UNIVERSITY OF CALIFORNIA

Uncertainty, Innovation, and Infrastructure Credits: Outlook for the Low Carbon Fuel Standard Through 2030

A Research Report from the University of California Institute of Transportation Studies

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16. Abstract

California's low carbon fuel standard (LCFS) specifies that the state's transportation fuel supply achieve a 20% reduction in carbon intensity (CI) below 2011 levels by 2030. Reaching the standard will require substantive changes in the fuel mix, but the specifics and the cost of these changes are uncertain. We assess if and how California is likely to achieve the standard, and the likely impact of infrastructure credits on this compliance outlook. We begin by projecting a distribution of fuel and vehicle miles demand under business-as-usual economic and policy variation and transform those projections into a distribution of LCFS net deficits for the entire period from 2019 through 2030. We then construct a variety of scenarios characterizing LCFS credit supply that consider different assumptions regarding input markets, technological adoption over the compliance period, and the efficacy of complementary policies. 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, but if the number of electric vehicles reaches Governor Jerry Brown's goal of 5 million by 2030, then LCFS compliance would require substantially less biomass-based diesel. Outside of rapid zero emission vehicle penetration, compliance in 2030 with the $200 credit price may be much more difficult. New mechanisms to allow firms to generate credits by building electric vehicle charging stations or hydrogen fueling stations have minor implications for overall compliance because the total quantity of infrastructure credits is restricted to be relatively small.

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Glossary

BAU	business as usual
BBD	biomass-based diesel
CARB	California Air Resource Board
CARBOB	California reformulated blendstock for oxygenate blending
CaRFG	California reformulated gasoline
CCS	carbon capture and sequestration
CI	carbon intensity
EIA	Energy Information Administration
EMFAC	EMission FACtors (EMFAC): a model to calculate statewide or regional emissions inventories
EER	energy economy ratio
EV	electric vehicle
GSP	gross state product
ICS	illustrative compliance scenario calculator
LCFS	low carbon fuel standard
ULSD	ultra-low sulfur diesel
VEC	vector error correction
VMT	vehicle miles traveled
ZEV	zero-emission vehicle

Executive Summary

California's low carbon fuel standard (LCFS) specifies that the state's transportation fuel supply achieve a 20% reduction in carbon intensity (CI) below 2011 levels by 2030. Reaching the standard will require substantive changes in the fuel mix, but the specifics and the cost of these changes are uncertain. Since the policy was extended in 2019, the price of LCFS compliance credits has been close to its maximum allowed value, which indicates that fuel-market traders expect compliance to be expensive to achieve, if it can be achieved at all. Uncertainty surrounding compliance stems from the unknown future market penetration of alternatives to the internal combustion engine, such as electric vehicles, as well uncertainty about growth in the state economy, oil prices, vehicle miles traveled, and fuel economy.

In this report, we assess if and how California is likely to achieve the proposed 20% reduction in CI values by 2030, and the likely impact of infrastructure credits on this compliance outlook. We take an approach similar to Borenstein et al. (2019) in their paper on cap-and-trade markets. We begin by projecting a distribution of fuel and vehicle miles demand under business-as-usual (BAU) economic and policy variation. We use the term BAU to imply continuation of the trends, correlations and volatility observed in the data since 1987. We transform our BAU projections into a distribution of LCFS net deficits for the entire period from 2019 through 2030, assuming a steady draw-down of the currently accumulated credit "bank." Given the stable long-run relationships between fuel markets, oil prices, vehicle miles, and general economic activity, we employ a vector error correction (VEC) model to account for the cointegration between these variables when estimating coefficients. This approach results in projected outcomes that become more uncertain as predictions move farther out of sample and allows us to project distributions of demand under BAU economic conditions. We fit our model using quarterly data from 1987-2018 and make projections for years 2019-2030, which we refer to as the compliance period.

We then construct a variety of scenarios characterizing LCFS credit supply that consider different assumptions regarding input markets, technological adoption over the compliance period, and the efficacy of complementary policies. By interacting our distribution of demand outcomes with various supply scenarios for LCFS credits, we are able to estimate the equilibrium number of LCFS credits supplied to the market for various credit-generating sources and analyze the change in those quantities across scenarios. Given our distribution of deficits and estimates of credits under each scenario, we can assess the fuel mix in the diesel pool required to achieve annual compliance.

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 Governor 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 zero tailpipe-emission vehicle (ZEV) penetration, compliance in 2030 with the $200 credit price may be much more difficult. For instance, a scenario in which carbon capture and sequestration (CCS) is widely adopted in ethanol plants would bring the median biomass-based diesel (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 amount 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, which is plausible, then the median draw requires nearly 100% of diesel to be biomass-based.

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 electric vehicles, 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. Nonetheless, because the total quantity of infrastructure credits is restricted to be relatively small, their effect on potential compliance scenarios is small.

1. Introduction

State and local policy makers in the U.S. and beyond are looking to low carbon fuel standards (LCFSs) as a policy instrument for reducing greenhouse gas emissions in the transportation sector. California implemented its LCFS in 2011, setting a target of a 10% 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% 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 10% from 2015 to 2025.[1,2] Washington State failed in several legislative attempts to pass an LCFS that proposed a 10% reduction over a 10-year period, most recently in 2019.[3] Also in Washington State, Puget Sound Air Quality Agency is considering a regional clean fuel standard to contribute to its 2030 greenhouse gas emissions goals.[4] 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).[5]

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 infrastructure related to electric vehicle (EV) charging facilities and hydrogen fueling stations. 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.

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

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

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

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

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

In this report, we assess if and how California is likely to achieve the proposed 20% 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 variation, 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 credit generation not yet prevalent in the policy, we use California Air Resource Board (CARB) 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.[6] Credit supply scenarios also cover certain state goals, showing sensitivity of results to, for example, meeting the Governor's goals for battery EVs 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 the BAU scenario 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 report is structured as follows. Section 2 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 3, we describe our data and econometric model used to forecast BAU demand for LCFS credits and discuss the projected outcomes. In section 4, we characterize a variety of scenarios regarding LCFS credit supply and assess annual compliance in each. Finally, in section 5, we conclude by discussing the implications of our analysis and highlight opportunities for future research.

2. Background: The California LCFS

The California LCFS was initially implemented in 2011, amended in 2013, re-adopted in 2015, and extended in 2019 to set targets through 2030. The LCFS is a standard whereby providers of transportation fuel (e.g., oil companies and refiners) are required to reduce the carbon intensity (CI) of their fuel mix each year. Each year, the CI must be reduced further below the CI

[6] CARB 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.

of a petroleum-based reference fuel (e.g., 0.25% below the reference fuel in 2011 to 10% below in 2020). 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 carbon intensity of transportation fuels measured in CO2e per megajoule of energy, 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 sales of 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.[7] 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 very 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.

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 7. LCFS credits are awarded to fuels with a reported CI rating below the standard, and LCFS 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.[8]

2.1 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

[7] See Holland, Hughes, and Knittel 2009.

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

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 fuel suppliers to generate credits through the installation of infrastructure, rather than the production of fuel.

Fueling infrastructure credits are limited to ZEVs—i.e., hydrogen fuel cell vehicles and battery EVs. 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 fuel. Rather, the credits subsidize a fixed cost of providing network infrastructure that may encourage adoption of EVs, a technology that 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.

2.2 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.[9] In its 2015 re-adoption rule, CARB introduced the credit clearance market, which is a cost-containment mechanism that would in theory limit price increases under some scenarios.

