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June 24, 2022

Clerk of the Board
California Air Resources Board
1001 I Street
Sacramento, California 95814
[submitted electronically]

RE: POET Comments on 2022 Draft Scoping Plan Update

Introduction

POET appreciates the opportunity to provide comments in response to the California Air Resources Board (CARB) 2022 Draft Scoping Plan Update.

The 2022 Scoping Plan update will set the direction California takes over the next several decades to meet its climate and air quality goals. To meet those goals the plan must include all necessary approaches to drive down greenhouse gas (GHG) emissions across the state. California has a long history of developing creative programs to cut GHG emissions, and the State must continue to find innovative and cost-effective ways to secure emission reductions from all economic sectors, including the transportation sector. As a leader in innovative technologies and products, POET can play a key role in California's efforts to achieve carbon neutrality while simultaneously delivering critically needed air quality, public health, and economic benefits for Californians.

About POET

POET is deeply committed to reducing GHG emissions and developing cleaner, affordable alternative fuels in California and the United States. POET is the world's largest biofuels producer and currently operates 33 biorefineries capable of producing three billion gallons of starch and cellulosic ethanol. Renewable, clean-burning biofuels like those produced by POET cut carbon emissions by an average of 46 percent compared to gasoline,[1] which can have an enormous impact on reducing the amount of GHG in the atmosphere.

POET continues to innovate and further reduce its products' greenhouse gas emissions. The Gradable project illustrates the potential greenhouse gas emissions reductions

[1] Melissa J Scully, et al., *Carbon Intensity of Corn Ethanol in the United States: State of the Science,* 2021

achievable through sustainable farming. POET worked with the Farmers Business Network and Argonne National Labs to create Gradable, a pilot program to encourage sustainable farming, validate data inputs, and calculate carbon intensity scores for agricultural inputs. POET believes that if coupled with a source of value for carbon, the Gradable program could enable reductions in agricultural emissions associated with biofuel production by 50 percent or more.

Specific Comments on the 2022 Draft Scoping Plan Update

The Proposed Scenario to achieve carbon neutrality by 2045 includes various strategies to move California beyond reliance on fossil fuels. Achieving this goal will require a sustained commitment to actions that will steadily and rapidly displace petroleum from California's transportation sector. As indicated in the Draft Update, this includes strategies to increase conventional and advanced biofuels and strategies to develop and implement a more stringent low carbon fuel standard (LCFS).[2] POET supports these strategies. However, to maximize the success of the approach the State takes to reduce GHG emissions, it is imperative that CARB take advantage of the significant and immediate climate, air quality, economic, and public health benefits that advanced low carbon biofuels can deliver as part of these efforts.

The 2022 Scoping Plan Update Should Maximize Action to Drive Down Emissions from Transportation Fuels

As the Draft Update shows, under the Proposed Scenario a significant amount of liquid petroleum fuel will remain in California's transportation fuel mix in 2045.[3] Strategies to drive down the carbon intensity of liquid fuels will be needed for California to achieve carbon neutrality successfully.

Advanced biofuels are readily available to support the transportation sector's decarbonization efforts effectively and at a low cost. An analysis from Environmental Health and Engineering shows that corn ethanol has a 46 percent average lower carbon intensity than gasoline.[4]

With technologies already being implemented or on the cusp of commercialization, bioethanol has the ability to become a zero-carbon fuel. The chart below compares bioethanol's carbon intensity (CI) score to a gasoline baseline and shows technologies, many of which POET has already implemented and others which the company is evaluating, that would allow bioethanol to become a zero-carbon fuel:

[2] *See* Draft 2022 Scoping Plan Update, page 62, 89, and 154
[3] *See id.*, page 153
[4] *See* Scully, supra n.1

Innovations across the biofuel production lifecycle have resulted in increasingly cleaner liquid biofuels. These innovations will only continue to drive down the CI of conventional and advanced biofuels.

The 2022 Scoping Plan Update Should Include a Strategy to Complete the Process that CARB has Already Initiated for Approval of E15 as a Fuel in California

Advanced biofuels, including bioethanol, have been leading contributors to the success of the California LCFS to date. These fuels must continue to play a key role as CARB works toward increasing the stringency of the LCFS program, which is a key pillar of the State's strategy to decarbonize the transportation sector. California is one of only three states in the nation that does not currently allow the sale of E15 and is thus foregoing valuable and critically needed climate benefits. By expanding the market for the largest LCFS compliance source by almost 50 percent in California, E15 would ease compliance burdens and support CARB's effort to set more stringent GHG reduction goals in coming years under the LCFS. The emissions benefits of displacing fossil fuels with clean-burning ethanol are significant across the California light and medium-duty fleets. For example, shifting from E10 to E15 in California would cut 1.8 million metric tons of GHG emissions from the State's transportation sector annually – the equivalent of removing 411,000 cars off the road each year.[5]

In addition to the environmental benefits that all Californians would enjoy with the immediate increase in fossil-free fuels being used in transportation, all consumers in the State, including those in disadvantaged communities, stand to benefit economically through more affordable transportation fuel options that can be accessed with existing vehicles and infrastructure. Renewable fuel blends, like E15, can provide meaningful cost savings to California drivers.[6]

The 2022 Scoping Plan Update Should Include a Strategy to Incentivize the Deployment of Flex Fuel Vehicles in California

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[5] *See* GHG Benefits of 15% Ethanol (E15) Use in the United States
[6] *See* Attachment A, Evaluation of Potential E15 Sales in California

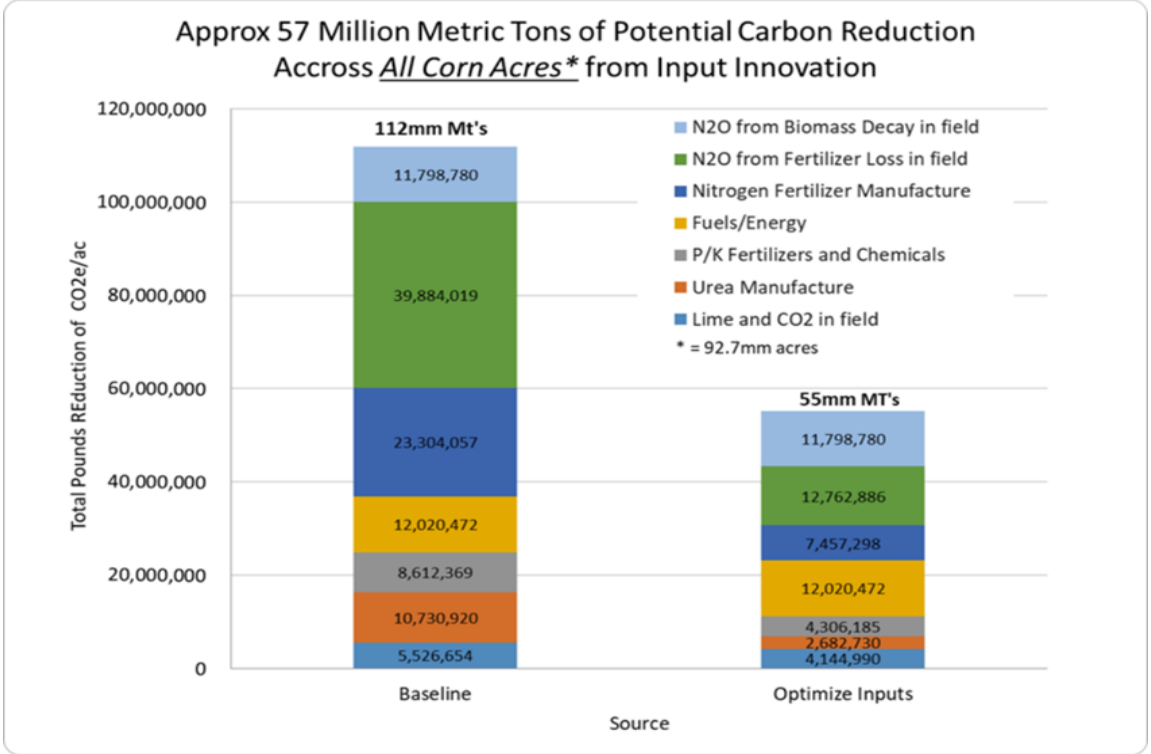
Full electrification of California's passenger vehicle fleet will take decades. In the interim, CARB can secure critically needed GHG reductions from the transportation sector by taking steps to equip vehicles in the State to run on increasingly lower carbon liquid fuels. Flex-fuel vehicles (FFV) provide a means to accomplish this end. Because FFVs can take almost any level of bioethanol, they allow consumers to respond to the incentives established by the LCFS and choose higher biofuel blends. While CARB is shrinking the pool of available liquid fuel to get petroleum out of the transportation system, CARB should also enable the replacement of as much of the petroleum as possible with low-carbon biofuels, and help to ensure that California's legacy fleet of internal combustion engine vehicles is being powered by the cleanest, most climate-friendly low carbon fuels available.

The 2022 Scoping Plan Update Should Include a Strategy to Incentivize Sustainable Low Carbon Farming Practices

The Draft 2022 Scoping Plan update recognizes the need for California to pursue innovative, climate-smart agricultural practices as part of the effort to achieve carbon neutrality.[7] California can demonstrate leadership nationally and internationally by putting in place policies and programs that effectively incentivize the lowest carbon, most sustainable and most advanced climate-smart agricultural practices across the planet. CARB is in a position to incentivize enormous changes in the agricultural supply chain that would lead to significant reductions in agricultural GHG emissions. By allowing site-specific agricultural inputs, CARB can encourage reduced agricultural GHG emissions through readily available technologies and practices such as better tillage practices, nitrogen reductions through improved fertilizer use, and biodiversity management. CARB can also encourage reduced agricultural GHG emissions through incentives for the agricultural supply chain to reduce GHG impacts in new and innovative ways.

Programs like Gradable, mentioned above, prove that low-carbon agricultural practices can lead to significant GHG reductions, and POET stands ready to work with CARB and other State agency partners to create a world-leading set of programs that account for, incentivize, and reward those practices. There is a range of actions California can take to support low-carbon agricultural practices and technologies. Specifically, in the near term, the Scoping Plan Update can set the stage for CARB to take action to recognize the benefits of climate-friendly farming by allowing for variable scoring as part of the upcoming LCFS rulemaking that will further support enhancing the stringency of the program. As demonstrated in the graph below, sustainable farming practices can potentially remove approximately 57 million metric tons of carbon across all corn acres in the United States on an annual basis.

[7] *See* Draft 2022 Scoping Plan Update, page 209



The 2022 Scoping Plan Update Should Maximize Strategies that Align with and Complement California's Efforts to Improve Air Quality and Public Health

In addition to setting California on a path to achieve carbon neutrality, one of the key goals of the 2022 Scoping Plan is to "deliver near term air quality benefits to communities with the highest exposures."[8]

Recent analyses from leading national experts demonstrate air quality and public health benefits from higher biofuel blends, particularly in disadvantaged communities. A recent study, which is the first ever large-scale analysis of data from light-duty vehicle emissions examined the real-world impacts of ethanol-blended fuels on regulated air pollutant emissions, including particulate matter (PM), carbon monoxide (CO), and total hydrocarbons (THC).[9] The study found that CO and THC emissions were significantly lower for higher ethanol fuels for port fuel injected (PFI) engines under cold-start

[8] *See id.*, page 15
[9] *See* Attachment B, Kazemiparkouhi, et al., Comprehensive US database and model for ethanol blend effects on regulated tailpipe emissions, 2022 (under review)

conditions. THCs include VOCs, meaning that both primary ozone precursors decreased with higher ethanol blends.

A second recent analysis builds on that work and demonstrates ethanol-associated reductions in emissions of primary PM, CO, and THCs.[10] Key findings of that study include:

- PM emissions decreased with increasing ethanol content under cold-start conditions. Primary PM emissions decreased by 15-19 percent on average for each 10 percent increase in ethanol content under cold-start conditions. Cold start PM emissions have consistently been shown to account for a substantial portion of all direct tailpipe PM emissions from motor vehicles. Lower PM emissions result in lower ambient PM concentrations and exposures, which, in turn, are causally associated with lower risks of total mortality and cardiovascular effects.

- Emissions of CO and THC generally decreased with increasing ethanol fuel content under cold running conditions, while NOx emissions did not change.

- Air toxic emissions showed lower BTEX, 1-3 butadiene, black carbon, and particle number emissions with increasing ethanol content in market fuels.

- Higher blends of ethanol fuels may be particularly beneficial for disadvantaged communities with high traffic density and congestion and are thus exposed to disproportionately higher concentrations of PM emitted from motor vehicle tailpipes. Vehicle trips within these communities tend to be short in duration and distance, with approximately 50 percent of all trips in dense urban communities under three miles long. As a result, a large proportion of these vehicle trips occur under cold start conditions when PM emissions are highest.

The air quality benefits demonstrated in these studies show how advanced biofuels can play a key role in helping CARB both meet state climate goals and secure needed air quality and public health benefits.

Conclusion

At POET, our mission is to cultivate a world in harmony with nature, where everyone has equal access to affordable, environmentally conscious fuel choices. We are constantly

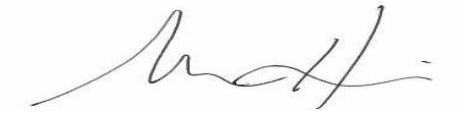
[10] See Attachment C, Potential Air Quality and Public Health Benefits of Real-World Ethanol Fuels

innovating to make biofuel production more efficient while developing more renewable bioproducts that will pave the way to a smarter, more sustainable future.

POET has a key role to play in California's efforts to achieve carbon neutrality. The 2022 Scoping Plan Update will set the direction California takes over the next several decades to meet its climate and air quality goals. CARB must ensure that the 2022 Scoping Plan Update includes all available strategies and actions to optimize the environmental, economic, and public health benefits that innovative, low-carbon biofuels can deliver for California.

POET appreciates the opportunity to comment and looks forward to working with CARB to make the 2022 Scoping Plan Update a success for California.

Sincerely,



Matt Haynie
Senior Regulatory Counsel

ATTACHMENT A

EVALUATION OF POTENTIAL E15 SALES IN CALIFORNIA

Edgeworth Economics

April 5, 2022

I. Introduction

Blending ethanol into gasoline provides a variety of benefits for consumers, the environment, and the U.S. economy more generally. Domestically produced ethanol has largely replaced other fuel additives (which may be harmful to health, more expensive, and/or less effective), and further reduces the need for imported crude oil, reduces carbon emissions, and reduces the total costs to produce gasoline. Most gasoline sold at retail today is a blend known as "E10" which contains approximately 10 percent ethanol combined with petroleum-based gasoline blendstock.

These benefits, however, are not limited to a 10-percent ethanol blend. Increasing the share of ethanol in gasoline is a trend that has accelerated around the U.S. in recent years. Increasing the ethanol blend up to 15 percent ("E15") results in gasoline with comparable quality to E10, while providing proportionately more of the benefits noted above. In 2012, the U.S. Department of Energy (DOE) conducted a rigorous test of E15 across a range of engine types and found no adverse impact on any measure of performance, including fuel economy as well as maintenance, stating:[1]

> The Energy Department testing program was run on standard gasoline, E10, E15, and E20. The Energy Department test program was comprised of 86 vehicles operated up to 120,000 miles each using an industry-standard EPA-defined test cycle (called the Standard Road Cycle). *The resulting Energy Department data showed no statistically significant loss of vehicle performance (emissions, fuel economy, and maintenance issues) attributable to the use of E15 fuel compared to straight gasoline.*

Currently, E15 is offered for sale in 30 states. However, the largest market for gasoline in the U.S., California, has yet to approve E15 for retail sale. This paper analyzes trends in E15 sales across the U.S. and assesses the potential benefits for California consumers and retailers from the introduction of that fuel blend.

II. Cost-Related Benefits of E15 to Consumers and Gasoline Retailers

As noted above, in addition to benefits related to energy security and sustainability, the use of E15 provides potential savings for consumers and retailers based on the difference in the wholesale cost of the components of E15 relative to E10. In particular, ethanol generally sells for less, per gallon, than gasoline blendstock, and the generation of credits under the national Renewable Fuel Standard program (known as Renewable Identification Numbers or "RINS") when blending ethanol into gasoline provides additional value from increasing the proportion of ethanol in retail gasoline. In California, ethanol provides further benefits due to the Carbon Intensity ("CI") value under the Low Carbon Fuel Standard ("LCFS") program. The

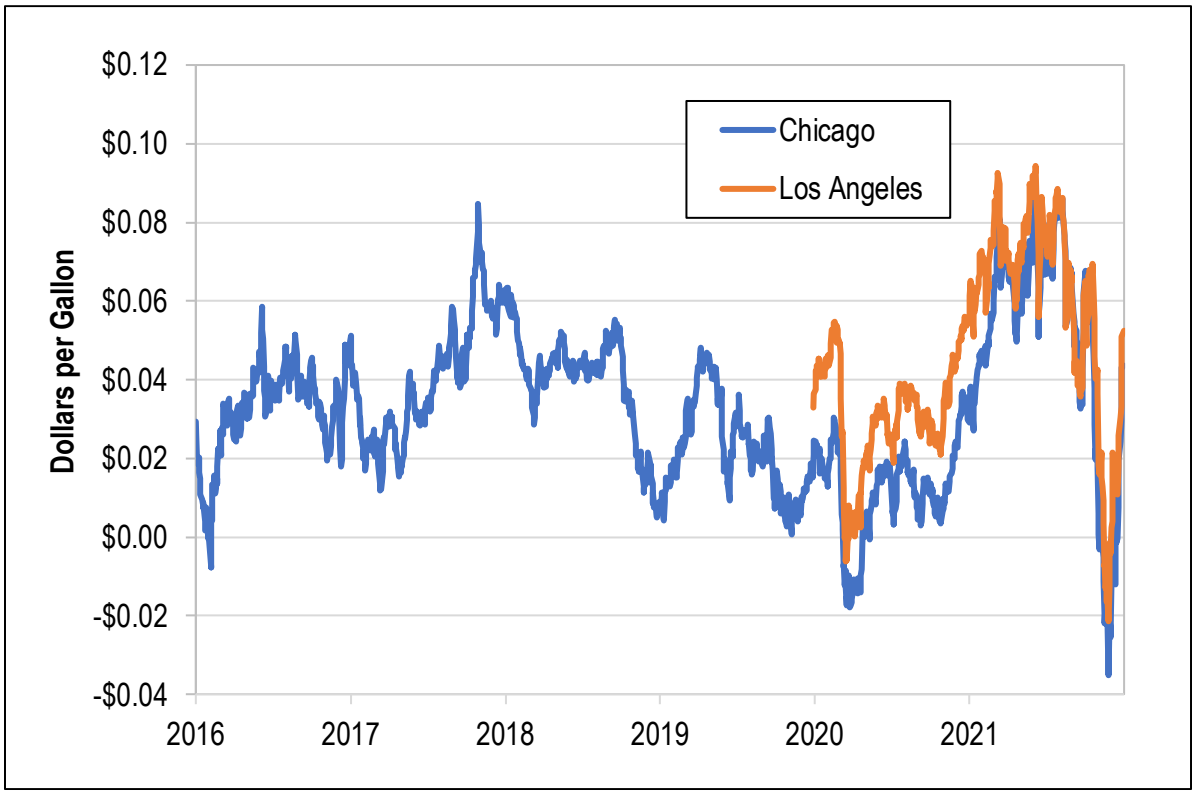
[1] DOE, "Getting It Right: Accurate Testing and Assessments Critical to Deploying the Next Generation of Auto Fuels," May 16, 2012 (emphasis added), available at www.energy.gov/articles/getting-it-right-accurate-testing-and-assessments-critical-deploying-next-generation-auto.

savings generated by E15 relative to E10 can be calculated from the wholesale prices of gasoline blendstock, ethanol, D6 (conventional) RINs, and (for California) CI value as follows:[2]

E15 Savings Relative to E10 per Gallon of Gasoline = (Blendstock Price - Ethanol Price + RIN Price + CI Value) × 5%

Using this formula, the savings as measured at Los Angeles and Chicago generally have fluctuated between zero and 8 cents per gallon over the last several years, as shown in Figure 1.[3] In 2021, the E15 discount averaged $0.051 per gallon using Chicago pricing and $0.060 per gallon using Los Angeles pricing combined with the CI value in California.

