

# Estimating Willingness to Pay for E85 in the United States\*

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# Estimating Willingness to Pay for E85 in the United States \*

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**Abstract:** Meeting US ethanol blending mandates proposed by the Environmental Protection Agency will require a substantial number of motorists with flex-fuel vehicles to switch from low ethanol-gasoline blends to high ethanol-gasoline blends. The lower the willingness to pay for high-ethanol blends, the greater the cost of complying with the proposed mandates. Existing estimates of the willingness to pay for high-ethanol blends use data from Brazil (where consumers have knowledge of and experience with high-ethanol blends), data generated when retail prices greatly favored low-ethanol blends, or stated data collected from mail and online surveys. To obtain more accurate estimates of US willingness to pay, we conducted an intercept survey in five US states of motorists with flex-fuel vehicles as they were refueling. We address a sample-selection problem caused by the lack of stations that sell high-ethanol blends; consumers who have a high willingness to pay are more likely to seek out the stations and hence to show up in our sample. We attempt to overcome the problem caused by prices favoring low-ethanol blends by augmenting revealed preference data with stated preference data generated by hypothetical prices that tended to favor high-ethanol blends. Our estimates of mean willingness to pay shows that the price at which the average US consumer will switch fuels is substantially below the price that equates the cost per mile of driving. The large discount that the average US consumer requires to switch suggests that the cost of proposed ethanol mandates will be higher than previously estimated.

**Keywords:** Biofuel, E85, Ethanol, Gasoline, Renewable Fuel Standard, Intercept Survey.

**JEL codes:** Q18, Q41, Q42.

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## I. Introduction

The Renewable Fuel Standard (RFS) in the United States uses biofuel blending mandates to achieve its policy objectives of reductions in greenhouse gas emissions, reductions in imports of fossil fuels, and enhanced rural incomes. The blending mandates are set annually by the Environmental Protection Agency (EPA) and must be met by gasoline producers (owners of oil refineries) and gasoline importers. Mandate compliance is achieved by accumulating sufficient tradable permits, called Renewable Identification Numbers (RINs). Gasoline producers can generate RINs by buying and blending biofuel, or they can enter the market and buy RINs which are generated by blenders who are not obligated under the RFS because they do not produce gasoline. Because each gallon of gasoline produced creates a RIN obligation, the RIN price multiplied by the percentage blending requirement is the marginal tax burden on gasoline producers. When mandates are binding, the RIN price is positive and covers the gap between the marginal cost of producing biofuel and the marginal willingness to pay for biofuels by blenders (Pouliot and Babcock 2016).<sup>1</sup>

Different mandates exist for different biofuels. EPA sets an overall renewable fuel mandate. Within the overall mandate a separate mandate exists for advanced biofuels, which are defined by whether they meet a greenhouse gas reduction target. The advanced mandate contains a separate mandate for biomass-based diesel. The difference between the overall renewable fuel mandate and the advanced biofuel mandate is often referred to as the conventional biofuel mandate or the corn ethanol mandate because it can be met with corn ethanol. In 2015, the corn ethanol mandate could be met with approximately 14 billion gallons of ethanol, whereas the advanced mandate could be met with approximately two billion gallons of biomass-based diesel. Hence the corn ethanol mandate by far receives the most attention by policy makers and industry.

Until 2016, the corn ethanol mandate was met by converting practically all US gasoline to E10, which is a blend of 10 percent ethanol and 90 percent petroleum-based gasoline. In 2015, for example, US gasoline consumption was 140.42 billion gallons (US EIA 2016) which means that the 14-billion-gallon mandate could be met with the 14 billion gallons of ethanol consumed in E10. With practically all US gasoline containing 10 percent ethanol by default, understanding consumer preferences about ethanol had little urgency because the cost of meeting EPA blending mandates did not depend on inducing consumers to choose fuel with greater concentration of ethanol per volume. However, EPA has proposed future mandates that cannot be so easily met, and new controversies have arisen regarding

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<sup>1</sup> The EPA allows limited banking and borrowing of RINs. See Rubin (1996) for how intertemporal trading affects current RIN prices.

the feasibility of expanding biofuels volumes (Knittel et al. 2015; Pouliot and Babcock 2016). For 2017, EPA has proposed a 14.8-billion-gallon corn ethanol mandate. With gasoline consumption forecasted to be 143 billion gallons (US EIA 2016), ethanol consumption through E10 will fall at least 500 million gallons short of the mandate.

The two approved alternative blends that could be used to increase ethanol consumption beyond E10 levels are E15 and E85, which on average contain, respectively, 15 percent and 74 percent ethanol. EPA is relying on increased E85 consumption to meet its ethanol blending mandate because so few stations are equipped to sell E15. The cost and feasibility of meeting RFS blending targets depends on consumer willingness to switch from E10 to E85. The decision to switch is complicated because fuel efficiency with E85 is 22 percent lower than that of E10 because ethanol has one third less energy than gasoline. The lower fuel efficiency also implies more frequent visits to the fuel station.

Salvo and Huse (2013) conduct an intercept survey of Brazilian motorists and estimate the distribution of willingness to pay for E100 relative to E25, which are the fuel choices in Brazil. They find that the median Brazilian motorist switches to E100 when its cost per mile falls below the cost per mile of E25, which is consistent with a motorist who wants to minimize fuel costs. Pouliot and Babcock (2014) use Brazilian preference data to estimate the demand for E85 in the United States to better understand the feasibility of meeting increased ethanol mandates. Their study accounts for the fact that fewer than 10 percent of US vehicles are flex-fuel vehicles (FFVs) that can use E85 and the quite limited availability of E85 across the country.<sup>2</sup> FFVs are typically alternate versions of conventional models, and the operation of an FFV is identical to the conventional version except for the lower fuel economy with E85. Their finding that potential consumption of E85 in the United States can easily exceed one billion gallons is dependent on the assumption that US motorists with FFVs have the same preferences for E85 as Brazilian motorists.

There are many reasons why US motorists with FFVs may not have the same preferences as Brazilian motorists. Almost all vehicles sold in Brazil since 2003 are flex vehicles, and almost all Brazilian fuel stations sell both E100 and E25. Brazilians typically know when the cost per mile driving on E100 is

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<sup>2</sup> Until 2014, automobile manufacturers received a substantial credit from the US Corporate Average Fuel Economy (CAFE) standards for producing FFVs (Anderson and Sallee 2011). The credit started declining in 2015 and will cease in 2020. Under the rule, up to an annual limit, FFVs were treated as though they were operated partially on E85, but the fuel economy was calculated as the total miles the vehicle could travel per gallon of gasoline input (the ethanol fuel input was excluded in the fuel economy calculation). The result is that the majority of FFVs in the United States today are large sedans, SUVs, pickup trucks, and minivans, and they are mostly manufactured by American automobile companies.

lower than on E25. Thus the average Brazilian motorist has much more experience and information about ethanol than does the average US flex motorist.

To better understand US preferences for E85 and whether they are consistent with Brazilian preferences, we followed the example of Salvo and Huse (2013) and conducted an intercept survey of US motorists in multiple states (Arkansas, California, Colorado, Iowa, and Oklahoma) as they refueled. Our survey was designed to overcome circumstances not faced by Salvo and Huse (2013). In contrast to Brazil, very few US stations sell E85. Thus many US flex motorists must incur additional costs to drive out of their way to fill up with E85. This implies that our observed sample of flex motorists have, on average, a higher willingness to pay for E85 than the population of flex motorists. We included questions in our survey that allow us to correct for this selection bias.