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

[9] 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.

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 may be able to sell their credits at a higher price in the future. Thus, the credit clearance market provides only a soft cap. However, CARB 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 EV 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, CARB proposed amendments that would backstop this cost containment mechanism, enforcing additional borrowing of future credit generation from residential electricity charging for EVs 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.

3. 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.

3.1 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.[10] 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

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:

$$Y_{1t} = \beta_{10} + \beta_{11}Y_{4t} + \beta_{12}Y_{5t} + \beta_{13}Y_{6t} + z_{1t} \quad (1)$$
$$Y_{2t} = \beta_{20} + \beta_{21}Y_{4t} + \beta_{22}Y_{5t} + \beta_{23}Y_{6t} + z_{2t} \quad (2)$$
$$Y_{3t} = \beta_{30} + \beta_{32}Y_{5t} + z_{3t} \quad (3)$$

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.[11] 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:

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

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

[10] 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.
[11] The purpose of this third equation is to model the marginal cost of producing biomass-based diesel, which can then be used to model the LCFS credit price under the assumption that biomass-based diesel is the marginal compliance fuel. We do not conduct that analysis in this report; we defer it to future research.

deviations from the cointegration relationship. Putting equations 1-3 together with equation 4, we can write the model as:

$$\Delta Y_t = \alpha\beta_0 + \alpha\beta' Y_{t-1} + \Sigma_{j=1}^{p-1}\Gamma_j \Delta Y_{t-j} + \Sigma_{k=1}^{4}\omega_k s_k + \varepsilon_t \qquad (5)$$

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

3.2 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.[12] California GSP was collected from the Bureau of Economic Analysis.[13] The 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.[14] We chose to use Brent oil prices rather than West Texas Intermediate 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.[15] On-highway VMT data are reported in the aggregate, and not divided into gasoline and diesel vehicles.[16] Our model also requires soybean prices, which we collect from the Agricultural Marketing Service at the United States Department of Agriculture (USDA).[17] We aggregate monthly spot prices in Central Illinois to quarterly averages to be used in the model.

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[12] 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.

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

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

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

[16] 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 (EMission FACtors: a model to calculate statewide or regional emissions inventories), we find that on-highway VMT make up 56% of total VMT in California 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.

[17] 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.

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.[18] This measure captures all finished gasoline that is consumed in 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% 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% 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.[19] 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.[20] We therefore make the assumption, 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 do not consider altering this 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.

3.3 Coefficient Estimates from the VEC Model

The long-run coefficient estimates from the VEC cointegration model appear in Table 1. 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 1 correspond to the three cointegrating

[18] 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."

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

[20] 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

equations specified in equations 1, 2, and 3, and the rows, to their long-run relationships with GSP, VMT, and the oil price.

Table 1. Long-Run Coefficient Estimates of the Co-Integrating Equations

	ln(**CaRFG**)	*ln*(**Diesel**)	*ln*(**Soybean 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 1, 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 small, and statistically insignificant at the 5% level. This may reflect the 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 1, along with the short-run estimates located in the appendix in Table 5 and random shocks, to project a range of forecasts for gasoline, diesel, and vehicle miles demand out to 2030.

3.4 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 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:

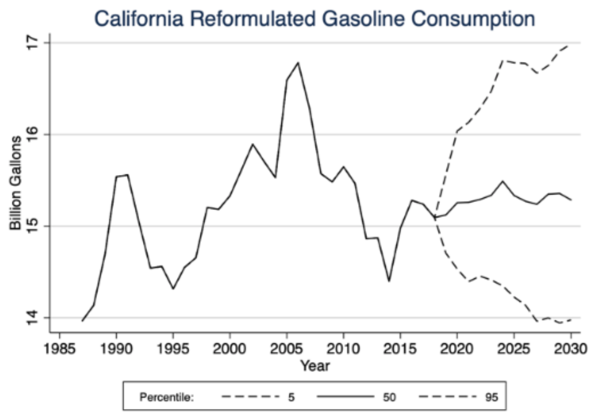
$$\hat{Y}_{kt} = \hat{Y}_{k,t-1} + \hat{\alpha}\hat{\beta}_0 + \hat{\alpha}\hat{\beta}'\hat{Y}_{k,t-1} + \Sigma_{j=1}^{p-1}\hat{\Gamma}_j\Delta\hat{Y}_{k,t-j} + \Sigma_{k=1}^{4}\hat{\omega}_k s_k + \hat{\varepsilon}_{kt}^{*}, \tag{6}$$

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 $i = 1,2,\ldots,6$.

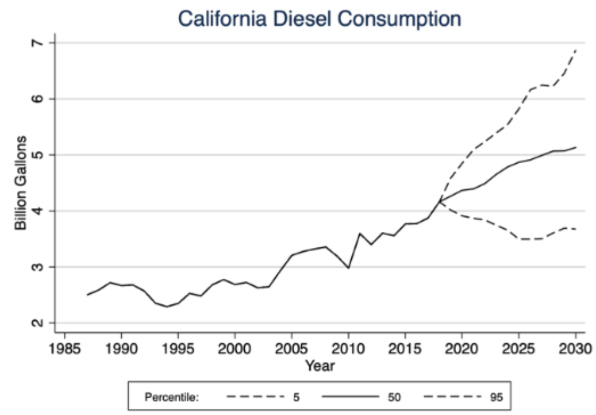
The hypothetical paths for blended gasoline, diesel, and VMT, simulated using equation 6, are described in Figure 1 with the median draw from each year (solid line) and a 90% pointwise confidence interval (dashed lines).[21] In addition to those variables, we calculate the fuel economy of gasoline vehicles that is implied under BAU conditions. To do so, we multiply each VMT projection by the percent estimated in CARB's EMFAC (Emissions FACtors) model to come from gasoline-powered vehicles (approximately 90%).[22] 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 1 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 greenhouse gas emissions per mile for model years 2022 through 2026.[23]

For each variable in our VEC model, the level of uncertainty grows as we move further into the future. In Figure 1, 90% of the draws from our sample fall between 14 and 17 billion gallons of CaRFG being consumed in 2030—a 13% decrease and 12% increase, respectively, from current levels. By similar calculations, the 90% confidence interval for consumption of diesel falls between a 10% reduction and 75% increase from current levels by 2030. The range of possibilities for diesel consumption is shown in Figure 1. Lastly, VMT increases above current levels in 90% of the draws as shown in Figure 1. 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.

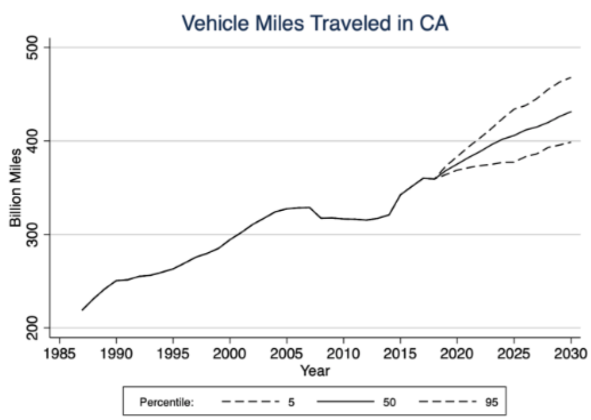
[21] Plots of GSP, oil prices, and soybean prices can be found in the Appendix A.
[22] Using data from CARB's EMFAC model, we find that gasoline-powered vehicles make up approximately 90% of California VMT, and this is projected to decline slowly over the next decade due to EV penetration. We use this projected percentage in each year to find VMT attributable to gasoline vehicles for each draw of our simulations.
[23] See https://www.reuters.com/article/us-autos-emissions/california-four-automakersdefy-trump-agree-to-tighten-emissions-rules-idUSKCN1UK1OD.



