markets to determine the path to compliance. There are three currently operating CI standards: California's Low Carbon Fuel Standard (LCFS), Oregon's Clean Fuels Program (CFP), and British Columbia's Renewable & Low Carbon Fuel Requirements (RLCFR, also known as LCFS).[56]

These policies set an average CI benchmark, measured in grams of carbon dioxide equivalent per megajoule of fuel energy (gCO_2e/MJ, based on equivalent-mass 100-year global warming potentials), that regulated fuels provided for use in the jurisdiction must, as a group, meet. All regulated fuel volumes are assigned a CI rating based on an assessment of their lifecycle (production to combustion) GHG emissions. Fuels with more emissions than the benchmark generate program deficits; those with fewer emissions earn program credits. The benchmark grows more stringent over time. Compliance requires sufficient credits to offset deficits. Fuel refiners, importers, or distributors are typically the obligated party, and can meet their obligation by reducing the CI of their fuel to meet the standard, generating credits internally, or purchasing credits from alternative fuel producers. Credits can be banked for future use and traded, creating a financial incentive to lower fuel CI.

The remainder of this report is structured as follows: Section 3.1 introduces and provides an overview of the policies in the three jurisdictions, their reported CI trends, and program credit/deficit balance. Section 3.2 describes the sources of alternative fuel energy use and crediting in each jurisdiction over time under the policies. Section 3.3 outlines trends in the reported CIs of alternative fuels over time. Section 3.4 describes the state of markets for program credits in each jurisdiction. Section 3.5 discusses trends in primary program credit generators – the major transportation fuels, i.e., ethanol, biomass-based diesel, natural gas, and

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[56] Washington, which enacted a Clean Fuel Standard to begin in 2023, pledged to pursue policies to create a market for lower carbon fuel in the region under the auspices of the Pacific Coast Collaborative Climate Leadership and Action Plan (Pacific Coast Collaborative, 2013). Brazil also has a transport fuel carbon intensity standard called RenovaBio, which applies only to renewable liquid fuels. Colorado, New Mexico, and New York have considered developing LCFS-like programs, and as of this writing, Canada has released a proposed federal fuel CI standard, to be finalized late in 2021 and take effect in December 2022.

electricity, emphasizing the role of feedstocks, as well as sources of credit generation beyond fuel use. Section 3.6 explores potential interactions among LCFS jurisdictions and relationships between LCFS credit markets and fuel markets. Section 3.7 offers concluding remarks and highlights potential avenues for future research.

3.1 Jurisdiction and Program Status – Overview

LCFS programs along the North American Pacific Coast covered transportation energy demand totaling 23.1 billion gasoline gallon equivalents (gge) in 2019, with California comprising 18 billion. Oregon and BC each have transportation energy demand between 10% and 15% of California's.[57] Each policy evaluates alternative fuel emissions against gasoline or diesel, effectively creating two "pools" of conventional fuel and substitutes. Deficit obligations can be satisfied with credits from either pool.

Diesel fuel and its substitutes (the "diesel pool") comprised a fifth of reported transportation energy demand in California, a third in Oregon, and half in BC in 2019. Each pool has a distinct mix of alternative fuel possibilities. For example, ethanol can be blended with gasoline, and biodiesel with diesel, up to blending limits established by vehicle type and regulation. Some fuels, such as electricity and hydrogen, can be used to displace both gasoline and diesel. Electricity is readily used in light-duty cars, and thus has primarily appeared as a gasoline substitute but is increasingly used in some types of heavy-duty vehicles.

LCFS policies regulate the average CI of all transportation energy consumed in jurisdiction. Figure 24 shows the schedule of annual CI reduction benchmarks as a percentage reduction from a base year for each jurisdiction. All three programs initially targeted a 10% reduction in CI over the first 10 years of implementation.[58] BC and California both set longer-term

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[57] Transport energy in Washington state will add nearly 18%, or 3.9 billion gge, under an LCFS-like program in the region when its Clean Fuel Standard begins in 2023 (Pacific Coast Collaborative, 2013).
[58] California's standard was frozen from 2014–2015 due to a state court challenge related to its environmental analysis. The state's standard resumed with a program re-adoption in 2016. California's

trajectories to achieve 20% reduction in the CI of transportation energy below 2010 levels by 2030 and lowered the 10% target for 2020 (to 9.1% and 7.5%, respectively). Oregon's program targets a 10% reduction from 2015 levels by 2025; a 2020 Executive Order set targets of 20% in 2030 and 25% in 2035, still to be formalized by regulation.[59]

Figure 24 also depicts the realized CI reduction for fuels reported under the program, measured as the percentage change in the energy-weighted average CI from baseline year levels, as a whole and by fuel pools. While average reported CI in all three jurisdictions remained close to target levels overall, the reductions were driven by diesel alternatives, especially in US jurisdictions. Where overall CI rating falls short of targets, compliance is achieved through drawing on a systemwide bank of credits from prior years.

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diesel standard was frozen in 2017 at 2016 levels (not depicted in Figure 24), also due to a state court case, and resumed in 2018.

[59] BC was the sole jurisdiction to adjust its 2020 standard because of COVID-19, from 10% to 9.1%, to assist the oil and gas sector with low oil prices and demand resulting from the pandemic.

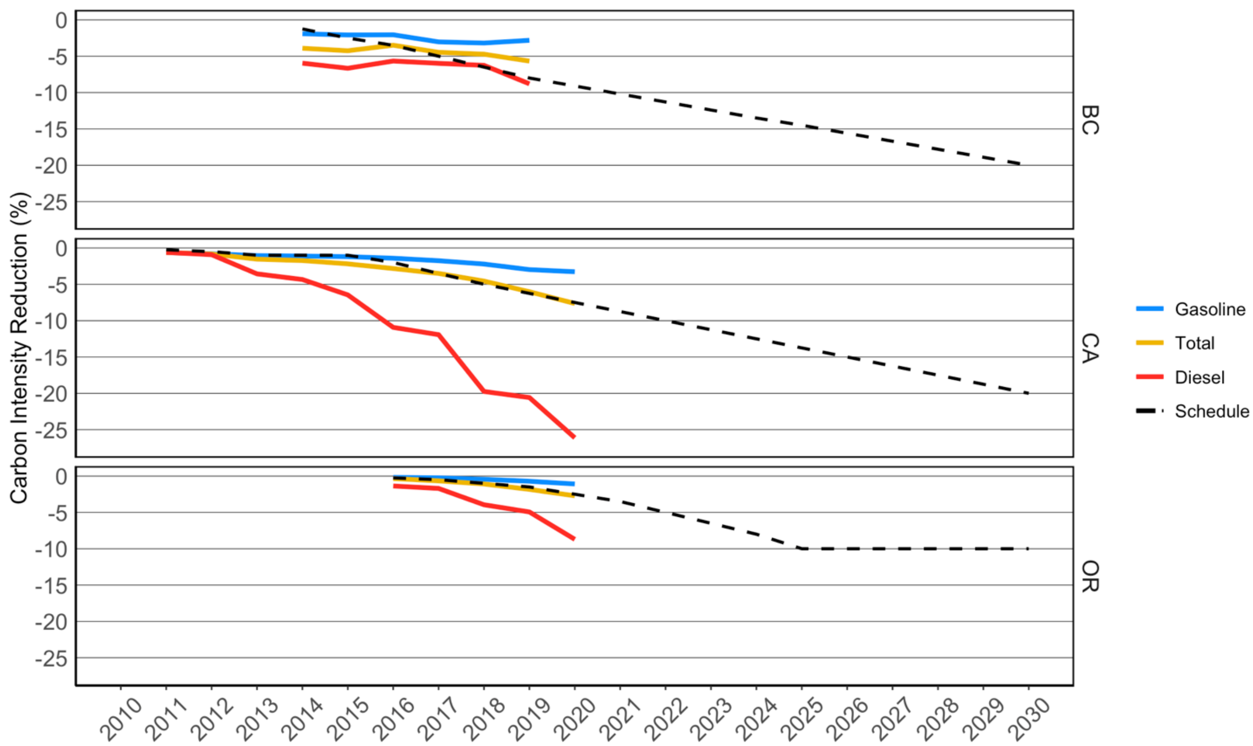

Figure 24. Percentage Reduction of Carbon Intensity by Fuel Pool and Schedules. 2020 data for Oregon, here and in other figures, do not reflect impact of residential electricity used as a fuel. In BC, there is insufficient information to plausibly estimate 2010–2013 credits by fuel pool. In California, the diesel standard was frozen at 2016 levels in 2017 (not depicted). Oregon has announced but not implemented a 2035 target of a 25% CI reduction. Sources: (CARB, Low Carbon Fuel Standard Reporting Tool Quarterly Summaries, 2021c; DEQ, Data for the Clean Fuels Program. Quarterly Data Summaries. Oregon Department of Environmental Quality, 2021a; Ministry of Energy, M.a.P.R., 2021c).

Figure 24 illustrates the divide between the gasoline and diesel pools and their roles in compliance with LCFS policies. Most of the transportation fuel consumed in each jurisdiction is E10, a blend of gasoline and 10% ethanol by volume. This 10% "blendwall" has limited the opportunities for credit generation by ethanol. In fact, alternative fuels in the gasoline pool accounted for less than half of all credits in all jurisdictions in recent years. In 2018, for example, gasoline and its substitutes constituted 80% of fuel energy in California, but the pool only generated about 40% of all credits.

In each program, fuels generated more program credits than deficits in early years, building a systemwide reserve, or bank, of credits available for compliance later (Figure 25). BC and California both grew credit banks through 2016, then began to draw on that compliance reserve, with deficits outpacing credits (Figure 24). In California, both 2019 and 2020 saw the pace of the bank drawdown slow, indicating that credit generation was "catching up" to deficit generation.[60]

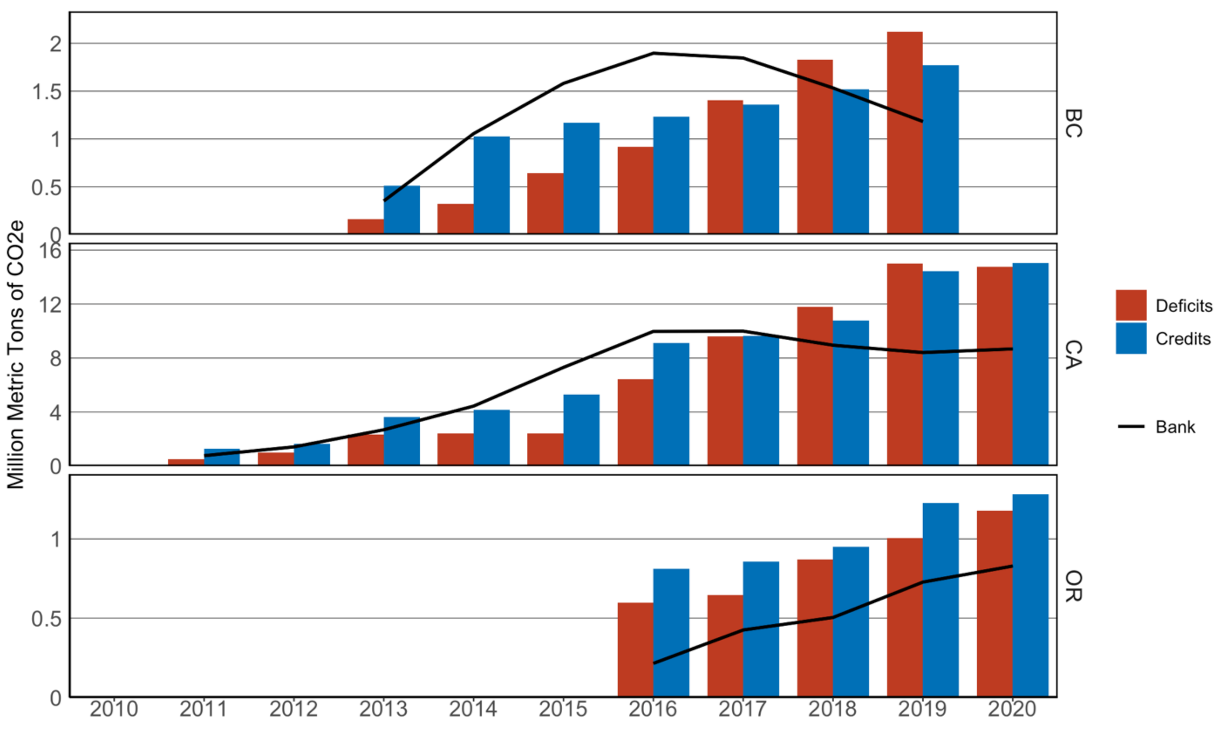

Figure 25. Total Credits, Total Deficits, and Cumulative Bank. Different scales per jurisdiction. Data coverage is as noted in Figure 24. Total program credits include those issued for infrastructure development for zero emission vehicle infrastructure in CA and "Part 3 Agreements" in BC. Sources: (CARB, 2021c; DEQ, Data for the Clean Fuels Program. Quarterly Data Summaries. Oregon Department of Environmental Quality, 2021a; Ministry of Energy, M.a.P.R., 2021c).