Salvo and Huse (2013) were able to observe preferences for E100 when its cost per mile was greater than E25 and when it was lower than E25. Thus they were able to estimate the distribution of preferences more accurately than if their data had less variation in relative fuel costs. Estimations of US preferences for E85 are hampered because it has been rare that the cost per mile of driving on E85 is less than the cost per mile with E10. Anderson (2012) tried to overcome this difficulty by specifying a parsimonious functional form for the distribution of preferences for E85 in Minnesota, but his data all fell within one tail of his distribution.<sup>3</sup> We overcome this lack of variation in relative prices by combining revealed preference data with stated preference data. As part of our survey, fuel choices were observed, and then we presented motorists with a hypothetical set of prices in an attempt to induce them to switch fuels. By combining the stated preference data with the revealed preference data we can much more precisely estimate the distribution of preferences for E85. However, because the hypothetical prices were not randomized, but rather selected to induce switching, we must carefully correct for the endogeneity problem created by our data collection method.

We find that US consumers have, on average, a much lower willingness to pay for high-ethanol blends than the average Brazilian motorist. California motorists have a higher willingness to pay for E85 than motorists in the other four states surveyed. Corn Belt motorists located in Iowa do not have a higher willingness to pay than motorists in Oklahoma, Arkansas, and Colorado. The policy implication of our results is that the RIN price that is needed to induce enough consumption of ethanol to meet proposed blending mandates is much higher than estimated by Pouliot and Babcock (2014) but that

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<sup>3</sup> Recent studies have used nationwide mail and online surveys to obtain stated-preference data on WTP for E85 (e.g., Jensen et al. 2010; Petrolia et al. 2010; Aguilar et al. 2015). However, these studies do not provide estimates of the distribution of WTP for E85 conditional on the relative prices of E10 and E85, and therefore their use is limited in policy analysis.

EPA's proposed blending targets are feasible. We also examine whether motorists consider the relative energy contents of E85 and E10 when making their fuel decisions and the impact of other factors that explain variations in motorists' willingness to pay.

## **II. Intercept Survey Design**

We designed an intercept survey of motorists who drive FFVs at fuel stations that sell E85 to obtain data on a broad range of factors that might affect willingness to pay for E85 as a substitute for E10. The survey shares similarities with the survey of motorists at fuel stations in Brazil conducted by Salvo and Huse (2013). After first observing motorists' fuel choices from afar, we conducted an interview while they refueled. We completed each interview in about two minutes which meant that, in almost every case, we did not detain the motorists longer than the time it took to refuel. Appendix A contains the complete questionnaire.

### *Intercept Survey Method*

For each station we visited, we recorded station-level data including the station name and brand, the station address, the prices of the E10 fuels (usually regular, midgrade, and premium), and the price of E85. We conducted almost all of the interviews personally, and we made an effort to interview all of the flex motorists who pulled alongside any of the station's pumps. When a second flex motorist pulled up to a pump during an interview, we did not interview the second flex motorist. Instead, when we completed the first interview, we reset and then waited to interview the next flex motorist. This sequencing rule avoided a selection bias. In practice, because the FFV-share of the vehicle fleet is small and the survey was over quickly, we managed to capture virtually all of the flex motorists who visited the E85 stations.

We visually identified FFVs in two ways. First, many newer FFVs have a badge on the back (or in rare cases on the side) of the vehicle that indicates they are FFVs. Second, most FFVs have a yellow gas cap, a yellow ring, or a yellow sticker inside the gas door indicating that it is capable of using E85. In practice, identifying FFVs required the interviewer to walk around the pumps and closely inspect vehicles as they were refueling. A third way to tell whether a vehicle was an FFV was if the motorist chose E85. However, a few motorists made a fueling mistake by choosing E85 for a conventional vehicle not equipped to use it or had a vehicle with aftermarket modifications to use E85.<sup>4</sup>

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<sup>4</sup> Over the course of conducting the survey, we learned that a small share of motorists have aftermarket modifications to conventional vehicles (not originally manufactured as FFVs) to use E85 because the higher octane

Before talking to a motorist, the interviewer passively observed each motorist's fuel choice and vehicle characteristics, including vehicle make, model, vehicle type (car, truck, SUV, or van), the state on the license plate, whether the vehicle had an FFV badge, whether the vehicle had a yellow gas cap, and the gender of the motorist. The interviewer also recorded the transaction volume and expenditure after the motorist finished refueling.

### *Survey Questions*

Once a motorist began refueling, the interviewer approached and asked whether the motorist was willing to participate in a short survey. The interviewer then followed with a series of questions about the motorist's characteristics and motorist's awareness of E85 and opinions on topics that might explain the motorist's fuel choice.<sup>5</sup> Appendix B contains details about these questions.

We wanted to know if the motorists we surveyed were random draws from the general population of flex motorists or if they were in our sample because they sought out E85. We know that flex motorists who chose E10 did not come specifically to the station for E85, so we presume that they would still have chosen to refuel at the particular station even if every station offered E85. We treat these flex motorists as random draws from the local population of flex motorists. But for motorists who chose E85 we asked, "Did you choose to fuel at this station because it offers E85?" If they responded positively, we followed by asking, "How far out of your way did you have to drive?" We use responses to these questions identify which motorists who chose E85 self-selected into the sample.

We asked a question to obtain stated preference (SP) data to complement the revealed preference (RP) data by proposing a single hypothetical price scenario to each motorist. For motorists who refueled with E10, the scenario was that we either increased the price of E10 or decreased the price of E85. For motorists who refueled with E85, the scenario was that we either increased the price of E85 or decreased the price of E10. The amount of the hypothetical price change was plus or minus \$0.25, \$0.50, or \$0.75 per gallon.

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content can improve the vehicles' (racing) performance. In most cases, the vehicles are modified so that they can use either E85 or E10, but in rare cases the vehicles are configured so that they can only use E85, and switching back to E10 requires modifying the vehicle.

<sup>5</sup> In one question, we asked about ownership of the vehicle. We are particularly interested in identifying government vehicles because government employees driving an FFV are required to refuel with E85. Related to that, Corts (2010) shows that government fleet adoption of FFVs led to an increase in the number of retail E85 stations, but cannot say whether the increase in E85 stations led to an increase in motorists purchasing FFVs. Specifically, Corts (2010) notes that most FFVs in the dataset were purchased prior to the widespread availability of E85 and that flex motorists may not even know of their vehicles' capabilities.

### III. Sample Selection and Models of Fuel Choice

In this section, we discuss the sample-selection problem in our survey data and how we obtain a random sample. We then describe motorists' fuel choices in random utility models. We develop two alternative models in which motorists make their fuel decisions based on either 1) the difference in the price of E85 and E10, which we call the E85 premium, or 2) the ratio of the price of E85 to E10, which we call the E85 ratio. We estimate models that are consistent with these two decision models and compare model fits to determine how motorists make their fuel decisions.

#### *Sample Selection*

Recall that we only surveyed flex motorists at stations that sold E85. The sample-selection problem arises from motorists self-selecting into the survey because of their high willingness to pay for E85. In the United States in 2014 and 2015 (when we conducted our survey) there were about 2,700 fuel stations that offered E85 while E10 was available in all of the nearly 110,000 fuel stations. Motorists could access E10 at any station along their normal driving routes. However, most motorists could not access E85 at what would otherwise be their most preferred or most convenient station, so many motorists had to deviate from normal driving routes or break from their normal refueling habits to access E85. Thus, many flex motorists who we observed refueling with E85 incurred costs associated with forgoing E10-only stations.