Figure 1
E15 Savings Relative to E10 (Wholesale), 2016 – 2021



Source: OPIS and Edgeworth Economics calculations (see text).

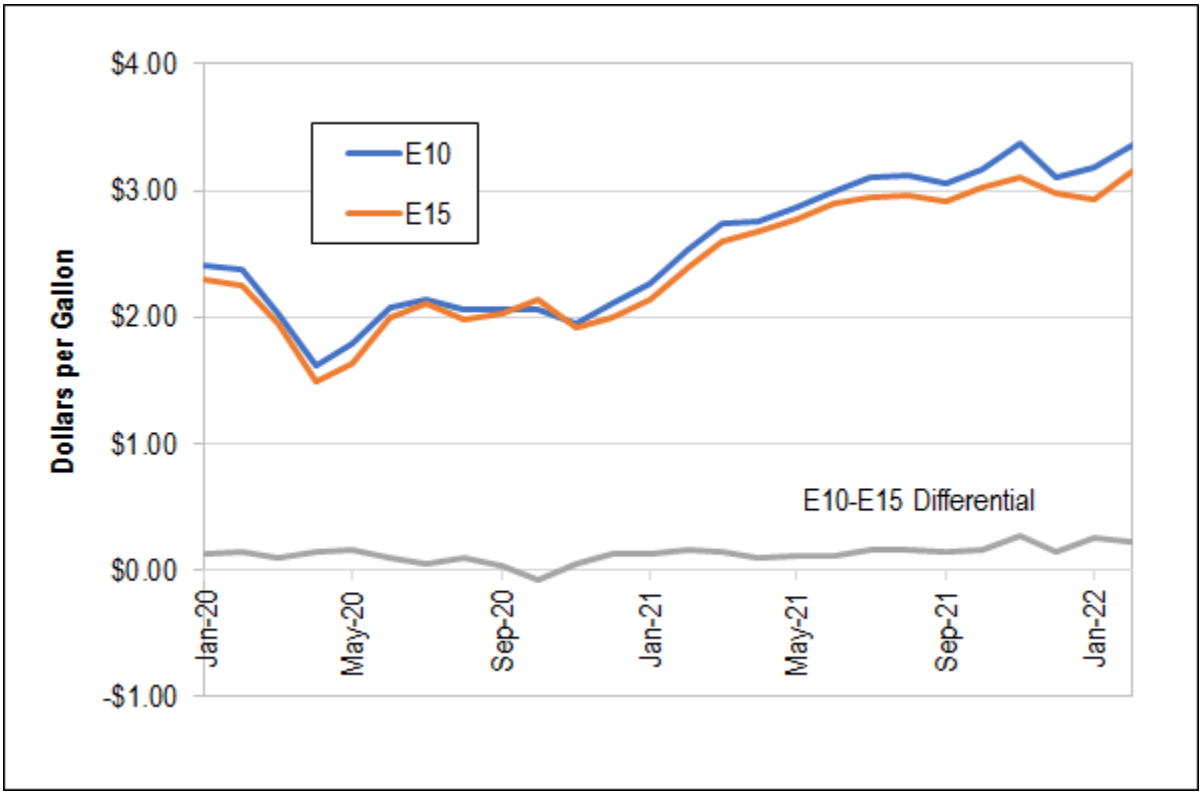
Moreover, these savings apparently are being passed on to consumers, as retail price differentials have generally equaled, if not exceeded, the wholesale differentials in recent months. As shown in Figure 2,

[2] For this calculation, the OPIS ethanol quote for Los Angeles is assumed to incorporate a CI score of 79.9. The average CI score for actual ethanol volumes in California is assumed to be 58.6, based on 2020 values. [RFA, "The California LCFS and Ethanol: A Decade of Reducing Greenhouse Gas Emissions," May 2021]

[3] As shown in Figure 1, for brief periods the discount for E15 relative to E10 has fallen below zero due to temporary increases in the prices of ethanol relative to gasoline blendstock, two fuels which otherwise generally move in similar directions. A variety of circumstances can lead to these conditions; but they usually last for short periods and usually are related to the higher volatility of gasoline prices relative to ethanol prices. For example, CBOB prices fell substantially in March-April 2020 due to conditions associated with the COVID pandemic, while ethanol prices were affected less significantly. The opposite circumstances occurred in late-2021, when CBOB prices rose significantly for about two months, while ethanol prices remained relatively flat.

according to data self-reported by certain stations to the Renewable Fuels Association ("RFA"), the discount for E15 relative to E10 has averaged approximately $0.12 per gallon since January 2020.[4]

Figure 2
Average E10/E15 Differential at Retail, January 2020 – February 2022



Source: RFA website, e85prices.com.
Note: These averages are based on self-reporting to RFA by dozens of stations across approximately 20 states.

III. E15 Sales/Station Growth

The experiences from a number of states across the U.S. demonstrate the potential for E15 growth in California. E15 was introduced in a few states in 2012, and growth in terms of the number of stations offering the product as well as sales per station began to accelerate around 2016/2017. While corn-producing states in the Midwest have led the industry, with some states now offering E15 at more than 5 percent and even more than 10 percent of all gas stations, significant gains have been seen in many other states, including large states distant from the corn-growing region such as Florida and Pennsylvania. Nationwide, there are now approximately 2,600 stations that offer E15 across 30 different states (see Table 1). This figure has more than doubled in just the last four years, as shown in Figure 3.

[4] There are a variety of reasons why retail discounts for E15 may exceed the wholesale values, as calculated above. For example, some stations may choose to price E15 below the notional spread from E10 as a loss leader. Other stations may expect different assessments by consumers regarding the octane value of ethanol-based fuels. Finally, the stations reporting E15 prices to RFA may not be representative of the entire industry due to regional factors or particular marketing strategies.

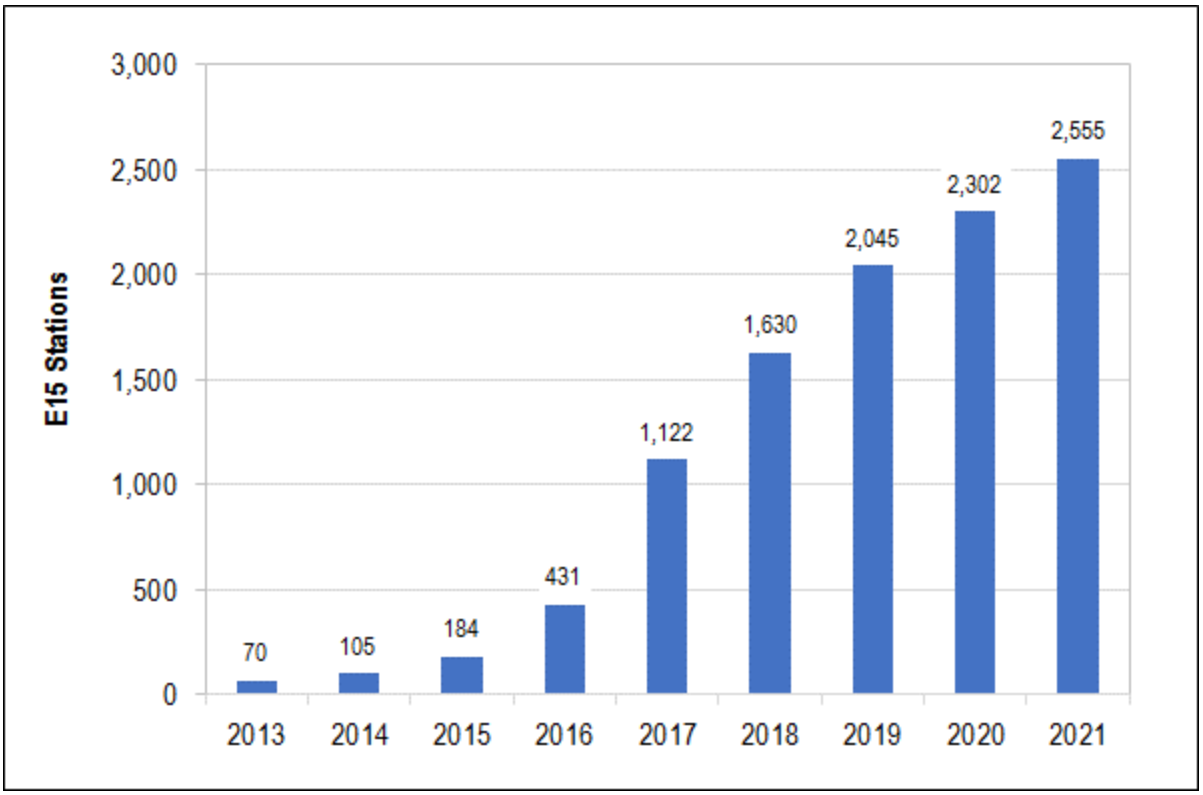
Table 1
Gas Stations Offering E15, by State, as of January 2022

State	Stations Offering E15	% of All Stations in the State
MN	372	14.4%
WI	302	9.1%
IA	274	12.6%
TX	196	1.6%
FL	186	2.3%
PA	155	3.7%
IL	135	3.8%
NE	110	7.8%
GA	95	1.2%
NC	85	1.5%
AL,AR,CO,IN,KS,KY,LA,MD,MI,MO,MS,ND,NM, OH,OK, SD,TN,VA,WV,WY	653	1.3%
AK,AZ,CA,CT,DC,DE,HI,ID,MA,ME,MT,NH,NJ, NV,NY, OR,RI,SC,UT,VT,WA	0	0.0%
U.S. Total	**2,563**	**1.8%**

Sources: RFA station list, as of January 2022; DOE website, afdc.energy.gov/files/u/data/data_source/10333/10333_gasoline_stations_year.xlsx.

Note: Total number of gas stations is based on 2012 data from the NACS, extrapolated to 2022 based on the 2007-2012 trend.

Figure 3
Total Number of Gas Stations in the U.S. Offering E15, 2013 – 2021



Source: RFA.

Two states, Iowa and Minnesota, have tracked E15 sales at the station level and publish data that allows a more granular assessment of these trends. As shown in Table 2, over the last few years, these two states have seen rapid increases in both the number of stations offering E15 as well as the volume of E15 sales per station, resulting in compound annual growth rates ("CAGR") for total E15 sales in the range of 80 to 90 percent annually over the 5-year period through 2020. Prior to the COVID pandemic in 2020, which caused substantial declines in nationwide gasoline consumption, E15 growth was even more rapid, with 4-year average growth rates in the two states exceeding 100 percent—*i.e.*, more than doubling each year. As of 2020, sales of E15 in each of these two states had reached approximately 4 to 5 percent of all gasoline sales.

Table 2
Gas Stations Offering E15 and Total E15 Sales in Iowa and Minnesota, 2016 – 2020

	Iowa				Minnesota			
	Number of Stations Selling E15	E15 Gallons per Station	Total E15 Gallons (Million)	E15 Share of All Gasoline Sales	Number of Stations Selling E15	E15 Gallons per Station	Total E15 Gallons (Million)	E15 Share of All Gasoline Sales
2016	160	34,588	5.5	0.3%	112	50,750	5.7	0.2%
2017	226	122,604	27.7	1.8%	257	74,149	19.1	0.8%
2018	220	161,203	35.5	2.3%	337	177,149	59.7	2.6%
2019	244	200,653	49.0	3.1%	363	217,420	78.9	3.4%
2020	251	241,387	60.6	4.5%	394	190,554	75.1	3.7%
2016-2019 CAGR	15.1%	79.7%	106.8%		48.0%	62.4%	140.3%	
2016-2020 CAGR	11.9%	62.5%	81.9%		37.0%	39.2%	90.6%	

Sources: Minnesota Commerce Department website, mn.gov/commerce/consumers/your-vehicle/clean-energy.jsp; Iowa Department of Revenue website, tax.iowa.gov/report-category/retailers-annual-gallons; and DOE website, www.eia.gov/dnav/pet/pet_cons_prim_a_EPM0_P00_Mgalpd_m.htm.
Note: Total gasoline sales in Minnesota are from DOE estimates of Prime Supplier Sales Volumes of Motor Gasoline.

Due to resistance from the integrated refiners[5], to date most of the growth in E15 sales nationwide has been generated by independent chains (*i.e.*, retailers without refinery/discovery operations) and owners of single stations or a small number of stations. Table 3 lists the major brands currently offering E15 across the U.S.

Table 3
Retail Gas Station Brands Offering E15, as of January 2022

Brand	E15 Stations	% of Total
Kwik Trip	451	17.6%
Casey's General Stores	398	15.5%
Sheetz	325	12.7%
Kum & Go	178	6.9%
RaceTrac	171	6.7%
Murphy USA	75	2.9%
Thorntons	75	2.9%
Kwik Star	73	2.8%
QuikTrip	70	2.7%
Holiday	56	2.2%
Integrated Refiners (e.g., Exxon, Chevron, Shell)	102	4.0%
Other	589	23.0%
Total	**2,563**	100.0%

Source: RFA.

[5] See, for example, American Petroleum Institute website, www.api.org/news-policy-and-issues/fuels-and-renewable-policy/truth-about-e15-fuel.

IV. Potential E15 Sales in California and Savings for Consumers

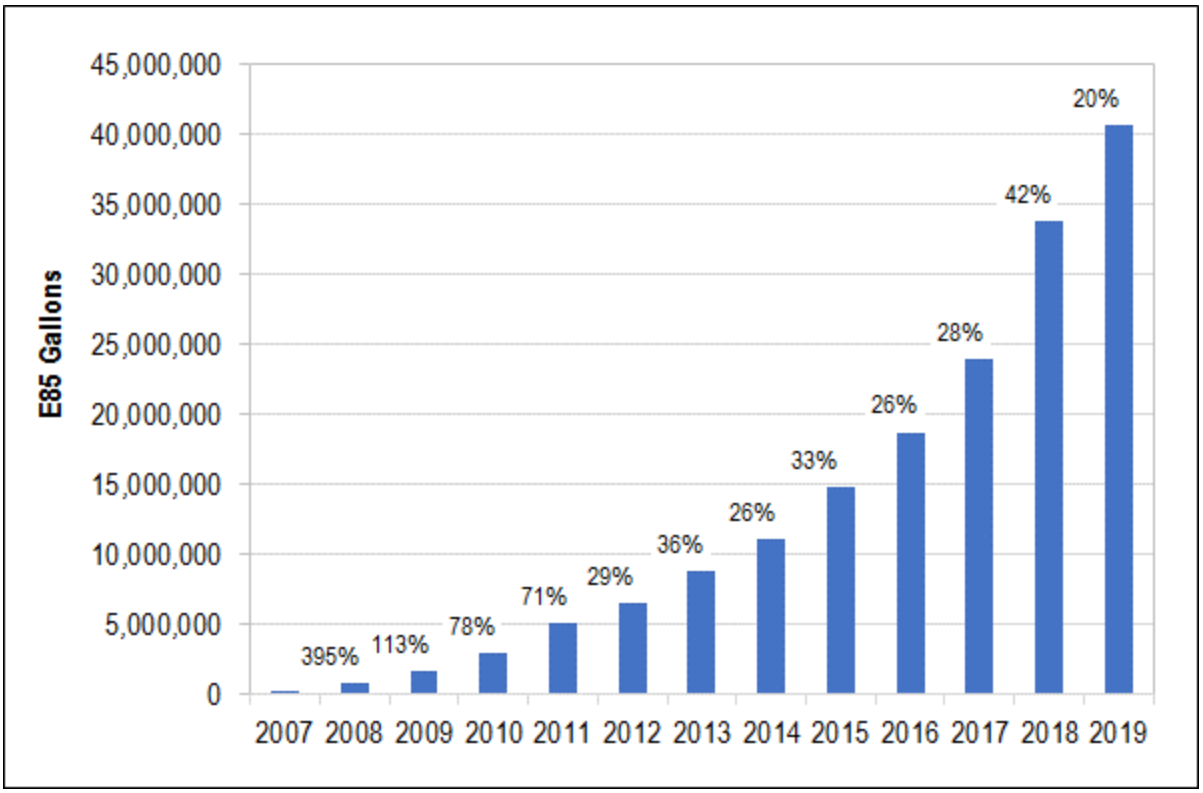
The pattern of growth evident in states that have allowed, and in some cases actively encouraged, the promotion of E15 provides evidence of the potential for E15 sales in California, as does California's own experience with other ethanol-based fuels, in particular E85.

California is home to a large number of independent retailers. Thus, continued resistance from the integrated refiners does not necessarily represent a limitation for the near-term expansion of E15 in California. According to the California Energy Commission, currently about 3,700 (43 percent) of California's approximately 8,700 gas stations are "unbranded" (*i.e.*, not affiliated with the integrated refiners) or operated by "hypermarts" (retailers whose primary business is unrelated to oil/gasoline such as Costco, Sam's Club, and Von's).[6]

This flexibility is evident from the expansion of E85 in California, which also has been led primarily by independent retailers. Currently, about 250 stations in California already offer E85, with total sales volumes exceeding 40,000,000 gallons in 2019. As shown in Figure 4, E85 volumes in California have grown steadily, with an average increase of 30 percent annually during the 5-year period through 2019.

[6] California Energy Commission, *Petroleum Watch*, July 2021, available at www.energy.ca.gov/sites/default/files/ 2021-07/2021-07_Petroleum_Watch.pdf. In addition to these two categories, the CEC notes that ARCO-branded stations, which represent an additional 10 percent of all California stations, purchase unbranded fuel from the rack. (See also, California Energy Commission, *Petroleum Watch*, January 2020, available at www.energy.ca.gov/sites/default/files/2020-02/2020-01_Petroleum_Watch.pdf.)