Not all credits issued are associated with emissions avoided due to cleaner fuels. BC's LCFS has, since its inception, allowed companies to contract in "Part 3 Agreements" for projects expected to lead to future low carbon fuel flows, often related to low carbon fuel production or delivery

[60] As described in the introduction, the transport realities accompanying pandemic may have made 2020 compliance easier to attain.

infrastructure; agreed-on credits are generated for the company at pre-agreed upon milestones in project execution. Part 3 Agreement credits were first distributed in 2015 and have accounted for between 5% and 15% of credits in years thereafter, though they can account for up to 25% of the previous year's system-wide obligation (Ministry of Energy, 2021b). California added credit generation for zero emission vehicle (ZEV) fueling infrastructure capacity in 2019; stations open to the public are eligible to earn up to 5% of deficits generated in the prior quarter (2.5% apiece for hydrogen fueling stations and electricity fast chargers) for unused fueling capacity. In 2020, fueling capacity ZEV infrastructure credits for hydrogen and DC fast charging accounted for nearly 9%, and just over 4% of their allowed allotments, respectively. Oregon has no analogous program; according to its rules, all credits must reflect actual emissions reductions.

California's is the sole program to include provisions to account for appreciable increases in the average crude oil CI value above 2010 levels and include credit generation opportunities for reducing carbon emissions in oil production and refining relative to business as usual.[61] "Incremental deficits" accrued to petroleum fuels for the first time in 2020 and are slated to continue in 2021, after the 2018 and 2019 assessments showed increased CI values of 0.23 and 0.41 gCO_2e/MJ, respectively. This resulted in about 400,000 additional deficits, or 2.5% of the total, in 2020. Since 2015, innovative methods in oil production (e.g., solar used as process energy) and investments in refineries have generated about 50,000 credits.

3.2 Alternative Fuel Energy and Credits

Alternative (non-petroleum) fuels' share of total transportation energy increased under all the LCFS programs. Under the longest standing programs, the percent of alternative energy more than doubled and increased by 30% in Oregon (Figure 26). California and Oregon program expansions to include electric off-road sources such as light rail accounted for a small portion of

[61] This set up differs from most crediting activity, which is for carbon emission reductions relative to the annual benchmark.

the alternative energy uptick starting in 2016 and 2018, respectively (CARB, Low Carbon Fuel Standard Reporting Tool Quarterly Summaries, 2021c; DEQ, Data for the Clean Fuels Program. Quarterly Data Summaries. Oregon Department of Environmental Quality, 2021a).

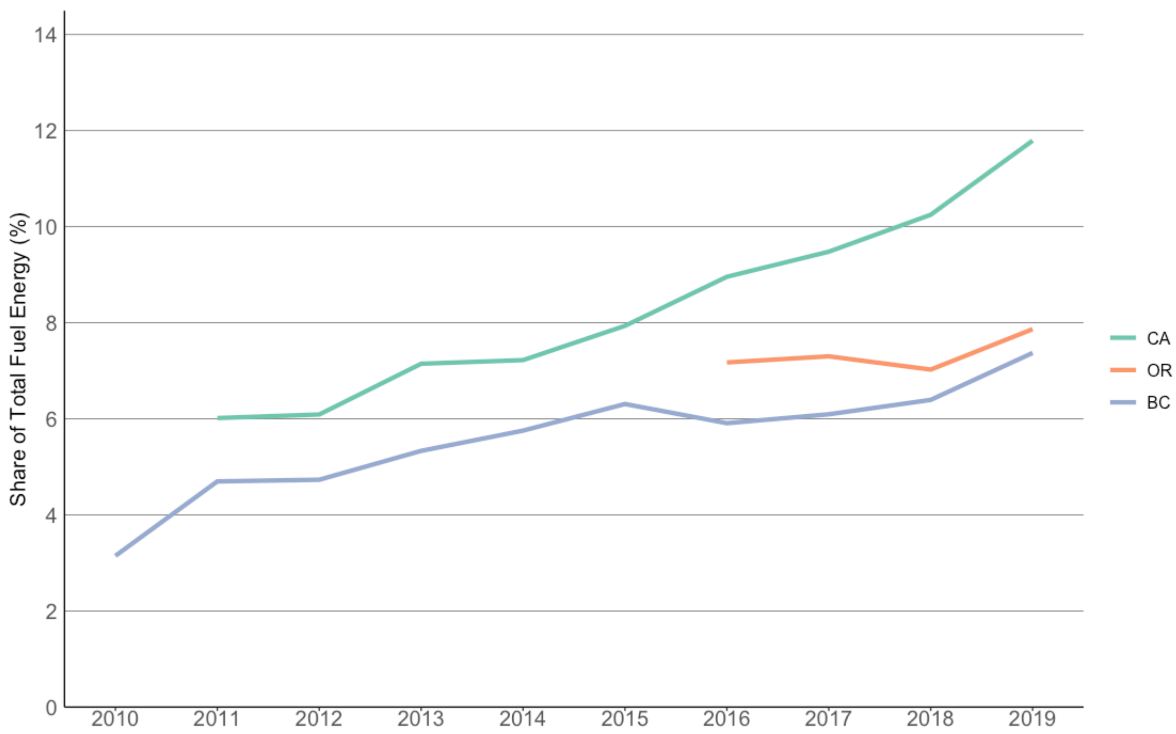

Figure 26. Alternative Fuels' Share of Total Transportation Energy in LCFS Jurisdictions. A small amount of alternative fuel energy increase in California and Oregon is due to program expansion. In this and other energy graphs, no adjustment is made for different fuels' on-road efficiency. Data coverage is as in Figure 24. Sources: (CARB, 2021c; DEQ, Data for the Clean Fuels Program. Quarterly Data Summaries. Oregon Department of Environmental Quality, 2021a; Ministry of Energy, M.a.P.R., 2021c).

Transport energy by fuel in each jurisdiction is detailed in Figure 27 and Table 13. Liquid biofuel use grew everywhere, and non-liquid fuels like electricity and natural gas appeared to varying degrees. Ethanol continues to comprise the largest share of alternative fuel by energy content in all jurisdictions. It grew almost 62% in BC between 2010 and 2018, before declining 11% in 2019 to a net growth of 44%. Liquid gasoline increased from 5% ethanol by volume systemwide at the program's outset to 7% in 2019. Ethanol remained near 10% by volume of liquid gasoline in the US jurisdictions, due to the E10 blendwall.[62]

Biomass-based diesel (BBD) — FAME biodiesel and HEFA RD[63] — rose robustly in all three jurisdictions, especially in 2019 primarily due to increased use of RD. That year, energy from BBD in California and Oregon neared that of ethanol's and in BC exceeded ethanol's by about 25%. In California, BBD accounted for nearly a quarter of liquid diesel by volume in 2020 (Table 13). In California and Oregon, RD saw dramatic year-on-year growth after the third program year, reaching 16% by volume of California's on-road liquid diesel fuel in 2019, and just over 4% in Oregon. Like Oregon, BC saw dramatic growth in RD beginning in 2019; making up over 5% of on-road liquid diesel and 30% of both alternative fuel energy and credits (Figure 27).

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[62] E85 blends used in flex-fuel vehicles are currently the principal way proportional ethanol use can increase. In 2019, US EPA put into place regulations to allow 15% blend of ethanol (E15) by volume in gasoline fuel year-round (EPA, 2019), recently vacated by the courts. Neither California nor Oregon currently carries E15 blends.

[63] FAME is fatty acid methyl ester and HEFA hydro-processed esters and fatty acid conversion processes. Biodiesel (BD) and renewable diesel (RD) in this report refer to FAME and HEFA process fuels, respectively.

Table 13. Transportation Energy (million gge) by Fuel Type.

Fuel Type	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
					British Columbia						
Gasoline	1,043	983.5	942.3	955.6	994.3	1,017	1,068	1,063	1,034	1,051	-
Diesel	810	895	901	893	907	849	842	930	963	895	-
Ethanol	34.9	39.3	37.4	41.2	45.0	51.4	55.8	56.4	56.4	50.1	-
Biodiesel	14.6	22.8	20.9	22.2	23.5	24.1	24.1	24.1	26.0	25.4	-
RD	7.0	14.0	15.9	22.8	29.2	27.9	17.1	24.7	26.6	49.5	-
Fossil NG	-	-	1.9	3.2	4.4	7.0	7.6	8.9	12.1	15.2	-
Biogas	-	-	-	-	-	-	-	-	-	-	-
On-Road Elec	-	-	-	-	0.0	0.0	0.0	0.0	0.1	0.0	-
Off-Road Elec	3.8	3.9	4.1	4.0	3.9	3.9	3.9	4.4	4.4	4.7	-
Other	-	12.7	11.4	10.8	10.2	11.4	11.4	10.8	10.8	10.2	-
Total Fuel	1,913	1,971	1,935	1,953	2,017	1,992	2,030	2,122	2,133	2,102	-
Ethanol (%)	4.7	5.6	5.5	6.0	6.2	6.9	7.2	7.1	7.3	6.5	-
BBD (%)	2.7	4.1	4.1	5.0	5.9	6.0	5.0	5.3	5.6	8.3	-
					California						
Gasoline	-	13,125	13,211	12,973	13,334	13,445	14,053	14,069	13,779	13,738	11,327
Diesel	-	4,169	4,158	4,068	4,055	4,030	3,933	3,886	3,734	3,468	3,210
Ethanol	-	1,004	993	996	1,000	1,010	1,076	1,061	1,079	1,049	875.2
Biodiesel	-	13.7	21.8	65.3	72.9	137.9	178.2	185.4	201.2	230.5	290.2
RD	-	2.0	9.9	131.1	126.5	185.2	286.7	376.1	430.1	691.6	659.2
Fossil NG	-	85.4	98.3	103.6	112.6	83.6	65.4	59.4	56.0	47.2	14.7
Biogas	-	1.8	1.9	11.9	33.4	77.2	103.8	124.2	139.4	161.7	176.9
On-Road Elec	-	0.4	1.3	3.5	8.2	12.6	21.4	30.8	50.0	63.5	54.0
Off-Road Elec	-	-	-	-	-	-	38.1	43.4	44.0	48.6	49.2
Other	-	-	-	-	-	-	-	0.3	0.7	8.0	32.2
Total Fuel	-	18,401	18,495	18,353	18,743	18,981	19,756	19,836	19,512	19,506	16,689
Ethanol (%)	-	10.2	10.0	10.2	10.0	10.0	10.2	10.1	10.4	10.2	10.3
BBD (%)	-	0.4	0.8	4.8	4.9	7.8	11.0	13.1	15.0	21.7	23.6
					Oregon						
Gasoline	-	-	-	-	-	-	1,425	1,444	1,539	1,565	1,278
Diesel	-	-	-	-	-	-	646	622	653	655	612
Ethanol	-	-	-	-	-	-	116.8	114.6	113.5	114.4	92.9
Biodiesel	-	-	-	-	-	-	40.6	43.7	44.1	51.4	58.4
RD	-	-	-	-	-	-	-	0.3	1.1	14.6	16.2
Fossil NG	-	-	-	-	-		0.5	0.8	1.3	1.1	0.7
Biogas	-	-	-	-	-	-	0.8	1.7	1.6	2.0	2.6
On-Road Elec	-	-	-	-	-	-	1.3	1.6	2.1	2.8	0.3
Off-Road Elec	-	-	-	-	-	-	-	-	1.6	2.0	3.0
Other	-	-	-	-	-	-	0.0	0.1	0.5	1.3	1.1
Total Fuel	-	-	-	-	-	-	2,231	2,229	2,358	2,410	2,065
Ethanol (%)	-	-	-	-	-	-	11.1	10.8	10.1	10.0	10.0
BBD (%)	-	-	-	-	-	-	6.3	7.0	6.9	9.7	11.4

Notes: "Other" includes hydrogen and propane (plus renewable propane in Oregon, and renewable naphtha and alternative jet fuel in California). gge = gasoline (blendstock) gallon equivalents. gge is calculated using each policy's own energy density for petroleum gasoline. Ethanol and BBD percentage columns are blend rates of finished gasoline and diesel, respectively. Data coverage is as in Figure 24. BBD = biomass-based diesel, RD = Renewable Diesel. Sources: (CARB, 2021c; DEQ, Data for the Clean Fuels Program. Quarterly Data Summaries. Oregon Department of Environmental Quality, 2021a; Ministry of Energy, M.a.P.R., 2021c).