The motorists in our survey who chose E10 had the opportunity to refuel with E10 at any other station, and their patronage of the surveyed station was not motivated by its offering of E85.<sup>6</sup> For these motorists, the opportunity cost of accessing E10 at the surveyed fuel station was zero. Likewise, for several motorists we surveyed who chose E85, the surveyed station was the same station where they would have fueled even if E85 was offered at every station. These motorists did not self-select into our sample. The motorists who self-selected into our survey were those who would not have refueled at the surveyed station except for the fact that it offered E85. For these motorists, there was an opportunity cost of refueling with E85, so they purchased E85 only if the value they assigned to E85 over E10 (given prices) exceeded the cost of accessing E85. This means that the intercept survey over-sampled motorists

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<sup>6</sup> It is conceivable that some of the flex motorists who chose E10 may have chosen to refuel at the E85 station specifically because it offered E85 because they wanted the E85 option and would have chosen E85 if the relative price on that particular day had been more favorable. But in talking to the E10 motorists about hypothetical prices and choices, refueling habits, and knowledge of E85, we rarely encountered motorists who could claim this behavior. Instead, some E10 motorists did not know they had FFVs, that the station offered E85, or really what E85 was. The flex motorists who were deciding between E85 and E10 seemed to be generally aware of the prevailing fuel prices and seemed to make their fuel choices before arriving at the station and viewing the exact prices.

who chose E85, especially those with high willingness to pay for E85. A further implication is that the distribution of preferences among E85 motorists who self-selected into the sample has mean willingness to pay that is higher than the mean willingness to pay for the distribution of preferences among E85 motorists who did not self-select into the sample.

Recall that we asked motorists who chose E85 two questions to inform self-selection. The first question was, “Did you choose to fuel at this station because it offers E85?” To the motorists who answered “yes,” we followed by asking, “How far out of your way did you have to drive?” We determine which motorists constitute a random sample based on the answers to these questions.

Using motorists’ responses to the first question to select a random sample may be too restrictive because of how motorists interpreted the question. It is possible that some motorists who answered “yes” to the question about whether their patronage was motivated by the offering of E85 would have chosen the same station even if E85 were offered at every station. Indeed, many motorists answered the follow-up question about how far out of their way they drove to access E85 with, “Not at all,” “I didn’t,” or “Zero.” The true random sample therefore likely consists of all of the motorists who chose E10, all of the motorists who chose E85 and answered “no” to the first question, and some of the motorists who chose E85, answered “yes” to the first question, and answered (some form of) “zero” to the second question.

We cannot determine which of the motorists who answered “zero” to the second question should be part of what constitutes a random sample. Our approach will be to compare models where the random sample includes the E10 motorists and only the E85 motorists who answered “no” to the first question to models where the sample also includes E85 motorists who answered “yes” to the first question and “zero” to the second question. Using these two competing estimation samples, we will estimate bounds on the population parameters and mean willingness to pay.

One could consider modeling the selection problem so that the empirical model uses the full sample of data. However, this would require either knowing how much it costs consumers to drive to an out-of-the-way fuel station or making identification of such transportation costs possible. One important difficulty in the identification of consumer transportation cost is that in the sample the distance driven to access E85 is positively correlated with the motorists’ choice of E85. In the population for FFV motorists, this correlation is negative. Instead of imposing strong assumption on the model to make identification of the transportation cost possible, we elect to work with smaller data samples that are nearly representative of the population of flex motorists.

If driving costs were zero, the distribution of preferences among motorists who self-selected into the sample for E85 would be the same as the distribution of preferences among the motorists who were random draws from the population and chose E85. In such a world, we could include the extra observations where motorists self-selected into our sample and use a model that corrects for the choice-based sampling. The problem of the stratified sampling that would occur with those data has been described and estimators have been proposed in prior literature (e.g. Manski and Lerman 1977; Manski and McFadden 1981; Imbens 1992; Imbens and Lancaster 1996). But driving costs do not equal zero and can be quite significant (e.g. Houde 2012; Wolff 2014). And because of driving costs, the distribution of preferences among the E85 motorists who self-selected into the sample is not the same as that of the E85 motorists who were random draws from the population. This violates a fundamental assumption in models of choice-based sampling.

### *Models of Motorists' Fuel Choice*

The random utility models below show how motorists make their choices when they select a fuel based on either the E85 premium or the E85 ratio. The model focuses on fuel choices and assumes that the demand for fuel is perfectly inelastic in the short run. That is, motorists choose either E85 or E10 based on the E85 premium or the E85 ratio but the amount of fuel they purchase is price-independent. We consider only motorists who do not incur a cost to access the E85 station, for whom the E85 station would be the most preferred station even if every station offered E85. Thus we do not consider the motorists' decisions of which fuel station to visit. Throughout, we use subscript  $e$  to denote E85 and a subscript  $g$  to denote E10.

In the E85 premium model, the indirect utility that motorist  $i$  derives from consumption of fuel  $j \in \{e, g\}$  takes a linear form and is given by

$$V_{ij}(p_{ij}, \mathbf{x}_i, \varepsilon_{ij}) = \alpha_j p_{ij} + \mathbf{x}_i' \boldsymbol{\beta}_j + \varepsilon_{ij} \quad (1)$$

where  $p_{ij}$  is the nominal price of fuel  $j$  for motorist  $i$ ,  $\mathbf{x}_i$  is a vector of characteristics about the motorist and the fueling station, and  $\varepsilon_{ij}$  is an unobservable stochastic shifter specific to the motorist and fuel choice. We assume that  $\varepsilon_{ij}$  is a type 1 generalized extreme value random variable so that the difference between  $\varepsilon_{ig}$  and  $\varepsilon_{ie}$  follows a logistic distribution. We let  $\alpha_e = \alpha_g \equiv \alpha$  so that that motorists' fuel choices do not depend on individual fuel prices but rather on the difference in the fuel prices. We let  $\boldsymbol{\beta} \equiv \boldsymbol{\beta}_e - \boldsymbol{\beta}_g$ , and we define  $d_i \equiv p_{ie} - p_{ig}$  to be the E85 premium observed by motorist  $i$ . A motorist chooses E85 if  $V_{ie}(\cdot) \geq V_{ig}(\cdot)$  which amounts to

$$\alpha d_i + \mathbf{x}_i' \boldsymbol{\beta} \geq \varepsilon_i,$$

where  $\varepsilon_i \equiv \varepsilon_{ig} - \varepsilon_{ie}$  is symmetric with a mean of zero and follows a logistic distribution.

In the price ratio model, the indirect utility flex motorist  $i$  derives from fuel  $j$  is

$$\tilde{V}_{ij}(p_{ij}, \mathbf{x}_i, e_{ij}) = p_{ij}^{a_j} \cdot \mathbf{x}_i^{\mathbf{b}_j} \cdot \exp(e_{ij}), \quad (2)$$

where again  $e_{ij}$  is a type 1 extreme value random variable. Taking logs on both sides, we can write that a motorist chooses E85 if  $\log \tilde{V}_{ie}(\cdot) \geq \log \tilde{V}_{ig}(\cdot)$  or

$$a \log(r_i) + \log(\mathbf{x}_i')\mathbf{b} \geq e_i,$$

where  $r_i \equiv p_{ie}/p_{ig}$  and  $e_i \equiv e_{ig} - e_{ie}$ . Thus, in the ratio model, preferences also follow a logistic distribution but the variables enter the model in logs.

