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California's Low Carbon Fuel Standard: Modeling financial least-cost pathways to compliance in Northwest California

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ABSTRACT

The transition to low-carbon transportation fuels plays a key role in ongoing efforts to combat climate change. This analysis seeks to optimize potential alternative fuel portfolios that would lead to a 10% reduction in fuel carbon intensity by 2020 as required under California's Low Carbon Fuel Standard (LCFS).

We present a novel, probabilistic modeling approach for evaluating alternative fuel portfolios based on their marginal greenhouse gas (GHG) abatement costs. Applied to a case study region in Northwest California, our model enables us to quantify the financial cost of GHG reduction via each fuel pathway, as well as for a portfolio deployed to meet the LCFS target. It also enables us to explore the sensitivity of the alternative fuel portfolio, evaluating the impact of fluctuating prices, fuel carbon intensities, and technology penetrations on the makeup of the portfolio and on the average cost of GHG abatement.

We find that battery electric vehicles play a critical role, as they offer the lowest-financial-cost significant abatement in almost all plausible scenarios. However, electric vehicles alone will not be sufficient to reach the target; low-carbon biofuels can be expected to play a role in the achievement of 2020 Low Carbon Fuel Standard targets.

1. Introduction

Transportation accounts for almost 23% of all energy-related greenhouse gas (GHG) emissions globally. Increasing economic development, especially in non-OECD Asia, is expected to cause transport sector emissions to rise faster than those of any other sector (U.S. Energy Information Administration, 2016), increasing more than 70% by 2050 barring major coordinated action on transport emissions (Sims et al., 2014).

Mitigation of the increasingly significant emissions from this sector will require aggressive policy action. However, emissions from transport are among the most difficult to reduce. Necessary change in this sector is inhibited by market barriers such as technology lock-in, the low price elasticity of fuel demand and vehicle choice (Greene et al., 2008; Small and Van Dender, 2007; US Congressional Budget Office, 2012), the entrenched interests of the petroleum industry, the fickle history of alternative fuel policy and investment (Melton et al., 2016), and the need for coordination among fuel producers, distributors, and consumers (Sperling and Gordon, 2009; Yeh and Sperling, 2010). Furthermore, while an economy-wide carbon price is widely considered the most economically efficient approach to emission abatement, it is improbable that such a policy will achieve significant near-term reductions

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from transport at politically-acceptable carbon prices, due to the higher abatement costs in transportation compared to other areas of the economy (Lutsey and Sperling, 2009; Morrow et al., 2010; Rhodes et al., 2015; van der Zwaan et al., 2013). U.S. government analysis of the American Clean Energy and Security Act of 2009 determined that its proposed nationwide GHG emissions trading scheme would generate almost no emission abatement from the transport sector, leading transport to account for over 50% of total emissions nationwide in 2050 (U.S. EPA, 2010; Yeh and Sperling, 2010).

Given the large and increasing role of transportation as a driver of global climate change, reduction in these emissions is critical to achieving climate goals (Williams et al., 2012). Since conventional carbon pricing mechanisms are not expected to generate much near-term emission reduction in transport, policymakers have turned to sector-specific instruments to reduce emissions from the sector.

While this may be considered a sub-optimal approach from an economic standpoint, some researchers have observed that given the market failures present and the scale of the emissions involved, sectoral action in this case is appropriate (Azar and Sandén, 2011; Bennear and Stavins, 2007; Vogt-Schilb and Hallegatte, 2014; Yeh and Sperling, 2010). Such policies enable the commencement of developments that will ultimately be necessary for deep emissions cuts to be achieved, and can stimulate cost reductions to the point that sectoral policies are no longer needed. One key element in the pursuit of deep emissions cuts from transportation will be the deployment of low-carbon alternative fuels. California's Low Carbon Fuel Standard (LCFS) is a policy tool targeting fuel carbon intensity directly.

1.1. California's Low Carbon Fuel Standard

In the state of California, transportation accounts for 37% of total GHG emissions – more than any other single sector (California Air Resources Board, 2016). One key tool in mitigating these emissions is the state's Low Carbon Fuel Standard (LCFS). Pursuant to the 2006 "Global Warming Solutions Act," the California LCFS seeks to reduce the average life-cycle carbon intensity (CI) of transportation fuels used in the state, setting a target of 10% reduction in average fuel carbon intensity (AFCI) below a fossil fuel baseline by 2020. The LCFS differs in important ways from the approach applied by the US federal Renewable Fuel Standard and the E.U. Renewable Energy Directive. Where those policies set targets for specific technologies and create CI thresholds for inclusion, an LCFS is designed to be technology-neutral across alternative fuel pathways and to incentivize transport fuels proportional to the relative carbon intensity of each specific fuel pathway. For detailed discussion of the design, current status, and impacts of LCFS policies see Lade and Lawell (2015) and Yeh et al. (2016). While California was the first jurisdiction to implement an LCFS in 2010, similar policies are currently in place in Oregon, British Columbia, and the European Union, and are in various stages of development elsewhere (Yeh et al., 2016). Lessons learned in California will prove critical to the success of these other policy frameworks.

It should be noted that there are legitimate critiques of the LCFS, its calculated CI values, and the use of this type of life cycle GHG accounting in policy (see e.g. Lemoine, 2017; Plevin et al., 2017, 2014). The LCFS does little to characterize or mitigate uncertainty in its calculated CI values – especially as it relates to market-mediated land use change, leakage, and possible rebound effects. As such, the true impact of the LCFS remains uncertain. However, as this paper investigates compliance with the policy itself, this uncertainty is outside the bounds of our study.

1.2. Evaluating decarbonization of energy in California

Many studies have investigated pathways for deep decarbonization of California's energy sector. Some (e.g. Long et al., 2011; Wei et al., 2013; Williams et al., 2012) use scenario analysis or energy-economic models to explore the roles of different sectors in reaching carbon reduction targets but don't specifically focus on transportation or robustly account for costs. Yang et al. (2015) applied the CA-TIMES model – an energy economic systems optimization model – to evaluate scenarios for deep decarbonization in California through 2050. They showed significant savings in the transportation sector, but given the broad scale of their analysis did not aim to characterize the implementation and impacts of specific policy mechanisms. A more recent iteration of the CA-TIMES model (Yang et al., 2016) investigates the LCFS directly, but with a focus on the presence/absence of this policy in conjunction with other policies impacting California energy use and GHG emission reduction.

Some studies have also focused on pathways to GHG abatement in the transportation sector specifically. Morrow et al (2010) used the NEMS model to evaluate policies aimed at reducing oil consumption and GHG emissions in the U.S. transportation sector. However, their investigation of sector-specific policies focused on vehicle fuel efficiency policies rather than those targeting fuel carbon intensity. Others have investigated pathways to reduced emissions from transport in California from both vehicle efficiency and fuel carbon intensity (Leighty et al., 2012; Yang et al., 2009). These studies lay important groundwork in exploring the technology pathways that could lead to deep decarbonization of the California transportation sector by 2050. However, they do not explicitly evaluate the cost-effectiveness of the different portfolios they discuss, do not focus on the LCFS, and do not evaluate nearer-term priorities.