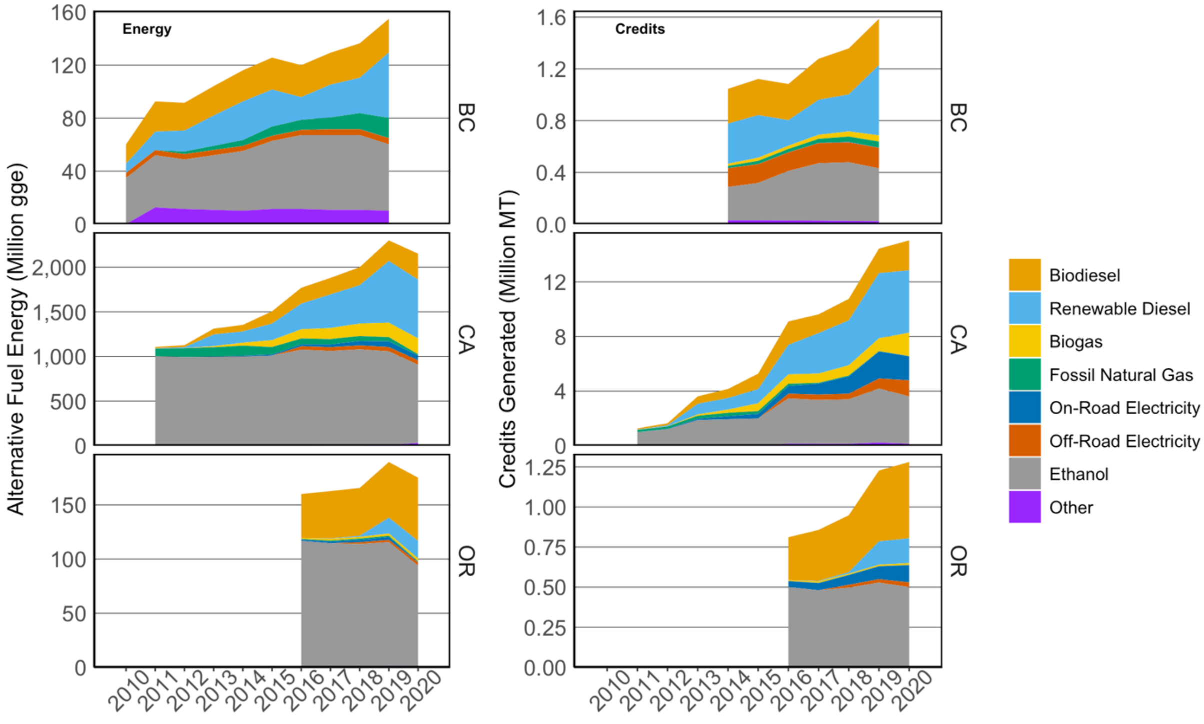

Figure 27. Alternative Fuel Energy and Credit Generation by Fuel Type. gge = gasoline (blendstock) gallon equivalents calculated using each policy's energy density for petroleum gasoline. Data coverage is as in Figure 24. In BC, credits by fuel type are estimated using data on fuel volumes and average CI ratings reported by BC Energy/Mines, for 2014 on; there is insufficient information to estimate BC 2010–2013 credits by fuel. "Other" includes hydrogen and propane (plus renewable propane in Oregon, and renewable naphtha and alternative jet fuel in California). Sources: (CARB, 2021c; DEQ, Data for the Clean Fuels Program. Quarterly Data Summaries. Oregon Department of Environmental Quality, 2021a; Ministry of Energy, M.a.P.R., 2021c).

Electricity and natural gas together constituted about 6% of alternative energy in California and BC, and 1% in Oregon, at each program's outset. By 2019, non-liquid fuel's energy contribution ramped up to 13% (BC), 14% (CA), and 5% (OR). In BC, natural gas energy about tripled, and came solely from fossil sources. Electricity use principally from off-road vehicles was steadier. In contrast, both natural gas and electricity grew sharply in California and Oregon. Natural gas use increased by about 140% in California (2010–2019) and in Oregon (2016–2019). Biogas accounted for 77% and 67% of transport natural gas use in California and Oregon, respectively, by 2019. Unlike California and Oregon, many heavy-duty vehicles in BC use propane, which accounts for much of the "Other" category – making up 8% of total energy in 2019.

Figure 27 also depicts program credits generated per fuel type over time. An outsized credit contribution relative to fuel volume, as in the case of electricity, is an indicator of lower CI scores and/or greater on-road efficiency of fuel/vehicle combinations (higher EER). The relatively higher ethanol CI is evidenced by smaller contributions to credit totals than volumes.

3.3 Carbon Intensity of Fuels

The lifecycle emissions of alternative fuels depend on feedstock production and extraction, fuel production, transportation of feedstocks and fuels, end use, and, in the US jurisdictions, the indirect land use change (ILUC) associated with feedstocks.[64] "Fuel pathways" encompass all these steps in the supply chain; GHG emissions estimates associated with each step are summed, normalized by energy in the fuel, and assigned as a CI rating for a particular fuel pathway, or lifecycle. Each jurisdiction uses its own CI estimation model, often applying

[64] ILUC is market-mediated land conversion caused by increasing aggregate consumption of similar products. For example, if soybean oil is shifted from its customary use in food or feed and instead used to produce fuel, the consumers of the now-displaced oil will need to procure alternative supplies. The demand for additional feedstock can lead to land conversion to expand crop production; even if the oil being used for fuels does not come from recently converted land, the resulting fuel sparks growth in demand that can lead to land clearance.

different analytical assumptions, so similar or identical fuel/feedstock combinations can receive different CI scores.[65]

Each type of alternative fuel encompasses a range of potential CI scores (

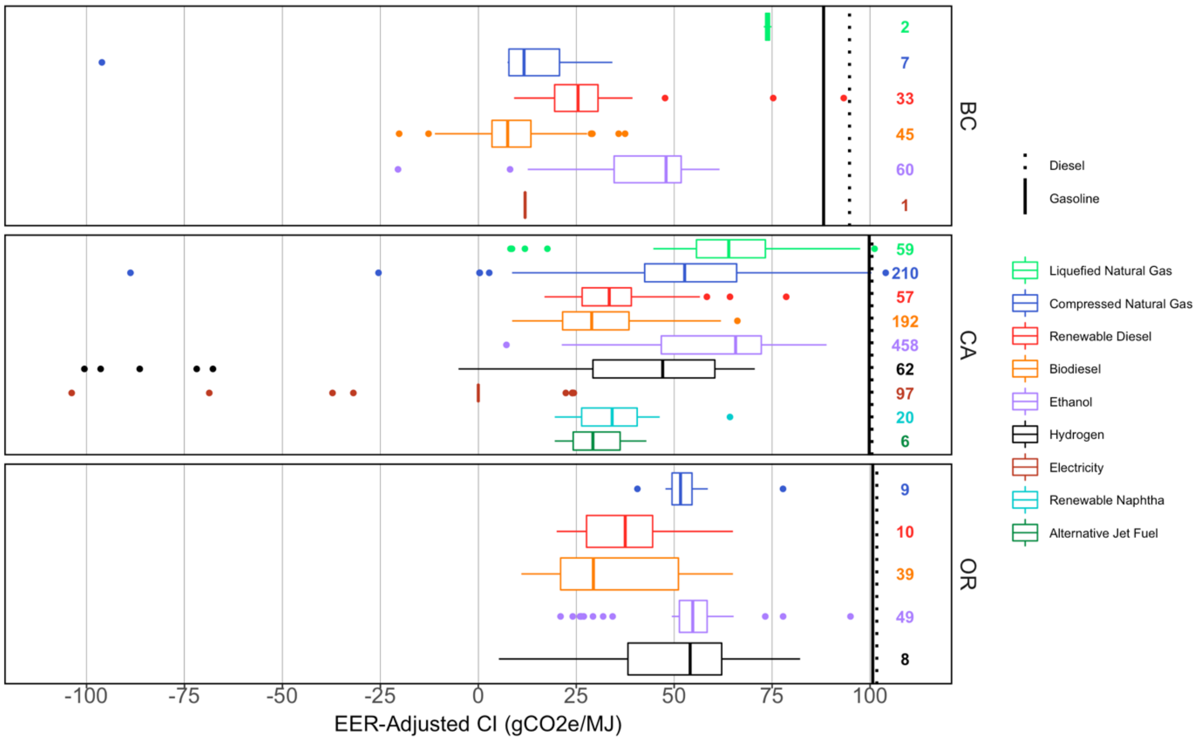

Figure 28, shown adjusted by EER),[66] which precludes a firm ordering of alternative fuels by CI score. In general, CI differences within a jurisdiction are driven by feedstock choice, production

[65] Oregon and California both use the GREET modeling system and adapt it to state conditions and estimate ILUC with a version of the GTAP model plus an emission factor model for land conversion, although Oregon uses a separate model for corn ethanol emissions factor conversion, resulting in a lower ILUC CI estimate (Kendall & Murphy, 2013). Pathways certified in California can be used in Oregon, with state-specific adjustments such as transport CI; Oregon has approximately 30 additional facilities not reporting to California (Peters, personal communication). BC acknowledges ILUC but does not account for it, and uses a different LCA model, GHGenius, built for Canadian fuels.

[66] EER is the motive efficiency of the alternative vehicle/fuel combination relative the ICE/petroleum fuel reference and is used in the calculation of GHG savings due to the fuel, for program crediting. For example, light duty electric vehicles use an EER of 3.4 under all three programs, which means that the conversion of electricity to transportation is approximately 3.4 time more efficient than the conversion of gasoline. For a list of program EERs for California and Oregon see (Mazzone & Smith, 2021).

process technology or energy, or transport mode – the LCFS is designed to elicit such choices or changes to lower the fuel's carbon footprint wherever along the supply chain is most cost-effective. Jurisdictional differences in electricity CI scores stem from different grid power sources and options claim CI scores below the regional grid average.[67] For any fuel, carbon-saving differences anywhere along the supply chain can improve its relative position.

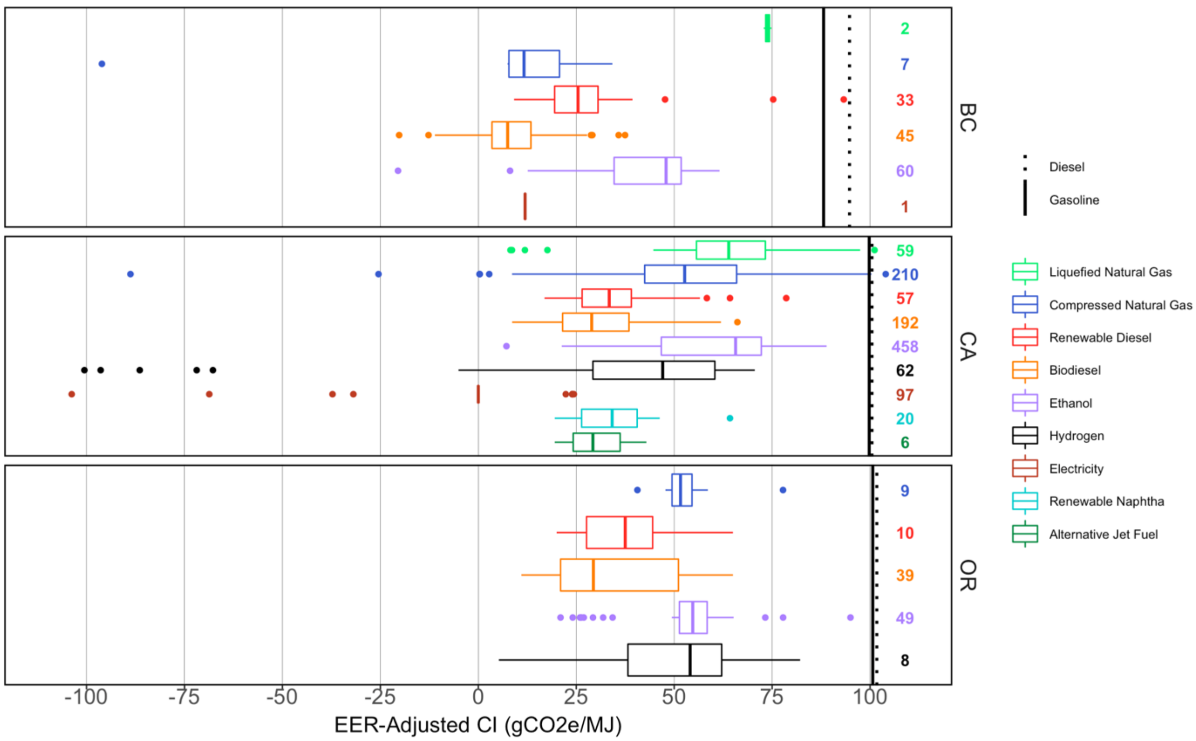

Figure 28 displays distributions of the EER-adjusted CI scores of pathways across fuel types. As of October 2021, California has 1,161 currently active pathways. Each of those pathways are available for use in Oregon (accounting for differences in transportation) along with 115 additional, currently active pathways. BC has 148 currently active pathways. Ethanol has the most pathway; approximately 40% of pathways are for ethanol in each jurisdiction. Regulated parties can apply for certification of new pathways, expanding the list of options over time. California and Oregon added third-party validation and verification programs for the

[67] In California, low- or zero-CI score electricity is accessible via book-and-claim contracts with low carbon sources. In Oregon, utilities can opt in to receive their area-specific CI score.

information going into CI calculations beginning in 2020. The BC government has verification authority.