#### IV. Data Collection and Summary Statistics

We obtained the cooperation of two E85 retailers to conduct our survey. We collected a total of 972 observations of flex motorists from 17 E85 stations in six urban areas between October 2014 and April 2015.<sup>7</sup> In chronological order, the urban areas we visited were: Ames/Des Moines, Iowa; Colorado Springs, Colorado; Tulsa, Oklahoma; Little Rock, Arkansas; Sacramento, California; and Los Angeles, California. We personally collected most of the observations. A small team of undergraduate students helped collect some of the observations in the Ames/Des Moines area. In each urban area, we visited between two and four stations and collected around 100 or more observations. All of the E85 stations we visited in Arkansas, Colorado, Iowa, and Oklahoma were operated by a retailer we will call 'Retailer Y', and all of the E85 stations we visited in California were operated by a retailer we will call 'Retailer Z'.

##### *Observed Data and Survey Responses*

From the initial 972 observations of motorists refueling their FFVs, we remove 79 observations where motorists chose not to or were unable to complete or participate in the survey. This represents a total non-response rate of 8 percent. We also remove 12 observations for which we do not have SP data either because we asked the question incorrectly or the motorist was unable to answer. That leaves us with an initial sample of 881 complete observations before we address the sample-selection problem. Table 1 summarizes the fuel choice data broken down by station, urban area, and retailer. In the entire sample of 881 flex motorists, the average E85 price was \$2.19 per gallon, and the average E10 price was \$2.58 per gallon. Therefore, the average E85 premium (defined as the E85 price per gallon minus the

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<sup>7</sup> We collected a total of 994 observations, but 22 were from conventional vehicles with aftermarket modifications to use E85. We observed these vehicles refueling with E85, but we exclude these observations because we can only identify the vehicles as flex when the motorists choose E85.

E10 price per gallon) was  $-\$0.39$ . The average E85 ratio (defined as the E85 price divided by the E10 price) was 0.85. Overall, 431 (49 percent) of flex motorists chose E85 while 450 (51 percent) chose E10.<sup>8</sup>

On average fuel prices were more favorable toward E85 at Retailer Z's stations where the average E85 premium was  $-\$0.54$ , and the E85 ratio was 0.83. We observed 231 flex motorists refueling at Retailer Z's locations, and 89 percent chose E85. Retailer Z's E85 prices were not drastically more favorable than Retailer Y's E85 prices, but each of Retailer Z's pumps served a larger share of the local E85-choosing community of flex motorists because E85 stations were less common in California. Also, Retailer Z ran promotions providing special fuel cards and other incentives to local flex motorists, marketing E85 as a clean-burning, high-performance fuel. We do not have evidence that any particular promotion was taking place while we conducted the survey.

For Retailer Y, E85 prices were lowest in Iowa, where the average E85 premium was  $-\$0.47$ , and the average E85 ratio was 0.83, the same as the average price ratio observed at Retailer Z's stations. Absolute fuel prices were higher in California, so the California E85 premium was larger in magnitude. The share of flex motorists who chose E85 among Iowa flex motorists was 42 percent, less than half of what we observed at E85 stations in California. We suspect that one reason for the difference is that stations that offer E85 are more common in Retailer Y's areas. Thus local flex motorists with high willingness to pay for E85 can choose between multiple E85 stations and will not all be observed in the sample.

Recall that we do not consider all interviewed motorists as random draws from the population of flex motorists. Instead, we have two rules that we use to identify and select motorists. The first rule is more restrictive and only motorists who answered that they did not go out of their way to the fuel station for E85 are part of the sample. Using that rule leaves us with a total 479 observations with 29 motorists selecting E85. The second rule is more inclusive and uses observations where motorists answered zero to the question about how far out of their way they drove to fuel with E85. This second rule gives us a sample of 670 observations with 220 motorists selecting E85.

Figure 1 shows the share of motorists who chose to refuel with E85 (RP choice) as a function of the E85 premium for the more inclusive sample with 670 observations. The corresponding figure with the sample of 479 observations is similar. We only show the figure for the E85 premium, but the figure for the E85 ratio is practically identical. Figure 1 shows that the share of motorists who chose E85 at Retailer Y declines with respect to the E85 premium as expected and ranges from a bit above zero to

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<sup>8</sup> Among the 450 flex motorists who chose E10, 414 (92 percent) chose regular grade 87 octane (85 octane in CO), 24 (5 percent) chose midgrade, and 12 (3 percent) chose premium.

almost 50 percent. At Retailer Z, the share of motorists who refuel with E85 increases with respect to the E85 premium. The variation in the E85 premium is small however, which might explain why we observe a positive slope. The share of motorists who refuel with E85 at Retailer Z is above 50 percent for all observed E85 premium values.

Figure 2 shows in two panels the share of motorists who chose to fuel with E85 as a function of the hypothetical E85 premium for the more inclusive sample with 670 observations. The hypothetical price scenario that we presented to motorists was conditional on their fuel choice and accordingly we present the shares conditional on motorists' fuel choice (RP choice). One of our empirical model accounts specifically for this. Observe that in both panels of Figure 2, variations in hypothetical prices are much greater than the variation in prices in Figure 1. Panel a) of Figure 2 is for observations we collected at Retailer Y and shows that the share of motorists who chose E85 declines with respect to the hypothetical E85 premium regardless of whether motorists' RP choice was E10 or E85. Panel b) is for observations we collected at Retailer Z. The share of motorists who chose E85 declines with respect to the hypothetical E85 premium for those who refueled with E85 but unexpectedly increased for those who refueled with E10.

## V. Empirical Models

In this section, we describe four empirical models that we use to obtain estimates of the distribution of willingness to pay for E85. The models differ depending on whether we apply a correction for the rare occurrence of E85 and whether we use the SP data.

In the description of the empirical models, we will use a generic notation for both the premium and the ratio models where  $\Lambda(\cdot)$  is the cumulative logistic distribution,  $\mathbf{z}_i$  is the vector of dependent variables that includes either the E85 premium or the log of the E85 ratio, and  $\boldsymbol{\theta}$  is the vector of parameters to estimate. We write that  $y_i$  equals one for a motorist who refuels with E85, and  $y_i$  equals zero for a motorist who refuels with E10.

### *Maximum Likelihood*

The first model we consider is the standard maximum likelihood estimator (MLE). Under standard assumptions,  $\mathbf{z}_i$  is exogenous so we can consistently estimate  $\boldsymbol{\theta}$  by maximizing the conditional log-likelihood given by

$$\log L = \sum_{i=1}^N \ln f(y_i | \mathbf{z}_i, \boldsymbol{\theta}) = \sum_{i=1}^N \left\{ (1 - y_i) \ln \left[ 1 - \Lambda(\mathbf{z}_i' \boldsymbol{\theta}) \right] + y_i \ln \left[ \Lambda(\mathbf{z}_i' \boldsymbol{\theta}) \right] \right\}. \quad (3)$$

This is the log-likelihood we will use to estimate models with the RP data only. It does not correct for the bias from the rare-choice problem discussed next.

#### *Finite-Sample Correction for Rare Choices*

When using our strictest sample-selection rule, we only have 29 observations where motorists choose E85 in the RP data. This is a sufficient source of concern for us to apply the finite-sample correction proposed by King and Zeng (2001) as a first solution to the rare-choice (rare-event) problem. To our knowledge, such a correction has not been applied to consumer choice data generated by intercept surveys.