Morrison et al (2015) offer a comprehensive investigation of California energy system models, identifying commonalities and differences among these models in their methods and projections. As these are broader energy system models, this inter-comparison paper, and the models it draws on, offers a relatively coarse treatment of transportation fuel carbon intensity and of the vehicle and infrastructure costs associated with some alternative fuel pathways. The authors do not investigate pathways to compliance with specific policies such as the LCFS, instead focusing on system-wide achievement of GHG reduction goals. In discussing their findings, Morrison et al (2015) indicate that there is interest among policy makers for analyses that investigate the effects of individual policies, that treat sensitive inputs as distributions rather than point estimates, and that evaluate performance on policy-relevant metrics such as g CO_2e/MJ and fuels and US$/T CO_2e for GHG abatement. Our research directly addresses these considerations.

1.3. Marginal abatement cost (MAC) curve analysis

Marginal abatement cost (MAC) curves are a common tool for evaluating and demonstrating the technological and economic feasibility of GHG mitigation. They were first applied to energy policy analysis in the aftermath of the 1970 s energy crises (Meier, 1982) and became a common tool to evaluate abatement alternatives as emissions trading came to the fore in subsequent decades. By presenting an array of possible interventions, both in terms of their total abatement potential and their cost per-unit of abatement, they are a powerful tool for evaluating and communicating the complex dynamics of emissions reduction choices.

The utility of MAC curves for evaluating greenhouse gas emissions abatement options was demonstrated by a series of high-profile reports from McKinsey Consulting between 2007 and 2009 (e.g. Nauclér and Enkvist, 2009). Subsequently, they have become a common tool for understanding and illustrating the economics of climate change mitigation across different scales, geographies, and sectors. For a detailed history of the use of MAC curves for GHG abatement analysis in different analytical and political spheres, see Kesicki and Strachan (2011).

Several studies have used some form of MAC curve analysis to evaluate emissions abatement potential in the transportation sector. Tomaschek (2015) investigated MACs for transportation in South Africa. Kesicki (2012) used a modeling framework to evaluate the technology-specific abatement potential and cost for the transport sector in the U.K. Kok et al. (2011) reviewed the literature on "cost effectiveness analysis" for transportation fuels. Most of this existing literature looks at transport emissions broadly, with very few studies investigating fuel switching in any detail. Lutsey (2010) conducted a MAC analysis of vehicle and fuel technologies for California, including treatment of fuel switching, but did not evaluate pathways for compliance with the LCFS.

Despite their utility, several researchers have called attention to the potential challenges of deriving MAC curves, and of using them as a key driver of policy formulation (see e.g. Kesicki and Ekins, 2012; Kesicki and Strachan, 2011; Kok et al., 2011; Murphy and Jaccard, 2011; Vogt-Schilb and Hallegatte, 2014). In particular, most MAC analyses draw on static inputs and report static results, failing to robustly characterize uncertainty or sensitivity to inputs (Kesicki and Ekins, 2012), leading to misplaced confidence in their results. Furthermore, interactions between segments are not addressed in most MAC studies, which draw the abatement potential for each technology from a static baseline (Levihn et al., 2014; Murphy and Jaccard, 2011). For example, adding low-carbon biofuels to the liquid fuel mix decreases the GHG mitigation potential of other technologies that would shift transportation away from liquid fuels. This nuance is typically not characterized in MAC analyses.

Finally, so called "measure-explicit" or "bottom-up" MAC approaches such as the work described here, typically only characterize financial costs rather than taking a broader view of social welfare or "intangible" costs (Jaccard, 2009). They also don't attempt to account for behavioral considerations such as consumer decisions (Murphy and Jaccard, 2011) and rebound effects (Kesicki and Strachan, 2011). Broader energy economy simulation or general equilibrium modeling approaches are necessary to more fully account for these social costs and behavioral considerations.

1.4. This paper

Our work seeks to provide insights into the alternative fuel portfolios offering cost-effective compliance with the LCFS. We have developed a novel, probabilistic approach for evaluating alternative fuel portfolios on the basis of their marginal GHG abatement costs. We then apply this framework to a case study region in Northwest California. This analysis seeks to identify and to optimize among potential alternative fuel portfolios that would enable the region to achieve the 10% reduction in transportation fuel carbon intensity (CI) by 2020 as required under California's Low Carbon Fuel Standard (LCFS). While 2020 is a short timeframe for the large-scale change implied by our research, we chose it because it is the LCFS regulatory target. This work provides valuable insights into the deployment of low-carbon fuels beyond that date as well.

Yeh et al. (2009) and Yeh and Sperling (2010) evaluated technology portfolios capable of meeting California's LCFS targets. Our work updates and builds upon these analyses. Where they focus only on fuel cost, since this is where the regulatory burden falls, we include the costs of alternative fuel vehicles and infrastructure as these are also critical to attainment of the regulatory target. If a low-carbon fuel were extremely inexpensive to produce, but the vehicles necessary to consume it were prohibitively expensive, an analysis looking only at fuels would assume a much broader deployment of this fuel than would be realistic. Further, we innovate in adding optimization and a robust simulation of uncertainty to the evaluation of a fuel portfolio capable of achieving LCFS targets. As is common in analyses such as this one (Lade and Lawell, 2015), this work does not model technology change that may be stimulated by the LCFS. Others have done so (Chen et al., 2017), but at the near to medium term timeframe considered here, we do not expect significant innovation.

Our study is designed to address or avoid many of the challenges faced by other MAC analyses as discussed in Section 1.3 above. Most importantly, by employing a probabilistic approach – characterizing inputs as probability distributions rather than constant estimates – we are able to robustly investigate many of the uncertainties and sensitivities of the model system. This work avoids the pitfall of intersegment interaction by evaluating the MAC of compliance with the LCFS rather than the MAC of transportation fuel options in general. The LCFS provides a standard fossil fuel baseline for fuels, meaning that a MJ of electricity with a given CI provides a constant abatement under the policy regardless of changes to the fuel being replaced. This makes the abatement provided by the LCFS itself slightly more uncertain, but allows our analysis to avoid the pathway interdependency issues that can limit other applications of MAC curves.

It is worth noting that while the approach taken offers useful insights, it also poses several limitations. First, we focus only on financial costs here, not attempting to characterize social welfare impacts or other forms of non-financial cost or benefit. Second, as with other similar MAC analyses (e.g. Kesicki, 2012) our model does not address the distribution of these costs among the actors, focusing instead on aggregate cost to the economy. Further, the study region, while geographically large, represents less than 2% of all vehicle miles travelled in the state of California, which is dominated by a few, populous, urban regions. However, the region is characterized by a diversity of driving environments common in the state, including small cities, suburbs, rural regions, and major interstate corridors. We have not attempted to extrapolate from our findings to the California level, as a statewide analysis would be necessary to quantify the impact at a broader scale.