Methane captured from animal manure can be used as a fuel or as input to electricity production for EV charging. These pathways account for the negative CI scores for CNG and electricity in California and Oregon, which go as low as -630 gCO2e/MJ. The negative CI scores are due to avoided methane emissions relative to in-state business-as-usual manure management. In BC, negative CI scores are associated with ethanol from landfill waste, and facilities that produce biodiesel from animal products, evaluated under their lifecycle analysis model. Negative CI scores imply that each unit of fuel consumed results in a net reduction of GHGs in the atmosphere compared to the no-fuel alternative according to the relevant model.

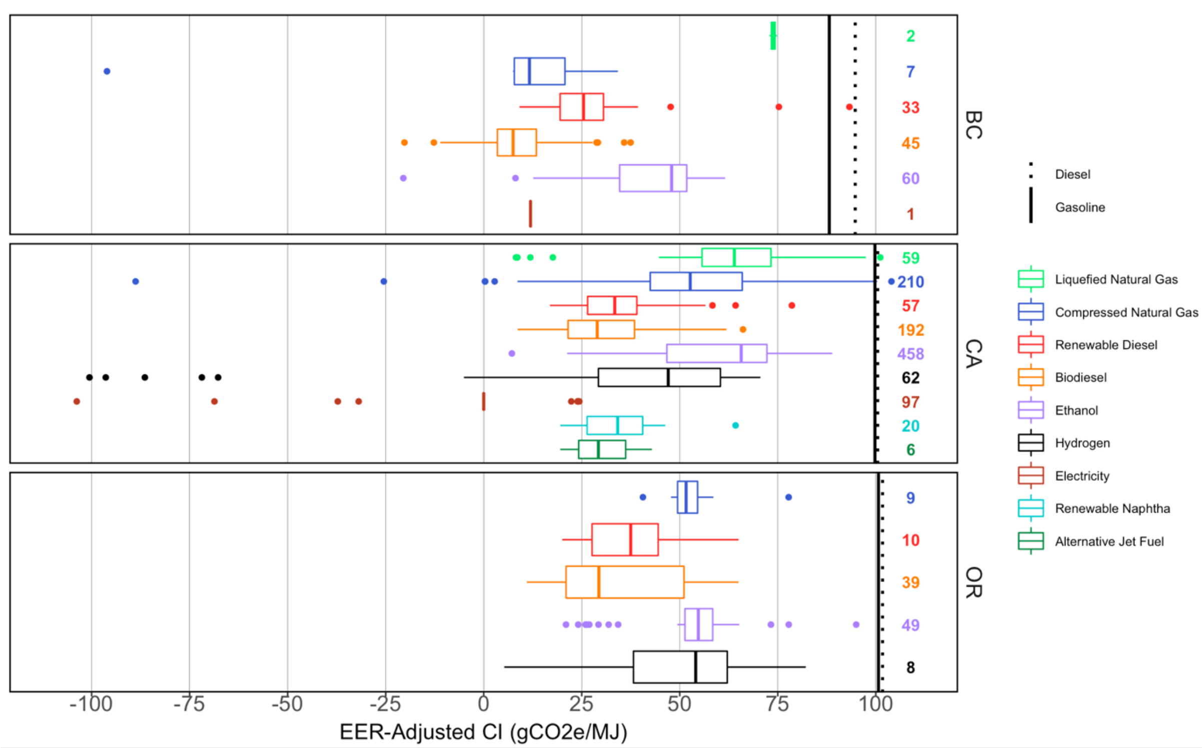

Figure 28. Summary of EER-Adjusted CI Scores for Certified Alternative Fuel Pathways by Fuel Type, and CI Reference Scores for Gasoline and Diesel, as of October 2021. Box-and-whisker diagrams for each fuel type indicate median (line in box), quartiles (box edges, and 1.5x interquartile range (whiskers); outliers beyond this are shown as dots. The total number of available pathways for each fuel type is reported to the right of each diagram. Oregon pathways depicted here are Oregon-specific, i.e., additional to California. The BC electricity CI score depicted is for light-duty vehicles, and not listed among their pathways. Pathways with an EER-adjusted CI score less than -110 are omitted for ease of exposition. In California, there are 51, 3, and 12 pathways for CNG, LNG, and electricity, respectively, and 1 CNG

pathway in Oregon with an EER-adjusted CI score below -110. Sources: (CARB, 2021b; DEQ, 2021c) and (Ministry of Energy, 2021a).

Based on first and most recent full data years available, alternative fuel reported CI scores declined an average 4.8% per year in BC, 5.4% in California, and 5.7% in Oregon. Both California and Oregon had annualized declines of about 4% for alternative gasoline, and 6% for alternative diesel. The California decline reflects modeling changes in mid-decade that lowered CI scores for crop-based biofuels by about 10 gCO_2e/MJ. In BC, alternative gasoline fuels' CI scores declined an average 5% per year, compared to 0.6% for alternative diesel fuels.

Figure 29 shows reported CI scores by fuel type over time. Ethanol reported average CI declined everywhere. In both BC and California, the average CI score of ethanol fell approximately 25 points, and Oregon, 5 points from each program's outset to 2019. Annualized ethanol CI score reductions in BC, California, and Oregon were 6%, 4%, and 2%, respectively. In California, the 2016 ILUC modeling change contributed about a 10 CI point reduction to the decline; lower-carbon process energy, yield improvements, and/or greater efficiency in co-product recovery were also factors (Lee, Kwon, Wu, & Wang, 2021). Each jurisdiction has ethanol pathways with notably low CI scores, usually from using low CI process energy, or add-on cellulosic processing capacity to allow corn kernel fiber to be converted to fermentable sugar. These (still uncommon) pathways could provide significant CI score reductions from the gasoline sector using existing technology if scaled, as could using higher blends of ethanol.

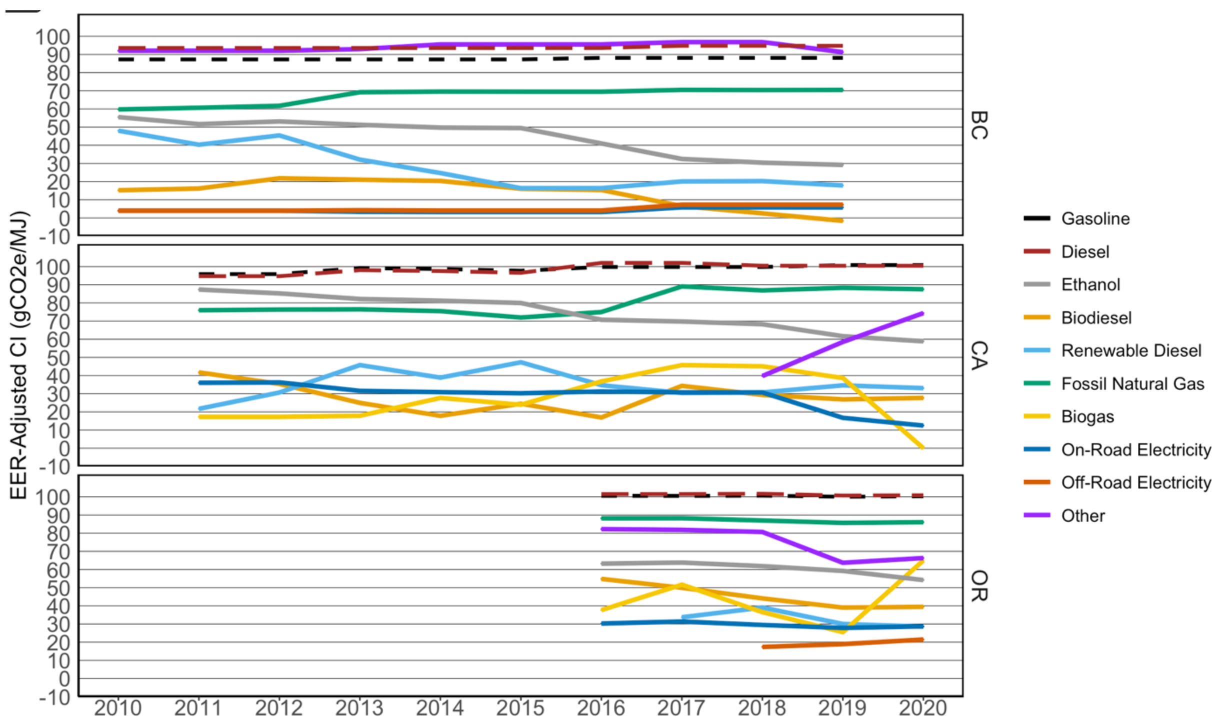

Figure 29. Average Reported EER-Adjusted CI Ratings. Data coverage as in Figure 24. EERs applied for electricity are for light-duty vehicles and light rail for on-road and off-road categories, respectively. For a full list of program EERs, see (Mazzone & Smith, 2021). An error in Oregon data for 2016 and 2017 non-residential electricity use and credits yields (inaccurate) negative CI scores (see (Witcover & Murphy, Status Review of Oregon's Clean Fuels Program, 2016–2018 Q3 (Revised Version), 2019); the displayed CI scores reflect only residential charging in those years. There is not enough publicly available information to calculate the off-road electricity CI score in CA. "Other" includes hydrogen and propane (plus renewable propane in Oregon, and renewable naphtha and alternative jet fuel in California). Sources: (CARB, 2021c; DEQ, Data for the Clean Fuels Program. Quarterly Data Summaries. Oregon Department of Environmental Quality, 2021a; Ministry of Energy, M.a.P.R., 2021c).

Light-duty EVs are another avenue for gasoline sector CI reductions. Electricity EER-adjusted CI scores are relatively low in these jurisdictions due to EV on-road efficiency and the mix of sources used to produce electricity, namely, a higher reliance on renewable energy, particularly hydropower in BC and Oregon. In BC, the electricity CI score increased due to source variability but remained low. In California, the EER-adjusted CI scores declined; an EER update from 3 to 3.4 for light-duty vehicles in 2013 was part of the decline, as was a lower state-level electricity grid average CI score, which fell approximately 27 points from the early part of the decade to 2020. The declining on-road electricity CI scores in California beginning in 2019 is due to new provisions allowing zero or low-CI rated electricity to apply to charging under contracts, via a book-and-claim system.

Oregon's grid average CI score, calculated as a multi-year rolling average, has been more stable. There, utilities have the option each year to apply utility-specific CI scores. New provisions allow book-and-claim for zero and low CI-rated charging, much like in California. Additional disaggregation in publicly available program data will be necessary for the ability to discern reported EER-adjusted CI scores that form the basis of credit generation as more electricity CI score options and EV types/EERs come into play in Oregon and California.

Among diesel substitutes, only biodiesel CI scores declined in all jurisdictions over the covered period. Oregon saw the steadiest drop in biodiesel CI scores, an annualized 8%. RD CI score averages varied between 22 and 47 gCO_2e/MJ in California, and 29 and 39 gCO_2e/MJ in Oregon, and declined 60% from 48 gCO2e/MJ in BC from the program's outset. Much of this variability may be explained by variation in feedstocks and supply chain practices, given the immaturity of RD production systems. Average biogas CI scores varied considerably in California and Oregon, reaching its lowest point in California (-0.02 gCO_2e/MJ) in 2020 and its highest point in Oregon (65 gCO_2e/MJ). Some biogas appeared in BC in 2019 but the average CI score was not reported.

An important driver in a pathway's CI score is feedstocks. Average fuel CI score by feedstock can be calculated using available California data (Figure 30). In 2020, California ethanol from sugarcane and molasses averaged 45 gCO_2e/MJ, and from corn, 64 gCO_2e/MJ (decreasing beyond the 10-point reduction from the ILUC modeling change). California assigns a higher ILUC value to corn than does Oregon. After entry into the LCFS in 2019, cellulosic ethanol's reported 82 million gallons in 2020 (over 5% of ethanol) had a reported CI average of 27 gCO_2e/MJ (over 10% of ethanol credits). Used cooking oil (UCO) earns the lowest CI score among all BBD feedstocks, leading to its newfound popularity (discussed in Section 5), and vegetable oils (soy and canola oil) earn the highest (partly due to ILUC). In between are corn oil and tallow – the most common biodiesel and RD feedstocks, respectively.[68] The principal sources for biogas, landfills and dairy digesters, had 2020 CI scores averaging around 54 and -260 gCO_2/MJ, respectively. Feedstocks are discussed further in Section 5.