Figure 4
E85 Sales in California, 2007 – 2019 (with annual growth rate)



Source: California Air Resources Board website, ww2.arb.ca.gov/resources/documents/alternative-fuels-annual-e85-volumes.

If E15 is approved for sale in California, a growth pattern in line with California's own experience with E85 as well as the history of E15 sales in other states would represent a significant addition to California's overall fuel mix and could provide significant savings for consumers. For example, consider that over 13 percent of stations in Iowa and more than 22 percent of stations in Minnesota now offer E15, less than ten years after the first introduction of the product. Moreover, the bulk of that growth has occurred in just the last four years, with total E15 sales growing from less than 1 percent to 4-5 percent of total fuel sales during that period in the two states. If California could attain the same level of E15 penetration, that would represent savings of at least $34 million annually (potentially shared between consumers and retailers), based on recent wholesale fuel prices.[7] If California stations implement pricing strategies more representative of the stations assessed by RFA, as shown in Figure 2, above, then the savings to consumers could be much higher, reaching $67 million annually.[8] Such a transition actually would require

[7] This figure is equal to a price differential of $0.06 per gallon multiplied by 4 percent of California's annual fuel consumption (approximately 14 billion gallons, based on DOE's figure for 2019). [DOE website, www.eia.gov/dnav/pet/pet_cons_prim_a_EPM0_P00_Mgalpd_a.htm]

[8] This figure incorporates a price differential of $0.12 per gallon, based on the retail differential shown in Figure 2, above.

proportionately less participation from gas stations in California than in the Midwest states, since overall sales volumes tend to be significantly higher at California stations.[9]

Moreover, if any of the integrated refiners were to introduce E15 in California, the trend could accelerate even more rapidly. Recent events may indicate that some refiners are positioning themselves for that eventuality. For example, earlier this year Chevron announced that it was spending more than $3 billion to acquire Iowa-based Renewable Energy Group, a company specializing in biofuel production and marketing.[10] Renewable Energy Group currently sells both E15 and E85, and the company's website identifies the benefits of those fuels to include reduced emissions, improved engine performance, and other contributions to the U.S. economy.[11] Chevron operates more than 1,500 gas stations in California, representing about 20 percent of the total.[12] Thus, If Chevron were to introduce E15 in California, the expansion of that fuel's share of the market could increase even more rapidly than the historical trends in the other states, described above. For example, if, in addition to the growth at independent stations, one half of all Chevron stations in California introduced E15 and reached sales levels now experienced in the Midwest states described above (a modest target, given the higher overall gasoline throughput at California stations), savings for California consumers/retailers could reach approximately $43 million to $86 million annually.[13]

V. Transition Costs

The rapid growth in the number of stations offering E15 elsewhere in the U.S. indicates that transition costs are not likely to be a significant impediment to expansion in California. Adding a new fuel blend or replacing a previously sold blend, such as a mid-grade E10, are both feasible solutions for a gas station seeking to include E15 among its choices for retail customers.[14] Pre-blended E15 currently can be obtained from almost 300 terminals located primarily across the Midwest and southern and eastern U.S., an increase from only five terminals as of 2017.[15] If California approves E15 for retail sale, it is likely that wholesalers will begin to offer pre-blended E15 at terminals in California, as well.

Another option is for stations to blend on-site, using E85 and conventional E10. Blender pumps can be installed to replace pre-existing pumps or added in the normal course of expansion or upgrades over time. Blending on-site apparently is a common option for many stations today, as about 80 percent of the stations that currently offer E15 also offer E85.[16] Thus, the 250 gas stations in California that already offer

[9] Average fuel sales per station in California are approximately 1.9 million gallons annually, compared to about 0.7 million in Iowa and 1.1 million in Minnesota (based on DOE figures for 2019) [DOE websites, www.eia.gov/state/?sid=US and www.eia.gov/dnav/pet/pet_cons_prim_a_EPM0_P00_Mgalpd_a.htm]

[10] Renewable Energy Group press release, "Chevron Announces Agreement to Acquire Renewable Energy Group," February 28, 2022, available at www.regi.com/blogs/blog-details/resource-library/2022/02/28/chevron-announces-agreement-to-acquire-renewable-energy-group.

[11] Renewable Energy Group website, www.regi.com/products/transportation-fuels/reg-gasoline-ethanol-blends.

[12] See footnote 6.

[13] This range incorporates the figures calculated above plus additional E15 sales of 200,000 gallons per year at one half of Chevron's 1,559 stations in California (as of 2020).

[14] See, for example, Jerry Soverinsky, "The Case for E15," *NACS Magazine*, February 2018, available at www.nacsmagazine.com/issues/february-2018/case-e15.

[15] Based on data collected by Growth Energy.

[16] RFA station list as of January 2022.

E85 would be likely candidates for early adoption of E15.[17] The cost of a new blender pump, at about $30,000, could be recouped from the savings generated by E15 in no more than one to three years, based on the range of price differentials observed at wholesale and retail, described above.[18]

Moreover, there exist a variety of programs to assist station owners with the introduction of new biofuels. For example, USDA's Higher Blends Infrastructure Incentive Program has made available up to $100 million in grants to expand the availability of biofuels.[19] Some of these funds already have been used to install blender pumps and new tanks at gas stations seeking to offer E85 and/or E15.[20] Private initiatives, such as Growth Energy's "Prime the Pump" program also offer support, including marketing assistance and funding to help cover transition costs.[21]

[17] One company, Pearson Fuels, currently supplies E85 to more than 200 stations in California. [RFA station list and Pearson Fuels website, pearsonfuels.com/e85-gas-stations]

[18] At 200,000 gallons per year (approximately the average throughput for E15 experienced at the stations tracked in Iowa and Minnesota, as described above), savings from selling E15 could generate $10,000 to $20,000 in additional profits per year, based on current wholesale/retail differentials. Moreover, since California gas stations generally experience greater levels of throughput than stations in those Midwestern states, payback of an initial investment in pumps likely would occur even more quickly in California.

[19] USDA website, www.rd.usda.gov/hbiip.

[20] See, for example, Environmental and Energy Study Institute, "E15 Bill Attempts to Solve Ethanol Conundrum," June 16, 2017, available at www.eesi.org/articles/view/e15-bill-attempts-to-solve-ethanol-conundrum.

[21] Growth Energy website, growthenergy.org/wp-content/uploads/2019/11/MDEV-19022-PTP-Overview-2019-11-12.pdf.

ATTACHMENT B

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Comprehensive US database and model for ethanol blend effects on regulated tailpipe emissions

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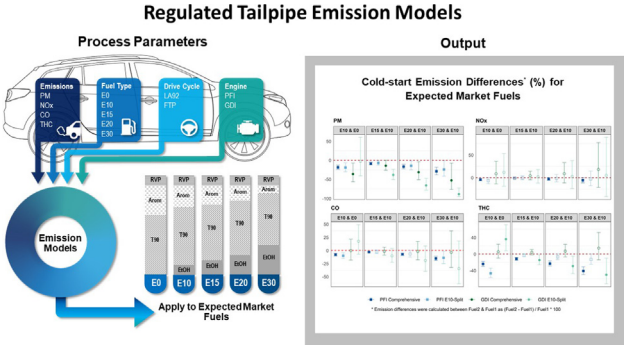
HIGHLIGHTS

- Comprehensive US database of emissions to develop models for inventory prediction
- Developed separate emission regression models for PFI and GDI engine vehicles
- Different blending behavior of ethanol below and above E10
- Different response of PFI and GDI to projected fuels
- Particulate matter levels reduction by ethanol addition

GRAPHICAL ABSTRACT



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ABSTRACT

Particulate matter (PM), oxides of nitrogen (NOx), carbon monoxide (CO), and total hydrocarbons (THC) in gasoline exhaust affect atmospheric quality, and hence human health. Ethanol produced from corn grain is a renewable resource with favorable anti-knock properties for gasoline blending. Refiners alter petroleum composition to produce a finished blend that meets specifications. Ethanol blending affects emissions from market fuels both directly and indirectly since aromatics are typically removed from the BOB as ethanol is added to reach a constant octane rating. Numerous studies have been conducted to assess the effect of ethanol blending on light duty vehicle emissions. However, few studies have examined market fuel blends directly and small studies yield insufficient information to be generally applicable. If blending of fuels for a study does not yield gasoline that adequately resembles the composition of a market blend, the generalizability of study results may be impacted by nonlinear blending effects. Most vehicle-based fuel effect studies employed fuel formulations that either facilitate examination of several fuel variables or blend ethanol into a baseline gasoline (splash blending). Such study results do not support direct quantification of emissions inventory effects. To examine real world blending implications on regulated emissions [PM, NOx, CO, THC], we compiled a comprehensive database of US emission studies, developed regression models based on fuel and vehicle properties, and used those models to estimate differences in emissions from expected market fuel compositions. We addressed nonlinear responses to ethanol composition by modeling both low (up to 10% ethanol by volume) and mid blends (split models). We used the Federal Test Procedure (FTP) and Unified Cycle (LA92) driving schedule data, with the cold-start eliciting the highest emissions. PM cold-start emissions were lower with higher ethanol content, and more so at higher blend levels but hot-running emissions showed no differences with respect to ethanol level. For all emissions, the effects differed between port fuel injection (PFI) and gasoline direct injection (GDI) powered vehicles and for NOx, CO and THC there were differences between comphrehensive and split models. NOx results varied

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over blend levels and THC results were scattered for the higher blends. CO emissions were lower with higher ethanol content in nearly all cases for PFI but only the hot-running GDI. Results did not differ between summer regular and premium fuels. To the extent that PFI and GDI models differ, an emissions inventory calculation should treat them separately. There is uncertainty directly associated with the regression process, and with model inputs since study methods vary and compositions are reported differently between laboratories and test methods. Small changes in modeled emissions should be considered in this light.

1. Introduction

The impact of light duty vehicle exhaust on human health typically is assessed by the quantification of species that reduce air quality through subsequent reaction in the atmosphere. Particulate matter (PM), oxides of nitrogen (NOx), carbon monoxide (CO), non-methane organic gases (NMOG) and formaldehyde (HCHO) are all regulated at the vehicle tailpipe under US Tier 2 standards, and for Tier 3 standards NOx and NMOG are combined (US EPA, 2021c). NMOG calculation relies substantially on measurement of total hydrocarbon (THC) emissions.

Following the phase-out of methyl tert-butyl ether (MTBE) as a gasoline additive, ethanol blending with gasoline was enabled by the renewable fuel standard and was widely adopted. E10, a 10% (by volume) blend of ethanol with a gasoline blendstock (BOB), is now the US norm for use in spark-ignited engines. E15 is also available in the marketplace. Ethanol has a high blending octane number and enhances the knock resistance of the BOB with which it is blended. For market fuels, the rise of ethanol fraction has been accompanied by a reduction of aromatic and olefinic content profile (US EPA, 2017).

Numerous studies have been conducted to assess the effect of ethanol blending on light duty vehicle emissions, which affect human health through changes in air quality (Clark et al., 2020; Karavalakis et al., 2018a; Manisalidis et al., 2020). Conclusions of major emission effect studies, reviewed in Section 3, have varied. Accuracy and relevance of conclusions are impacted by differences in engine technology, emissions measurement accuracy, and repeatability of fuel analyses. Typically, studies have employed fuels of varying ethanol content, each with an associated BOB. For market fuels, the BOB is a mixture of a wide range of hydrocarbons, constrained by the ability and value of refinery streams and blended to ensure that the finished E10 gasoline in the marketplace meets specifications, including volatility and anti-knock index (AKI) requirements (Clark et al., 2019). The BOB and ethanol blend in a highly non-linear fashion, and BOB composition has a profound effect on regulated emissions (Anderson et al., 2014; Foong et al., 2014). Few studies have employed market fuel blends directly, and small studies yield insufficient information to be generally applicable.

Detailed hydrocarbon analysis (DHA) of refinery streams and petroleum blends has become progressively more accurate and accessible over the last decade, leading to better understanding of gasoline composition and variability. If blending of fuels for a study does not yield gasoline that adequately resembles the composition of a market blend, predictions of regulated species may be impacted by nonlinear blending effects. In this research, we compiled a comprehensive database of published data to produce and test emissions models based on fuel properties and composition. To avoid variability due to vehicle technology and operation, we selected studies using US vehicles and two US test schedules (FTP and LA92) that each included cold-start and hot-running phases. We then identified properties representative of current and proposed market fuels, and applied the models to the market fuel properties to estimate differences in regulated emissions. In particular, we have taken into account the typical reduction in aromatic content of gasoline in response to the blending of ethanol.

2. Materials and methods

A mixed method approach was used in this study. First, we reviewed the major emission effect studies and identified studies by type and by ethanol level. We selected the studies that provide sufficient information for use in broader emissions analysis and commented on the findings of suitable studies (Section 3).

Second, we extracted the data from selected studies shown in Table 1. For each fuel and vehicle, we included in our database fuel properties such as ethanol volume, aromatics volume, 50% volume distillation temperature (T50), 90% volume distillation temperature (T90), and Reid Vapor Pressure (RVP); and vehicle properties such as vehicle model year and engine type. A vehicle was included in the study if at least two fuels with different ethanol level were tested on it. We also noted whether the vehicles were designated as flexible fuel vehicles

Table 1
Summary information of studies included in the compiled database.

Study	Tested vehicles (#)			Tested fuels (#)							Tested cycles	Modeled items
	PFI	GDI	FFV	E0	E6	E10	E15	E20	E25	E30		
CRC E-129	0	4	0	3	0	1	1	0	0	0	LA92	NOx, CO, THC
CRC E-80	7	0	7	0	1	0	0	0	0	1[c]	FTP	NOx, CO
CRC E-94-3	0	4	0	4	0	4	0	0	0	0	LA92	PM, NOx, CO, THC
CRC E-98/A-80	15	0	3	1	0	1	1[b]	0	0	0	LA92	PM, NOx, CO, THC
EPA Tier3 Cert. Fuel	3	8	0	1	0	1	0	0	0	0	FTP	PM, NOx, CO, THC
EPAct Phase 3	15	0	3	8	0	9	3	7	0	0	LA92	PM, NOx, CO, THC
Karavalakis 2014b	3	2	0	0	0	1	1	1	0	0	LA92, FTP	NOx, CO, THC
Karavalakis 2015	0	2	0	0	0	1	1	1	0	0	LA92, FTP	NOx, CO, THC
Karavalakis 2018b	0	5	0	2	0	2	3	1	0	0	LA92	PM, NOx, CO, THC
Sobotowski 2015	3	1	0	2	0	0	3	0	0	0	LA92	PM
West 2018	0	3	0	0	0	1	0	0	1	0	FTP	NOx, CO
West ETC 2012	29 (8)[a]	0	0	1	0	0	1	1	0	0	FTP	NOx, CO, THC
West SwRI 2012	75 (25)[a]	0	0	1	0	1	1	1	0	0	FTP	NOx, CO, THC
West TRC 2012	68 (22)[a]	0	0	1	0	0	1	1	0	0	FTP	NOx, CO, THC
Yang 2019b	0	1	1	0	0	2	0	0	0	1	LA92	NOx, CO, THC

[a] Emissions data were acquired at three or four instances during the extended ageing period of each automobile, and we elected to consider each instance separately (as if a separate vehicle) due to ageing and potential laboratory and fuel drift effects.
[b] The E16 fuel is displayed in closest ethanol category, E15.
[c] The E32 fuel is displayed in closest ethanol category, E30.

(FFV). We considered a vehicle to be FFV if the study stated that it was FFV or if it was tested on a fuel that was E51 or higher. We included in our database PM, NOx, CO, and THC emissions for each vehicle/fuel combination. Most studies used the Federal Test Procedure (FTP) and Unified Cycle (LA92) dynamometer driving schedules, and we noted the phase for which emissions were recorded: (1: Cold-start, 2: Hot-running, 3: Hot-start, 4: Weighted: Average of all phases).

Third, we developed and validated statistical models that estimate emissions for different ethanol fuel blends and engine types as a function of fuel properties. For each pollutant and emission phase, we ran a mixed model that allowed for a random intercept for each vehicle. The averages of runs for each vehicle, fuel and emissions species were used, decreasing the number of zero or negative emissions instances in the database. We employed the statistical program R (RStudio 1.4.1106) to determine independence of variables and establish models for emissions. We used linear space for controlling variables, but log space for emissions. This ensured that high emitting vehicles did not dominate the analysis, thereby focusing results on emissions ratios in response to fuel composition changes. We noted that the change in fuel behavior and properties when comparing gasoline (E0) and E10 typically differs from the comparisons of E10, E15 and E20. We therefore developed two separate models, using only the E0 and E10 data for the first model, and E10 and higher data for the second model (split models). We also developed combined models. The regression results and total number of data points (average of runs) and vehicles employed in each model are provided in Tables 2, 3 and S4 to S9. We discuss the modeling approach in more detail in Sections 2.1 and 2.2.

Finally, we applied the developed models to the market fuel properties to estimate regulated emissions changes with respect to ethanol level and the 95% confidence interval of those estimates (See section S1 in the supplementary material for more information).

2.1. PFI emissions models

The EPAct Phase 3 study is a major source of data for modeling regulated port fuel injection (PFI) emissions (US EPA, 2013a). The study itself offers full and reduced variable models for cold-start and hot-running phases (see Section S2 in the supplementary material, Fig. S1), and the study data have been modeled by others (Clark et al., 2021; Gunst, 2013). We reviewed the EPAct data by considering the effects of both ethanol and aromatic changes moving from E0 to E20, the lowest and highest ethanol blends considered in the study. Since the EPAct study employed two target aromatic levels, 15% and 35%, actual aromatic levels were grouped around these two values.

We first considered PM mass emissions from the EPAct study. The original EPAct reduced mixed model used standardized parameters and contained higher order terms:

$$\ln PM_{2.5} = \beta_0 + \beta_{EtOH} * EtOH_z + \beta_{Arom} * Arom_z + \beta_{T50} * T50_z + \beta_{T90} * T90_z + \beta_{T50^2} * T50^2{}_z + \upsilon + \varepsilon \quad (1)$$

where $PM_{2.5}$ has units of mg/mile, EtOH and Arom are volumetric percentages of ethanol and aromatic content in the fuel, distillation temperatures are in degrees Fahrenheit, the subscript z notes the use of standardized scales, and υ represents the random vehicle effect. The model coefficients are shown in Fig. S1 for cold-start and hot-running phases.

We developed our mixed model (denoted "EPAct Comprehensive") using ethanol content, aromatic content, and T90:

$$\ln PM_{2.5} = \beta_0 + \beta_{EtOH} * EtOH + \beta_{Arom} * Arom + \beta_{T90} * T90 + \upsilon + \varepsilon \quad (2)$$

We did not employ T50, noting that T50 showed correlation with ethanol content (see Section S3 in the supplementary material, Fig. S2), that T50 was match blended in the EPAct study in a way that it may not represent the lowered values of T50 in an ethanol market blend, and that T50 is a quixotic variable due to the nonlinear blending properties of ethanol in gasoline. Separate modeling that we conducted showed that PMI was very strongly correlated with aromatic content and T90, in agreement with Butler and Sobotowski (2021).