The structure of this paper is as follows: Section 2 lays out methods, including detailed descriptions of the alternative fuel pathways considered, the limits we apply to their penetration, and the approach used to determine fuel, infrastructure, and vehicle cost distributions for each pathway. It also describes our innovative, probabilistic approach to developing a marginal abatement cost curve. Section 3 lays out and discusses the results of this analysis, including describing the uncertainty characterized by our model, results of targeted sensitivity analyses, and the limitations of this research. Section 4 lays out some implications of this research and resulting policy recommendations. We are also publishing a Supporting Online Material (SOM) document, offering further detail on our methods, tables of input assumptions, and results of additional sensitivity analysis.

2. Methods

Many alternative fuel technologies could play a role in the development of a low carbon transportation infrastructure, with each carrying its own set of opportunities and challenges, costs, market penetration constraints, and emissions abatement potential. For example, ethanol fuels can be used in current gasoline vehicles, but only up to a blend wall of 10–15% by volume. Beyond that blend, additional costs are accrued through the purchase of flex-fuel vehicles and specialized distribution. Electric vehicles require up-front investment in a more expensive vehicle, but provide cost savings over time through purchase of fuel that is typically less costly than the gasoline alternative. However, the limited range of these vehicles constrains their penetration into the vehicle market by limiting the number of vehicle owners willing to bear this range restriction.

We developed our probabilistic marginal abatement cost curve (PMACC) modeling approach to address these and related complexities. Our modeling framework divides the regional transportation sector into market segments (such as gasoline and diesel, light and heavy duty, different geographies, and so on) and characterizes the potential for alternative fuel pathways to serve as substitutes for conventional gasoline and diesel fuel in each segment. The model draws on vehicle, fuel, and distribution costs as well as market penetration constraints associated with each fuel pathway in each market segment. It then calculates the marginal abatement cost (MAC) associated with each fuel pathway/market segment combination – or “segment alternative.”

Financial costs are calculated per unit of energy weighted by the conversion efficiency of different fuel drivetrains, making them effectively calculated per unit of travel. Relative conversion efficiencies are characterized using standard LCFS multipliers (called “energy economy ratios”). For example, battery electric vehicles (BEVs) are assumed to convert a MJ of electricity into miles traveled 3.4-times more efficiently than conventional vehicles convert a MJ of petroleum. Per LCFS methodology, we therefore adjust the costs per MJ for BEVs by a factor of 3.4 to account for this enhanced efficiency. These costs are marginal, or incremental, above or below the fossil fuel baseline to represent the additional cost to society of each segment alternative. It bears noting that these costs are shared across the public sector, private sector, and individuals. Where there is, for example, a subsidy associated with a specific pathway – such as the federal tax credit for purchase of electric vehicles or the value of credits associated with sale of a biofuel under the federal Renewable Fuel Standard – these costs are still included here.

$$\text{Marginal abatement cost}\,(\text{US\$/T CO}_2e) = \left(\frac{cost_{AF}/EER - cost_{base}}{CI_{base} - CI_{AF}}\right) * \left(\frac{10^6\,\text{g CO}_2e}{1\text{T CO}_2e}\right)$$

where:

$cost_{AF}$ = aggregate financial cost of alternative fuel (2016US$/MJ)
$cost_{base}$ = aggregate financial cost of displaced conventional fuel (2016US$/MJ)
EER = energy economy ratio (unitless)
CI_{base} = carbon intensity (g CO_2e/MJ) of the displaced conventional fuel
CI_{AF} = carbon intensity (g CO_2e/MJ) of the alternative fuel

The MAC for a given technology is defined by as many as 20 different inputs ranging from various commodity prices to vehicle prices to financing characteristics. Rather than using constant, average values for these inputs, we analyzed historical prices to understand the variability of these costs and the correlations between them, creating correlated distributions for most of the input variables. Using Monte Carlo simulation, we sample from each input distribution 2500 times, yielding a distribution of cost estimates for each alternative fuel pathway. All vehicle, fuel, and infrastructure costs were modeled as distributions. Other parameters such as demand levels, penetration limits, and financing assumptions were not modeled probabilistically but were subjected to sensitivity analysis as discussed later in this paper.

These cost distributions are used to build MAC curves. Total abatement for each market segment is determined based on the GHG savings associated with the relevant fuel pathway and the total conventional fuel energy it can displace in that segment. These segment alternatives are then deployed in MAC order until the total abatement meets the LCFS target for 2020, creating a unique

MAC curve for each realization of the Monte Carlo simulation. The resultant probability distribution of MAC curves is then averaged to yield an estimate of the most likely scenario for cost-effective attainment of the LCFS target[1]. This approach enables us to rigorously explore the uncertainty and sensitivities that are often ignored in MAC curve analyses.

The following sections describe our approach to transport demand estimation as well as to cost modeling for fuels, infrastructure, and vehicles for each alternative fuel pathway. Further detail on the methods used in this study can be found in the Supporting Online Material (SOM).

2.1. Fuel and transportation demand

We base regional estimates of fuel consumption on outputs of the California Air Resources Board (CARB) Emissions Factor (EMFAC) database (California Air Resources Board, 2016). EMFAC provides estimates of emissions from on-road vehicles using total vehicle population and vehicle miles traveled based on statewide surveys and socio-econometric forecasting. Data are available by county, by vehicle class, by fuel type, and by vehicle model year. We used the 2020 EMFAC estimates to characterize travel demand for this analysis. It should be noted that the 2014 EMFAC model only incorporates policies in place up to that point. Impacts of subsequent policies on transportation demand or mode choice are therefore not characterized here.

Different alternative fuel pathways have varying applicability in different segments of the vehicle fuel market throughout the region. For example, biodiesel and ethanol are only relevant as fuels for diesel and gasoline-fueled vehicles, respectively. Similarly, we assume that plug-in electric vehicles will only make substantial penetrations into the new, light duty vehicle market in the near term. To accommodate the variable nature of alternative fuel market penetration, we split the Northwest CA region into 48 market segments based on EMFAC categories, each a unique combination of the following characteristics:

– *Region* - we divided our area of study into six regions: Del Norte, Humboldt, Mendocino, Trinity, and Siskiyou counties, and the Interstate 5 corridor.
– *Vehicle Type* - we divided the EMFAC vehicle classes into two broad categories, light duty and heavy-duty vehicles (LDV and HDV).
– *Vehicle Status* - vehicles are considered new or existing based on whether the model year for the vehicle is 2017–2020 (new) or earlier (existing).
– *Fuel Type* – existing vehicles are divided between gasoline-fueled and diesel-fueled vehicle types.

2.2. Alternative fuel pathways

The alternative fuels considered in this analysis are those major fuels built into the original LCFS system as default (Method 1) pathways. We include all fuels that are presently available in sufficient amounts, sufficiently low carbon intensity, and sufficiently low cost to make a significant contribution to meeting LCFS goals; these include various biofuels, electricity, and hydrogen. We have chosen to exclude natural gas from this analysis for two reasons. First, it has been a minor component in LCFS compliance to date. Further life-cycle emissions studies – inclusive of methane leakage from infrastructure (e.g Brandt et al., 2014) – imply that it would not play a significant role in a low carbon transportation system. Biomethane may play a significant role in a future transportation system, and has contributed to LCFS compliance to date. However, we have not included it in this analysis as we expect this fuel to be significantly supply-constrained in the near term. Future efforts in this space should include the biomethane pathway.