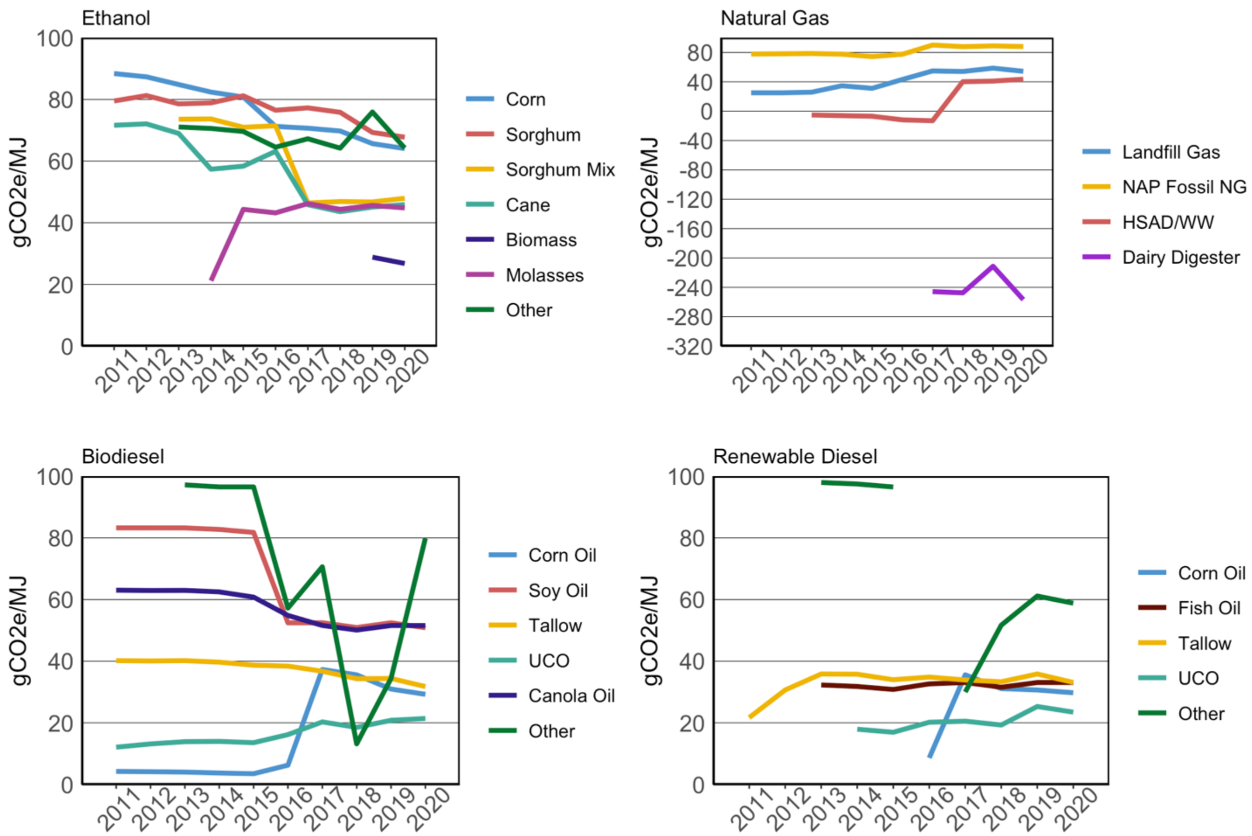

Figure 30. Average Reported Carbon Intensities by Feedstock in California. HSAD = High-Solids Anaerobic Digestion, WW = Wastewater, NAP = North American Pipeline, NG = Natural Gas, UCO = Used Cooking Oil. Sources: (CARB, 2021; DEQ, Data for the Clean Fuels Program.

[68] Renewable diesel typically has a CI score slightly higher than biodiesel, as it requires additional processing.

Quarterly Data Summaries. Oregon Department of Environmental Quality, 2021; Ministry of Energy, M.a.P.R., 2021).

3.4 LCFS Credit Trading and Prices

LCFS policies include credit trading to allow firms to flexibly comply with the regulation, prompting credit markets. Regulated parties purchase credits generated from alternative fuel producers to match thee deficits incurred from higher-carbon fuels, indirectly raising the cost of supplying those fuels and lowering the cost of supplying alternative fuels. The regulation is designed to send the necessary price signals to fuel markets.[69] If low carbon fuels are scarce, there are fewer credits, driving up the credit market price, adding to the relative incentive to bring low carbon fuel to market.

Credit prices theoretically reflect the industry's marginal cost of compliance, or the cost of supplying the marginal energy unit of alternative fuel relative to its petroleum counterpart, subject to market and policy uncertainties and overlapping state and/or federal incentives (Yeh, Witcover, Sperling, & Lade, 2016).[70] Most notably, many renewable transportation fuels generate Renewable Identification Numbers (RINs), tradable compliance instruments for the U.S. Renewable Fuel Standard (RFS). Fuel producers selling eligible biofuels into a state with an LCFS earn both RINS and LCFS credits. Beyond policy interactions and uncertainty, related markets such as agricultural products or crude oil may impact credit prices.

LCFS policies have generated substantial value to alternative fuels, shaped by the market price for credits and the CI reduction target. California's LCFS generated around $3 billion worth of

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[69] Regulators don't place any unit tax or subsidy on any particular fuel or technology, but the policy acts as an implicit tax-subsidy scheme through the credit price.

[70] Other incentives can close a cost gap for bringing a fuel to market, meaning a fuel becomes cost competitive at a lower LCFS credit price than would be the case if the LCFS were the only policy in play.

credits in 2019, Oregon's $150 million, and BC's $55 million (80 million CAD). Since the three programs are at different stages, demand for credits, and the resulting impact on prices, would differ even if the rest of the programs and policy environments were the same. As it is, differences in lifecycle accounting as well as policy environment (for example, mandated biofuel blend levels in Oregon and BC before their programs' starts, absent in California, but later supported by U.S. policy) can impact the additional cost of bringing fuels into a given market – thus also impact the credit price for that program.

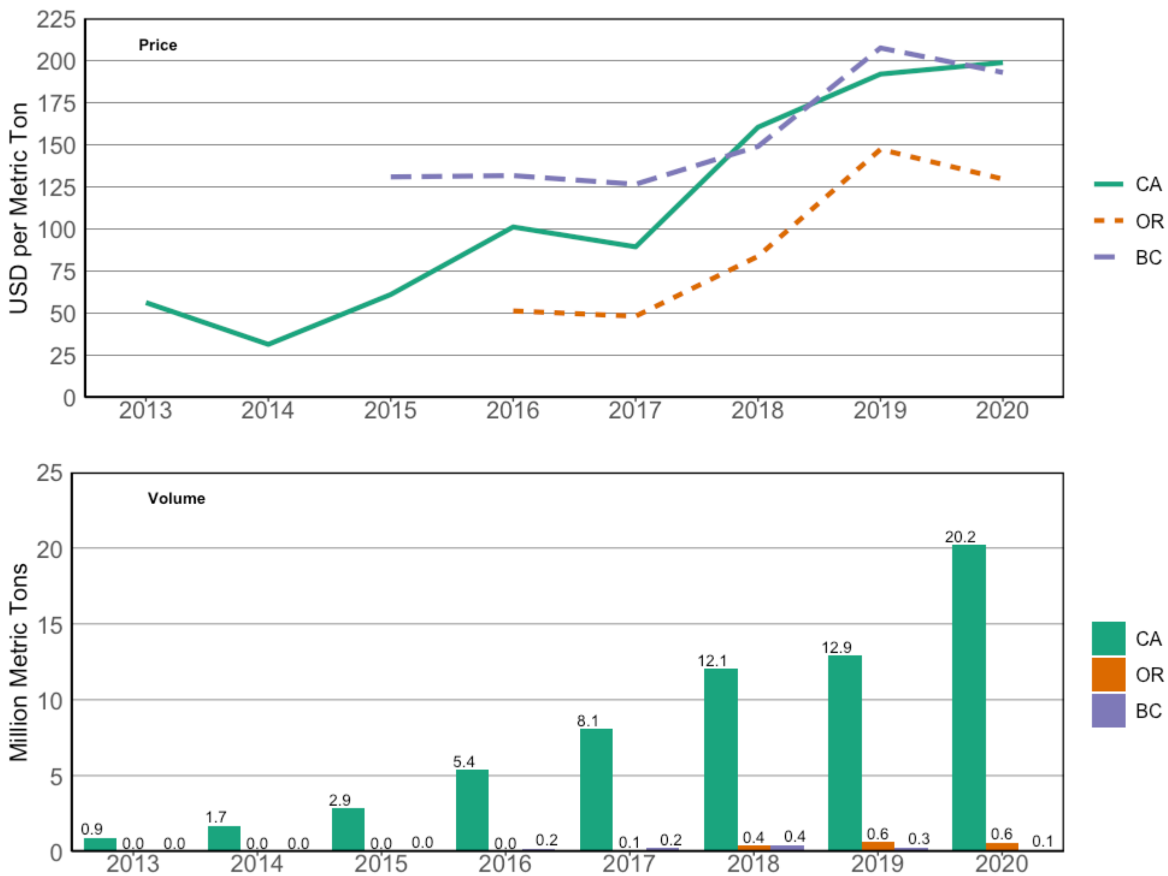

Figure 31. Credit Market Scope. Annual price is a volume-weighted average, in nominal US dollars (not adjusted to real terms). 2020 credit market data presented here are through the full year. Volumes refer to traded volumes. Sources: (CARB, 2021a) (DEQ, 2021b) (Ministry of Energy, M.a.P.R., 2021d).

Cost containment is a protective measure for market-based environmental policies to limit the risk of economic harm under unexpected market conditions and solidify political coalitions needed to adopt the policy. California's LCFS implemented a Credit Clearance Mechanism (CCM) as its primary cost containment measure in 2016; Oregon's CFP also uses a CCM. Under the CCM, any entity with unmet deficit obligations at the end of a compliance period would be required to buy a prorated number of credits pledged to CCM by those with credits to sell. Transactions occur at up to the ceiling price, established at $200 per credit in 2016 and increasing at the rate of inflation thereafter. Remaining deficits can be carried forward to the following year with a 5% interest penalty. This mechanism was designed to resolve deficits that arose due to illiquidity, difficulty identifying counterparties for transactions, or deficits intentionally left unmet. In 2020, California's program added a backstop to the CCM, advancing credits from utilities' future allocations of residential EV charging credits up to a specified limit when obligated parties are otherwise unable to cover their deficits. These parties must purchase the advanced credits from utilities at the ceiling price; the utilities receiving the advanced EV credits must then repay the borrowed credits in subsequent years. BC doesn't have a CCM, though Part 3 Agreements could be used as a *de facto* cost containment mechanism, if needed.

Figure 31 shows that the price of traded credits grew substantially in all three jurisdictions since program implementation, to an average $200/MT, $132/MT, and $192/MT in California, Oregon, and BC, respectively, in 2020.[71] Trade volume grew year-on-year in California and Oregon and hit a peak for BC thus far in 2018.[72]

[71] If a shift in the marketplace allowed for low carbon fuels to become more readily available at lower cost, credit price could decrease with more stringent CI targets.
[72] Note that one credit may be traded more than once before being retired for compliance and can be traded in years after it was generated, meaning the number of credits being traded in the credit market may be greater than the number of credits generated from alternative fuels in any given year.

California's LCFS underwent several legal challenges, one of which led to a freeze of the program's target due to issues with the program's environmental analysis; this necessitated a policy readoption in 2016 (Witcover, Status Review of California's Low Carbon Fuel Standard, 2011–2018 Q1 September 2018 Issue, 2018). Over this period (2013-2015) credit prices remained relatively low, likely due to the lower standard coupled with uncertainty whether the policy would emerge intact from legal challenges. As the standard tightened and policy uncertainty eased by the passage of SB 32 in 2017, and the LCFS extended to 2030 in 2018, credit prices rose.

3.5 Fuel Incentives, Feedstocks, and Non-Fuel Credits

Profit margins for fuel blenders and utilities, the entities that realize LCFS credit value, depend on the incentives per unit of fuel, which are determined by the credits generated per unit of fuel multiplied by the credit price. Figure 32 shows average incentives per gallon of liquid fuels and natural gas and per kilowatt-hour (kWh) of electricity in each jurisdiction. Of liquid fuels, BBD earns the most on a per-gallon basis in each jurisdiction, and ethanol the least. Liquid fuel incentives are generally much larger in BC than U.S. jurisdictions, mainly because Canada doesn't currently provide the level of additional federal support that the U.S., with the RFS and tax credits, does. Electricity incentives are substantial in all three jurisdictions. In California and Oregon, incentives exceeded the average retail price of electricity of 16.9 and 9 cents/kWh, respectively. The strikingly large biogas incentives as of recently are due to increasing avoided methane credits. Differences between fuels each year are driven primarily by differences in CI and thus feedstocks, which are the focus of the remainder of this section.