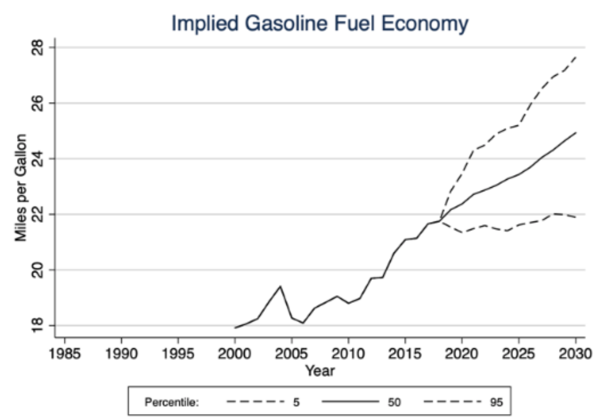
(a) CaRFG



(b) **Diesel**



(c) **VMT**



(d) **Implied MPG of Gasoline**

Figure 1. Demand Forecasts under BAU Variation

3.5 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% of CaRFG, with the remaining 10% being ethanol. Therefore, the BAU projection assumes that the E10 blend wall persists through 2030. Pursuant to our definition of BAU, the currently observed BBD blend rate in the liquid diesel pool persists through 2030 as well. That is, we assume that 20% 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 2.

Table 2. 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 (EVs). We have to make an assumption regarding the penetration of EVs 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.[24] EMFAC projects 1.3 million EVs on California roads by 2030. Table 3 shows how EMFAC 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 3 also shows our BAU assumptions regarding the CI rating of electricity. We use the current grid average CI rating and energy economy ratios (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 alternative scenarios to the BAU and sensitivity analyses on the results.

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

Table 3. 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 3, 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% fewer miles" assumption also to heavy-duty EVs and assess the displaced petroleum fuel all from the gasoline pool.[25] With these assumptions, we can project a quantity of kilowatt-hours 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. Specifically, we calculate the number of kilowatt-hours for light-duty EVs according to the following equation:

$$kWh_t = s_t \times (0.7 \times X_{4t}) \times 0.32 , \tag{7}$$

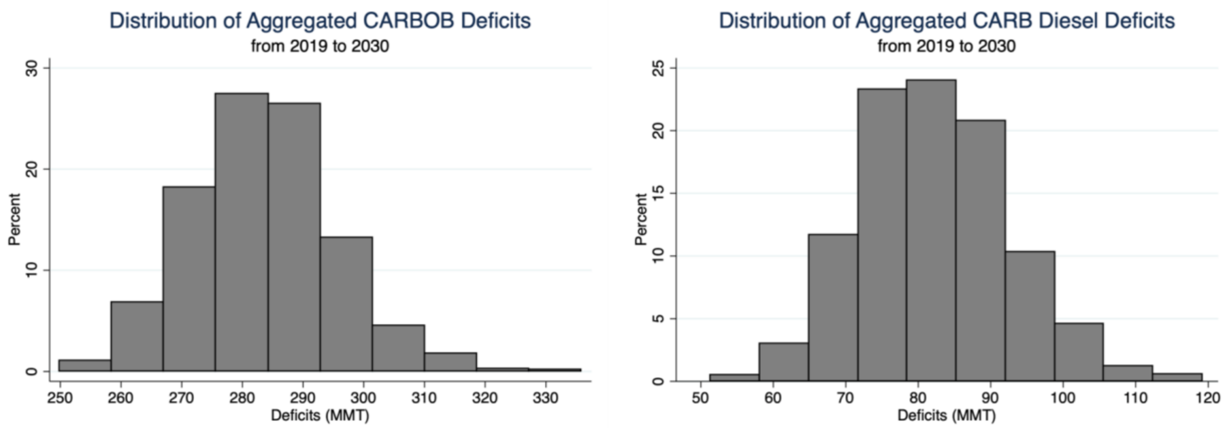
where s_t is the share of EVs to all vehicles in year t, X_{4t} is vehicle mile demand from the VEC model, and the 0.32 scale factor translates miles into kilowatt-hours.[26] Then, credits from electricity can be calculated by plugging in the number of kilowatt-hours into equation 18.

Using the parameters from Table 2 and Table 3, 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.[27] The distributions of deficits from each fuel are plotted in Figure 2. Figure 2a 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

[25] 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.
[26] The AFDC reports this: https://afdc.energy.gov/vehicles/electric_emissions_sources.html.
[27] See equation 18 in the Appendix Afor more details.

given CI rating generates more deficits in later years because the gap between it and the required CI increases due to the annual decrease in the CI standards.

The total demand for LCFS credits plotted in Figure 3 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 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 year-to-year credit availability.