The finite-sample correction in King and Zeng (2001) assumes that the sample is representative of the population. King and Zeng (2001) show that the bias in logit models from the rare-choice problem is given by

$$bias(\hat{\boldsymbol{\theta}}) = (\mathbf{z}' \mathbf{w} \mathbf{z})^{-1} \mathbf{z}' \mathbf{w} \boldsymbol{\xi}$$

where  $\xi_i = 0.5 Q_{ii} \left( 2 \Pr(y_i = E85 | \mathbf{z}_i' \hat{\boldsymbol{\theta}}) - 1 \right)$ ,  $Q_{ii}$  are the diagonal elements of  $\mathbf{Q} = \mathbf{z} (\mathbf{z}' \mathbf{w} \mathbf{z})^{-1} \mathbf{z}'$ , and

$\mathbf{w} = diag \left\{ \Pr(y_i = E85 | \mathbf{z}_i' \hat{\boldsymbol{\theta}}) \left( 1 - \Pr(y_i = E85 | \mathbf{z}_i' \hat{\boldsymbol{\theta}}) \right) \right\}$ . The method to correct the bias requires first

estimating the parameters in the logistic regression using the MLE in (3) and then applying the correction such that  $\tilde{\boldsymbol{\theta}} = \hat{\boldsymbol{\theta}} - bias(\hat{\boldsymbol{\theta}})$ . Following King and Zeng (2001), we then calculate the variance-covariance matrix as  $V(\tilde{\boldsymbol{\theta}}) = (n/(n+k))^2 V(\hat{\boldsymbol{\theta}})$  where  $n$  is the number of observations and  $k$  is the length of  $\boldsymbol{\theta}$ .

The method proposed by King and Zeng (2001) works better if we know the true population weights to compensate for the difference in the fraction of respondents in the sample from the fraction of the population who select E85. In the expressions above, we assume that the fractions of respondents are the same in the sample and in the population. Alternatively, we could have used aggregate E85 and E10 consumption data to calculate the population fraction of E85 motorists. However, this would likely not have been an improvement over assuming that the fractions of respondents are the same. Aggregate gasoline consumption data are conditional on prices observed in

the past and as such are likely not to apply when we conducted the survey. Moreover, the level of aggregation of E85 and E10 consumption data might be too high and thus fractions from those data may not be appropriate for the areas where we conducted our survey.

King and Zeng (2001) recommend using their method even when there is no apparent rare-choice problem. The arguments are that their method is simple to implement and that there is no sample size large enough to evade the finite sample-size problem if an event is sufficiently rare. For these reasons, not only will we use the finite-sample correction on the MLE but also on the coefficients estimated with the SP-off-RP approach we describe below.

### *Two Methods for Augmenting RP Data with SP Data*

Our second solution to the rare-choice problem is to augment our RP data with SP data. As we will show, the MLE in (3) is not a correct approach for estimation of models that add SP data.

SP data have been used to complement RP data in previous studies to increase the number of observations and expand the choice set to include alternative(s) that are sometimes not available on the market. The traditional method for estimating models using combined RP and SP data in the transportation and the environmental economic literature has been described by Ben-Akiva and Morikawa (1990), Hensher and Bradley (1993), Adamowicz et al. (1994), and Hensher et al. (1999). The intuition behind the traditional approach is that the unobserved factors are different for the two types of data. To account for this, the RP and SP data are stacked together and the empirical model allows for different intercept and scale parameters for the distributions of error terms for the SP and RP data. This traditional approach is appropriate when the attributes of the hypothetical choices in the SP data collection are independent of the RP choices so that respondents' unobservable characteristics are not correlated with the hypothetical options.

Train and Wilson (2008) and Train and Wilson (2009) consider SP data constructed from RP choices. They refer to these data as "SP-off-RP" data. The important distinction from the traditional SP data is that the hypothetical choice scenario depends on the consumer's observed choice, which causes an endogeneity problem. Recall that in our case, if we observed a motorist choosing E10, we offered hypothetical prices that were more favorable to E85. If we observed a motorist choosing E85, we offered hypothetical prices that were more favorable to E10. A motorist's RP fuel choice depends on both observed characteristics and unobservable factors. The same unobservable factors that affect the motorist's observed RP fuel choice (and therefore the hypothetical prices) carry over to the SP

experiment, so that the unobserved factors in the SP experiment are correlated with the hypothetical prices, and we need to account for this when incorporating the SP data.

We define the utility that flex motorist  $i$  derives from fuel  $j$  in the SP experiment as

$$W_{ij}(\mathbf{z}_{ij}, \varepsilon_{ij}, \eta_{ij}) = \mathbf{z}_{ij}'\boldsymbol{\theta}_j + \varepsilon_{ij} + \eta_{ij},$$

where  $\mathbf{z}_{ij}$  is the vector of dependent variables that includes either the hypothetical E85 premium or the hypothetical E85 ratio calculated from the hypothetical prices  $\dot{p}_{ie}$  and  $\dot{p}_{ig}$ , and  $\eta_{ij}$  is a generalized extreme random variable with scale  $(1/\zeta)$  that captures additional unobservable aspects of the SP scenario not present in the RP scenario. Note that in the SP data, the relationships between both the observable and unobservable factors that determine the utility in the RP data in  $V_{ij}(\cdot)$  in equations (1) and (2) are preserved. This means that the unobservable  $\varepsilon_{ij}$  term for motorist  $i$  that affects the RP choice carries forward to the SP choice. The total unobservable error term in the SP model is  $\varepsilon_{ij} + \eta_{ij}$ , where  $\varepsilon_{ij}$  derives from the motorist's RP choice. We use that choice to generate the hypothetical prices  $\dot{p}_{ie}$  and  $\dot{p}_{ig}$  in the SP experiment. Thus the hypothetical prices in the SP data are endogenous because they are correlated with the total error term,  $\varepsilon_{ij} + \eta_{ij}$ .

A motorist chooses E85 in the hypothetical price scenario if  $W_{ie}(\cdot) \geq W_{ig}(\cdot)$ , which we can re-write as

$$\zeta(\mathbf{z}_i'\boldsymbol{\theta} - \varepsilon_i) \geq \eta_i,$$

where  $\eta_i \equiv \zeta(\eta_{ig} - \eta_{ie})$  is symmetric with a mean of zero and follows a logistic distribution. The  $\zeta$  term normalizes the logistic distribution of  $\eta_i$  to have a scale of one. The probability that a motorist chooses E85 in the experiment is  $\Pr(\text{SP E85}_i) = \Lambda(\zeta[\mathbf{z}_i'\boldsymbol{\theta} - \varepsilon_i])$ , and the probability that a motorist chooses E10 in the experiment is  $\Pr(\text{SP E10}_i) = 1 - \Lambda(\zeta[\mathbf{z}_i'\boldsymbol{\theta} - \varepsilon_i])$ . The joint probability of a motorist's specific RP and SP choice combination is the product of the probability of the RP choice and the conditional probability of the SP choice (conditional on the RP choice). We write  $\dot{y}_i = (\dot{y}_{i1}, \dot{y}_{i2})$  where  $\dot{y}_{i1}$  is the RP choice and  $\dot{y}_{i2}$  is the SP choice. The SP-off-RP likelihood function is

$$L = \prod_{\dot{y}_i=(0,0)} \Pr(\text{RPE10}_i) \Pr(\text{SPE10}_i | \text{RPE10}_i) \prod_{\dot{y}_i=(0,1)} \Pr(\text{RPE10}_i) \Pr(\text{SPE85}_i | \text{RPE10}_i) \prod_{\dot{y}_i=(1,0)} \Pr(\text{RPE85}_i) \Pr(\text{SPE10}_i | \text{RPE85}_i) \prod_{\dot{y}_i=(1,1)} \Pr(\text{RPE85}_i) \Pr(\text{SPE85}_i | \text{RPE85}_i). \quad (4)$$