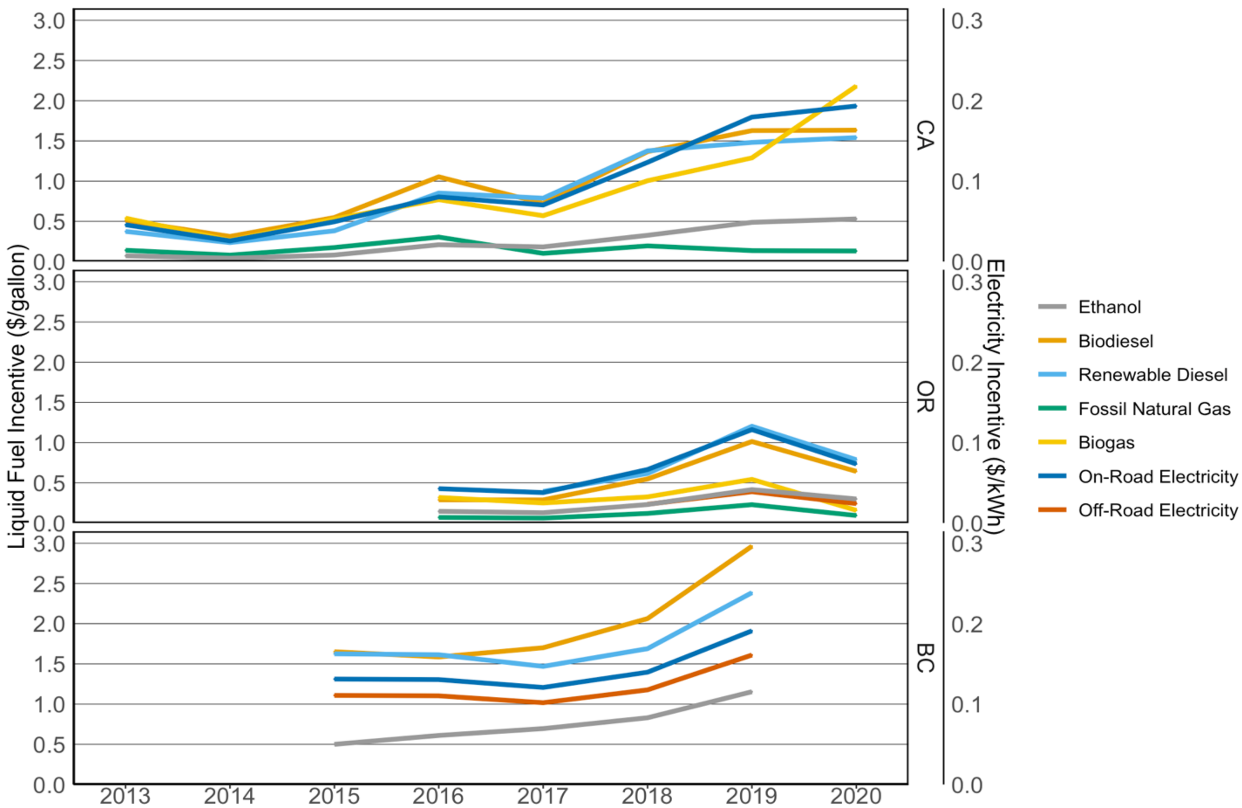

Figure 32. Alternative Fuel Incentives. Liquid and natural gas fuels are evaluated in $/gallon (left axis) and electricity in $/kWh (right axis). Biogas and fossil natural gas are in terms of diesel gallon equivalents. Sources: (CARB, 2021c; DEQ, Data for the Clean Fuels Program. Quarterly Data Summaries. Oregon Department of Environmental Quality, 2021a; Ministry of Energy, M.a.P.R., 2021c; CARB, 2021a; DEQ, 2021b; Ministry of Energy, M.a.P.R., 2021d).

Ethanol

Each jurisdiction's ethanol is produced primarily from corn. Cellulosic ethanol first entered California at 29 gCO_2e/MJ in 2019, falling 2 CI points the next year. In 2020, cellulosic biomass contributed 5% of California's volume and over 10% of credits. Figure 32 illustrates the premium for cellulosic ethanol, a 50 cent/gallon premium over corn in 2020 on average, which led cellulosic ethanol generating $92 million in LCFS credit value - 20% of the value generated by corn ethanol.[73] Lower CI scores are associated with greater LCFS incentives, in the case of

[73] Here and throughout this section, total credit value reflects credits generated in a given year evaluated at the average market price for LCFS credits that year.

cellulosic fuels, partly due to no ILUC emissions. Only California supplies the publicly available data needed to calculate policy incentives by feedstock. Virtually all of Oregon's ethanol is produced from corn (Figure 33). Much of the ethanol used in BC is produced from wheat — over a third in 2019 — which is seldom used in U.S. ethanol production.

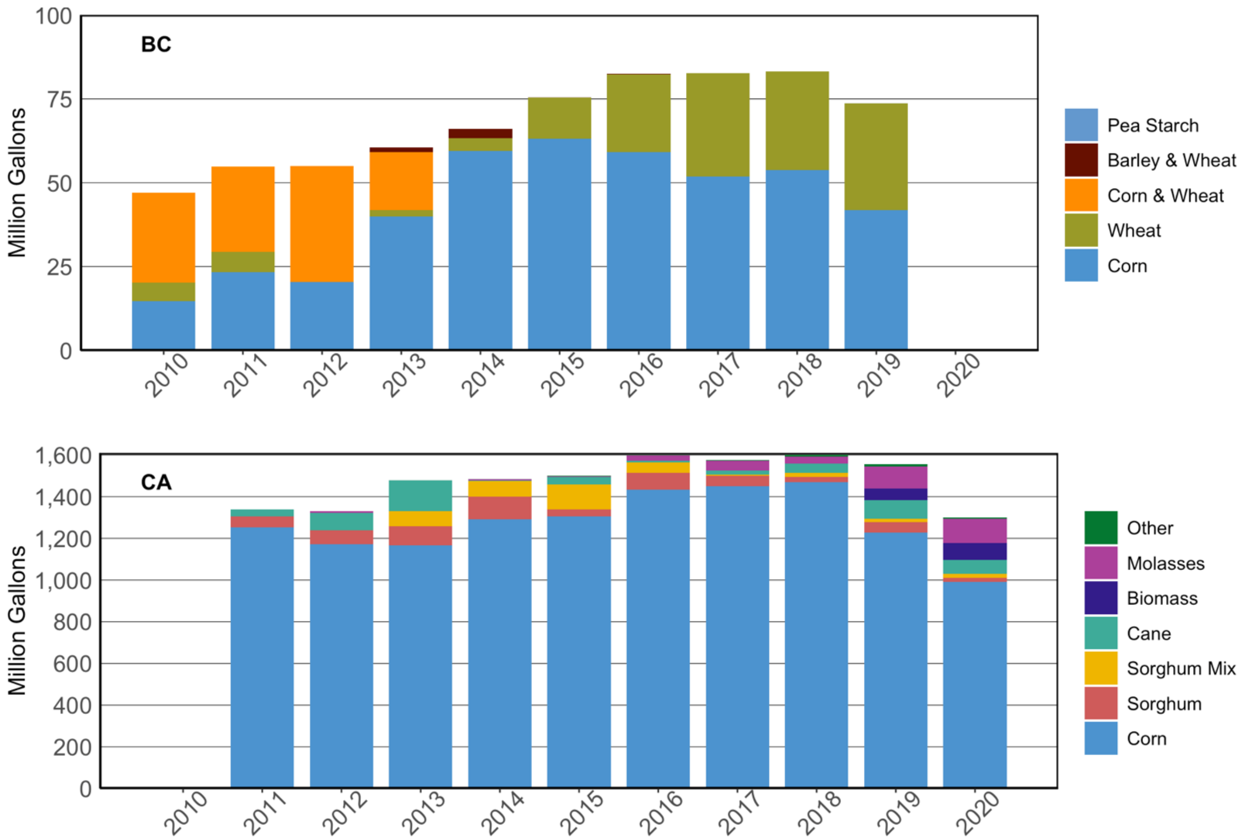

*Figure 33. Ethanol Volume by Feedstock***.** *Oregon not depicted because all ethanol is from corn. Sources: (CARB, 2021c; DEQ, Data for the Clean Fuels Program. Quarterly Data Summaries. Oregon Department of Environmental Quality, 2021a; Ministry of Energy, M.a.P.R., 2021c).*

Biomass-Based Diesel

The biodiesel and RD components of BBD are sourced from similar lipid feedstocks. Biodiesel faces certain blending constraints in liquid diesel, often requiring labeling above B5 and more engine modifications, especially above B20; RD, as a drop-in fuel, faces no restrictions on blending with petroleum diesel, is more easily stored, and generally produces less NOx when burned. RD production also occurs via co-processing or batch processing of non-fossil oils at operational refineries, which can undergo relatively modest retrofits to biofuel-only configurations.

Impressive RD growth was noted above. Notable also is the rising use of lipid residues used as feedstocks, such as used cooking oil (UCO) and tallow from animal rendering, which make up most of the BBD across all three jurisdictions as of 2019 (Figure 34). Tallow made up most of the RD in California since 2013 and has accounted for virtually all of Oregon's. Like in Oregon, tallow appeared in BC in large quantities in 2019, now comprising nearly 10% of all BBD.

The most striking trend in BBD was the dramatic increase in UCO in 2019; volumes doubled in BC, increased 80% in CA, and 70% in OR from 2018. UCO is the most lucrative BBD feedstock under California's LCFS, reflecting its relatively low average CI score, due in part to no ILUC or indirect effects assessment (about 22 gCO_2e/MJ in 2020). UCO-based BBD earned nearly $1.8/gallon in 2020 on average, generating over $580 million of LCFS credit value.

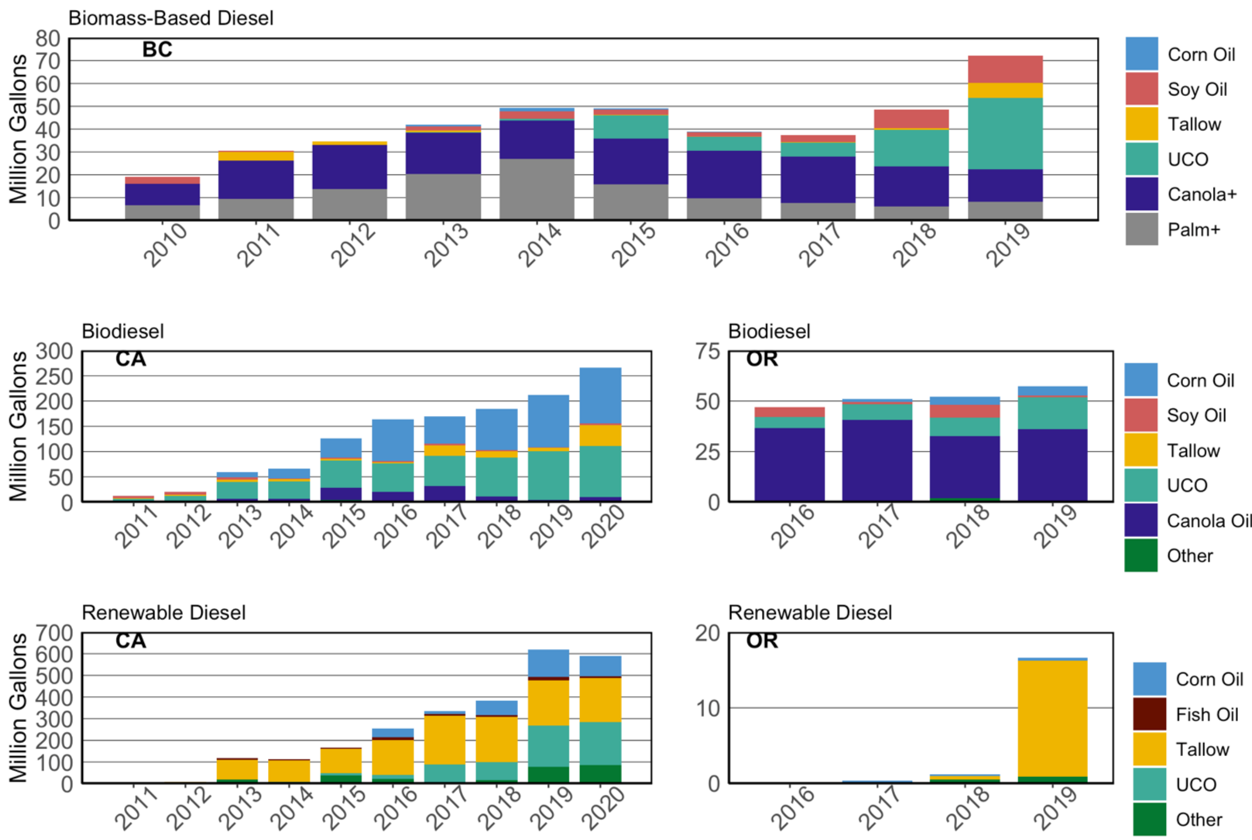

Figure 34 shows that the feedstock composition of BBD in BC had been dominated by canola and palm products but transitioned away from palm starting in 2015 and increasingly toward UCO, tallow, and soybean oil. In 2019, 11% of BBD in BC used palm feedstocks, down from 50% in 2013. Oregon biodiesel is over 50% canola but has also diversified into lower-CI residue feedstocks over time. Canola oil is only sparsely used in California. Instead, corn oil is the dominant feedstock there, responsible for about half of biodiesel used in state.