The EPAct Comprehensive PM model used all EPAct data for cold-start, hot-running, and weighted phases of the LA92 cycle. We developed models both by using separate data for each test run, which introduces bias for vehicles or fuels that were the subject of additional test runs, and by using average values for each fuel and vehicle combination. Model differences were small, but averages were less likely to yield zero or negative emissions values. We also ran the model on fuels at or below E10 (denoted E10− model) and on fuels at or above E10 (denoted E10 + model) to address behavioral changes at or about E10.

Note that a relative difference in emissions of an E0 fuel and a higher ethanol blend, say E20, can be estimated by taking the product of the E10/E0 ratio and the E20/E10 ratio, or else the sum of the two log differences. The two models (E10− and E10+), both linear, operate about an E10 breakpoint, and obviate the need for higher order model terms that may not be suited to extrapolation to unseen fuels.

We then applied a similar approach to develop models for CO, NOx, and THC based on the EPAct data. We included ethanol and aromatic content in all models; T90 in PM, CO, and NOx models; and RVP in THC models. These variables were selected based on their previous associations with tailpipe emissions. We removed T90 and RVP from the model if the variable was highly correlated with ethanol or aromatic content. Cold-start and hot-running emissions are traditionally combined to form a weighted average, but cold-start emissions tend to be higher than hot-running emissions and drive the average. Table 2 presents only the models for weighted emissions data for the EPAct

Table 2
Comprehensive and E10-Split models and goodness of fit data for weighted emissions of PM, NOx, CO, and THC developed using data from EPAct Phase 3 study.

Data	Item	Model	EtOH	Arom	T90	RVP	R^2	AIC	N	Vehicles
EPAct Phase 3	PM	Comprehensive	0.0138**	0.0190**	0.0062**		0.68	631.8	405	15
		E10−	0.0160**	0.0168**	0.0059**		0.71	352.7	255	15
		E10+	0.0106	0.0208**	0.0070**		0.68	488.9	285	15
	NOx	Comprehensive	0.0070**	0.0061**	−0.0001		0.87	144.6	405	15
		E10−	0.0055*	0.0066**	−0.0010		0.89	72.3	255	15
		E10+	0.0080**	0.0063**	−0.0001		0.86	130.8	285	15
	CO	Comprehensive	−0.0079**	0.0050**	−0.0025**		0.96	−96.4	405	15
		E10−	−0.0115**	0.0044**	−0.0028**		0.97	−80.4	255	15
		E10+	−0.0053**	0.0057**	−0.0023**		0.96	−31.6	285	15
	THC	Comprehensive	−0.0027*	0.0027**		−0.0461**	0.85	14.9	405	15
		E10−	−0.0037	0.0018		−0.0408**	0.85	33.2	255	15
		E10+	−0.0044	0.0035**		−0.0541**	0.86	13.0	285	15

Abbreviations: EtOH = ethanol volume %; Arom = aromatics volume %; T90 = 90% volume distillation temperature; RVP = Reid Vapor Pressure; R^2 = adjusted R-squared; AIC = Akaike information criterion; N = number of observations.

** $p < 0.05$.

* $0.05 < p < 0.1$.

Table 3
Comprehensive and E10-Split models and goodness of fit data for weighted emissions of PM, NOx, CO, and THC, developed using data from all studies with "LA92 and FTP" data from PFI, GDI, and "PFI and GDI" vehicles.

Data	Item	Model	EtOH	Arom	T90	RVP	R^2	AIC	N	Vehicles
PFI	PM	Comprehensive	0.0137**	0.0199**	0.0074**		0.70	779.3	467	36
		E10−	0.0139**	0.0174**	0.0062**		0.71	446.6	290	33
		E10+	0.0110*	0.0208**	0.0072**		0.65	571.6	321	30
	NOx	Comprehensive	0.0062**	0.0065**	−0.0003		0.93	982.5	811	205
		E10−	0.0033	0.0075**	−0.0009		0.86	318.4	321	48
		E10+	0.0078**	0.0063**	−0.0001		0.89	241.3	333	33
	CO	Comprehensive	−0.0082**	0.0054**	−0.0020**		0.94	640.4	812	205
		E10−	−0.0111**	0.0045**	−0.0021**		0.94	235.0	321	48
		E10+	−0.0046*	0.0056**	−0.0019**		0.97	76.5	333	33
	THC	Comprehensive	−0.0133**	0.0100**		−0.0877**	0.72	1631.9	732	166
		E10−	−0.0377**	0.0099**		−0.1351**	0.59	784.5	317	46
		E10+	−0.0027	0.0035**		−0.0575**	0.99	166.4	333	33
GDI	PM	Comprehensive	0.0267*	0.04300.0	0.0119*		0.62	249.5	89	18
		E10−	0.0338*	0.0336	0.0114		0.54	211.3	68	17
		E10+	0.0217	0.0850**			0.91	61.1	30	5
	NOx	Comprehensive	0.0035	0.0066	0.0016		0.71	153.8	139	29
		E10−	−0.0013	−0.0004	0.0023		0.73	110.1	84	21
		E10+	0.0046	0.0108			0.71	86.5	71	17
	CO	Comprehensive	−0.0140**	0.0094	−0.0001		0.94	130.7	139	28
		E10−	−0.0097	0.0123	−0.0002		0.94	103.1	84	21
		E10+	−0.0110	0.0096			0.95	76.0	69	16
	THC	Comprehensive	0.0008	0.0155*		0.0278	0.88	111.0	134	26
		E10−	0.0046	0.0167		0.0037	0.86	106.2	83	21
		E10+	0.0018	0.0170*		−0.0913	0.94	46.7	69	14
PFI & GDI	PM	Comprehensive	0.0138**	0.0202**	0.0079**		0.77	1037.1	556	54
		E10−	0.0164**	0.0173**	0.0070**		0.77	686.0	358	50
		E10+	0.0104*	0.0214**	0.0077**		0.73	629.3	345	35
	NOx	Comprehensive	0.0059**	0.0068**	−0.0001		0.93	1164.7	952	234
		E10−	0.0030	0.0077**	−0.0006		0.87	411.8	405	69
		E10+	0.0068**	0.0065**	−0.0000		0.87	314.5	404	50
	CO	Comprehensive	−0.0087**	0.0057**	−0.0016**		0.95	775.2	951	233
		E10−	−0.0114**	0.0048**	−0.0017**		0.95	317.2	405	69
		E10+	−0.0063**	0.0058**	−0.0017**		0.97	141.0	402	49
	THC	Comprehensive	−0.0121**	0.0106**		−0.0830**	0.76	1846.7	866	192
		E10−	−0.0294**	0.0099**		−0.1294**	0.60	939.4	400	67
		E10+	−0.0026	0.0037**		−0.0574**	0.98	201.5	398	47

Abbreviations: EtOH = ethanol volume %; Arom = aromatics volume %; T90 = 90% volume distillation temperature; RVP = Reid Vapor Pressure; R^2 = adjusted R-squared; AIC = Akaike information criterion; N = number of observations.
** $p < 0.05$.
* $0.05 < p < 0.1$.

Comprehensive, E10−, and E10+ models for PM, CO, NOx, and THC. Other models for separate EPAct LA92 phases are presented in the supplementary material (Table S4).

As an example, we compared the ability of our models and the EPAct reduced model to predict a difference between PM emissions for the LA92 cold-start and hot-running phases for two different fuels, EPAct Fuel 27 (E15, 14.9% aromatics) and Fuel 12 (E10, 34.8% aromatics) using the original EPAct model and models presented in Table S4. Results are shown in Fig. S10.

We show the ability of the EPAct Comprehensive model to predict the average cold-start, measured PM, NOx, CO, and THC emissions differences from EPAct in Fig. 1. Since the models predict differences, the predicted emissions were relative to the base fuel used in the EPAct emission model calculator (Fuel 3 — E10, 15% aromatics, 7 psi RVP, 220° T50, 300° T90) (US EPA, 2013b).

PFI vehicle emissions data are available from a wide range of ethanol studies, using splash, match, and available blends, as discussed in Section 3. We broadened the modeling database to include all studies using the LA92 and providing sufficient PFI data to yield emissions predictions (Table S5). The database was then broadened further to include all PFI FTP data, on the grounds that a model was needed that would be broadly applicable and on the grounds that working in log space provided relief for emissions absolute differences arising from FTP and LA92 differences. Both the FTP and LA92 include cold-start and hot-running (US EPA, 2021b). The data sources shown in Table 1 for PFI vehicles were added and the catalyst study (West et al., 2012) in particular swelled the count of points for gaseous emissions. Table 3 shows the models for weighted emissions data for the Comprehensive and E10-Split (E10− and E10+) models. Other models for separate LA92 and FTP phases are presented in the supplementary material (Table S6).

The coefficients in Tables 2 and 3 differ due to the addition of data. The effect of the West et al. (2012) study is best shown by the ability of the models derived from EPAct data along to predict the West et al. experimental results. Fig. 2 shows the ability of the EPAct Comprehensive model for cold-start emissions to predict measured NOx, CO, and THC differences of West et al. (2012).

2.2. GDI and combined emission models

For gasoline direct injection (GDI) vehicles there was no major foundation study and model set akin to those available from the EPAct study. However, data for modeling were available from the GDI studies shown in Table 1. We used the same modeling approach as for PFI vehicles. Table 3 also shows the coefficients for weighted emissions models of GDI vehicles. Coefficients for separate LA92 and FTP phases are presented in the supplementary material (Table S7). Table 3 and supplementary material Table S8 also show models for pooled PFI and GDI data, without regard for the differing engine technology. However, it should be recognized that the GDI data represent newer model year vehicles on average, due to the prevalence of PFI technology in earlier model years.

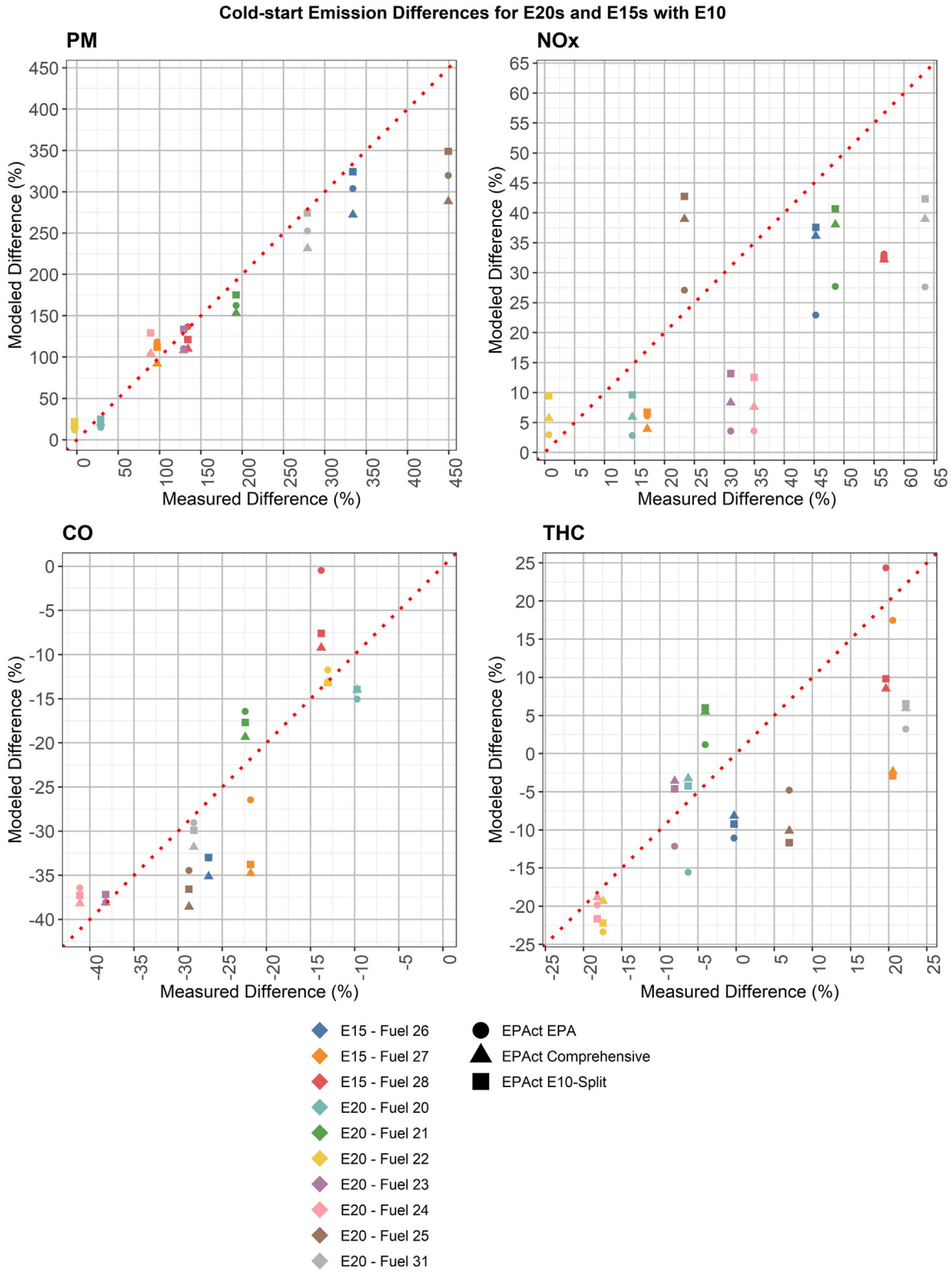

Fig. 1. Comparing cold-start measured and modeled emission differences between E15 and E20 fuels and an E10[a] in EPAct study using EPAct, EPAct Comprehensive, and EPAct E10-Split[b] models. Shapes indicate the model and colors the fuel.
[a]This is Fuel 3 in EPAct study with 15% aromatics, 7 psi RVP, 220° T50 and 300° T90.
[b]The E10-Split model represents an E10− model used to estimate the E10 to E0 difference, and an E10+ model used to estimate the E15, E20, and E30 differences from E10.

2.3. Applying emission models to market fuel properties

Conclusions should not be reached on ethanol emissions effects by using data directly from many of the studies discussed in Section 3. Splash and match blend emissions data may be useful in development of understanding and models, but do not necessarily represent real world fuel effects. Crawford et al. (2021) observed that the EPAct fuels "may also be less representative of *typical* (original emphasis) commercial gasolines

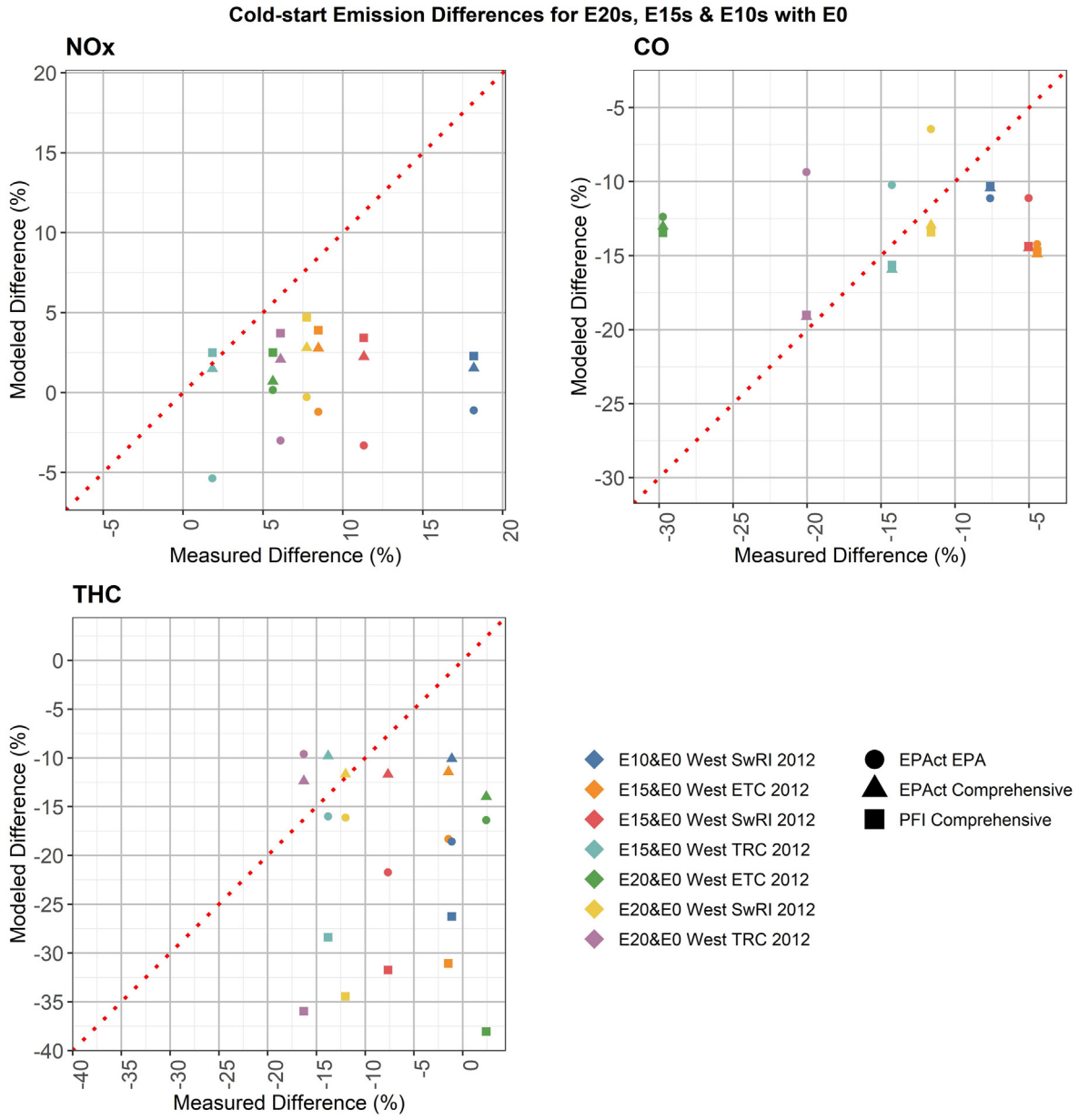

Fig. 2. Comparing cold-start measured and modeled emission differences between E10, E15, and E20 fuels and E0 fuels in West et al. (2012) study using EPAct, EPAct Comprehensive, and PFI Comprehensive models. Shapes indicate the model and colors the fuel.

found in the market." We have therefore applied our developed models to estimate emissions from the summer regular, winter regular, and summer premium fuel compositions presented in Table 4. Table 4 also contains splash blends for the specific purposes of considering higher AKI fuels and assessing aromatic effects, in addition to the oxygenate effects. Although the splash blends and premium gasoline may elicit more efficient engine performance and alter emissions profiles, the models presented above are not equipped to address the reaction of the vehicle to octane changes in a quantitative fashion.