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

Figure 2. Projected Distributions of BAU Deficits by Fuel

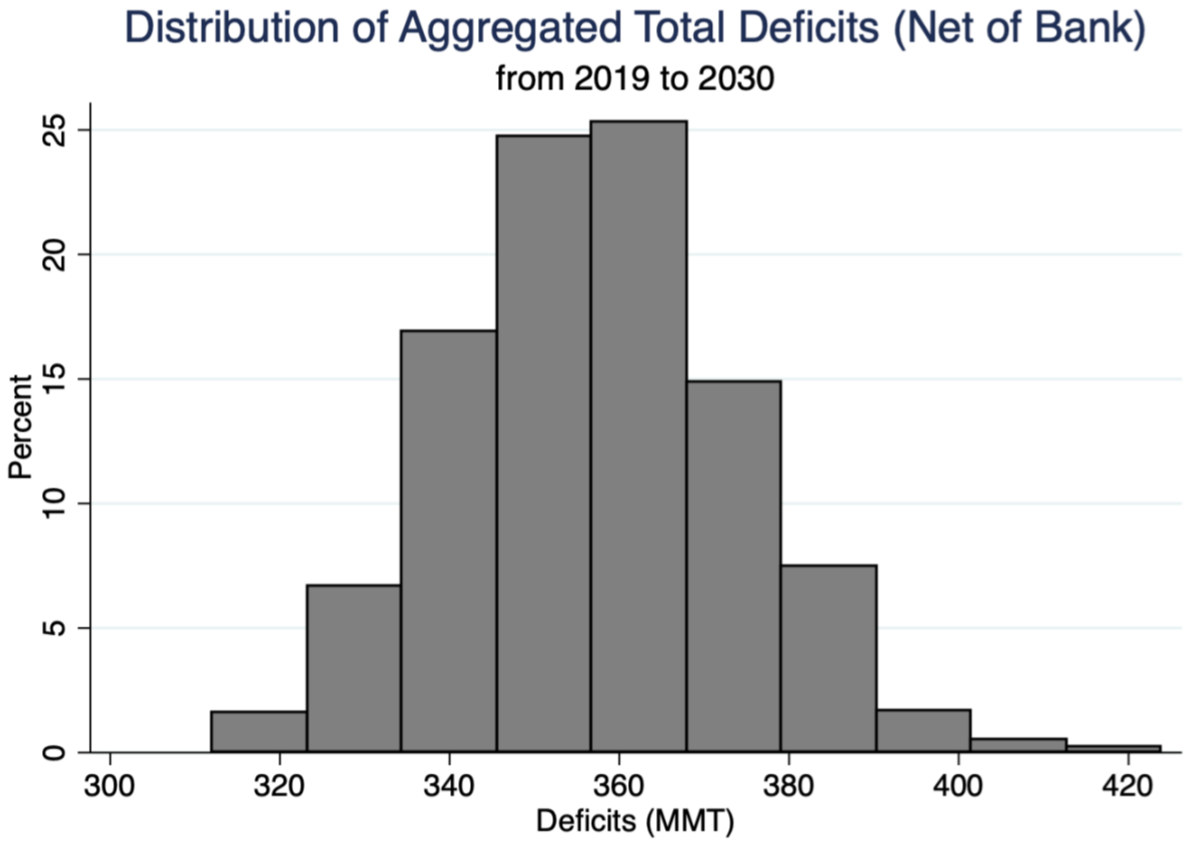


Figure 3. Projected Distribution of BAU LCFS Deficits

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 4, BBD, ethanol, and on-road electricity make up 90% of the credits that were generated in 2018. For the remaining pathways, we assume 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—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.

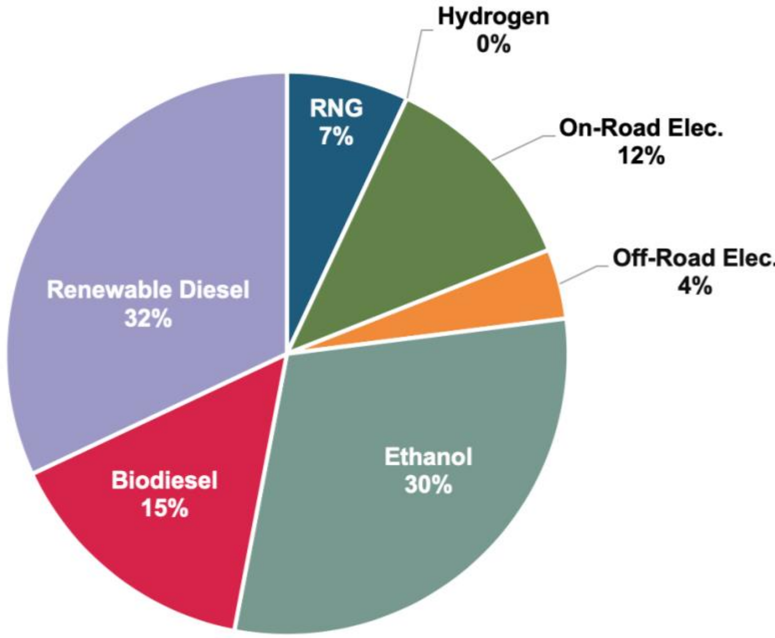


Figure 4. LCFS Credit Generation by Pathway in 2018 (RNG, renewable natural gas)

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 variation. We present these results in Figure 5 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 5 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 the magnitude of change required for compliance if past trends in fuel consumption and the state economy continue. On average across simulations, deficits are 163.61 MMT greater than credits over the entire compliance period. Figure 3 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.

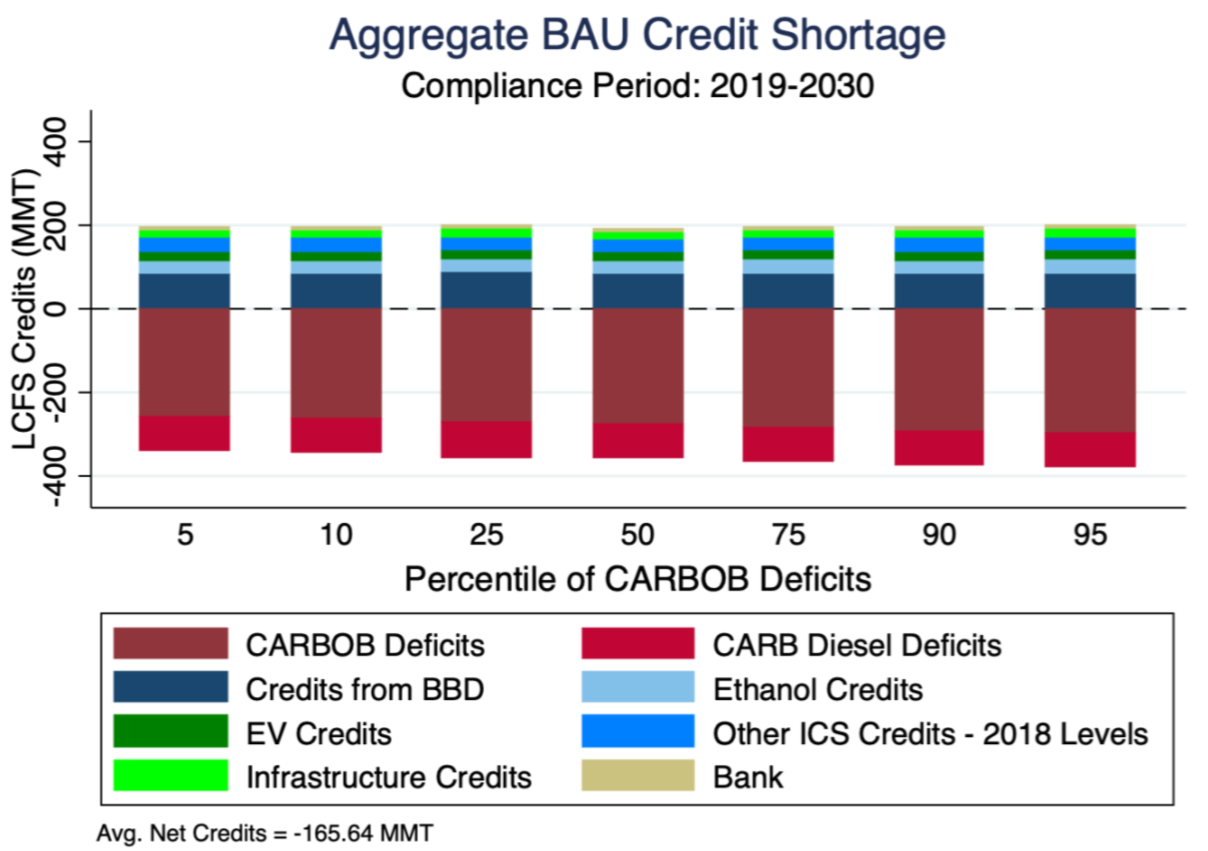


Figure 5. Projected LCFS Credit Generation under BAU

The BAU case depicted in Figure 5 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.

4. Compliance Scenarios

Our projection of deficits under BAU variation 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 blend wall 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.[28] Massive growth in newer technologies such as hydrogen, natural gas, or EVs would require those technologies to have a 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 renewable natural gas 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 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.

4.1 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

$$ND_t^C \equiv D_t^C - elec_t^{on} - eth_t - infra_t - other_t - bank_t\,, \tag{8}$$

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 section A.4 of 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 7. 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. In contrast, the future of reported CIs of BBD is uncertain and will depend on a few different factors.