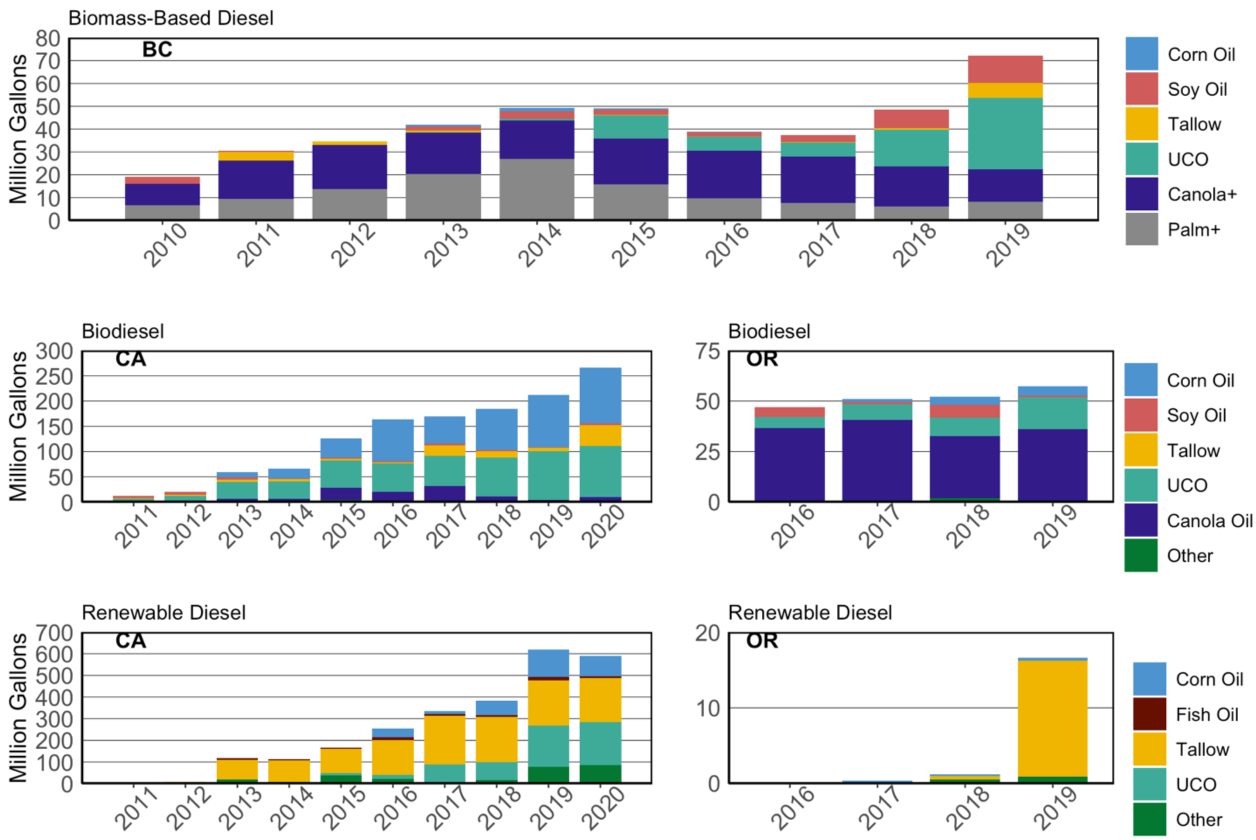

Figure 34. Biomass-Based Diesel Volume by Feedstock. (Oregon CFP feedstock data is not yet publicly available from the Department of Environmental Quality (DEQ) but can be found at (Mazzone & Smith, 2021)). Canola+ refers to a mix of canola oil with tallow and soybean oil. Palm+ represents the sum of refined palm oil, palm sludge oil, spent bleaching earth oil, and rapeseed oil. Sources: (CARB, Low Carbon Fuel Standard Reporting Tool Quarterly Summaries, 2021c; Ministry of Energy, M.a.P.R., 2021c; Peters, 2020)

RD produced from soybean oil (SBO) appeared recently in California; CI scores for available pathways indicate SBO as the primary component of the "other" category. SBO may be attractive to refiners that seek to retrofit larger-scale facilities because vegetable oils provide a cleaner more homogeneous product that can be supplied in larger volumes (Kotrba, 2019). The recent UCO boom has placed considerable pressure on domestic stocks; the feedstock is in high demand worldwide for low carbon fuels due to its favorable CI rating (Sanicola, 2021). Increasing demand has been met by supply constraints, especially due to the pandemic as restaurant dining, and thus waste oil collection, fell worldwide. UCO prices grew 50%, and tallow 30% over the last year (Nickel, Kelly, & Plume, 2021).

Hydrotreated biojet fuel, a type of alternative jet fuel, or AJF (termed sustainable aviation fuel, or SAF, when sustainably sourced and produced), is made using similar feedstocks and processes as RD. California is home to one of the few AJF production facilities currently operational, and imports from other producers. In 2020, two of California's petroleum refineries with an aggregate capacity of over 380,000 barrels/day announced plans to convert to renewable fuel production in the early 2020s, though final capacity is likely to be less than when they were operating as conventional petroleum refineries. Additional expansion of biojet/RD production has been announced at other, smaller facilities.

Natural Gas

When organic matter decomposes in the absence of oxygen, the resulting "digester gas," composed primarily of methane, carbon dioxide, and water vapor, can be captured and purified into renewable natural gas (RNG). RNG is an alternative to conventional fossil natural gas, and, when purified to jurisdiction specifications, can use conventional natural gas transmission, distribution and infrastructure. As noted above, California's LCFS allows RNG produced anywhere in North America and delivered into a common-carrier pipeline to be contractually conveyed to CA and credited as if it were consumed in-state using book-and-claim accounting. RNG's increasing share of natural gas started in 2014, when biogas became eligible for higher RFS incentive, also using a book-and-claim system, and has been dominated by landfill gas, primarily from out of state. The growth in biogas from animal manure, usually from dairies, while still small in volume terms, is an important recent trend.

The first LCFS pathways for dairy gas were operational in 2017. While its use has risen sharply, it currently constitutes a small share of natural gas used in California. Despite its small contribution by volume — 11% of transportation natural gas in 2020 — it was responsible for more than half of natural gas credits in the same period. Dairy biogas generated $220 million of credit revenue in 2020, more than all other feedstocks combined. Given its negative CI scores (see Section 3.2), dairy gas earned $9.5/dge on average in 2020, $8.5 more than landfill gas. Recent fuel pathway submissions leverage the low carbon nature of dairy gas beyond the natural gas vehicle fleet by using it as a fuel to generate electricity, which is then used to charge EVs.

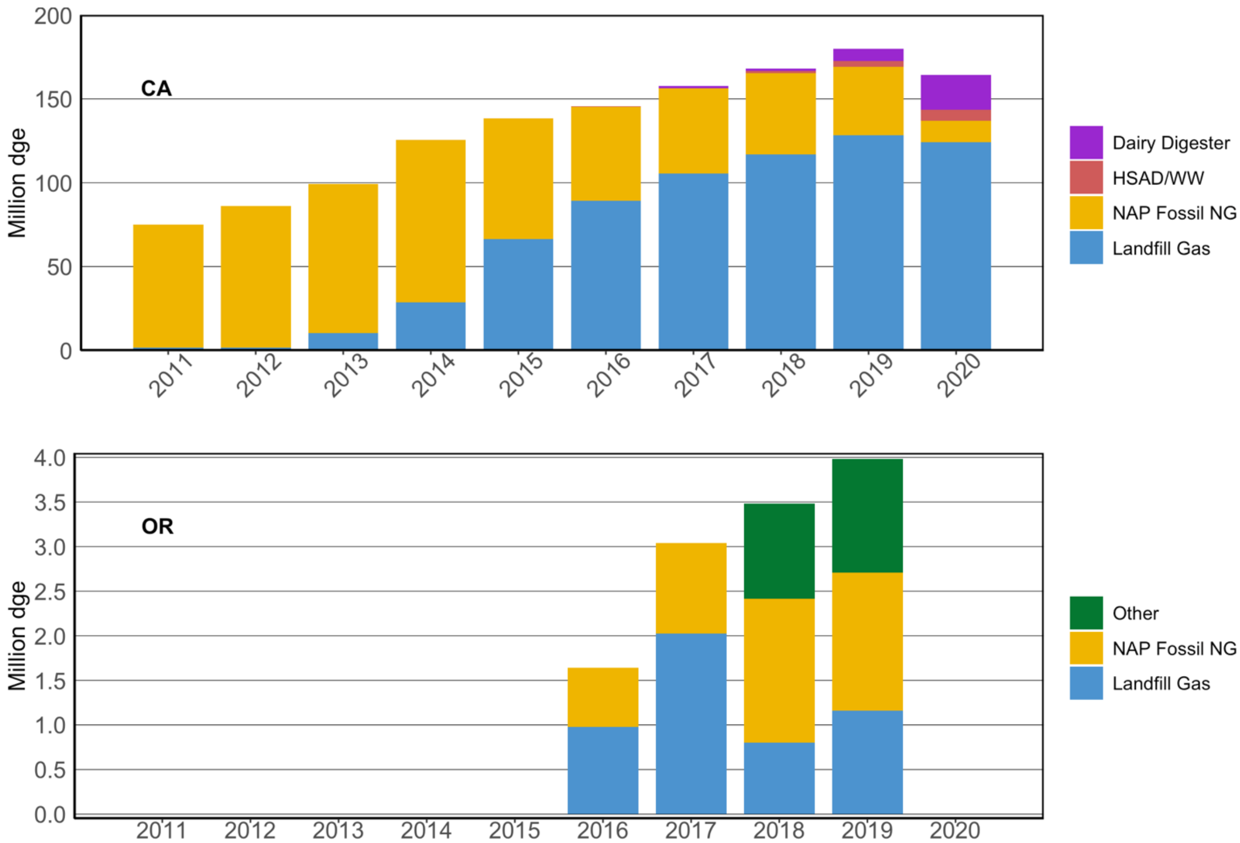

Figure 35. Natural Gas Volume by Feedstock. HSAD = High-Solids Anaerobic Digestion, WW = Wastewater, NAP = North American Pipeline, NG = Natural Gas, and dge = diesel gallon equivalents. "Other" in Oregon is unidentified biogas feedstocks like landfill gas and dairy gas. All natural gas in BC is fossil natural gas. Sources: (Peters, 2020; CARB, Low Carbon Fuel Standard Reporting Tool Quarterly Summaries, 2021c)

While most of the biogas reported in the LCFS comes from out of state, California has ambitious goals for reducing methane emissions from the uncontrolled decomposition of organic waste; incentivizing RNG production through anaerobic digestion is one key measure in this effort. Once in-state methane reduction is regulated, new RNG pathways, regardless of source, will no longer benefit from avoided methane emissions in the lifecycle analysis.

Figure 35 shows that RNG is also appearing in the Oregon transportation mix. In 2019, nearly a third of Oregon natural gas was from landfills, another third from fossil sources, and the remainder a mix of feedstocks (landfill gas and dairy gas using electricity, natural gas, or renewables as process energy). RNG appeared in BC in 2019 at 0.8 million gallons.

Electricity

Earlier sections noted the growth of electricity as a transportation fuel and expanding opportunities for crediting. In California, after crediting became available in 2019 for EV charging at below the grid average CI score using book-and-claim accounting, uptake of the opportunity has been strong, especially for public access charging. According to LCFS data, almost 90% of light-duty EV charging occurred at home, about a quarter of which received credit for a CI score below the grid average.[74] Low-CI sources comprised most of the remaining light-duty charging: approximately 95% non-residential EV charging in 2020 (Figure 36). Among all EV applications, heavy-duty EV charging experienced the most rapid growth in low-CI electricity, reaching 80 percent in the fourth quarter of 2020. In Oregon, non-residential charging grew from 4% of all reported electricity use in 2016 to 8.5% in 2019. For Oregon residential charging, in 2019 utility-specific CI scores (below the state grid average) accounted for 11.3% of the energy and 17.1% of the credits (Peters, 2020).