3. Review of prior studies

There is a body of literature addressing the emissions effects of fuels using steady-state operation on engine dynamometers and examining interactive engine control strategies (Singh et al., 2021; Park et al., 2010; Dutcher et al., 2011). These studies suggest important variables to be employed in modeling, but are not readily translated to on-road emissions predictions. We used only transient chassis dynamometer-based vehicle study data with US vehicles to develop our models. These studies have addressed the effect of anhydrous ethanol at the 10% level, and several have examined E15 and E20 as well. Fewer studies have considered blends above 20%. We did not examine fuels with ethanol at or above 51% by volume (these fuels are classified as E85) and did not employ studies with a predominance of vehicles from early model years. Table 1 shows the ethanol levels for the studies we included in our database.

Prior studies and models have reached substantially different conclusions about the effects of ethanol blending on vehicle emissions. Clark et al. (2019) identified causes as the difficulty in measuring low emissions levels (and their differences) accurately, the complex response of gasoline to ethanol blending (Foong et al., 2014), the effect of using varied dynamometer test cycles, and the advances in engine technology between major studies, particularly with the step from PFI to GDI (US EPA, 2021a). Vehicle to vehicle variations, small study vehicle fleets, and few repeat runs erode the statistical certainty and general applicability of many program conclusions. In addition, vehicle control

Table 4
Proposed properties of market fuels for use with emissions models.

Fuel grade	Fuel ID	EtOH vol (%)	T50 (°F)	T90 (°F)	Arom vol (%)	AKI	RVP (psi)
Summer	E0	0	219	325	30	87	8.6
	E10	10	192	320	22	87	8.6
	E15	15	162	316	19	87	8.6
	E15S[a]	15	162	316	21	89	8.5
	E20	20	165	314	15	87	8.6
	E20S[a]	20	165	314	20	90	8.4
	E30	30	167	310	8	87	8.6
	E30S[a]	30	167	310	15	93	8.3
Winter	E0	0	189	317	27	87	12.5
	E10	10	162	312	19	87	12.5
	E20	20	165	306	12	87	12.5
Summer Premium	E0	0	242	317	33	93	8.2
	E10	10	215	308	25	93	8.6
	E20	20	188	297	18	93	8.2

Abbreviations: EtOH = ethanol; T50 = 50% volume distillation temperature; T90 = 90% volume distillation temperature; Arom = aromatics; AKI = Anti-knock Index; RVP = Reid Vapor Pressure.
[a] Splash blended from E10.

systems adapt to fuel properties, necessitating assured vehicle conditioning (Morgan and Lobato, 2014; West et al., 2012). Yan et al. (2013) echo many of these concerns in studying fuel effects on engine efficiency. Clark et al. (2021) showed that predictions from five different published models derived from the same data set yielded different emissions changes with a previously unseen scenario. This was due to interdependency and choice of property and composition variables, and effects of nonlinear model terms. Studies have also differed in reaching conclusions because blending of ethanol at low levels (below E10) has different effect than at mid levels (E15 to E30) (API, 2010).

Often it is the aromatic level in the BOB that dictates emissions changes rather than the ethanol itself (Anderson et al., 2014; Clark et al., 2021). With market fuels, aromatics are generally reduced as ethanol is added to hold octane rating constant. When splash blending is used in a study, aromatics are reduced only by dilution and octane rating rises. When match blending is used to facilitate multivariate analysis, the resulting study fuels do not usually represent a market composition and the behavioral responses to mixing are atypical. Developing a model from a combination of data from several studies provides broader coverage of controlling variables, but may not elicit the nonlinear effects and dependencies found in market fuels.

3.1. EPAct and related studies

The EPAct study is a keystone data source for PFI vehicles, with 27 fuels and 15 cars and light duty trucks (US EPA, 2013a). The vehicles were all 2008 model year and Phase 3 of the EPAct study reported emissions from E0, E10, E15, and E20 blends. It was a multivariate study, seeking to find the influence of several variables simultaneously, namely ethanol content (E0, E10, E15, and E20), aromatic content (15% and 35%), RVP and dry vapor pressure equivalent (DVPE; 7 psi and 10 psi), T50 (5 levels), and T90 (3 levels). In general, the fuels did not represent fuels sold at the pump, but were blended to match a distribution of the study variables. "It is important to note that the effects of different fuel properties are not cleanly separable. It is difficult to modify one property in an actual fuel without affecting one or more of the others. The study design and analysis of the data are structured so as to allow assessment of fuel effects as though they were independent of each other. However, in interpreting or applying the models, it is critical to consider the effects of all five fuel properties in conjunction with each other. Consideration of single coefficients in isolation can easily result in misleading conclusions." (US EPA, 2013a). We have employed the Phase 3 EPAct data set and used EPAct-based models for comparative purposes.

The EPAct study did not control distillation temperatures other than T50 and T90 in formulating the study fuels. Butler and Sobotowski (2021) have recently commented on the importance of T90 in determining PM. Anderson et al. (2014) have been critical of the use of only T50 and T90, and Darlington et al. (2016) have shown that a correlation with 70% volume distillation temperature (T70), which was not a control variable, provided a very good fit to the EPAct PM data, but led to different emissions conclusions. This difficulty centers around the fact that ethanol addition suppresses the T50 distillation point temperature in a nonlinear fashion, and so the study fuel distillation curve had to be manipulated to arrive at desired study values for T50. So, for example, the T50 values for fuels 26 and 27 (both E15) differ widely at 160 °F and 222 °F, but the two T70 values are 277 °F and 275 °F. Further, the EPAct modeling cannot account readily for the behavior of ethanol in blending with a petroleum BOB and the effect of BOB composition on that nonlinearity.

EPAct-related studies provided insight for our modeling. Gunst (2013) produced alternate emissions models that fitted the EPAct data well. Also, Butler et al. (2015) modeled the EPAct data using the Particulate Matter Index (PMI) to good advantage. PMI is based on the propensity of each species in the fuel to produce PM (Aikawa et al., 2010; Chapman et al., 2021; Crawford et al., 2021). These models, arising from the same data set, predict the emissions properties of unseen fuels differently (Clark et al., 2021).

The Butler data required DHA (performed using ASTM D6729) for computation of PMI. ASTM D6729 provided data on total aromatic content and olefin content of the EPAct fuels, and both aromatic and olefin levels differ from the original EPAct data acquired using ASTM D1319. In consequence, we addressed emissions estimates using data from both standards.

Although the final "Phase 3" EPAct models derived from the study data suggest that ethanol alone raises NOx and PM emissions, they show that emissions are reduced when aromatic and T50 reduction, in response to ethanol addition, are considered (see Section S4 in the supplementary material). Morgan et al. (2017) concluded that the EPAct study showed that ethanol raised PM, NOx, and other emissions, whereas the reduction of aromatics in response to ethanol blending may actually reverse that finding. This reinforced our decision to employ multidimensional modeling for emissions estimation.

Phases 4, 5 and 6 followed the main Phase 3 EPAct study (Whitney and Shoffner, 2014) but did not offer data appropriate for our study.

3.2. CRC E94-2, E94-3, and E129

Emissions of PM are typically influenced by both the ethanol and aromatic content of a fuel (Clark et al., 2021). PMI is expected to reflect aromatic content and molecular weight. The E94-2 CRC study (Morgan et al., 2017) used GDI vehicles. Two different AKI values and two different gasoline PMI levels (1.4 and 2.4 targets) were used to examine E0 versus E10 emissions, yet there was a single target for aromatics (25 vol%). The PMI difference was achieved in part by varying the balance of light and heavy (C10+) aromatics. We were not able to employ the CRC E94-2 data in our study because the fuel formulation strategy thwarts the use of total aromatic content as a distinguishing emissions variable.

A follow-on study, E94-3 CRC, (Morgan et al., 2018) used four GDI vehicles and four E0 fuels from the E-94-2 program, splash blended with 10% ethanol, with low and high AKI (91 and 96) and low and high PMI targets. In splash blending the ethanol is added to gasoline and that dilution is the only composition effect. We employed the E94-3 data in our modeling.

We also employed data from the CRC E-129 study that measured tailpipe emissions of four 2012–2013 GDI vehicles using ethanol splash blends and the LA92 driving cycle (Schuchmann and Crawford, 2019). The E0, low AKI, low PMI fuel from the E94-2 project composition was re-blended for E94-3, and then splash blended to produce E10 and E15.

Measured emissions from E-129 showed that E0 and E10 had substantially similar PM but PM was significantly reduced for E15. Although

NOx was lower on average for E10 and E15, there was no statistically significant difference from the E0 level. The CRC E-129 data opposed the E94-3 E-10 conclusions, where PM increased with ethanol content. However, the four GDI E129 vehicles were not the same as the E94-3 vehicles and vehicle choice is known to have effect on conclusions (Clark et al., 2019).

3.3. CRC E-98/A-80

Jimenez and Buckingham (2014) authored CRC Report E-98/A-80 and used the fifteen EPAct study vehicles (all PFI) with E0 (35.4% aromatics), E10 (27.4%) and E16 (24.6%). Some statistically significant differences were observed for PM, but it should be noted that, from inspection of fuel properties, the fuels were not related by either match or splash blending. The report showed that EPAct and Gunst models, discussed in Section 3.1, could not predict reliably the differences in regulated emissions from unseen fuels found in the studies. We have used the Jimenez and Buckingham (2014) study data in model development.

3.4. Department of energy catalyst study

A major catalyst ageing study (West et al., 2012) reported vehicle ageing and emissions measurement work on an extensive fleet at three separate facilities (SwRI, TRC, and ETC/SGS). Two locations used E0, E15 and E20 splash blended fuel, and SwRI also used E10. Eighty-two vehicles, arranged in matched sets, were operated for more than six million miles, and 55 of these vehicles were operated on gasoline (E0) and ethanol blend road fuel. Emissions data were acquired at several points during the ageing of each vehicle using certification gasoline and its splash blends for each ethanol level. Vertin et al. (2012) provided additional detail in a report addressing the research at the ETC/SRS site. There was a substantially higher NOx increase on E10 than on E15 and E20, but we noted that only one site used E10, leading to possible bias.

Different fuel was used over time, but the splash blend fuels and the baseline E0 corresponded for each test set. We assembled representative fuel properties with data from West et al. (2012) and Vertin et al. (2012), with additional information from Sluder [personal communication] (see Section S5 in the supplementary material, Tables S1 to S3). We have employed the catalyst study data for model development and model comparison. We elected to consider emissions data acquired at three or four instances during the extended ageing period of each automobile separately (as if from a separate vehicle) due to ageing and potential laboratory and fuel drift effects.

3.5. EPA Tier 3 certification fuel impact test program

An EPA study examined the difference in emissions between Tier 2 certification fuel (E0, 92.6 AKI, 32.3 vol% aromatics) and Tier 3 certification fuel (E10, 87.3, 23.8) (US EPA, 2018). Three PFI and eight GDI vehicles were used, with the transient FTP as one of the test schedules. The Tier 3 E10 certification fuel enjoyed a reduction in aromatics relative to Tier 2 E0 fuel in response to the ethanol increase, in a ratio that is typical of market fuels. The study yielded valuable data for our modeling.

3.6. Studies at University of California, Riverside

Studies at University of California, Riverside (UCR) examined both conventional vehicles and FFVs and were important in providing GDI data. Yang et al. (2019b) used a single flex fuel GDI vehicle to examine four fuels, two E10 blends, an E30, and an E78. Both E10 blends had high aromatics, at 28 and 37%, and the E30 was a splash blend of the 28% aromatic E10 with additional ethanol. Aromatics in the fuel were presented by molecular weight. We employed these data for modeling.

Yang et al. (2019a, 2019c) also reported on a study for Growth Energy (Karavalakis et al., 2018b). Five 2016 and 2017 GDI vehicles were evaluated on eight fuels. E0, E10, and E15 fuels were blended with two different aromatic levels. One fuel, E10 with 20% aromatic content, was a Tier 3 emissions certification fuel. Two additional fuels were prepared by splash blending to yield E15 and E20. Gaseous and particulate emissions were measured using the transient LA92. Data showed a strong effect of aromatic content on the PM emissions for both the cold-start phase 1 and overall LA92 results.

Karavalakis et al. (2015) studied the impact of both ethanol and butanol on emissions using two GDI vehicles, one with spray-guided injection and one with wall-guided injection. We used these E0, E10, and E20 data.

Karavalakis et al. (2014b) also reported ethanol (E10, E15, E20) data for three PFI and two GDI vehicles over the FTP and LA92. Results were mixed for THC, CO, and NOx. These data were employed in our model development. Karavalakis et al. (2014a) presented additional study data, but only E10 data were outside of the E85 fuel range. These data were not employed because we sought to model using data for at least two ethanol levels of E50 or below. Another UCR study by McCaffery et al. (2020) was not employed for the same reason.

Since Yang et al. (2019a, 2019c) and Karavalakis et al. (2014b, 2015) provided cumulative PM emission rates rather than phase-specific emission rates, we did not use their PM data in model development. We did not employ a study by Karavalakis et al. (2012) because most vehicles in the study had early model years.

3.7. Other studies

West et al. (2018) examined a Ford F150 pickup and a Mini Cooper using the FTP and the US06. The Mini was tested at its own road load and at a higher road load to explore knock. The pickup was tested with two different compression ratios. A Tier 3 certification fuel (E10) and the same fuel splash blended to E25 were used. These data were employed for GDI modeling.

Haskew and Liberty (2011) examined E6 and E32 fuels in a study of gaseous exhaust and evaporative emissions under the CRC E-80 program. The E32 was prepared from a blend of E6 and E85. Seven vehicles were used with model years of 2006 and 2007. The data, for LA92 and FTP schedule, were included in our database and were valuable in modeling blends of over E20.

Sobotowski et al. (2015) presented additional data after completion of the EPAct study. Four vehicles, three with PFI engines and one with GDI, were tested using the LA92 cycle. AKI was not held constant. Ethanol was at the E0 and E15 levels. PMI had a strong effect on PM emissions, but our modeling used the aromatic content as an input.

3.8. Studies not included in our database

We did not use data from studies that lacked fuel properties or employed unsuitable fuels (Thomas et al., 2015; Hubbard et al., 2014; Gramsch et al., 2018; Hilton and Duddy, 2009). Jin et al. (2017) used blending fuel that contained MTBE. Durbin et al. (2005) examined PFI vehicles but did not vary aromatic content as a study variable. A publication by Graham et al. (2008) described two studies, but the vehicle model years ranged from 1998 to 2003, considered to be too early for inclusion in our models. Dardiotis et al. (2015), Clairotte et al. (2013), and Suarez-Bertoa et al. (2015) reported on European vehicles and cycles, and these were not employed due to possible technology differences from US vehicles. We also did not employ a study by Ahmed et al. (2018) that used European vehicles and offered only E5 in our blend range. A recent study by Yuan et al. (2019) used on-road portable emissions measurement, and we did not employ those data.

3.9. Petroleum BOB composition and blending

For most studies considered, the ratios of emissions from two different ethanol blend levels are not representative of market fuel effects.

We applied models developed from the emission studies to estimates of properties of market blend fuels to yield a real-world representation of emissions changes. A discussion of the gasoline composition is therefore important. The petroleum BOB typically is prepared by a refinery so that the BOB yields a finished gasoline, when blended with ethanol at a terminal. The composition of the BOB plays a substantial role, along with the ethanol, in determining emissions. The BOB composition also changes with ethanol level, because it is tailored to suit that level, particularly to meet anti-knock requirements. The BOB is blended from streams at the refinery that are least valuable to the refinery as a whole, under constraint of meeting finished product specifications (Clark et al., 2020, 2021). For niche markets, a BOB could be created that in its own right offers reduced emissions, or that offers higher octane rating that leads to improved engine performance. A higher cost of the BOB and the finished fuel should then be anticipated.

Since the composition of the BOB varies widely, its nonlinear blending behavior with ethanol must be anticipated. Petroleum fuels and BOB often are described by fractional content of paraffins, isoparaffins, aromatics, napthenes (cycloparaffins), and olefins (PIANO analysis). These species are provided using diverse refinery streams, including straight naptha, reformate, alkylate, and isomerate. Octane ratings (anti-knock properties) are met primarily by reformate (high in aromatics) and alkylate (high in isoparaffins) in the BOB, along with the blended ethanol. The aromatics are produced primarily by reformers that improve the properties of low-octane napthas at refineries. Sjöberg et al. (2016) and Sjöberg and Vuilleumier (2017) have discussed influence of fuel composition on engine knock behavior.

A report from the American Petroleum Institute (API, 2010) provides insight into the nonlinearity of the blending behavior. Gasoline is characterized by a distillation curve, presented as temperatures at which each percentage of the fuel is evaporated following an ASTM D86 procedure. Ethanol blending serves to depress that curve such that the 40% evaporation temperature, T40, is substantially reduced even with blends as low as E10 (Anderson et al., 2014; API, 2010; CONCAWE, 2012; Jiao et al., 2011). T50 is difficult to predict for E10, because the location of the depression depends on the BOB composition, but T50 is always suppressed for high ethanol blends. Ethanol also suppresses the evaporation of aromatics in the blend (Ratcliff et al., 2019; Ratcliff et al., 2021). Hence T50, a parameter commonly used to describe E0, becomes quixotic in blend studies (Andersen et al., 2010; Anderson et al., 2014).

Ethanol also raises the RVP of the BOB to higher values than would be expected from the ethanol and BOB volatility. Ethanol raises the AKI of a blend more than would be expected: moreover, that synergistic "blending octane number" is affected by the BOB composition (API, 2010; Foong et al., 2014; Gaspar et al., 2019; Yuan, 2018). Splash blending of ethanol invariably raises the AKI of the fuel, which can change the control strategy of a modern engine operating under high load, and hence affect efficiency and emissions (Stein et al., 2013). Whether the engine benefits from the AKI depends upon the vehicle and cycle that are employed, adding to the complexity and variability of data analysis.

Studies derive confidence limits for model predictions from the statistical fit to the data that were used, but do not consider the application of the model to unseen fuels. Analysis of properties or compositions of fuels may have high uncertainty. For example, different ASTM standardized methods return values for olefin or aromatic content that differ substantially (Beens et al., 2003). Uncertainty in model input data is addressed in the supplementary material section S6. Uncertainty in gasoline or BOB composition is less critical if the fuels being considered are all splash blended from the same baseline composition.

3.10. Vehicle fleet

The US light duty vehicle fleet has an average age of nearly 12 years (Bureau of Transportation Statistics, 2021). An automotive technology trends report presents the substantial change in propulsion system design since 1975 (US EPA, 2021a). We excluded vehicles with EPA Tier 1 and early Tier 2 emissions technology as being unrepresentative of the current fleet. The gasoline engine market consisted historically of PFI engines, but now PFI and GDI vehicle sales are similar in count. These two injection technologies have substantially different fuel and air mixing strategies and fuel evaporation environments, and GDI engines are associated with elevated PM levels (Kalwar and Agarwal, 2020; Leach et al., 2013; Saliba et al., 2017; Zhao et al., 2002; Zhu et al., 2016). For these reasons, we have modeled PFI and GDI emissions separately and compared their reactions to fuel composition effects.