The carbon intensities of these representative fuels were calculated using the September 2015 release of the CA-GREET model (California Air Resources Board, 2015) parameterized with default assumptions and values. It bears noting that these default pathway carbon intensity (CI) values represent a pessimistic scenario as to the calculated life cycle carbon intensity of the broad fuel types they represent. Where emission-saving practices are applied to fuel supply chains, these are assessed in operator-specific “pathways” approved by ARB. As of December 2017, over 400 such pathways had been approved by ARB (California Air Resources Board, n.d.). Each of these pathways, however, represents the proprietary process of a single operator, about which little information is publicly available. By employing default CI values, the fuels in our model are representative of each fuel type as a whole, but do not account for some best-case examples. This is a conservative approach and could cause the model to overestimate the average LCFS carbon intensity rating of a given category of fuel.

Each fuel pathway in each market segment bears distinct vehicle, fuel, and infrastructure costs as well as market penetration constraints based on that fuel’s specific characteristics and market positioning. The following sections describe the approach taken for quantifying these costs for each alternative fuel pathway.

2.3. Fuel cost

The following sections describe our approach to alternative fuel cost estimation. Further detail on the methods used in this study can be found in the Supporting Online Material (SOM).

[1] It should be noted that our results may differ in important ways from the actual dynamics of LCFS compliance. The eventual alternative fuel portfolio will be shaped by ongoing changes in LCFS regulation, by the individual pathways approved by ARB, by federal alternative fuel subsidies, and by the myriad dynamics influencing producer and consumer uptake of alternative fuel technologies.

2.3.1. Biofuels

This analysis considers most of the biofuels consumed in significant amounts in California. These are:

– Canola biodiesel
– Corn ethanol (dry mill)
– Corn ethanol (wet mill)
– Corn oil biodiesel
– Sugarcane ethanol
– Sorghum ethanol
– Soybean biodiesel
– Soybean renewable diesel
– Used cooking oil biodiesel
– Tallow renewable diesel

Absent from this list are cellulosic biofuels; although cellulosic fuels have great potential as a very low-carbon and abundant liquid fuel source, they are to date not being produced in significant quantities. Moreover, owing to the ambitious cellulosic mandate under the US federal Renewable Fuel Standard, any cellulosic fuels being produced are under high demand nationwide. While the LCFS subsidy in California could draw in some of this fuel from the rest of the country, we have not seen this happening to significant degree. In 2015 California consumed none of the 2.2 million gallons of cellulosic ethanol used in the United States (Yeh and Witcover, 2016). We assume that only marginal quantities of cellulosic ethanol will be available for consumption in the Northwest California region in the 4-year study timeframe. In this regard, our study diverges from Chen et al. (2017), which projects that technology innovation could lead to a significant increase in cellulosic fuel production.

For each of the biofuel pathways modeled, five distinct costs are considered: feedstock cost, refinery capital cost, refinery operation and maintenance costs, coproduct value (a negative cost to the fuel), and transportation cost. Feedstock price distributions and correlations are drawn from 6-year quarterly average commodity market data. Capital and operating expenditures for biofuel production facilities were drawn from the U.S. DOE Energy Information Administration (EIA) Annual Energy Outlook documentation (U.S. Energy Information Administration, 2015). For fuel transportation costs, we derived average transportation demand and mode for each fuel type from the CA-GREET model version 2.0 (California Air Resources Board, 2015) employed for LCFS-related GHG calculations. Fuel costs are modeled based on historical price data and do not vary by level of penetration. In reality, the costs of low-carbon fuels may fall over time as the industries come to scale and mature. However, they may also rise due to increasing demand stimulated by a variety of low carbon fuel policy frameworks. We do not attempt to characterize these dynamics in our modeling.

2.3.2. Electricity

We model electricity prices as the sum of two components: a variable wholesale cost, and a constant retail margin. This approach produces a time series of retail electricity prices that vary along with the wholesale market but reflect the retail cost of energy. This enables us to correlate electricity prices to other transportation fuels despite the fact that utility rate schedules do not vary with the real-time market. We base our electric fuel costs on retail pricing, which is expected to be inclusive of the capital and operational expenditures of building power plants and producing electricity.

2.3.3. Hydrogen

Hydrogen fuel costs for this work are based on the US$8/kg cost of hydrogen delivered from a steam methane reformation facility in southern California for the AC Transit Fuel Cell bus system (Levin, personal communication, 2015). We turned this constant estimate into a time series of costs by disaggregating the cost into energy inputs and the balance of production costs and then adding additional cost for transportation of the hydrogen to the Northwest California region.

2.4. Infrastructure cost

2.4.1. Biofuel infrastructure

For the cases of ethanol, biodiesel, and renewable diesel fuels at appropriate blend levels for conventional gas and diesel vehicles, there is no additional infrastructure or vehicle cost. However, in the flex-fuel vehicle case, the higher blend of ethanol into the fuel mix necessitates both vehicle and distribution infrastructure expenditures to accommodate the lower energy density and the hydrophilic properties of ethanol fuel. We derive distribution infrastructure capital expenditures from a 2014 National Renewable Energy Lab (NREL) study (Moriarty et al., 2014), levelized across the station lifetime, and allocated to the fuel. We assume that at the blends of up to B20 allowed in our analysis, biodiesel can be delivered through the conventional diesel infrastructure and with minimal additive cost. However, California's ongoing Alternative Diesel Fuels regulation process could lead to added costs for B20 blends.

2.4.2. Electricity infrastructure

The electricity transmission and distribution infrastructure in the Northwest California region is well established and has a good deal of spare capacity. The only incremental cost incurred with distribution is therefore the cost of the charging infrastructure. We base our estimate for public charging infrastructure off of the authors' previous work developing the Northwest California regional electric vehicle charging infrastructure deployment guidelines (Redwood Coast Energy Authority, 2013). In that analysis, a detailed agent-based model of electric vehicle mobility and charging behavior was used to find the number and spatial distribution of public charging stations that would minimize expected delays and stranding events experienced by travelers, subject to an infrastructure budget. For this analysis, we extrapolated the public charging infrastructure previously determined for Humboldt and Siskiyou counties to the other counties in the region in proportion to the electric vehicle population. Using results from the CA Electric Vehicle Owner Survey (Center for Sustainable Energy, 2014) we estimate the deployment of home chargers among battery electric vehicle (BEV) and plug-in hybrid electric vehicle (PHEV) drivers separately. Finally, we use region-specific cost estimates of chargers to derive an overall cost of infrastructure for the region (Redwood Coast Energy Authority, 2013).