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

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 and tallow currently generate the lion's share of LCFS credits from BBD. However, it is plausible that used cooking oil 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 (ψ_t^B), we can solve the following system of two equations for the two unknowns, B_t and U_t for $t = 2019, \dots, 2030$.

$$D_t = B_t + U_t \tag{9}$$

$$ND_t^C = \psi_t^b B_t + \psi_t^U U_t \tag{10}$$

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

$$U_t^* = \frac{D_t - \frac{ND_t^C}{\psi_t^B}}{1 - \frac{\psi_t^U}{\psi_t^B}} \tag{11}$$

$$B_t^* = \frac{D_t - \frac{ND_t^C}{\psi_t^U}}{1 - \frac{\psi_t^B}{\psi_t^U}} \tag{12}$$

Using equations 11 and 12, we can calculate the diesel pool blend rate that would be required for compliance under each of our scenarios accordingly:

$$BR_t^* = \frac{B_t^*}{B_t^* + U_t^*} \tag{13}$$

4.2 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 4 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 CARB'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.[29] 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 4. 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 ZEVs on California roads by 2025 and 5 million by 2030.[30] 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 increase at a constant rate to 5 million by 2030. We refer to this set of assumptions as A2 in Table 4.

Table 4. 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
A3	Dec. Ethanol CI	1.3M by 2030	65 → 40	32	Min
A4	Inc. BBD CI	1.3M by 2030	65	32 → 50	Min

The CI rating of ethanol is also independent of demand. The future path of the CI value for ethanol will depend on technology development and adoption. CARB, in the ICS, assumes 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% reduction from the current level.[31] 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

[29] We do not explicitly model credit price, but extrapolate from trends visible under historical credit pricing.
[30] 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.
[31] The specific path for the ethanol CI rating assumed in the ICS can be found in Figure 10 in the Appendix.

scenario in which the ICS CI projections are realized. We refer to these set of assumptions as A3 in Table 4.

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 4.

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 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 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.

4.3 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 equations 11, 12, and 13, respectively. Figure 6 shows the implied blend rate resulting from the baseline scenario and Figure 7 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 9.

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 7, 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 were not 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 11-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 6 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 6, 90% of the blend rates from our simulations fall between 60% and 80% 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 7 shows that allowing for the largest number of credits from the other sources in the ICS (see discussion above for context on CARB'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 CARB scoping plan model.

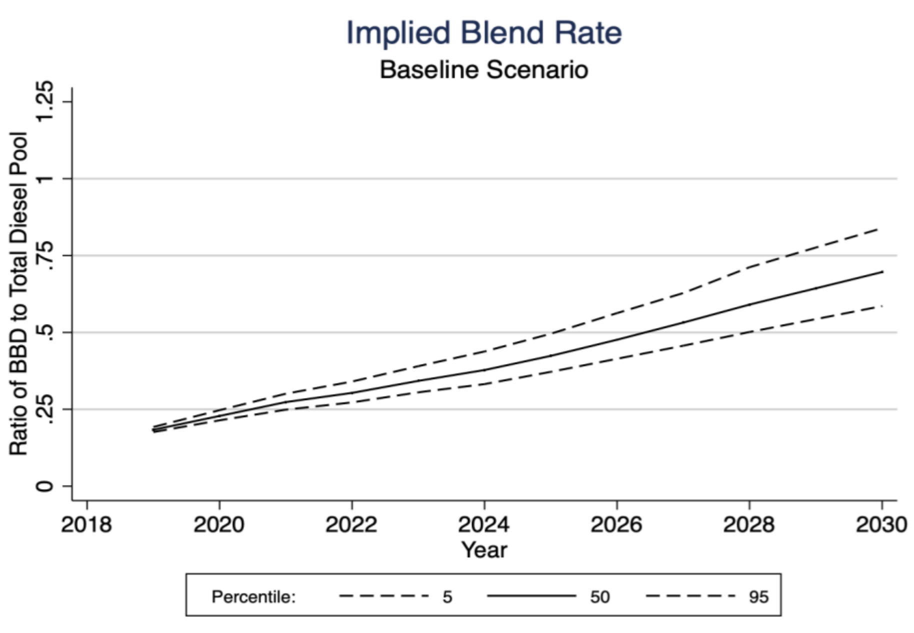
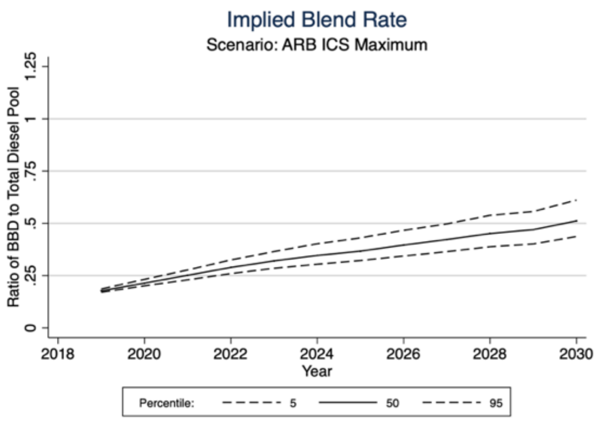
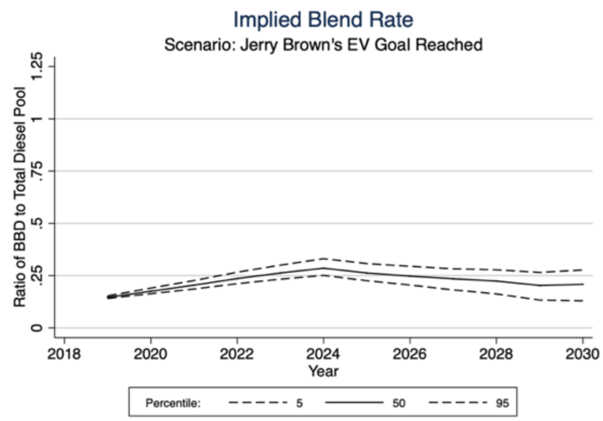


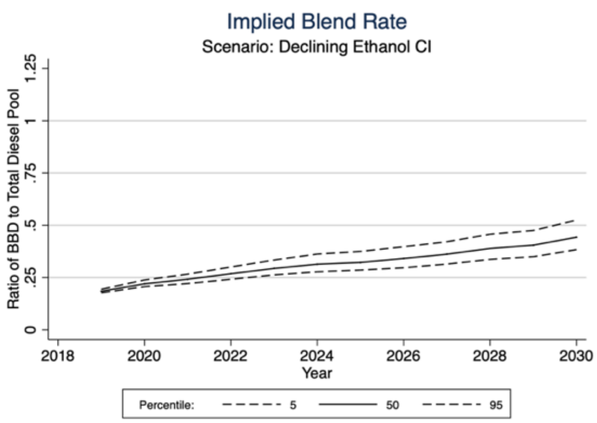
Figure 6. Projected Baseline Implied Blend Rate



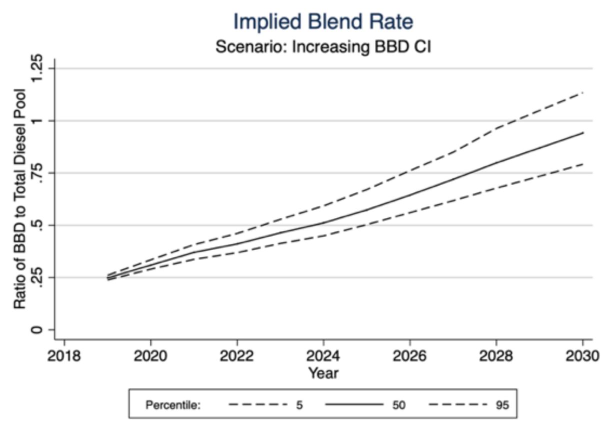
(a) **A1. ICS Maximum Credits**



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



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



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

Figure 7. Projected Implied Blend Rates under Compliance Scenarios Plan Modeling.