The  $\varepsilon_i$ 's that enter the SP probability expressions are not observed but we know their conditional distributions so we can integrate over the density to calculate the expected value of the logits given the

correlated errors. For example, the logit probability of a motorist choosing E85 in the SP experiment conditional on that motorist choosing E85 in the RP data is

$$\Pr(\text{SP E85}_i | \text{RP E85}_i) = \Lambda(\zeta[\mathbf{z}_i' \boldsymbol{\theta} - \varepsilon_i | \varepsilon_i \leq \mathbf{z}_i' \boldsymbol{\theta}]),$$

which we can write as

$$\Pr(\text{SP E85}_i | \text{RP E85}_i) = \int \Lambda(\zeta[\mathbf{z}_i' \boldsymbol{\theta} - \varepsilon_i]) \lambda(\varepsilon_i | \varepsilon_i \leq \mathbf{z}_i' \boldsymbol{\theta}) d\varepsilon_i,$$

where  $\lambda(\cdot)$  is the marginal density of the logistic distribution. We evaluate the integrals by simulation, taking draws of  $\varepsilon_i$  from its conditional density following the method described by Train and Wilson (2009). The probability  $\Lambda(\cdot)$  is calculated for each draw and the results are averaged. We estimate the parameters by maximizing the log of the likelihood function in equation (4) using 1,000 conditional logistic draws for each observation.

## VI. Estimation Results

In this section, we present estimates of the empirical models described in the previous section. We identify and present the models in the following manner: A) MLE with the RP data only; B) finite-sample correction on the estimates in A); C) traditional augmentation of RP data with SP data; and D) SP-off-RP method for data augmentation. We add a model: E) finite-sample correction on the estimates in D) to investigate whether applying the finite-sample correction had much of an impact when using the SP-off-RP approach.

Each model uses the following explanatory variables: vehicle ownership (personal, government, company, other), vehicle type (car, truck, SUV, van), whether the vehicle had an FFV badge, number of miles driven per year, gender, age, opinions about which fuel is better for the environment, the engine, the economy, or national security, opinion on which fuel yields more miles per gallon, and the state where the station was located (Arkansas, California, Colorado, Iowa, or Oklahoma). We do not include the variables that describe the characteristics of the fuel stations because the state dummies summarize most of that information.

We will not show results for all of the estimated coefficients, but the interested reader can refer to Appendix C for complete results. Rather, we will focus on parameters that summarize the distribution of preferences. We report the location and the scale parameters that summarize the logistic distribution (for the E85 premium models) and the scale and shape parameters that summarize the log-logistic distribution (for the E85 ratio models). The location parameter in the premium models and the scale parameter in the ratio models summarize motorists' perceptions of the value of E85 relative to E10.

These parameters are straightforward to interpret, and their values can be directly used in models for policy analysis.

For the premium models, we calculate the mean of the logistic willingness to pay distribution as  $\mu = \frac{1}{N} \sum_i (\mathbf{x}_i' \hat{\boldsymbol{\beta}}) / -\hat{\alpha}$ , where  $N$  is the number of observations, and the scale parameter as  $s = 1 / -\hat{\alpha}$ .

Similarly, for the ratio models, we calculate the scale parameter as  $\rho = \exp\left(\frac{1}{N} \sum_i (\log(\mathbf{x}_i)' \hat{\mathbf{b}})\right) / -\hat{\alpha}$

and the shape parameter as  $\sigma = -\hat{\alpha}$ . We expect the propensity to purchase E85 to decline with respect to the price of E85 relative to E10 such that  $\hat{\alpha} < 0$  and  $\hat{a} < 0$ . Thus, because we must have that  $s > 0$  and  $\sigma > 0$ , we add a negative sign in front of  $\hat{\alpha}$  and  $\hat{a}$  in our calculations of the distribution parameters. Alternatively, we could have defined the price variables as the price of E10 minus the price of E85 or the price of E10 divided by the price of E85. We calculate the standard errors of the distribution parameters using the delta-method.<sup>9</sup>

We compare Retailer Y and Retailer Z using the estimated location parameters in the E85 premium models and the estimated scale parameters in the E85 ratio models. We find moderate differences in the location parameters for the four states where we conducted interviews at Retailer Y. However, these differences are small when compared to the difference in the value of the location parameter for motorists in California buying fuel from Retailer Z. Thus, we will focus the discussion on summarizing the willingness to pay distribution at all of Retailer Y's locations collectively relative to willingness to pay at Retailer Z's locations in California.

For the premium models, given an average price of E10 of \$2.38 per gallon at Retailer Y, a value for the location parameter below negative \$0.52 per gallon indicates that the average motorist prefers E10 to E85 when prices are equal on a cost-per-mile basis. With an average E10 price of \$3.12 per gallon at Retailer Z, a mean willingness to pay below negative \$0.70 per gallon indicates that the average motorist prefers E10 to E85 when prices are at cost-per-mile parity. For the ratio models, a value for the scale parameter below 0.78 indicates that the median motorist prefers E10 to E85 at cost-per-mile price parity.

We begin with the estimates of the distribution parameters with the sample of 479 observations in Table 2. Looking at the location parameters for the premium models, observe that across all models

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<sup>9</sup> We also calculated the standard errors in models A, B and C by bootstrap, and the bootstrap standard errors are smaller than the standard errors from using the delta-method. However, we do not report bootstrap standard errors because their calculation is too computationally intensive in models D and E (which we integrate by simulation) even when the number of draws is low.

the average motorist discounts E85 relative to E10 by about \$1.80 per gallon at Retailer Y and by about \$1.00-1.20 per gallon at Retailer Z. These are large discounts because the average price of E10 was about \$2.38 per gallon at Retailer Y and \$3.12 per gallon at Retailer Z. Comparing Models 1-A and 1-B, the effect of the finite-sample correction is that it increases the estimated values of both the location and scale parameters without improving the precision.

In Model 1-C, where we estimate the model using the traditional approach of stacking up the RP and the SP data, we find values for the location and scale parameters not too different from those in Model 1-A, but the standard errors are much smaller. The model for the SP-off-RP data we show above demonstrates the endogeneity problem created from the collection of the SP data. This endogeneity problem does not appear too large based on the comparison of the estimated distribution parameters of Model 1-C to those of Model 1-A. However, looking at individual regression coefficients or the marginal effects in Appendix C, the difference is more apparent.

Model 1-D yields values for the mean willingness to pay that are lower than those in Model 1-A, and the estimated value for the scale parameter is larger than in Model 1-A. Furthermore, the standard errors in Model 1-D are much smaller than those in Model 1-A. Comparing the estimated distribution parameters of Model 1-E to those of Model 1-D, we find that the finite-sample correction has an effect similar to the one we obtained between Model 1-A and Model 1-B.

Estimates of the log-logistic distribution parameters in Table 2 also show that motorists significantly discount E85. Recall that prices are in cost-per-mile parity when the price ratio is 0.78. Estimates of the scale parameter, which is the median of the log-logistic distribution, are far below the parity price ratio. MLE in Model 2-A yields a median for the distribution of willingness to pay of 0.51 at Retailer Y and 0.68 at Retailer Z. The distribution of willingness to pay is wide with an estimated value for the shape parameter of 7.84. The finite-sample correction in Model 2-B slightly increases the value of the scale parameters and reduces the value of the shape parameter. When stacking the RP and SP data, the median willingness to pay declines to 0.44 at Retailer Y and to 0.55 at Retailer Z and a smaller value for the shape parameter at 6.12. The standard errors in Model 2-C are much smaller than those in Model 2-A. Compared to Model 2-A, the SP-off-RP estimates in Model 2-D of the scale parameter and shape parameter are smaller and more precisely estimated. Applying a finite-sample correction to Model 2-D, the estimate in Model 2-E for the scale parameter increases, but the estimate of the shape parameter declines.