2.4.3. Hydrogen infrastructure

We base our cost estimate on the publicly available set of proposals submitted to the California Energy Commission (2014) in response to a grant funding opportunity for hydrogen fueling infrastructure development. Only the 23 stations that were awarded funding and were designed for hydrogen retail without onsite generation were considered. The station cost, including match funds, was divided by the station capacity to calculate the levelized average and standard deviation of cost per MJ of hydrogen delivered. These estimates fall within the range of other estimates summarized by NREL (Melaina and Penev, 2013). Modeling by NREL was used to estimate O&M costs for the station (Ramsden et al., 2013)

2.5. Vehicle cost

The incremental cost of alternative fuel vehicles is an important consideration when prioritizing low carbon fuels. It can be difficult to determine the additional cost of an alternative fuel vehicle given that vehicle models differ in more than just their fuel type, making it difficult to select a "comparable" vehicle for direct price comparison. We base our average incremental vehicle cost estimates on modeling work published by the National Research Council (NRC, 2013). The NRC report details the incremental manufacturer's cost of advanced internal combustion, PHEV, BEV, and fuel cell hybrid electric vehicles (FCEV) for an average light-duty car and truck.

Flex-fuel vehicles are not modeled in the NRC study. However, this is the one alternative fuel vehicle technology that is widely available as an option on pre-existing vehicle models. This enables us to use the difference in MSRP between *identical* vehicles as a proxy for the incremental cost of a flex-fuel vehicle. As both cars and light-duty (pickup) trucks were modeled in the LDV category for our analysis, we combined these prices weighted by the relative prevalence of these vehicle classes in the region. Further information on vehicle price calculations is presented in the SOM.

All capital expenditures in this analysis were modeled using a 6% discount rate. Input assumptions such as discount rate have been shown elsewhere to have a significant effect on MAC analyses (Kesicki and Ekins, 2012). The sensitivity analysis detailed in our SOM did not show alterations in discount rate to significantly alter the portfolio average abatement cost or the AF portfolio makeup. However, the discount rate applied across the analysis – including to consumer vehicle purchases – could be seen as a limitation.

2.6. Market penetration limits

As in many other energy system models (see e.g. Yang et al., 2015) each alternative fuel pathway is constrained to particular market segments and presents practical limitations to uptake. Our assumptions for these limits are summarized in Table 1, and explained in more detail in the SOM. These are not meant to be targets for expected deployment, as some of them are overly

Table 1
Market penetration constraints applied to alternative fuels.

Alternative fuel pathway	Segment/Penetration limit	Rationale summary
BEV	70% of *new* LDV fuel	BEVs are range limited and so are constrained to the fraction of new vehicles purchased by households with more than one vehicle.
PHEV	100% of *new* LDV fuel	The dual-fuel, extended range nature of PHEVs makes them a suitable replacement for any new vehicle.
H_2	51–93% of *new* LDV & HDV fuel	Limit varies by region and is based on the ratio of population near urban centers to reflect access to new fueling infrastructure.
Ethanol at E85 blend in Flex-fuel Vehicles	85% blend in 51–93% of *new* gasoline LDV fuel	Vehicle penetration limit varies by region and is based on the ratio of population near urban centers to reflect access to new fueling infrastructure.
Ethanol at E15 blend level	15% of all gasoline vehicle fuel	Ethanol can penetrate all gasoline market segments, but only up to 15%. The "blend wall" could be elevated to E15 in order to ease LCFS compliance.
Biodiesel at B20 from soy and canola feedstocks	20% of all diesel vehicle fuel	Biodiesel can penetrate all diesel market segments, but only up to a 20% blend due to vehicle performance considerations at higher blends.
Biodiesel at B20 from used cooking oil	0.08–0.9% of all diesel vehicle fuel	Used cooking oil is a waste product from other industries and is therefore supply-limited. We limit it to only the waste oil produced in the study region.
Renewable Diesel from soy	100% of all diesel vehicle fuel	Renewable Diesel is a drop-in fuel and therefore has unlimited potential to penetrate the diesel market.
Renewable Diesel from tallow	0.1% of all diesel vehicle fuel	Tallow is a waste product from another industry and will be supply limited. We limit it to 20% of the tallow produced in California.

optimistic for the timeframe considered here. Instead, the limits in Table 1 should be taken as a hypothetical ceiling for near-/ medium-term alternative fuel technology deployment under the LCFS program with implications for compliance beyond the 2020 timeframe. It is also notable that we are not explicitly characterizing other policies such as the Zero Emission Vehicle (ZEV) mandate in California. These policies will stimulate uptake of some of the vehicle technologies we consider in our analysis, but not to the point that they would exceed the limits we imposed to their deployment. We report on the sensitivity of our analysis to some of these assumptions in Section 3.2 of this paper.

2.7. Innovation in MAC curve methodology for cost-effective achievement of a specific emission goal

As discussed in Section 3, we use the marginal cost of GHG abatement as our metric for ranking alternative fuel pathways within each market segment and across segments. After a MAC is calculated for each segment alternative in a given iteration of the model, the model resolves the penetration of each alternative fuel alternative within each segment. For example, if BEVs have the lowest MAC in a particular market segment, then we assume them to be deployed that segment up to their penetration limit, leaving the remainder of the market segment available for the next most cost-effective alternative fuel alternative. This process continues until the LCFS target is reached or all of the market segments are fully allocated to alternative fuel alternatives in MAC rank order.

In the context of alternative fuels, choosing to adopt one alternative fuel pathway necessarily precludes other pathways from being realized, because the demand for transportation is approximately constant. This was found to create a unique challenge for use of a MAC curve analysis in this context. Frequently, adopting the alternative fuel technologies in MAC order as described above results in a final portfolio falling short of the LCFS 2020 target for GHG abatement. This is because of what Vogt-Schilb and Hallegatte (2014) refer to as “cheap” vs. “deep” abatement options. If, for example, in a given iteration of the model, dry mill corn ethanol (used as E15) emerges as the “cheapest” abatement option (in US$/T CO_2e), this fuel will capture a large segment of the market because it is able to penetrate 100% of gasoline fuel use. However, corn ethanol in an E15 blend with gasoline offers only a slight GHG reduction. As such, if the curve were to be populated in the conventional manner based only on MAC order, this “cheap” technology would displace others that could have offered much “deeper” abatement, if at a slightly higher MAC. This would lead to a fuel portfolio that fails to achieve the abatement target. To overcome this challenge, our model evaluates each individual MAC curve result to determine whether it meets the portfolio target. If it does not, it systematically substitutes individual market segments with successively more expensive (but potentially higher abatement) alternative fuel options until it arrives at a portfolio that reaches the overall target. This process is repeated for each of the 2500 model runs in the Monte Carlo simulation to find an outcome that combines the “cheap” and “deep” imperatives to arrive at cost-effective achievement of policy goals. Detailed discussion of the approach we employ to address this challenge can be found in the SOM.