3.11. Market fuel composition

The fungibility of reformate, alkylkate, and ethanol in raising anti-knock properties is well known, but the precise blending practice is dictated by refinery economics, availability of feedstocks and other finished blend property constraints. We present the rationale for determining the properties of fuels with elevated ethanol content, and with both a regular octane rating of 87 and elevated octane ratings associated with splash blending from an 87 octane E10 base. Elevated octane rating is advocated to raise future GDI engine efficiency (Johnson et al., 2015; Miles, 2018; Szybist et al., 2021; vom Lehn et al., 2021).

McCormick et al. (2017) presented octane changes when ethanol was added to a surrogate mix of isooctane, heptane, toluene, and 1-hexene. From graphical representation, RON increased by 0.6 and motor octane number (MON) increased by 0.28 per percent increase of ethanol. Waqas et al. (2017) showed higher values for octane blending into FACE research fuels and recognized that aromatics in the base fuel hinder the octane enhancement by ethanol. Gaspar et al. (2019) presents that ethanol has blending octane rating [(RON + MON) / 2] into a gasoline surrogate of 129.5 for E20 and 119 for E30. This is substantially higher than the octane rating for ethanol alone.

Stratiev et al. (2017) presented various methods for modeling gasoline RON and MON from hydrocarbon, ethanol, and MTBE blends, and determined that a modified model of Zahed et al. (1993) offered a best fit. From the coefficients and data in Stratiev et al. (2017), the addition of 1 volume of ethanol (RON = 114.0, MON = 98.3) would enable the removal of 1.14 volumes of reformate (RON = 100.2, MON = 89) to keep the blend AKI constant. Naturally, 0.14 volumes of an AKI-neutral component would be needed to account for the difference. The reformate used had a 67.7% aromatic content, and so this implied that a 1% ethanol addition could facilitate a 0.77% aromatic removal while maintaining the same AKI. Rankovic et al. (2015) examined the effect of blending ethanol, reformate (111 RON) and isoparaffins (trimethyl pentane, 104 RON) into a 91 RON gasoline (34.1% aromatics) and a 71 RON naptha and gasoline blend (21.3% aromatics). They found that ethanol boosted RON substantially more on a volume percent basis than the reformate and the isoparaffins, suggesting that ethanol addition enables high reformate or alkylate removal from a blend. Yuan (2018) presents extensive additional blending detail.

Historical data for conventional summer gasoline are presented by the US EPA (2017), and show that the change from 0.84% ethanol blending in 2000 to 9.28% in 2016 corresponded to a 6.74% reduction in aromatics. This equates to 0.8% aromatic reduction per percent of ethanol added, in fair agreement with the findings from the model presented by Stratiev et al. (2017). The EPA report also shows a high variation in aromatic content across the nation.

An expected refinery pathway in the US to produce an E0 gasoline, in contrast to an E10 gasoline, would be to increase dependency on the reformer. Aromatics from reformate are also widely used as octane enhancers internationally, but regulation of benzene and total aromatic content varies. This yields a higher octane, higher aromatic, market product than an E10 BOB, to compensate for the loss of the ethanol anti-knock benefits. Likewise, a higher ethanol blend BOB would call for reduced reformer dependence (Clark et al., 2021).

Fuel properties most reasonably are anchored to today's E10 fuel formulations, which dominate the US market. Texas data for summer 2017, averaged across field tests for finished regular unleaded E10 of all grades, have average aromatics, at 26.8% by volume (ASTM D1319, 26.1% by volume for all gasoline) (Eastern Research Group, 2017). Similar Texas data for summer 2020 have average E10 aromatics at 20.33% by volume (ASTM D5769, 21.0% all gasoline) (Eastern Research Group, 2020). EPA data for 2016 show ethanol-adjusted aromatics at 21.8% for summer conventional gasoline and 17.1% for summer reformulated gasoline (US EPA, 2017). The EPA report shows that for 2016, conventional gasoline sales were almost three times the reformulated gasoline sales, and that premium sales were only 10.5% of total sales. We have devoted most effort to examining gasoline that represents an average summer regular conventional gasoline.

Table 4 shows estimated properties of an average conventional summer regular E10, with projections of E0, E15, E20, and E30 fuels, based on the discussion above. Table 4 also includes estimated properties for fuels that would be splash blended from the E10, denoted E15S, E20S, and E30S. For this splash blending of ethanol, aromatics decrease proportionally solely due to dilution as the ethanol is added. Yang et al. (2019a, 2019c) showed an increase of AKI of 2 for 5% more ethanol addition to E10, and an increase in AKI of 3.7 for 10%. The API blending study shows substantial variation in ethanol blending octane rating and an average AKI rise of 8 for an E0 to E30 splash blend. The CRC E94–3 study showed increases in AKI of 3.6, 3.1, 2.6, and 1.9 for 10% addition of ethanol to E0 (Morgan et al., 2018). These splash data suggested the elevated AKI values for the E15S, E20S, and E30S. T90 values for the splash blends are lowered due to the dilution of heavy components, as shown in the API blending report (API, 2010) and the analyses of Yang et al. (2019a). Additional discussion of AKI effect is addressed in the supplementary material section S7.

Our RVP for blended fuel did not consider RVP waivers and was set at 8.6 psi (US EPA, 2017) except for the winter fuel. API (2010) data suggest small RVP decreases for splash blending ethanol in the E10 to E30 range.

Recently, in an appendix to the latest version of the MOtor Vehicle Emission Simulator (MOVES3) document, properties are presented for E0 "Low Biofuel #1," compared to a reference E10 (US EPA, 2020). There is a 6.1% increase in aromatics (by volume) in summer and 6.7% in winter associated with the reduction of 9.9% of ethanol. Further, this is shown as requiring new sources of alkylate and isomerate. US refineries have existing available reformer capacity (Tamm et al., 2018) that is more likely to be used if an E0 is sought, raising the aromatic content of an E0 further. Based on the refinery blending model, historical data, and the availability of reformer capacity, a present day E0 could be expected to have 7.7% to 8% higher aromatics (by volume) in comparison to a conventional summer E10 (US EPA, 2020) also present an E0 "Low Biofuel #2," with very little additional aromatic content than the E10 reference fuel. This fuel specification, adopted for MOVES 3 modeling, requires an aspirational increase in alkylate production, noting the available US reformer capacity. In contrast, the recent study to support change from Tier 2 to Tier 3 certification fuel (so that certification fuel is "more representative of in-use fuel") reduced aromatics by 7.7% for an increase in ethanol of 10.15%, aligning well with the aromatic levels that we estimate (US EPA, 2018).

More limited ethanol effects research was performed on conventional winter fuels and on premium summer fuels, representing lower and higher aromatic levels, respectively. Based on E10 adjusted data, winter fuels track summer fuel historical trends with approximately 3% less aromatic content, and premium fuels track approximately 3% higher (US EPA, 2017). These data were used, although the Texas survey data (Eastern Research Group, 2020) showed a smaller aromatic content increase for premium fuels, and highest aromatic content for mid octane blend. Proposed winter gasoline RVP was 12.5 psi and premium summer fuel was 8.2 psi (US EPA, 2017). US EPA (2017) reports E200 and E300 rather than T50 and T90 — we were hesitant to translate between the two approaches and used Texas data for the premium E10 and Clark et al. (2019) for the winter E10. Only E0 and E20 winter regular and premium summer fuels were considered additionally, and the aromatic differences with ethanol content were intentionally set to be the same as for summer regular fuel, as shown in Table 4. Due to lack of data we did not go beyond E20. Blends are presented above with best estimates of typical properties based on tradeoff between ethanol and aromatics, but the models are available to estimate emissions for fuel properties chosen by a user. In particular, the database includes splash blending study data where aromatics are higher than for the market blend estimates, and experimental study data where ethanol and aromatics were varied independently. This broadens the estimation capability of the models.

4. Results

4.1. PFI and GDI emissions models

The EPAct study, a major source of data for modeling regulated emissions, showed a wide scatter of the data, accounting for the vehicle to vehicle variations. However, we found that the E0 to E20 change results in greater PM increase during cold-start and hot-running phases when the aromatics change simultaneously from 15% to 35%. Conversely, PM is actually lower for E20 compared to E0 during cold-start when the aromatics are simultaneously reduced (Fig. S3). This difference is also clearly seen when we consider only high T90 values, which most likely correspond to elevated quantities of heavier aromatics (Fig. S4). We also observed greater cold-start NOx increase for 35% aromatics E20 compared to 15% aromatics E0 (Fig. S5). CO cold-start emissions were lower on average for all E20 fuels compared to E0 (Fig. S6). Differences in THC emissions are not apparent (Fig. S7).

As an example, we compared the ability of our models and the EPAct reduced model to predict difference between PM emissions for two fuels (Fig. S10). The E15 fuel, with reduced aromatics, would be expected to have lower PM emissions than the E10 fuel. For cold-start our EPAct E10-Split (E10+) model matched the original measured average difference closely, while our EPAct Comprehensive model and original EPAct models predicted slightly lower reductions for the E15 fuel than was found experimentally (see supplementary material Section S8, Fig. S10). For hot-running PM the EPAct Comprehensive model prediction is closer to the measured emission ratio.

We also show the ability of our EPAct Comprehensive and E10-Split models to predict differences between E15 or E20 and E10 regulated emissions (Fig. 1). Our EPAct Comprehensive model behaves similarly or shows an improvement in estimated differences for PM and NOx compared to the original EPAct model for most fuels. For CO and THC, the models behave similarly but some fuels show better fit with the original EPAct model and some show better fit with our models. As an example, Fig. 2 shows the ability of the PFI Comprehensive model for cold-start emissions to predict measured NOx, CO, and THC values of West et al. (2012). It shows that the modeled NOx results, driven by a larger database, generally underpredicted the splash blend measurements of West et al. (2012). This stresses the importance of using a large database rather than data from a single study to derive emission models. The modeled THC reductions ranged from agreeing with West et al. (2012) data to predicting higher reductions than they measured. For CO the measured differences showed more variation than the modeled differences, but if averaged across all cases showed similar reduction.

Table 3 shows results for the PFI, GDI, and combined PFI and GDI models developed using the entire dataset. The combined PFI and GDI models introduce bias because the quantity of PFI data substantially exceeds the quantity of GDI data. As discussed in Section 3.10, to the extent that PFI and GDI models differ, an emissions inventory calculation should treat them separately and combine the two predictions in proportion to their presence or vehicle miles traveled within the fleet.

Further, the coefficients in Table 3 are limited in accuracy if they are extrapolated to high ethanol blends due to lack of high blend data. The catalyst study (West et al., 2012) did not include PM measurements, reducing the count of tests for the model input and causing the PM and gaseous emissions PFI models to have different fleet bases.

4.2. Emissions estimates based on market fuel properties

Figs. 3 through 6 present estimates for market fuels and splash blends, denoted with an S (e.g., E15S), of our PFI, GDI, and combined models, developed using both FTP and LA92 study data. Cold-start and hot-running data are shown separately rather than weighted to emphasize the cold-start influence. The E10-Split model represents an E10− model used to estimate the E10 to E0 difference, and an E10+ model used to estimate the E15, E20, and E30 differences from E10.

The summer fuel PM cold-start results in Fig. 3 show a marked difference between PFI and GDI PM, with market fuels showing PM reductions with higher ethanol blends for all PFI and GDI vehicles, with the exception of the E0 to E10 GDI split model. The estimates from the combined PFI and GDI models are close to those from the PFI models due to the dominance of PFI vehicles in the assembled database. In Fig. 3, the E20 to E0 PM change estimates may be made either with the comprehensive model or by combining the steps or ratios of the E0 to E10 (E10− model) and E10 to E20 (E10+ model), and these two approaches may be compared. For PFI market blend PM cold-start, the PM change from E0 to E10 is similar to the change from E10 to E20, suggesting no breakpoint in behavior above and below E10. For GDI, the trends above and below E10 differ, providing evidence for the need to split the modeling at the E10 breakpoint. Relative to the combined model for the GDI market fuels, the split modeling ascribes no PM reduction below E10 and higher PM reduction above E10. However, it is important to recognize that the GDI data are few in number, arise from different studies that did not cover all blend levels, and are subject to the numerous uncertainties arising from vehicle effects, blending strategies, analyses, and measurements. This uncertainty is clearly reflected in the wider confidence intervals for GDI vehicle estimates. The PM hot-running emissions, which are far lower in g/mile values than cold-start emissions, showed no clear percentage differences between market fuels (Fig. 4).

The market fuels behaved differently than the fuels that are splash blended from E10, which have less aromatic reduction. Splash blended fuels showed no differences in cold-start PM emissions for PFI vehicles and a reduction for GDI vehicles with higher ethanol blends (Fig. 3). These results reflect directly the higher PM coefficients for aromatic contribution than for ethanol contribution. Hot-running PM emissions were higher with higher splash-blended ethanol fuels for PFI vehicles (Fig. 4).

There are differences in the NOx cold-start emissions changes for the comprehensive models versus the split models. The cold-start NOx emissions comprehensive models show a small reduction for ethanol market fuels between E0 and E10, E10 and E20, and E10 and E30 with PFI vehicles, and no difference when using the split models (Fig. 3). Splash blended fuels showed a small increase in NOx emissions between E10 and E15S, and E10 and E20S for PFI vehicles. However, it must be stressed that these percentage changes are small, and also subject to uncertainty. No differences were observed for cold-start

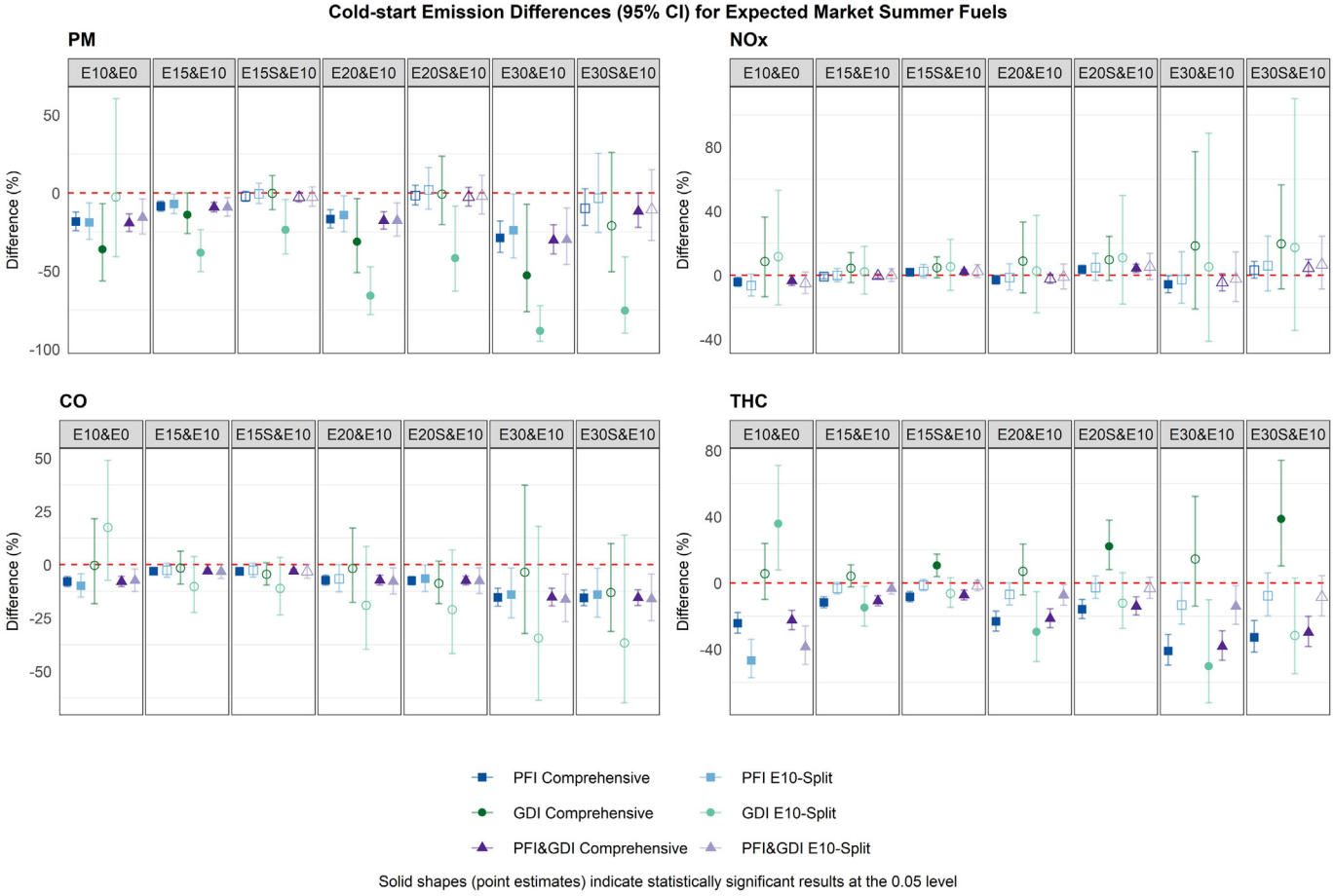

Fig. 3. Cold-start PM, NOx, CO, and THC emission estimates for PFI and GDI vehicles for summer market blends and splash blends modeled using the Comprehensive and E10-Split[a] models. Coefficients for the corresponding weighted models are shown in Table 3. Splash blends are denoted by "S".
[a]The E10-Split model represents an E10− model used to estimate the E10 to E0 difference, and an E10+ model used to estimate the E15, E20, and E30 differences from E10.