Table 3 shows estimates of the willingness to pay distribution parameters using the sample of 670 observations. The estimates in Table 3 for the location parameter for the E85 premium models and

the scale parameter for the E85 ratio models show higher willingness to pay for E85 than the estimates in Table 2. This is a result we expect because the sample of 670 adds observations for E85 but keeps the number of observations for E10 the same. Recall that we selected the data sample from the motorists' answers to questions about whether they drove to the station specifically for E85 and how far out of their way they drove. As such, our estimates from the more restrictive sample with 479 observations give a lower bound on the willingness to pay while the more inclusive sample with 670 observations give an upper bound on willingness to pay. The comparison across models for the results in Table 2 also holds for Table 3. Observe in particular that the standard errors in the SP-off-RP Models 3-D and 4-D are smaller than the corresponding ones in the MLE Models 3-A and 4-A.

Figure 3 illustrates the precision gain from adding the SP data by comparing the E85 purchase probabilities from Model A to those from Model D for motorists at Retailer Y from the sample of 670 observations for the E85 premium in Panel (a) and for the E85 ratio in Panel (b). In both panels, the purchase probabilities are quite similar for Models A and D and are not statistically different from each other at a 95 percent confidence interval for the ranges of E85 premium and E85 ratios in Table 1. At the average E85 premium or the average E85 ratio observed in the data, the confidence intervals for Models A and D are similar. As the prices move away from the sample averages, the confidence interval for Model A grows rapidly, but the confidence interval for Model D is much more stable. The gain in precision from Model D is especially important at lower values for the E85 premium and the E85 ratio.

The results presented in Table 2, Table 3, and Figure 3 show that augmenting RP data with SP data significantly reduces the size of the standard errors for the estimated parameters of the distribution of willingness to pay for E85. However, we cannot directly assess whether the SP-off-RP approach effectively reduces the bias from the rare event problem. Augmenting the RP data with SP data should, of course, reduce the bias from the rare event problem because it increases the number of observations where motorists select E85 and hence improves the statistical properties of the estimated distribution parameters. However, this is done using an experiment where a hypothetical price scenario is presented to motorists. An issue, then, is whether there is a hypothetical bias from the SP data that may present a bigger issue than the rare-choice problem.

There are many potential causes of hypothetical bias and they can have either positive or negative impacts on estimated coefficients.<sup>10</sup> For instance, it is possible that it is slightly easier for motorists to say that they would switch fuels under the hypothetical prices than it is in practice because

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<sup>10</sup> Hensher (2010) examines hypothetical bias in estimates of willingness to pay from a number of recent studies where RP and SP data are both available and reviews possible causes and remedies.

switching might require using a specific island at the fuel station. On the other hand, the ‘inertia’ effect could go in the other direction because respondents tend to overstate their willingness to stay with their current fuel choice.

Another issue is anchoring where respondents base their responses on what they first observe. In our case, some motorists may use the actual posted fuel prices as an anchor for judging how favorable or unfavorable the hypothetical prices for the fuel choices are. Another factor contributing to hypothetical bias that may persist in our experiment is prominence, where the attribute that is varied in the hypothetical scenario (the fuel price) is thereby made more prominent to the respondent. In the intercept survey of flex motorists conducted by Salvo and Huse (2013), motorists were asked what was the ‘main reason’ motivating their fuel choice, and the overwhelming majority response was the fuel price.<sup>11</sup> So while proposing motorists a hypothetical price scenario may make the price a more prominent attribute of the fuel choice, it is likely already the most prominent factor driving the decision. Even so, it is possible that motorists are more subject to habit and routine than they realize, and if they had actually pulled in to the station and the hypothetical prices had been prevailing, motorists may never have even noticed or bothered to make a comparison before making their same usual fuel choices.

We do not believe that there is a significant hypothetical bias in our SP data. With the survey conducted on-site, biases that are typically associated with laboratory settings are minimized. Moreover, immediately before the survey began, motorists had just made a fuel purchase decision. Thus the survey was conducted in the ideal setting for asking flex motorists about the influence of price on fuel choices. For these reasons, we believe it is likely that the gain from reducing the rare-event bias by augmenting the RP data with SP data outweighs the hypothetical bias from the SP data in our study.

## **VII. Motorists’ Decision Rule**

One behavioral question we wish to answer is: What is the decision rule that motorists employ to select a fuel?<sup>12</sup> A rational motorist who cares only about cost per mile would refuel with E85 when its price is below 78 percent of the price of E10. But motorists may not be aware of the difference in energy content and may use a rule-of-thumb based on the difference in price. We investigate this question here by comparing the fit of the E85 ratio models to the E85 premium models. The measures of fit should not

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<sup>11</sup> In hindsight, this is a question we wished we had asked to motorists in our survey.

<sup>12</sup> In hindsight, we wish we had asked motorists what price decision rule they use in making their fueling decision. However, even if we had asked motorists that question, we would still have verified whether the data reveal the decision rule that motorists use.

be used to compare a model for the E85 premium to another E85 premium model, and likewise for the E85 ratio models, because of the finite-sample corrections and the augmentation from the SP data. Note that we report measures of fit for Model C, and that we will not discuss fit for the other models because, as we described above, these models are inherently biased although they appear to produce reasonable results.

The first measure of fit we use is McFadden's pseudo R-squared. McFadden's pseudo R-squared is a transformation of the log-likelihood value and a measure of how much of the observed variation in fuel choices is explained by the model. The pseudo R-squared values tend to be about half of traditional R-squared values from OLS estimation, and values of 0.2 to 0.4 represent excellent fit (Domencich and McFadden 1975). For the models with the finite-sample correction, we used the corrected coefficients to calculate the pseudo R-squared. For the SP-off-RP data, the pseudo R-squared is calculated using the log-likelihood in equation (3).<sup>13</sup>

On the basis of the values for pseudo R-squared, Table 2 shows that the E85 premium models fit the data slightly better than the E85 ratio models for the sample with 479 observations. In Table 3, with the sample with 670 observations, the values for the pseudo R-squared are very similar for the two decision models except for Models D and E that use the SP-off-RP approach where the E85 premium models have higher pseudo R-squared than the E85 ratio models.

The second measure of fit we employ is how well the models predict the motorists' actual choices, using 50 percent probability as a threshold. In Model A and B, we calculate the correct prediction rates with the RP data. In Models D and E, with the SP-off-RP approach, we calculate the correct prediction rates only for the RP data.<sup>14</sup> Looking at the rates of correct prediction in Table 3, the first thing to notice is that the models do poorly at predicting consumption of E85 but do very well at predicting consumption of E10. This, of course, is typical of models with a rare event and is a drawback of this measure of goodness of fit. In Table 4, with the sample of 670 observations, consumption of E85 is more frequent, and the models do much better at predicting E85 consumption, worse at predicting E10 consumption, and worse overall. The rates of correct prediction do not, in general, favor either model.

Overall, the goodness of fit measures cannot differentiate between the two decision rules. There are several possible reasons why we cannot identify which decision rule most motorists use. First,

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<sup>13</sup> In Models C with the stacked RP and SP data, the pseudo R-squared is calculated over all the SP and RP data.