3. Results and discussion

Our estimates of the average marginal abatement cost of each of the major fuel pathways considered are presented in Fig. 1. BEVs

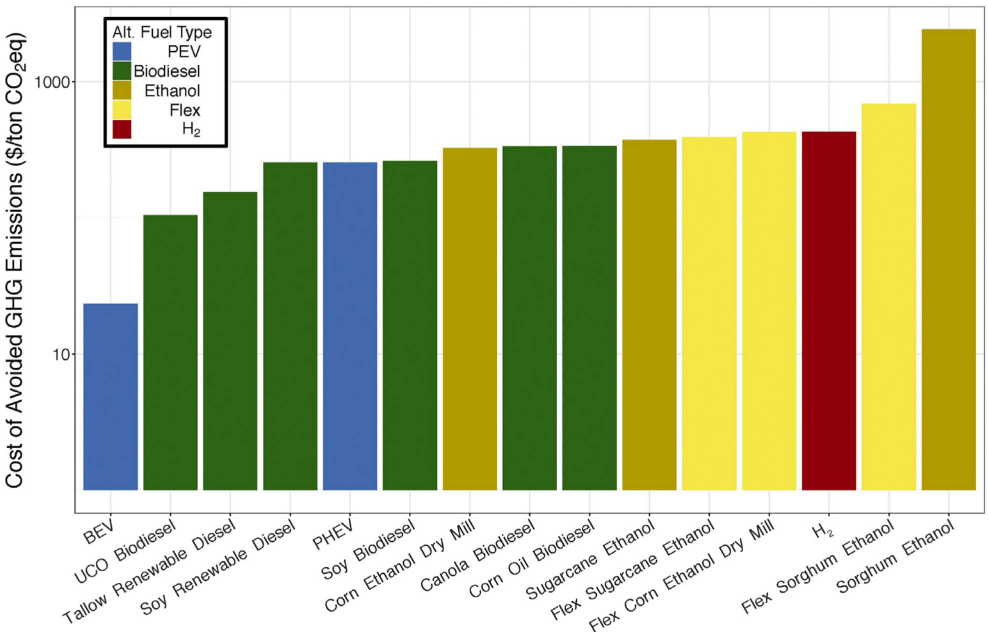

Fig. 1. Average marginal abatement cost of alternative fuel pathways (log scale). “Flex” refers to a given ethanol fuel being used in a flex-fuel vehicle at up to an E85 blend.

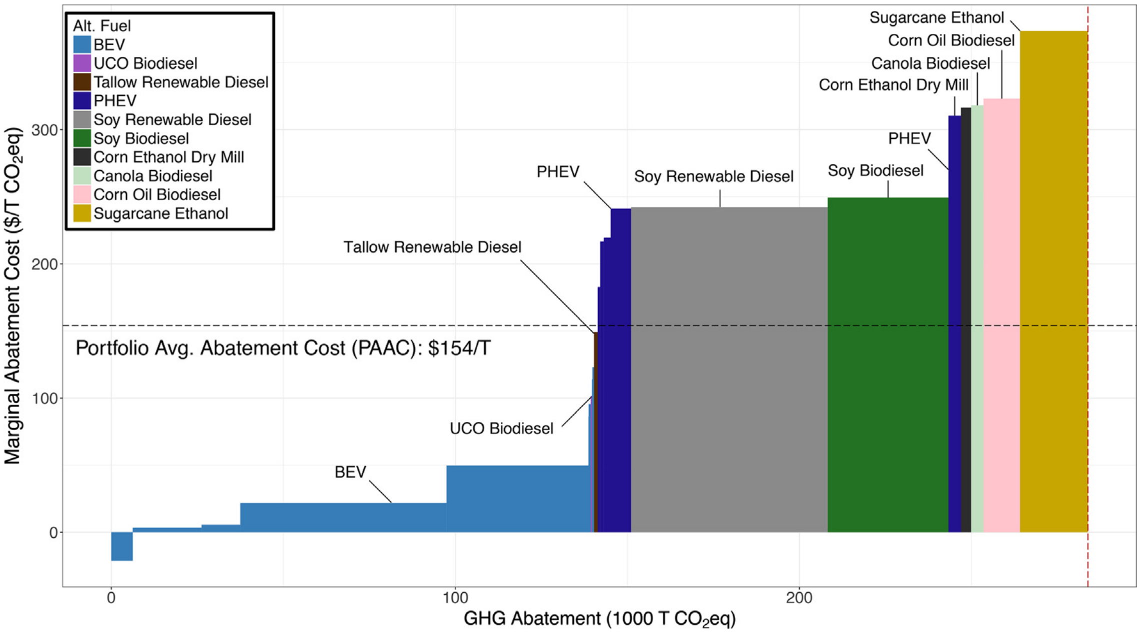

Fig. 2. Average marginal abatement cost (MAC) curve across 2500 trials for the base scenario.

are the lowest cost alternative followed by biodiesel from used cooking oil and renewable diesel from beef tallow.

While Fig. 1 presents average abatement costs, using a MAC curve to build a portfolio capable of meeting the LCFS target adds the critical dimension of abatement potential. In Fig. 2, the y-axis still represents the marginal cost of abatement, but the x-axis represents the total abatement potential of each alternative fuel pathway in its respective market segment. The portfolio average abatement cost (PAAC) to achieve the LCFS target is approximately US$150/T CO_2e. While this is a high MAC compared against other abatement options, the incremental cost of achieving the target is only a 4% increase over business as usual for transportation in the region.

The portfolio is notably dominated by BEVs, which represent the least-cost abatement alternative across almost all segments for which they are able to be deployed. The differences in cost visible among BEV segments are a product of regional differences in electricity cost, vehicle fleet and use characteristics, and the cost of displaced fossil fuels. Used cooking oil biodiesel and tallow renewable diesel are present in the portfolio but at such small penetrations as to be practically negligible. Many analyses assume large-scale deployment of these low-CI biofuels (e.g. Christensen and Hobbs, 2016). We constrain their role, however, because while they may be available to California as a first-mover, they are ultimately supply-limited fuels. These fuels have represented a significant fraction of compliance to date, but much of this “low-hanging fruit” is already being used. Further deployment of these fuels would come at the expense of their utilization elsewhere. Finally, as described in the SOM, our sensitivity analysis indicates that even at significantly greater deployment levels (up to 10-times our defaults), these fuels do not substantially alter the least-cost technology portfolio.

Diesel fuel alternatives such as soy and canola biodiesel and renewable diesel fuels also play a key role in this base case average portfolio as they are low cost drop-in fuels that are not meaningfully supply constrained. At present, they offer the most practical approach to large scale fuel CI reduction in medium and heavy-duty transport. Ethanol fuels are not significantly represented in our base case with the exception of sugarcane ethanol. This is at odds with what has been seen in the LCFS to date, but as the target becomes more stringent in the coming years, lower carbon fuels will need to be used for compliance.

3.1. Cost uncertainty and robustness of results

A key innovation and value of our probabilistic modeling framework is its ability to investigate the range of possible outcomes, evaluating the uncertainty of our results as well as their sensitivity to specific input assumptions. Considerable uncertainty underlies the alternative fuel cost estimates, though the rank ordering of the portfolio technologies is largely robust because of the considerable correlation among the historical price fluctuations for different fuel pathways.

This phenomenon is illustrated in Fig. 3, which depicts nine MAC curves, each representing the average of a segment of the result distribution. For each of the 2500 trials a MAC curve is constructed and the PAAC is calculated, then the 2500 results are sorted by their PAAC and divided into nine equal result segments. The average MAC curve for each group is displayed in Fig. 3 in order to represent the distribution of outcomes across the result space. Despite the uncertainty in possible costs, the overall ordering of the alternatives and the degree to which they contribute to meeting the LCFS target is largely invariant. The actual aggregate cost we will bear to achieve these emissions reductions is quite uncertain, but the efficient technology portfolio to get us there is much less of an unknown.