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[74] The calculation assumes that these credits are generated at a zero CI score. ARB does not provide information on electricity energy volumes being credited below the grid average.

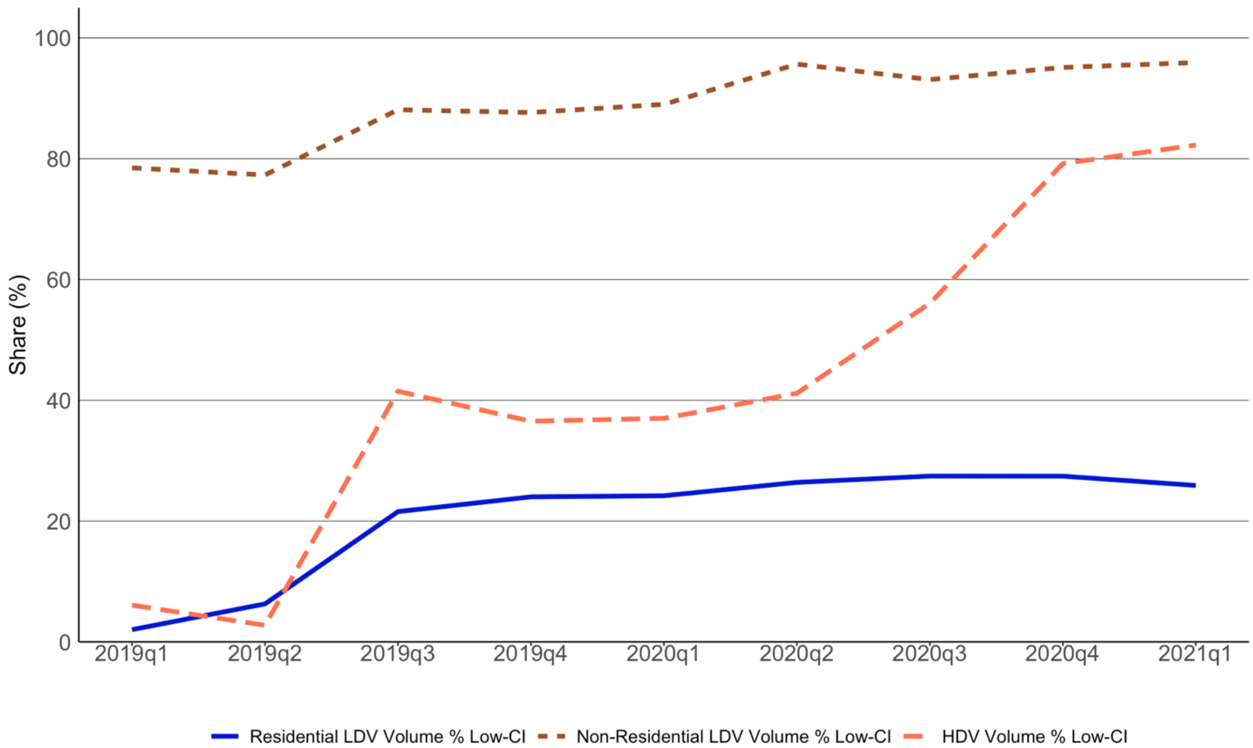

Figure 36. Share of On-Road EV Charging earning Low (Below-Grid-Average) CI Score by Quarter, 2019 Q1–2021 Q1. Assumes that all residential EV charging earning incremental credits earns a zero CI score. Source: (CARB, 2021c).

As for all credits, electricity credit revenue is realized upon sale of the credit, at timing up to the discretion of the credit holder. EV charging credits typically accrue to utilities supplying residential electricity, or the owner of charging infrastructure for non-residential.[75] Other parties can be contractually designated as the credit generator, and incremental credits from residential charging at below grid-average CI can be claimed by a variety of parties, such as the utility, automaker, or third party, provided they can accurately quantify the amount of charging. In Oregon, unclaimed residential credits accrue to a designated backstop aggregator, which works with DEQ on expenditures. California has had general guidelines directing the electricity credit value to purposes that support the EV market; investor-owned utilities in Oregon face similar

[75] Both California and Oregon estimate electricity use for non-metered residential charging — currently the vast majority — on the small proportion of metered residential charging for which data are available. The regulations point to use of the best available information to develop the estimate, but methods and results are not currently made public.

restrictions from the Public Utilities Commission regarding CFP EV credit revenue use. Credit value, in other words, does not necessarily or generally go toward lowering the retail price of electricity.

Starting in late 2020, the majority of California's residential EV charging credit revenue moved from funding utilities' existing programs broadly supportive of EVs to funding a statewide EV rebate program, typically $1,500. Unlike the federal EV tax credit and California's Clean Vehicle Rebate Program, the $1,500 rebate is available at the time of sale, rather than afterward. New provisions stipulate that a proportion of the remaining credit revenue go toward transport electrification benefiting disadvantaged, low income, and rural communities.

In 2021, Oregon adopted electricity provisions in response to a gubernatorial order to explore ways to use the Clean Fuels Program to promote state EV goals. They include book-and-claim accounting for below-the-grid CI scores, like the California system, to generate incremental credits.[76] Unclaimed residential incremental credits will accrue to a newly designated incremental aggregator, to be spent in consultation with a new Equity Advisory Committee as well as DEQ. Oregon also instituted a system to advance EV credits for public vehicle or service fleets, essentially providing upfront credit loans to help get EVs into these fleets, which are then paid back over time through holding back electricity credits as they are generated for the life of the loan.

Infrastructure, Carbon Capture and Sequestration, and Other Non-Fuel Credits

As noted in Section 3.1, BC was the first jurisdiction to allow LCFS credit generation, via Part 3 Agreements from the program's outset, for activities supporting future low carbon fuel flows, rather than low carbon fuel flows themselves. California followed in its 2018 amendment

[76] However, unlike the California system, where "incremental credits" are only earned on residential charging (although low-CI charging is accessible for charging elsewhere), in Oregon incremental credits can be earned for both residential and non-residential charging.

package, but in a way that targeted ZEVs in line with its state goals, with ZEV infrastructure capacity credit provisions.[77] The provisions essentially credit applicable hydrogen refueling infrastructure (HRI) and direct current (DC) fast charging infrastructure (FCI) as if it were being used at its rated capacity, ensuring at least a partial income stream for new projects deployed before a sufficient vehicle fleet has emerged to fully use the capacity. ZEV infrastructure credits are awarded according to the station's capacity minus the quantity of energy dispensed, which earns charging credits. As of July 2021, 61 hydrogen stations and 1,155 DC fast chargers at 205 sites in California have been approved for ZEV infrastructure crediting under the LCFS.[78] In Oregon, by contrast, CFP credits must represent actual GHG reductions by law.

During the 2018 amendment and extension rulemaking, CARB became the first jurisdiction to adopt a protocol outlining requirements for carbon capture and sequestration (CCS) underground to generate LCFS credits. Project developers are subject to a variety of requirements pertaining to site selection and long-term monitoring for decades after underground injection has ceased. Crediting is prorated by volume of fuel delivered to California. Notably, CARB allowed projects that capture and sequester CO_2 from ambient air (as opposed to an exhaust or byproduct stream) to be eligible for LCFS credit generation, even if they are located outside of California and are unconnected to a fuel production system. Direct air capture was judged to be a critical technology for long-term climate mitigation, for which no existing carbon or environmental markets appeared capable of providing sufficient revenue to support new projects. At the time of writing, there are no CCS or direct air capture certified LCFS pathways, however several CCS pathways underwent the public comment process in 2020.

[77] For hydrogen stations, this is based on the station's daily dispensing capacity. For fast chargers, it employs a formula which results in an assumption that a charger's capacity is a number of kWh approximately equal to its nameplate capacity in use for four hours out of any 24-hour period.
[78] See https://ww2.arb.ca.gov/resources/documents/lcfs-zev-infrastructure-crediting.

3.6 Interactions between LCFS Markets

Effects of Proximate LCFS Markets

The three currently operating LCFS programs operate independently of each other, however there are avenues for potential interactions. All three jurisdictions share access to trans-Pacific shipping routes, as well as North American road, rail, petroleum pipeline, electrical and natural gas networks. All three receive most of their biofuels from agricultural regions to the east, with water-borne shipment a secondary route of import. While any alternative fuel policy potentially draws from similar global pools of alternative fuels, these three jurisdictions may be more likely to have overlap in potential fuel suppliers due to proximity. Fuel producers that sell into one market may have the logistical capacity to sell into the others. Differences in transport distance, regulatory or tax structure, and vehicle fleets would create differences in delivered price, CI, or total alternative fuel demanded in each jurisdiction, which would impact producers' allocation decisions.

Transportation costs and capacity or regulatory constraints may functionally limit the capacity of some fuel producers to be competitive in certain. The potential for competition over a finite alternative fuel supply could be exacerbated for proximate markets by the similarity in transport distances and potentially cost to bring fuels to the various markets. With LCFS-like policies on the rise — e.g., in PCC jurisdictions committed to adopting — jurisdictional-level projections of fuel availability and demand should account for demand from other markets, especially ones that are geographically near, or that share regulatory, economic or technical characteristics (Malins, et al., 2015).

California, in particular, has significant demand for transportation fuels and despite agriculture's significant contribution to its overall economy, it has only supplied between 10% and 15% of its own demand for liquid biofuels, a trend expected to continue according to various projections (Jaffe, Dominguez-Faus, Scheitrum, Wilcock, & Miller, 2016) (Williams, Jenkins, & Kaffka, 2015). Research has identified likely sufficient supplies for the PCC jurisdictions to meet 2030 targets (Malins, et al., 2015), and a recent study assessing the feasibility of a Colorado LCFS found fuel availability not to be a significant obstacle.

Harmonization and Linkage of Markets

Linkage between market-based carbon policies can take a variety of forms, from explicit linkage in a common market, like the Western Climate Initiative that oversees the joint cap and trade market adopted by California and Quebec, to policies that facilitate more efficient low carbon fuel supply for use within market jurisdictions without the need for additional transportation of physical fuel. California, Oregon, and BC are all signatories, along with Washington, to the Pacific Coast Action Plan on Climate and Energy (2013) and the Pacific Coast Climate Leadership Action Plan (2016), committing members to the adoption of LCFS programs and creating a framework for information exchange and informal coordination between regulatory officials. CARB has offered significant support to policy makers and staff in other jurisdictions, and the implementing agencies coordinate on emerging issues, leading to a discernable commonality between many provisions of these programs.

Even without formal linkage, fuel and credit markets in LCFS jurisdictions are connected via common fuel suppliers and shared infrastructure. Jurisdictions that possess comparatively less regulatory capacity can reduce their policy development burdens by adopting provisions that have been developed and refined elsewhere. Adopting similar tracking, analysis, trading, and settlement practices can put fuel producers in a position to adapt more easily to changing market conditions, including switching markets to maximize revenue. Policy adaptations to a range of conditions, with information exchange, can lead to more robust policy across the board.

The three jurisdictions that have implemented carbon markets have done so with limited formal alignment of program provisions. Oregon recognizes fuel pathways certified in California as valid, provided appropriate modifications are made to reflect the differing transport distances and methods. LCFS jurisdictions have harmonized the evolution of the policy by moving in similar policy directions, often with California acting first. Specific provisions targeting equity improvements have recently been included in California's and Oregon's programs.

3.7 Conclusion

This report overviews and compares public data from LCFS programs in California, Oregon, and BC, finding that more and lower carbon fuels appeared in each jurisdiction. As noted in various sections, additional transparency and common data standards or formats across programs would facilitate market trend analysis. In particular, EV data include aggregations of credit or volume data that make the reported CI score difficult or impossible to discern. Estimates of unmetered residential EV charging activity used for crediting in the US jurisdictions are not publicly available, nor is the underlying data used to derive these estimates.

While California periodically publishes a histogram summarizing credit holding patterns, more nuanced data and reporting from all jurisdictions would permit a better sense of aggregate exposure across the fuel sector to future fluctuations in credit or fuel markets. Additional quantitative transparency into the LCAs used to generate pathway CI scores would also allow a better understanding of the scalability of alternative fuel production pathways and the bottlenecks which prevent such expansion.

Finally, further research into fuel market response as these programs increase in stringency and evolve and as other jurisdictions adopt similar policies will help shed light on complexities of market interaction and aggregate demand. This research is critical for the compliance outlook for these programs, as well as to explore incompletely understood relationships surrounding global capacity for biomass production and the associated land use change risks, technological evolution in energy systems, and consumer preferences.

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