In contrast, rapid EV growth has the potential to reduce the blend rate below 25% in 2030, as shown in Figure 7. 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 7 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% in 2030 to achieve compliance, as shown in Figure 7. 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.[32]

5. Conclusions

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) variation, 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 11-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 variation 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 EVs, as well as uncertainty around adoption of technologies such as carbon capture and sequestration (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 EVs reaching 1.3 million by 2030, however if the number of EVs increases more rapidly than what is captured under BAU conditions and reaches Governor 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

[32] 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.

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 to 50, the median draw requires nearly 100% of diesel to be biomass-based.

Since 2016, CARB 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 EV 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.

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Holland, Stephen P., Jonathan E. Hughes, and Christopher R. Knittel (2009). “Greenhouse Gas Reductions under Low Carbon Fuel Standards?” In: *American Economic Journal: Economic Policy* 1.1, pp. 106–146. issn: 1945774X. doi: 10.1257/pol.1.1.106.

Appendix A

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

A.1 Additional Output from Simulations and the VEC Model

The estimates of the β and Γ matrices from the VEC model in equation 5 appear in Table 5.

Table 5. 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)

	ΔY_{1t}	ΔY_{2t}	ΔY_{3t}	ΔY_{4t}	ΔY_{5t}	ΔY_{6t}
$\Delta Y_{3,t-3}$	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)
$\Delta Y_{4,t-3}$	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 6 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 6. 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

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 7
- $CI_{reported,i,t}^{XD}$ 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.

$$Credits_{i,t}^{XD}\ (MT) = \left(CI_{standard,t}^{XD} \& -\ CI_{reported,i,t}^{XD}\right) \times E_{displaced,i,t}^{XD} \times C \qquad (14)$$

where

$$CI_{reported,i,t}^{XD} = \frac{CI_{it}}{EER_i^{XD}} \qquad (15)$$

and

$$E_{displaced,i,t}^{XD} = E_{it} \times EER_i^{XD} \qquad (16)$$

and

$$E_{it} = ED_i \times Q_{it} \tag{17}$$

Substituting equations 15, 16, and 17 into equation 14, we can then express credits as:

$$Credits_{it}^{XD}(MT) = \left(CI_{standard,t}^{XD} - \frac{CI_{it}}{EER_i^{XD}}\right) \times ED_i \times Q_{it} \times EER_i^{XD} \times C \tag{18}$$

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

$$Aggregate\ LCFS\ Credits = \Sigma_{i\in I}\Sigma_{t=0}^{T} Credits_{it}^{XD} \tag{19}$$

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 7. LCFS CI 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

A.3 Credit Generation from 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:

$$Credits_{FCI}^{i}(MT) = (CI_{standard,t}^{XD} \times EER - CI_{FCI}) \times C_{elec} \times (Cap_{FCI}^{i} \times N \times UT - Elec_{disp}) \times C \quad (20)$$

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 $EER = 3.4$

A.4 Cap on Total FCI 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:

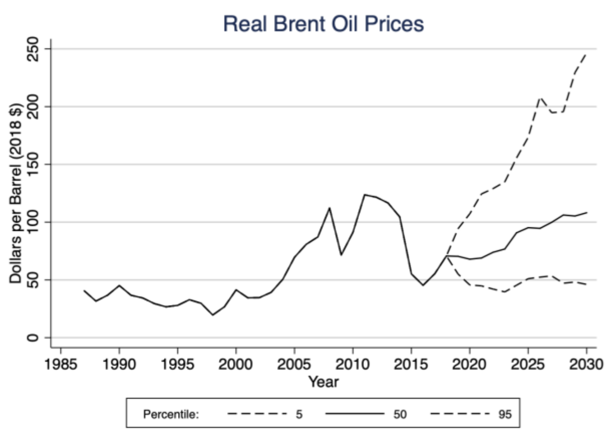
$$Credits_{FCI}^{potential}(MT) Credits_{FCI}^{prior\ qtr} \times \left(\frac{CAP_{FCI}^{approved}}{CAP_{FCI}^{rational}}\right) \quad (21)$$

Applications to generate credits are approved until

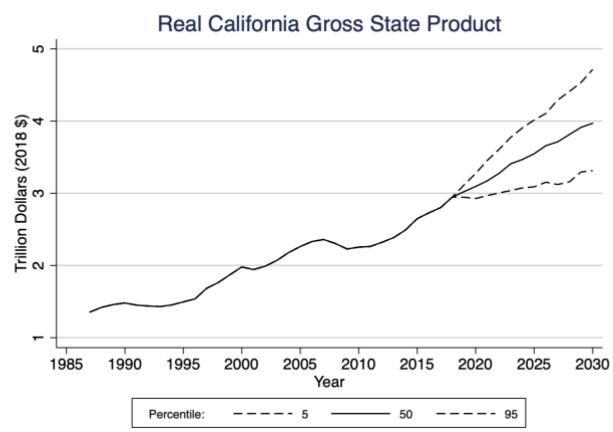
$$Credits_{FCI}^{potential} \geq 0.025 \times Deficits^{prior\ qtr} \quad (22)$$

A.5 Additional Figures

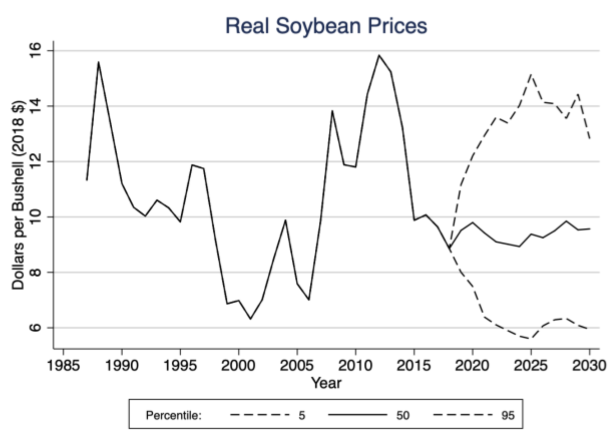
This subsection of the appendix contains figures referenced in the text. Figure 8 shows projections for Brent oil prices, soybean prices, and CA GSP from the BAU simulations. Figure 9 compiles a summary of the ULSD and BBD demand resulting in each compliance scenario, along with the corresponding diesel pool blend rate. Figure 11 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**