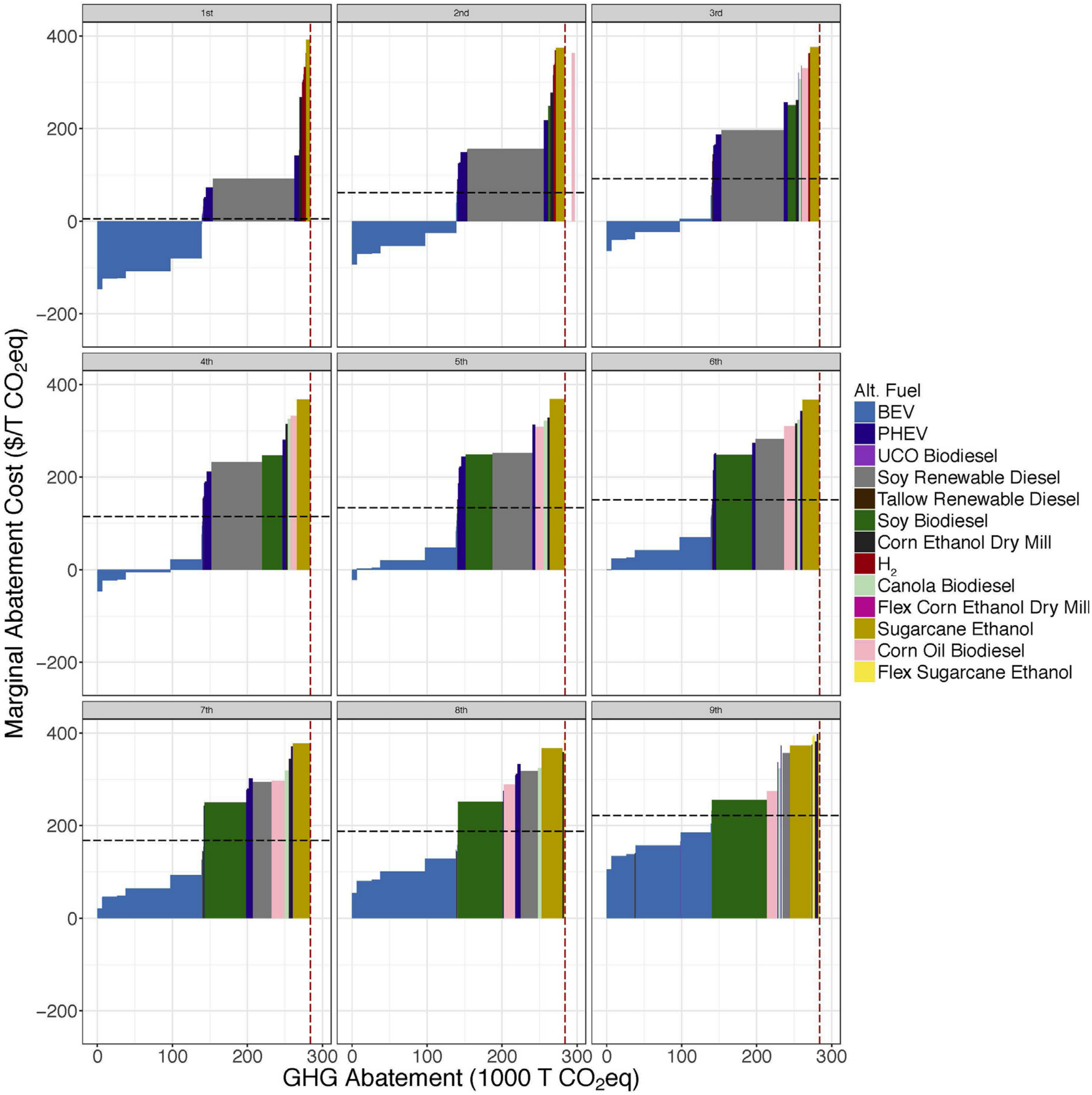

Fig. 3. Average MAC curve for each of nine segments of the 2500 trials when ordered by their PAAC.

3.2. Sensitivity analysis

Having determined the basic portfolio of fuels that play important roles in the least-financial-cost achievement of the LCFS target, it becomes important to determine the sensitivity of those results to key variations in the model inputs. This sensitivity analysis aids us in evaluating the robustness of the patterns that arise in the base case MAC curve. It also allows us to run experiments, investigating scenarios of possible changes to the alternative fuel landscape and their impact on technology deployment in the region. The results of some of these experiments are detailed below and in the SOM.

Given the central role of BEVs in a cost-effective alternative fuel portfolio for the Northwest California region, the nature and robustness of this finding warrants investigation. One key element of the MAC for BEVs was found to be the vehicle cost itself. Varying the vehicle cost ± 25% from the baseline led to almost $100 in variation in the PAAC. It is notable that a 25% reduction in BEV cost premium - a plausible outcome given current trends - drove the MAC for the BEV pathways into negative territory, meaning that the cost savings on fuel over time outweigh the up-front cost of the vehicle.

Beyond their cost of deployment, rate of adoption will likely constrain the ambitious role for BEVs indicated by our findings in the near term. Our base scenario allowed almost 25% of the new LDV fleet to be all-electric. This is an upper bound, but is clearly very ambitious. Fig. 4 presents the results of our scenario analysis investigating the importance of this uptake rate on the resulting

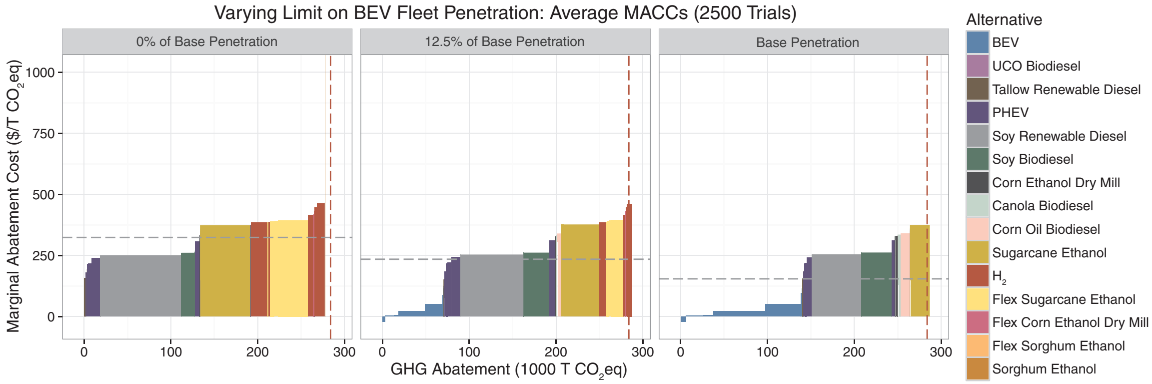

Fig. 4. Sensitivity of the alternative fuel portfolio and average abatement cost to the penetration rate of BEVs into the light duty vehicle fleet.

alternative fuel portfolio. As BEV penetration falls, the LCFS target becomes more difficult to reach, leading to the deployment of higher cost fuel options. The reduced BEV emission abatement is largely made up by an increase in sugarcane ethanol in both E15 and flex-fuel applications along with PHEVs. It is also worth noting that if low-MAC BEVs are constrained in the portfolio, the overall PAAC rises by approximately $82/T and $175/T at 50% and 0% of the base penetration scenarios, respectively (Fig. 4).