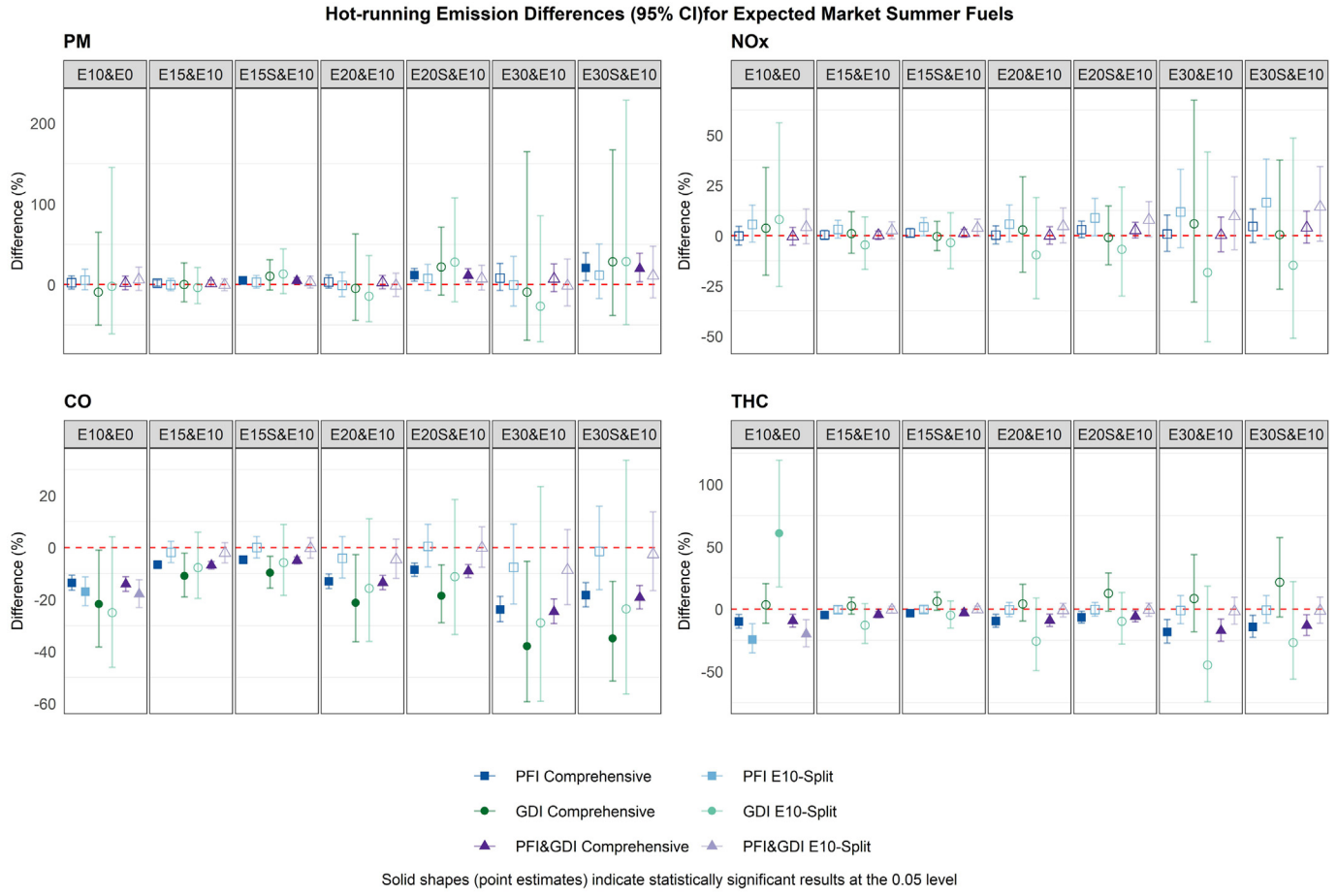

Fig. 4. Hot-running PM, NOx, CO, and THC emission estimates for PFI and GDI vehicles for summer market blends and splash blends modeled using the Comprehensive and E10-Split[a] models. Coefficients for the corresponding weighted models are shown in Table 3. Splash blends are denoted by "S".
[a]The E10-Split model represents an E10− model used to estimate the E10 to E0 difference, and an E10+ model used to estimate the E15, E20, and E30 differences from E10.

emissions of GDI vehicles, and hot-running emissions of PFI and GDI vehicles (Figs. 3 and 4).

In almost all PFI cases, higher ethanol blends have lower CO emissions for market and splash blends, as shown in Fig. 3. The comprehensive model and the E10-Split models differ for E15 versus E10, and E20 versus E10, but both suggest a reduction for E10 versus E0, and E30 versus E10 in PFI vehicles. No differences were observed for cold-start emissions of GDI vehicles. Hot-running emissions show higher percentage reductions for PFI and GDI comprehensive models (Fig. 4), but their absolute values are known to be lower.

Figs. 3 and 4 show that THC predictions also differ substantially between GDI and PFI vehicles. There is also justification for using the split models instead of the comprehensive model for both cold-start and hot-running phases for GDI and PFI alike. The E10-Split model shows a reduction in THC cold-start and hot running emissions between E0 and E10 for PFI vehicles, and no difference at higher blends. The E10-Split model shows an increase in THC cold-start and hot-start emissions between E0 and E10 for GDI vehicles, but higher blends showed a decrease for cold-start and no difference for hot-running emissions.

Figs. 5 and 6 show the results for the only two concentration steps considered for the winter regular (reduced aromatics) and summer premium (increased aromatics) fuels. The general pattern for cold-start and hot-running emissions is in sympathy with the results for the summer fuel PM, NOx, and CO emissions in Figs. 3 and 4 for PFI and GDI vehicles; and for THC for PFI vehicles. The premium market fuel PM emissions show a similar pattern of change as the winter fuels. This is due to the linear nature of the models, supported by the good fits of the models to the data. Although the winter, summer regular, and summer premium fuels have different aromatic levels, similar aromatic reductions are likely in response to ethanol addition, leading in turn to similar emissions changes. This implies comfort in estimating emissions when blending is considered based on a single BOB, because possible inaccuracy in the BOB aromatic analysis does not imply variable conclusions about the relative PM emissions. Although more complex models, with nonlinear terms, may offer a better fit to the data or obviate the need for two models split at the E10 point, blending outcomes would be affected by analytic inaccuracy and extrapolation may become unreliable.

5. Discussion

A substantial body of emissions data for ethanol blends in PFI vehicles exists in the literature, in addition to the traditionally employed EPAct data set. Many studies do not employ BOB compositions or blending strategies reflecting real world practice, so that it is difficult to capture real world nonlinear blending effects. However, models developed from the study data may be applied to estimated market fuel compositions to assess effects of major variables on blending. PFI studies that used the LA92 or FTP test schedules at certification temperatures and at ethanol blend levels from E0 to E30 were identified as a basis for regression modeling of distance specific NOx, PM, THC, and CO. We limited our study to US vehicles and test cycles, and did not use studies employing older vehicles because few are represented in the fleet and would in most cases have very high milage relative to the time when they were studied. Vehicles in our study represented Tier 2 federal standards, with a few Tier 3 federal standards, and all the vehicles were

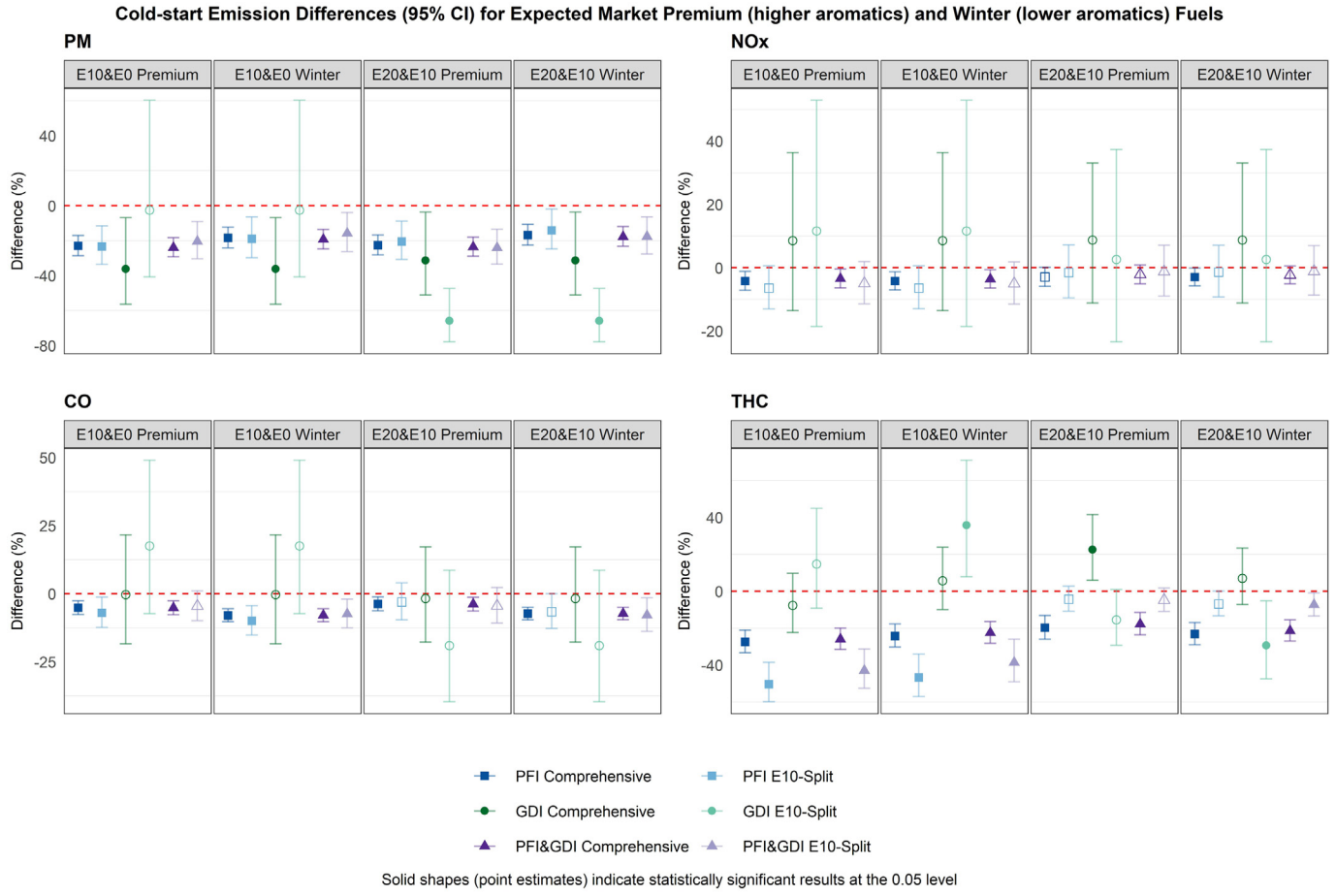

Fig. 5. Cold-start PM, NOx, CO, and THC emission estimates for PFI and GDI vehicles for market premium and winter blends using the Comprehensive and E10-Split[a] models. Coefficients for the corresponding models are shown in Table 3.
[a]The E10-Split model represents an E10− model used to estimate the E10 to E0 difference, and an E10+ model used to estimate the E15, E20, and E30 differences from E10.

equipped with three way catalysts. The technology for PFI vehicles was substantially similar, and vehicles may be expected to react in similar ways to fuel changes. Since the model is fundamentally relative in its predictions, higher and lower emissions levels should not affect conclusions. The major technology divide is between PFI and GDI vehicles. Fewer data exist for GDI vehicle modeling, and study plans for both GDI and PFI varied widely.

Regression is possible across a range of vehicle model years, with different emissions levels, if the emissions are considered as a ratio or a percentage change. This is afforded by using logarithmic space for emissions. Review of combined PFI data revealed that NOx, PM, and CO were best described using ethanol fraction, aromatic fraction, and T90 as independent variables, where T90 serves in most cases to describe the molecular weight distribution of the aromatics. For THC prediction RVP was employed instead of T90. T50 was not employed because it was correlated with ethanol content (Fig. S1) and is known to vary in a manner that is difficult to predict, by introducing a local, steep slope in the ASTM distillation curve (API, 2010). As emphasized by US EPA (2013a), the coefficients in emission models should not be interpreted in isolation.

Model formulation was found to be affected at a low level by the specific method used to determine aromatic content and by the selection of individual emissions test run data versus the use of average emissions values for each vehicle and fuel combination. A large count of regression models was prepared to cover the LA92, FTP, cold-start, hot-running, and weighted emissions. In many cases there was a difference in emissions response to ethanol addition in the E0 to E10 range, and for blends above E10, termed "E10+". The same is true for dependency of properties of the fuel, such as T90 and RVP. Extrapolation of low level blend data to higher level blends is therefore questionable. Rather than considering a nonlinear model, two separate models were considered, as well as a comprehensive model.

Models showing good fit with the combined data set were applied to expected composition of market fuels. Summer, regular grade, conventional market fuel composition was based on current E10 Texas and national compositions, although composition is known to vary widely. Aromatic content was modeled in response to ethanol level (E0 to E30) from consideration of the changes in reformate needed to hold AKI constant. Variation in T90 was determined primarily from an API property study (API, 2010). In addition, splash blends based on E10 were considered, and aromatic change was by dilution for these fuels. Winter regular grade conventional fuels and summer premium grade conventional fuel estimated properties (E0 to E20) were also used with the models.

For the summer regular fuel, and for both the comprehensive and split (E10−, E10+) models, PFI PM cold-start emissions were substantially reduced by ethanol addition. E20 PM emissions were 35.2% of E0 emissions by the comprehensive model and 33.1% by the split models (Fig. 3). Further reduction occurred for the E30 composition that was selected. The splash blends showed PM reductions relative to E0, though smaller, but were on a par with E10. Market fuel hot-running emissions, typically far lower than cold-start emissions, showed no differences with respect to ethanol level (Fig. 4). For GDI vehicles, the PM reductions were higher, with E20 showing over a 65% E10-Split (E10+) model reduction with respect to E10 (Fig. 3). This leads to the conclusion that PFI and GDI data should not be mixed to form a unified model for PM.

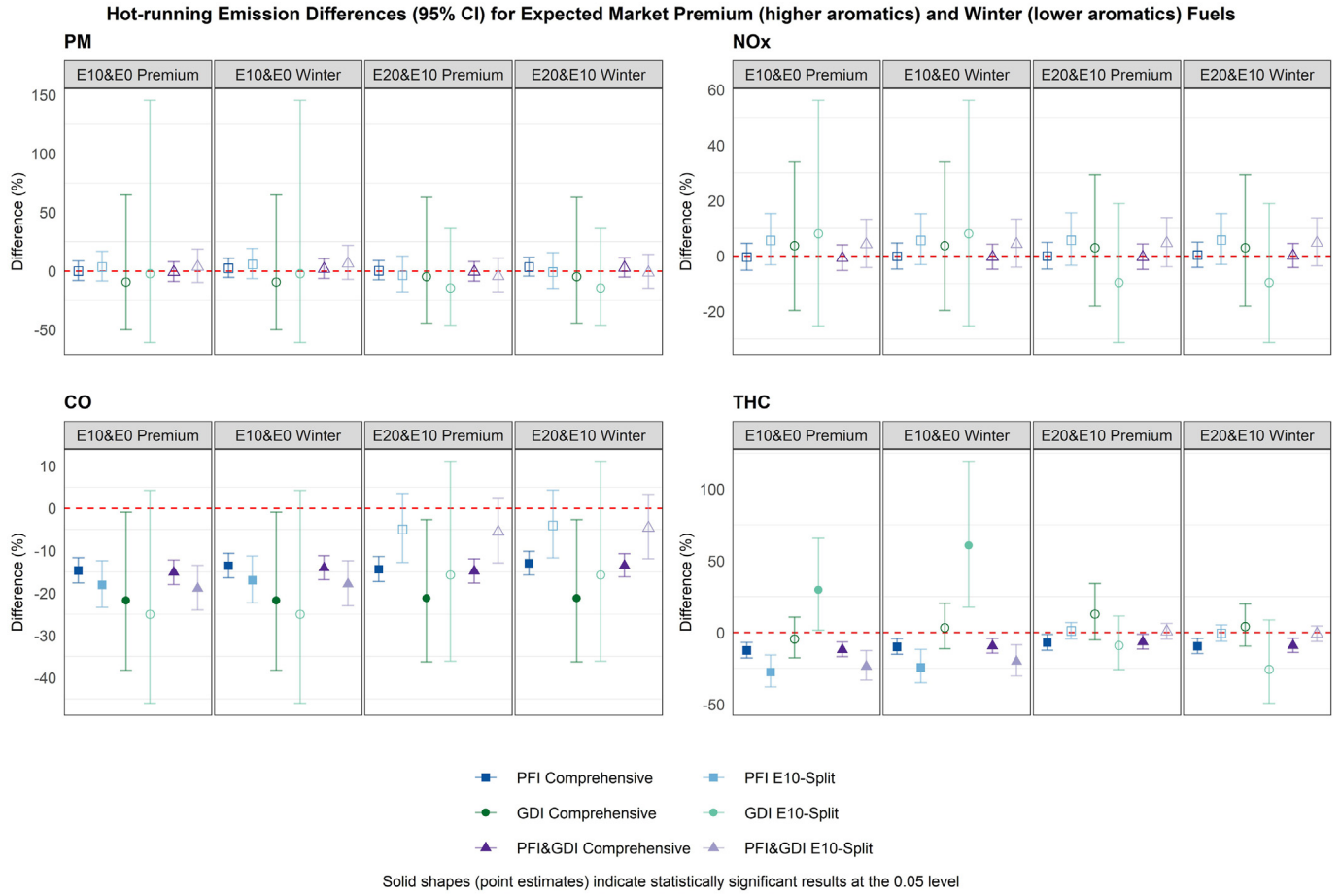

Fig. 6. Hot-running PM, NOx, CO, and THC emission estimates for PFI and GDI vehicles for market premium and winter blends using the Comprehensive and E10-Split[a] models. Coefficients for the corresponding models are shown in Table 3.
[a]The E10-Split model represents an E10− model used to estimate the E10 to E0 difference, and an E10+ model used to estimate the E15, E20, and E30 differences from E10.

All of the ethanol market fuel blends, except E15, showed lower cold-start NOx than for E0 for PFI vehicles with the comprehensive model but no differences with split models (Fig. 3). No differences were observed for GDI cold-start (Fig. 3) and PFI and GDI hot-running emissions (Fig. 4). The CO cold-start emissions were lower for higher ethanol blends for PFI vehicles but not different for GDI vehicles. But hot-running CO emissions were lower for both PFI and GDI comprehensive models.

For both cold-start and hot-running emissions, THC results were scattered for the higher blends. For PFI vehicles E10 THC was lower than E0, and vice versa for GDI, emphasizing the difference between the two engine technologies.

Results for the market and premium fuels did not differ in conclusions from the summer regular fuel in terms of ethanol blending trends. Although the baseline E0 fuels have different aromatic content, the blending comparisons are similar insofar as the aromatics are reduced from the E0 level in a similar fashion to the summer fuel change.

Our models presented above represent the most complete data sets known to the authors under selective constraints for emissions certification level, test cycle, and test temperature. The source data include different study blending strategies and are not balanced in test runs across the fuels or across the study variables. The reported aromatic levels were determined by different standardized methods. While these circumstances introduce some bias in weighting data describing fuels, the use of multiple sources blunts effects attributable to the design, execution, and analysis of one single study and supports the interest of achieving a defensible fit. The database contained both conventional and FFV vehicles, which may react differently to fuel composition changes (Schulz and Clark, 2011), but separate modeling with only the conventional fleet produced little change (Table S9). Although we presented final results in terms of market fuels, the models may be applied by the reader to any pair or set of fuels to estimate emissions differences. Although our data are derived from the US FTP and LA92 cycles, on-road emissions estimation would require assessment of vehicle speed and load and the proportion of cold-start behavior, as embodied in emissions inventory models such as MOVES (US EPA, 2021d) or CARB (2021). Likewise, inventory translation would be required for estimation outside US borders (Davison et al., 2021; Fontaras et al., 2014).