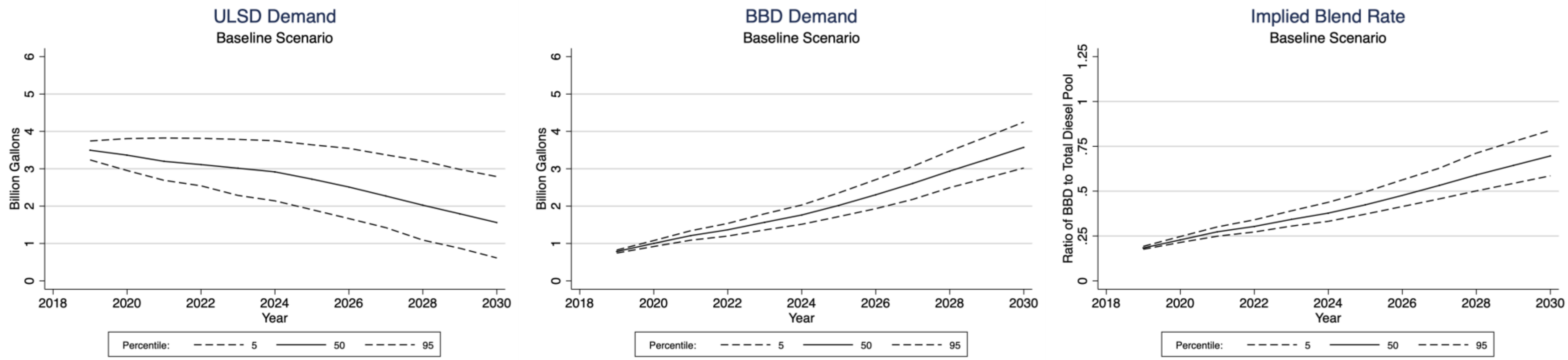


(b) **GSP**

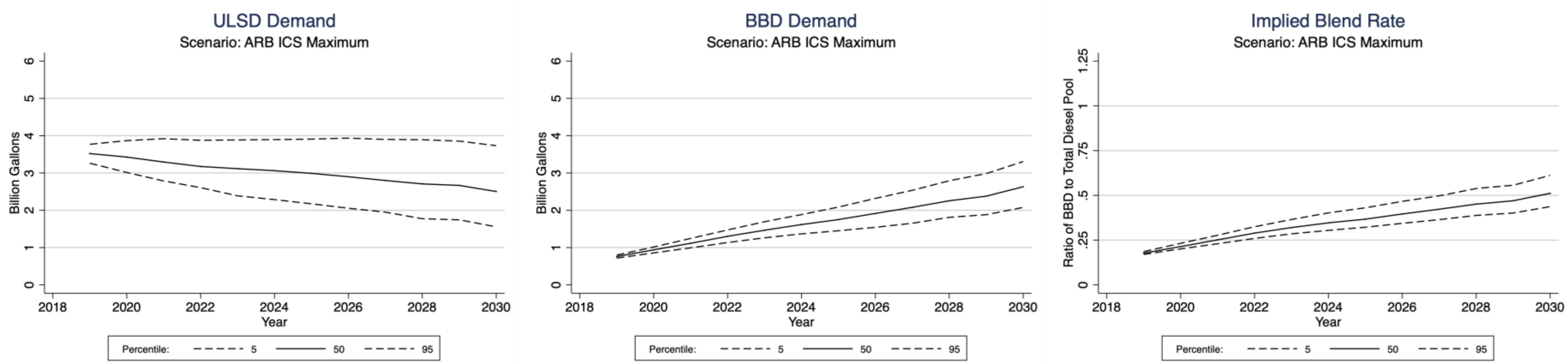


(c) **Soybean Prices**

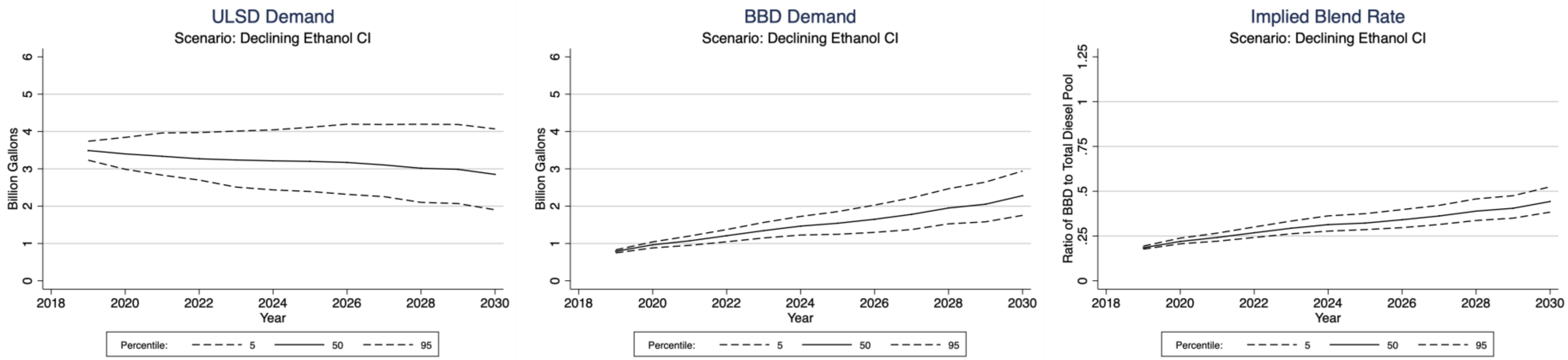
Figure 8. Price Forecasts under BAU Variation