3.3. Limitations of this analysis

A key limitation of our approach is that it seeks only to evaluate least-financial-cost pathways to compliance with the LCFS policy as written, not optimal approaches to reducing transportation GHG emissions. This prevents us from evaluating the efficacy or efficiency of the LCFS as a policy tool, comparing it to other approaches for GHG mitigation, or from characterizing uncertainties in GHG abatement inherent to the LCFS structure. For example, we take ARB fuel carbon intensity ratings and drive-train efficiency calculations as given, when in fact these values are subject to uncertainty due to calculation error, rebound effects, or changes in CI over time.

Similarly, our focus on aggregate financial cost means that our analysis is unable to project or optimize across other forms of social cost or to address issues of where these costs fall in society. Further, as it focuses only on the Northwest California region, our analysis cannot be extrapolated to the statewide context without further analysis.

While alternative fuel costs are dynamic in this model in that they are characterized by probability distributions rather than point estimates, they are drawn only from historical trends. They therefore do not reflect future directional shifts that may result from the increased scale of low carbon fuel deployment stimulated by the LCFS. Driving this "learning curve" is an important goal of policies such as the LCFS, but we do not attempt to characterize it here beyond targeted sensitivity analysis described above. Future fuel costs could fall due to technological innovation but could also rise due to new commodity market pressures, and we are not sufficiently confident in any specific projections of future fuel price to include them in our modeling.

Finally, our projections concern the technically achievable deployment level of alternative fuel technologies. However, there is often a mismatch between financially optimal outcomes and practically achievable ones. Private, subjective choices of vehicle owners will determine the extent to which the least-cost portfolios we identify will be achievable and we have not attempted to model these dynamics. This work therefore indicates what *could* happen in least-financial-cost LCFS compliance, but cannot project what *will* happen.

4. Conclusions and policy implications

The analysis detailed in this paper has important implications for policymakers at a variety of levels. It is clear that the LCFS will require deployment of a portfolio of alternative fuel technologies in order to reach the 2020 emission intensity target. The average abatement costs of the technology portfolios suggested by our model results are often over $100/T, and in many cases, up to $250/T or more. These estimates are in line with other projections for individual alternative fuel technologies and for LCFS policies (Christensen and Hobbs, 2016; Kesicki, 2012; Lutsey and Sperling, 2009; Rubin and Leiby, 2013; Tomaschek, 2015; US Congressional Budget Office, 2012; Yeh and Sperling, 2010).

Our findings imply that LCFS credit prices should be expected to continue their recent significant rise as the AFCI targets begin to drop more steeply in the coming years. While the average credit price early in the program was around $20/T, they have been trading near or above $100/T since the beginning of 2016. These comparatively high prices come despite the fact that the CI reduction required in 2016 was only 2%. The required reductions are slated to become much steeper from this point forward leading to the 10% target in 2020. It should be noted that not all of the costs incorporated into our projected economy-wide MACs will be incorporated in the cost to fuel providers, so we do not expect credit prices to rise to the MAC of the marginal fuel in this analysis, but consistent credit prices in excess of $100/T may well remain a feature of the LCFS system.

Of the fuel used under the California LCFS in 2015, almost 90% was 1st generation crop-based biofuel (Yeh and Witcover, 2016).

These technologies have been sufficient to meet the relatively modest reduction targets up to this point. However, supplies of truly low-carbon biofuels such as those derived from tallow, used cooking oil, and cellulosic material are limited, and barring a significant change in the availability of cellulosic fuels or distribution and use of low-CI E85 in the coming few years, it will become increasingly difficult for operators to meet rapidly-tightening targets using these technologies.

Regulated entities have signaled their recognition that this cap will become more difficult to meet by stockpiling credits while targets were less stringent; through the end of 2015, operators had used less than half of all credits that had been generated (Yeh and Witcover, 2016). However, as the cap is progressively tightened in the coming years, this stockpile will not be sufficient to meet the demand. This process seems to have already begun, as 2017 saw operators consistently using more credits than they were generating, causing the total stockpile of LCFS credits to shrink for the first time since the policy was first implemented. The above evidence indicates that credit costs may well rise to the point that triggering of a cost containment mechanism becomes necessary - ultimately preventing or delaying the attainment of the 2020 AFCI target.

The critical role of battery electric vehicles as the lowest-financial-cost abatement option with significant deployment potential appears to be very robust, with BEVs edging into negative abatement cost in some plausible scenarios for transportation system development. This finding is notable, especially in the face of an important critique of MAC curves' use in policy formulation. We find BEVs to be what Vogt-Schilb and Hallegatte (2014) have termed both a "cheap" and "deep" abatement option. They offer the lowest aggregate MAC of all technologies considered in almost every iteration of our model, while also providing one of the deepest emission abatements. Furthermore, it is reasonable to expect EVs to become still cheaper *and* lower-GHG in the coming years.

Given the current, and reasonably foreseeable alternative fuel technology landscape in California, we expect large-scale deployment of BEVs to be critical to the achievement of LCFS targets. The long-term success of the policy in achieving the AFCI target could hinge on the rate at which uptake of these vehicles continues to rise. What is not clear is the extent to which the LCFS will stimulate the market for EVs. Future policy design, both within and outside of the LCFS system, should directly target growing this market in order to promote achievement of fuel CI reduction goals.

While this analysis targets the regional achievement of the 2020 LCFS goals, it is worth noting that this may not be the ultimate outcome. LCFS is a statewide average market-based standard, so if some carbon intensity reductions can more affordably achieved elsewhere (e.g. in a region where population density, geography, investment in public infrastructure, and economic factors enable a faster uptake of BEVs), they will be. As a result, 2020 might see statewide compliance with the LCFS without the five Northwest counties having met this target. This would be a fine outcome from a climate perspective but could have a regressive impact as rural counties effectively subsidize uptake of low-carbon alternative fuels in wealthier urban areas.

Our analysis offers useful insights into the transportation system change that will be necessary for cost-effective attainment of LCFS goals. In the words of Kesicki and Strachan (2011), this analysis "should not be used as an exclusive decision-making aid to rank abatement policies." Instead, the MAC analysis detailed here indicates the sort of change that will be needed to reach California's LCFS targets. As such, it can be a useful tool to bring about the coordinated action – among state policy-makers, auto manufacturers and retailers, local and regional planning and permitting agencies, fuel providers, and other stakeholders – that will be necessary to achieve the ambitious goals the state has put forth.

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Appendix A. Supplementary material

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