Results of ethanol studies demand care in application to real world inventory. One should not compare directly the emissions from study fuels having different ethanol levels unless those study fuels reasonably represent formulations expected in the marketplace: general results rather should be the basis for a multidimensional model. Given such a model, one should not consider the emissions model coefficient for ethanol in isolation from the influence of other composition changes imposed by the refiner and associated with changing the ethanol content. Absent availability of a study that embraces expected market fuel compositions, it is best practice to combine a multidimensional model with the projected fuel composition to yield a good faith estimate of the net direct and indirect ethanol blending effects.

In this research we compiled a comprehensive database of published data to produce and test emissions models based on fuel properties and composition. We then identified properties representative of current and proposed market fuels, and applied the models to the market fuel properties to estimate regulated emissions. In particular, we have taken into account the typical reduction in aromatic content of gasoline in response to the blending of ethanol.

6. Conclusions

We compiled a comprehensive database of US emission studies, developed separate regression models for different engine types based on fuel properties, and used those models to estimate emissions from expected market fuel compositions. Our results showed that for summer regular grade conventional fuels, cold-start PM was reduced by ethanol addition, and more so at higher blend levels but hot-running emissions showed no differences with respect to ethanol level. For all emissions, the effects differed between port fuel injection (PFI) and gasoline direct injection (GDI) powered vehicles and for NOx, CO and THC there were differences between comprehensive and split models. NOx results varied over blend levels. Hot-running emissions, which are very low for modern vehicles, varied in direction and effects were small for market blends of up to 20% ethanol. CO emissions were reduced by ethanol in nearly all cases for PFI but only the hot-running GDI, and THC results were favorable for ethanol with the exception of some GDI results. To the extent that PFI and GDI models differ, an emissions inventory calculation should treat them separately and combine the two predictions in proportion to their presence or vehicle miles traveled within the fleet.

There is uncertainty directly associated with the regression process. Model inputs also carry uncertainty since study methods vary and compositions are reported differently between laboratories and test methods. Although we presented final results in terms of market fuels, the models may be applied by the reader to any pair or set of fuels to estimate emissions differences.

Our fuel effects estimates were derived from US studies, but with appropriate inventory model adjustment would be applicable to other markets with stringent regulation of vehicle emissions and fuel specifications. Emerging international economies may reflect less advanced vehicle technology, with implications for emissions effects.

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Data availability statement

The data that support the findings of this study were extracted from published studies and reports and are publicly available.

CRediT authorship contribution statement

Fatemeh Kazemiparkouhi: Data curation, Formal analysis, Methodology, Validation, Visualization, Writing – original draft. **Tania M. Alarcon Falconi:** Project administration, Resources, Supervision, Validation, Visualization, Writing – review & editing. **David L. MacIntosh:** Conceptualization, Supervision, Validation, Writing – review & editing. **Nigel Clark:** Conceptualization, Formal analysis, Methodology, Validation, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2021.151426.

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ATTACHMENT C

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Potential Air Quality and Public Health Benefits of Real-World Ethanol Fuels

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Introduction

For over twenty years, ethanol has been used as a fuel additive in gasoline to boost octane without the harmful impacts on the environment posed by previous fuel additives such as MTBE and lead. While ethanol's benefits to groundwater and lead contamination are well established, uncertainty remains regarding the impacts of ethanol on air quality and public health based on existing literature. This uncertainty largely results from the previous lack of studies that have been conducted using fuels that reflect the actual or real-world composition of gasoline with differing ethanol content.

This document addresses this uncertainty by providing new scientific evidence of the air quality and public health benefits provided by higher ethanol blends. We specifically present findings from our two recent studies, which characterized ethanol blending effects on light duty vehicle regulated emissions of criteria air pollutants[1] and air toxics. Findings from these studies demonstrate ethanol-associated reductions in emissions of key air pollutants and by extension, provide further evidence of the potential for ethanol-blended fuels to improve air quality and public health, particularly for environmental justice communities.

Impact of Ethanol-Containing Fuels on Air Pollutant Emissions

Kazemiparkouhi et al. (2022a) and Kazemiparkouhi et al. (2022b) are the first large-scale analyses of data from light-duty vehicle emissions studies to examine real-world impacts of ethanol-blended fuels on air pollutant emissions, including PM, NOx, CO, and THC (Kazemiparkouhi et al., 2022a), as well as BTEX (benzene, toluene, ethylbenzene, xylene) and 1,3-butadiene (Kazemiparkouhi et al., 2022b). In each study, we used similar approaches. We extracted data from a comprehensive set of emissions and market fuel studies conducted in the US. Using these data, we (1) estimated composition of market fuels for different ethanol volumes and (2) developed regression models to estimate the impact of changes in ethanol volumes in market fuels on air pollutant emissions for different engine types and operating conditions. Importantly, our models estimated these changes accounting for not only ethanol

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volume fraction, but also aromatic volume fraction, 90% volume distillation temperature (T90) and Reid Vapor Pressure (RVP). Further, our models examined the impacts of ethanol fuels on emissions under both cold start and hot stabilized running conditions and for gasoline-direct injection engines (GDI) and port-fuel injection (PFI) engine types. In doing so, our two papers provided important new information about real-world market fuels and their corresponding air pollutant emissions, as highlighted below.

- ***Aromatic levels in market fuels decreased by ~7% by volume for each 10% by volume increase in ethanol content*** (Table 1)**.** Our findings of lower aromatic content with increasing ethanol content are consistent with market fuel studies by EPA and others, and with octane blending studies (Anderson et al., 2010, Anderson et al., 2012, Stratiev et al., 2017, US EPA, 2017). As discussed in EPA's Fuel Trends Report, for example, ethanol volume in market fuels increased by approximately 6.66% between 2006 and 2016, while aromatics over the same time period were found to drop by 5.4% (US EPA, 2017).

  We note that our estimated market fuel properties differ from those used in the recent US EPA Anti-Backsliding Study (ABS), which examined the impacts of changes in vehicle and engine emissions from ethanol-blended fuels on air quality (US EPA, 2020). Contrary to our study, ABS was based on fuels with targeted properties that were intended to satisfy experimental considerations rather than mimic real-world fuels. It did not consider published fuel trends; rather, the ABS used inaccurate fuel property adjustment factors in its modeling, reducing aromatics by only 2% (Table 5.3 of ABS 2020), substantially lower than the reductions found in our paper and in fuel survey data (Kazemiparkouhi et al., 2022a, US EPA, 2017). As a result, ABS's findings and their extension to public health impacts are not generalizable to real world conditions.

Table 1. Estimated market fuel properties

Fuel ID	EtOH Vol (%)	T50 (^{o}F)	T90 (^{o}F)	Aromatics Vol (%)	AKI	RVP (psi)
E0	0	219	325	30	87	8.6
E10	10	192	320	22	87	8.6
E15	15	162	316	19	87	8.6
E20	20	165	314	15	87	8.6
E30	30	167	310	8	87	8.6

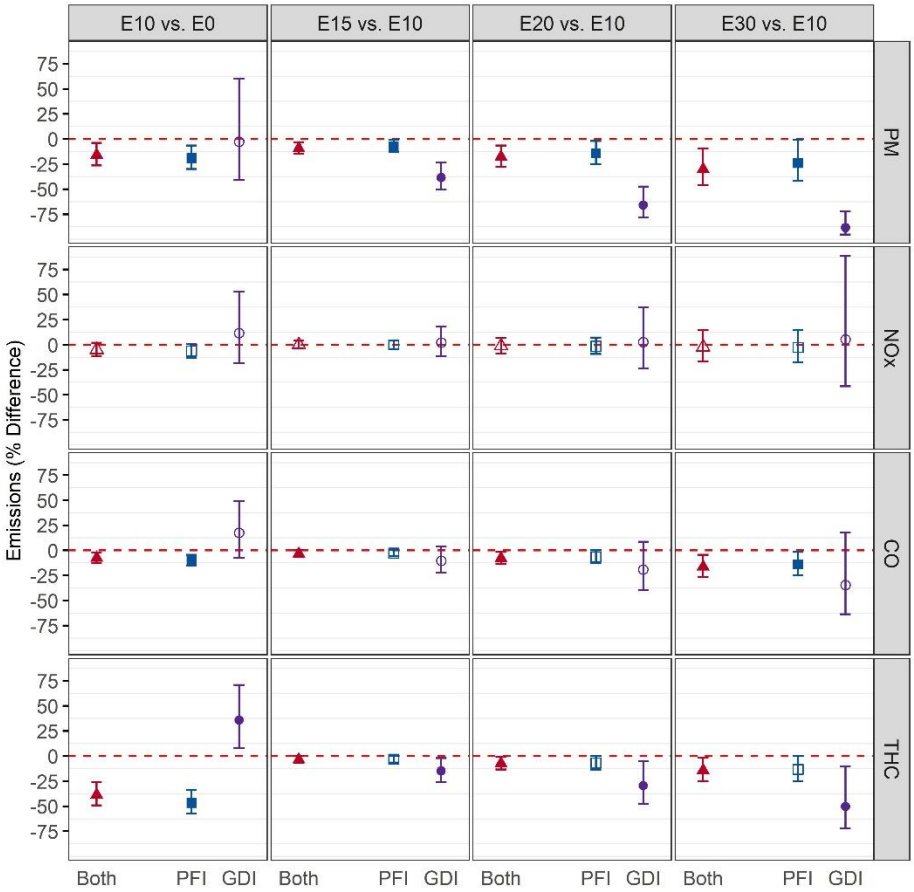
Abbreviations: EtOH = ethanol volume; T50 = 50% volume distillation temperature; T90 = 90% volume distillation temperature; Aromatics=aromatic volume; AKI = Anti-knock Index; RVP = Reid Vapor Pressure.

- ***PM emissions decreased with increasing ethanol content under cold-start conditions.*** Primary PM emissions decreased by 15-18% on average for each 10% increase in ethanol content under cold-start conditions (Figure 1). While statistically significant for both engine types, PM emission reductions were larger for GDI as compared to PFI engines, with 88% and 24% lower PM emissions, respectively, when engines burned E30 as compared to E10. In contrast, ethanol content in market fuels had no association with PM emissions during hot-running conditions.

Importantly, our findings are consistent with recent studies that examined the effect of ethanol blending on light duty vehicle PM emissions. Karavalakis et al. (2014), (2015), Yang et al. (2019a), (2019b), Schuchmann and Crawford (2019), for example, assessed the influence of different mid-level ethanol blends – with proper adjustment for aromatics – on the PM emissions from GDI engines and Jimenez and Buckingham (2014) from PFI engines. As in our study, which also adjusted for aromatics, each of these recent studies found higher ethanol blends to emit lower PM as compared to lower or zero ethanol fuels. Our findings of PM reductions are also consistent with recently published studies, for example from a California Air Resources Board (CARB) study (Karavalakis et al., 2022, Tang et al., 2022) that assessed the impact of splash-blending E10 to E15 on PM and other air pollutant emissions for late model year vehicles (2016-2021). The CARB study found a 16.6% reduction in cold start PM in comparison to a 23% PM reduction for E15S versus E10 in our study.

Together, our findings support the ability of ethanol-blended fuels to offer important PM emission reduction opportunities. Cold start PM emissions have consistently been shown to account for a substantial portion of all direct tailpipe PM emissions from motor vehicles, with data from the EPAct study estimating this portion to equal 42% (Darlington et al., 2016, US EPA, 2013). The cold start contribution to total PM vehicle emissions, together with our findings of emission reductions during cold starts, suggest that a ***10% increase in ethanol fuel content from E10 to E20 would reduce total tailpipe PM emissions from motor vehicles by 6-8%.***

Figure 1. Change (%) in cold-start emissions for comparisons of different ethanol-content market fuels[a]



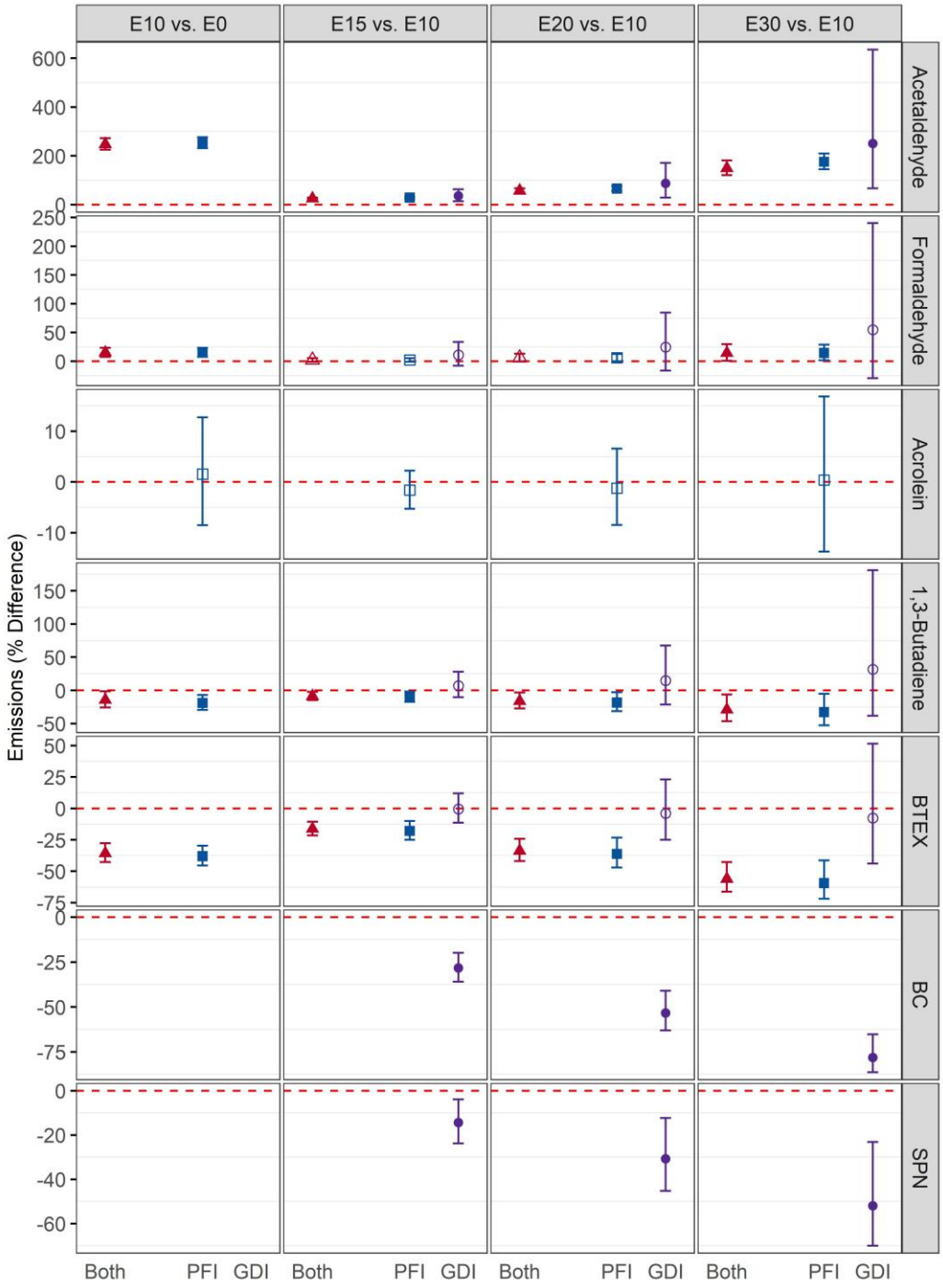
[a] Emissions were predicted from regression models that included ethanol and aromatics volume fraction, T90, and RVP as independent variables (Kazemiparkouhi et al., 2022a)

- ***Emissions of CO and THC generally decreased with increasing ethanol fuel content under cold running conditions, while NOx emissions did not change*** **(**Figure 1). The magnitude of the decrease in CO and THC emissions were comparable to those from the CARB-sponsored Karavalakis et al. (2022) study, which also found significant reductions in cold start THC and CO emissions for splash blended E15, with reductions of 6.1% and 12.1%, respectively. Under hot running conditions, CO, THC and NOx emissions were comparable for each of the examined ethanol fuels. Together, these findings add to the scientific evidence demonstrating emission reduction benefits of ethanol fuels for PM that are achieved with no concomitant increase in emissions for CO, THC, and NOx.

- ***Air toxic emissions showed lower BTEX, 1-3 butadiene, black carbon, and particle number emissions with increasing ethanol content*** in summer market fuels (Figure 2). Acrolein emissions did not vary with ethanol fuel content, while formaldehyde emissions showed little to no significant change with increasing ethanol fuel content. As expected, emissions of acetaldehyde, produced directly from ethanol combustion, increases with ethanol content. Notably, our findings are similar to those from the CARB study of splash-blended fuels (Karavalakis et al.,

2022), for which ethylbenzene and xylene were significantly reduced by ~10% for splash-blended E15 (No significant change for Benzene and Toluene).

Figure 2. Change (%) in cumulative run toxics emissions for comparisons of different ethanol-content market fuels[a]



[a] Emissions were predicted from regression models that included ethanol and aromatics volume fraction, T90, and RVP as independent variables (Kazemiparkouhi et al., 2022a)
SPN = Solid Particle Number

Implications for Public Health and Environmental Justice Communities

The estimated reductions in air pollutant emissions, particularly of PM, indicate that increasing ethanol content offers opportunities to improve air quality and public health. As has been shown in numerous studies, lower PM emissions result in lower ambient PM concentrations and exposures (Kheirbek et al., 2016, Pan et al., 2019), which, in turn, are causally associated with lower risks of total mortality and cardiovascular effects (Laden et al., 2006, Pun et al., 2017, US EPA, 2019, Wang et al., 2020).

The above benefits to air quality and public health associated with higher ethanol fuels may be particularly great for environmental justice (EJ) communities. EJ communities are predominantly located in urban neighborhoods with high traffic density and congestion and are thus exposed to disproportionately higher concentrations of PM emitted from motor vehicle tailpipes (Bell and Ebisu, 2012, Clark et al., 2014, Tian et al., 2013). Further, vehicle trips within urban EJ communities tend to be short in duration and distance, with approximately 50% of all trips in dense urban communities under three miles long (de Nazelle et al., 2010, Reiter and Kockelman, 2016, US DOT, 2010). As a result, a large proportion of urban vehicle operation occurs under cold start conditions (de Nazelle et al., 2010), when PM emissions are highest. Given the evidence that ethanol-blended fuels during cold-start conditions substantially reduce PM, CO, and THC emissions while keeping NOx emissions constant, it follows that ethanol-blended fuels may represent an effective method to reduce PM health risks for EJ communities.

Summary

Findings from Kazemiparkouhi et al. (2022a, 2022b) provide important, new evidence of ethanol-related reductions in vehicular emissions of PM, CO, and THC based on real-world fuels and cold-start conditions. Recent experimental data from CARB studies reinforce this evidence. Given the substantial magnitude of the emission reductions and their potential to improve air quality and through this public health, our findings demonstrate the potential for policies that encourage higher concentrations of ethanol in gasoline to improve public health. These improvements are especially needed to protect the health of EJ communities, who experience higher exposures to motor vehicle pollution and are at greatest risk from their effects.

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