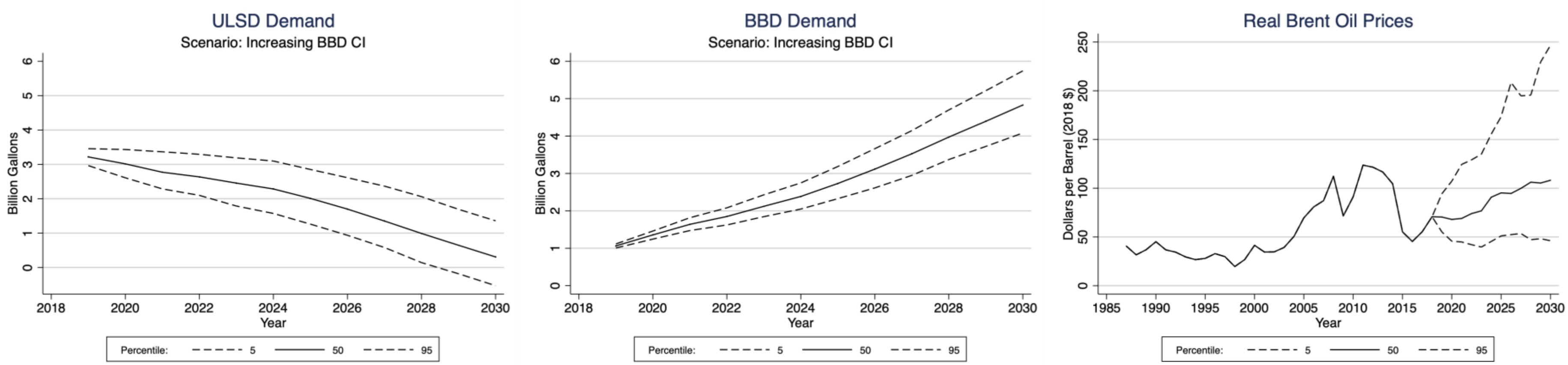
(a) **A0. Baseline**



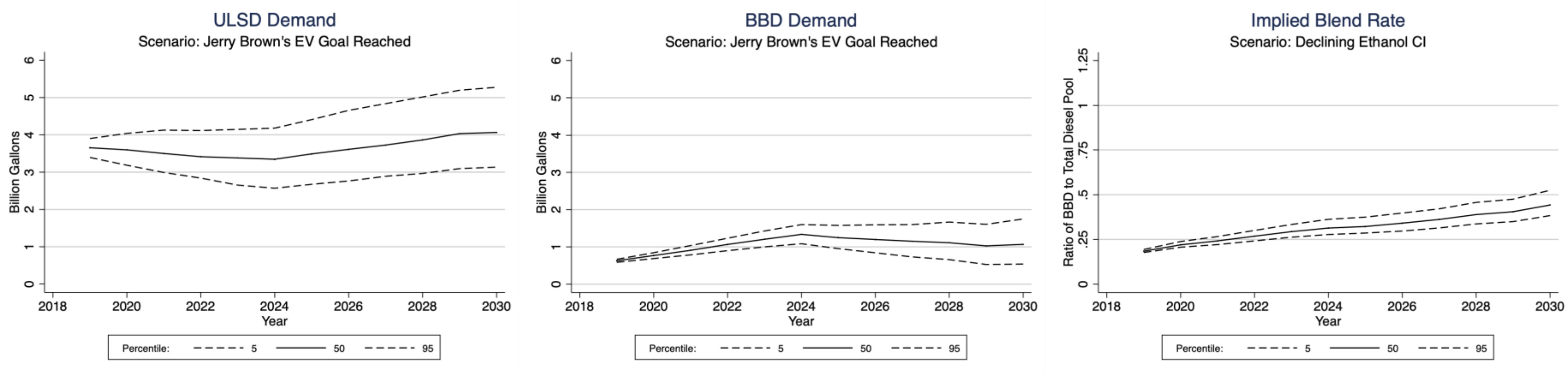
(b) **A1. Maximum Credits from ICS**



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



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



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

Figure 9. Summary of the Diesel Pool under Compliance Scenarios

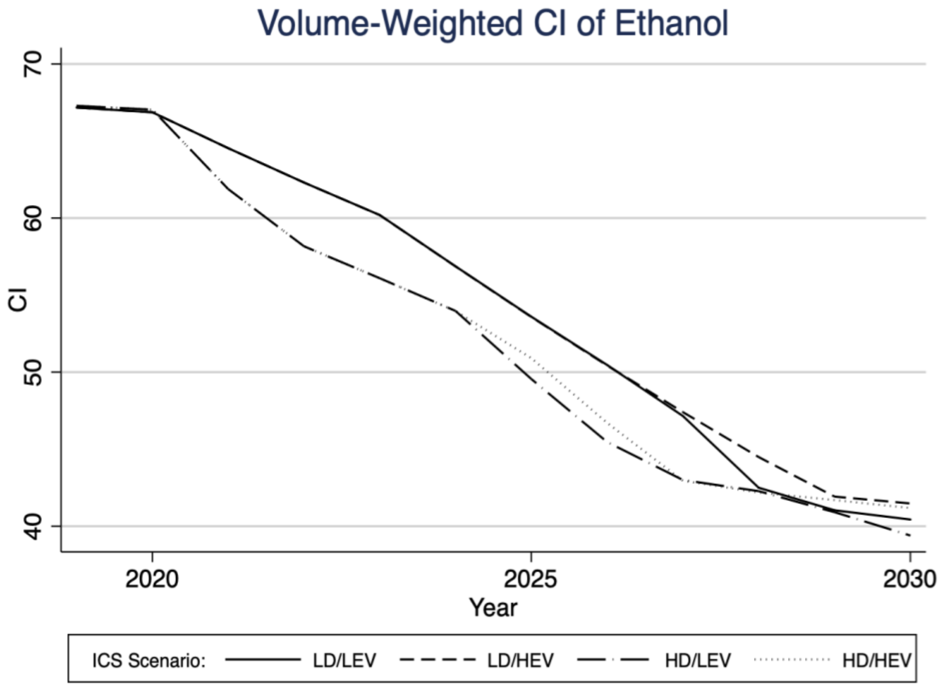
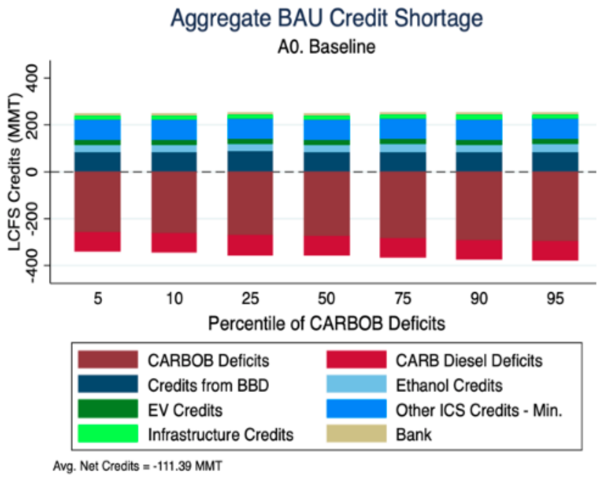
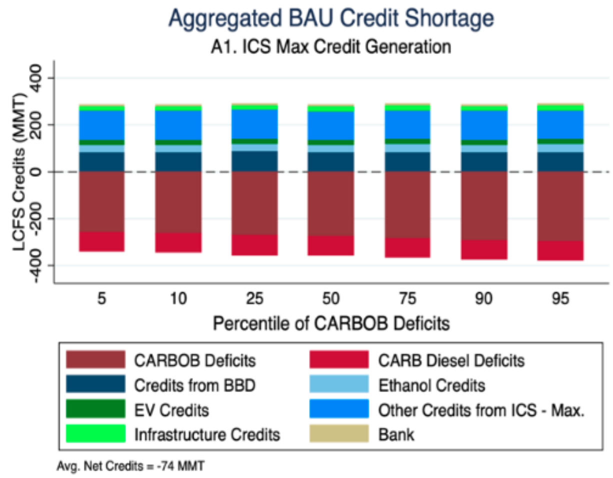


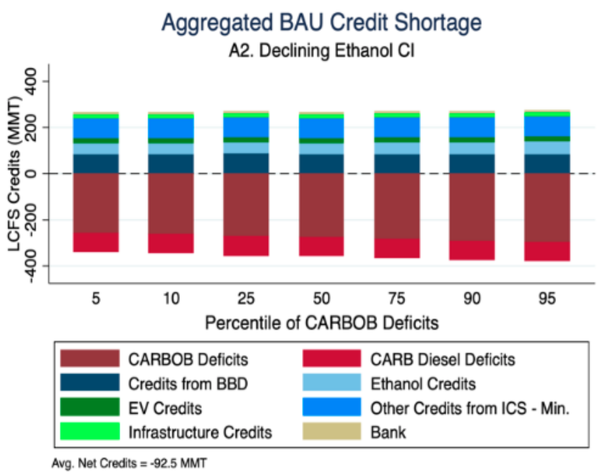
Figure 10. Volume-Weighted CI of Ethanol from CARB ICS



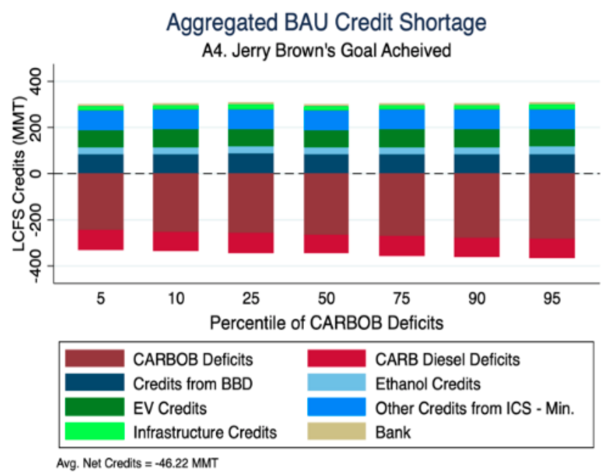
(a) **A0. Baseline**



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



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



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

Figure 11. Summary of Credit Shortages under Different Assumptions