<sup>14</sup> For Models C, we calculate the rates of correct prediction without differentiating between the SP and the RP data.

there simply might not be a dominant interpretation of prices among motorists and hence neither decision rule is more preponderant than the other. Second, there may not be enough variation in prices in the RP data for us to identify which decision rule motorists favor. The SP data offer more variation in prices and add information that could have helped us identify the decision rule. But one concern with these data is that motorists typically responded quickly to the hypothetical price scenario. Perhaps, they would have required more time to calculate the price ratio to provide an answer that is consistent with their real life fuel choice if the hypothetical price were actually offered by the fuel station. But anecdotal evidence we collected during the survey suggests that most motorists do not calculate the price ratio when making their fuel choice.

The survey contained several questions about motorists' knowledge of E85 and E10. Appendix B provides a summary and a discussion of these data. Gaps in motorists' general knowledge of E85 appear in answers to several questions. For instance, 14 percent of motorists who refueled with E10 did not know that their vehicle was flex and capable of using E85. Moreover, among all the E10 motorists, 62 percent of them had never refueled with E85 and 27 percent of them did not know that the fuel station offered E85. The lack of knowledge about the relative energy content of E85 and E10 is apparent regardless of motorists' fuel choice. To the question "which fuel yields more miles per gallon," 10 percent of motorists whose RP choice was E10 responded E85, 68 percent responded E10, 4 percent responded no difference and 17 percent responded that they did not know.<sup>15</sup> To the same question, motorists whose RP choice was E85, 23 percent responded E85, 54 percent responded E10, 10 percent responded no difference and 13 percent responded that they did not know. Overall, if we look at all the motorists we surveyed, 39 percent of motorists did not correctly answer that E10 is the fuel that gives more miles per gallon. This means that 39 percent of all motorists cannot be using relative prices as they relate to cost per mile to make their fuel decision. It is therefore not surprising that we do not find evidence that motorists use the price ratio to make their fuel decisions.

These results suggest that informing motorists about E85 and its relative energy content would help them make better fuel choices and hence be welfare-improving. A first step would be to educate motorists about the existence of E85 and its general properties compared to E10. A second step would be to provide more information about the ethanol content of E85 at a given pump and hence its relative energy content compared to E10. Recall that E85 contains between 51 and 83 percent ethanol and that the relative ethanol content can vary as a function of relative wholesale prices, region, and seasonality.

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<sup>15</sup> We asked motorists to compare ethanol and gasoline. But answers from the comparison of these two fuel directly translate to the comparison of E85 and E10, with E85 having a much greater ethanol content than E10.

### VIII. Explaining Mean Willingness to Pay

In Tables 2 and 3, we report the mean of the distribution of willingness to pay in the premium model as  $\mu = \frac{1}{N} \sum_i (\mathbf{x}_i' \hat{\boldsymbol{\beta}}) / -\hat{\alpha}$ . This value summarizes characteristics, opinions and perceptions of motorists of the value of E85 compared to E10. We can break down this value to obtain a description of what affects willingness to pay for E85 relative to E10 according to each of the motorist's characteristics and the responses to the questions we asked. For example, the impact of motorists' responses about a question  $\ell$ , we calculate  $\mu_\ell = \frac{1}{N} \sum_i \left( \sum_{k \in \ell} \beta_k x_{ik} \right) / -\hat{\alpha}$ . We will do this only for premium models where we use the SP-off-RP approach (i.e. Models 1-D and 3-D). Mean willingness to pay in the premium models is measured in dollars per gallon and hence is easier to interpret. We show how different factors affect mean willingness to pay in Tables 4 and 5.

We begin by discussing Table 4 for Model 1-D which used the SP-off-RP approach on our data sample with 479 observations. We break down willingness to pay for Retailers Y and Z separately and calculate the difference. The model parameters, except for the state fixed effects, are the same for the two retailers but motorists answered our questions differently. As such, the intercept is the same for motorists at the two retailers and shows that ignoring motorists' characteristics, opinions and where they live, the mean motorist is willing to pay about \$1.90 less per gallon for E85 compared to E10. None of the characteristics and opinion questions are statistically significant from zero for either retailer; nor are there significant differences between the two retailers. In several cases, the regression coefficients are statistically different from zero but the variance of responses is large thus causing the net contribution of each characteristic and opinion to not be statistically different from zero. Adding the intercept, the characteristics, and the opinion questions, we find a total value of about negative \$2.00 per gallon at both retailer Y and Z and the difference between the two retailers is not statistically different from zero.

The fixed effects in the regression models are for individual states with motorists in the state of Iowa as the reference group. Thus, we calculate the fixed effect for Retailer Y as the mean fixed effect for the states of Colorado, Oklahoma and Arkansas with reference to Iowa and is therefore expected not to equal zero. The mean fixed effect for Retailer Y is \$0.17 per gallon and not statistically different from zero. This indicates that motorists in Iowa, a Corn Belt state, do not have statistically different willingness to pay for E85 than motorists in the other three states where we surveyed at Retailer Y's stations, which include oil-producing states and states with little ethanol production. This result differs

from that of Salvo and Huse (2013) who found that the willingness to pay for E100 in Brazil was higher in ethanol-producing states than in other states.

The fixed effect for Retailer Z is about \$0.80 per gallon and statistically different from zero. The difference in the retailer fixed effects is negative \$0.62 per gallon and statistically different from zero at a 90 percent confidence interval. All totaled, the mean motorist at Retailer Y is willing to pay negative \$1.74 per gallon whereas the mean motorist at Retailer Z is willing to pay negative \$1.22 per gallon, both of which are statistically different from zero. However, taking the difference between these totals, we find that the difference in willingness to pay for the mean motorist at Retailer Y and at Retailer Z is not statistically different from zero.

We can draw very similar conclusions from the results in Table 5 for Model 3-D, which used the SP-off-RP approach on our data sample with 670 observations. The totals for the willingness to pay without the fixed effect at each retailer are statistically different from zero but their difference is not statistically significant. The retailer fixed effect is only statistically significant from zero at Retailer Z and the difference in the fixed effects is statistically different from zero. Calculating the total values for the willingness to pay of the mean motorists, we find a value of negative \$1.13 per gallon at Retailer Y that is statistically different from zero, but at Retailer Z, the willingness to pay of the mean motorist is negative \$0.06 per gallon and is not statistically different from zero. The difference in the willingness to pay of the mean motorist at the two retailers is not statistically different from zero at the 90 percent confidence interval with a p-value of 0.126.

Overall, we find an unexplained (i.e., given by the fixed effects) difference in willingness to pay across the mean motorists at the two retailers. However, when considering the total explained and unexplained willingness to pay of the mean motorists at the two retailers, we find a difference that is not statistically different from zero.<sup>16</sup>

## **IX. RFS Compliance Cost Implications**

Salvo and Huse (2013) estimate that the “median” consumer in Brazil has a 60-percent probability of choosing E100 when the cost per mile is equal across the two fuels. Our results, shown in Figure 3b, show that 60 percent of drivers outside of California will not choose E85 until the cost per mile is 32

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<sup>16</sup> Estimating the SP-off-RP models takes several minutes even when the number of draws in the simulation is low, making it very difficult to calculate bootstrap standard errors. For the other regression models, we find that bootstrap standard errors are slightly smaller than those calculated using the delta-method. Thus, bootstrap standard errors for the SP-off-RP models would have likely been smaller than our standard errors calculated using the delta-method.

percent below parity. At cost-per-mile parity, only 27 percent of drivers outside of California will choose E85. Our results indicate that the willingness to pay for E85 by US owners of flex vehicles is much lower than Brazilian owners' willingness to pay for E100. The implication of our results on compliance costs can be calculated using Figure 7 in Pouliot and Babcock (2014), which was generated assuming that the median US owner of a flex vehicle has a weak preference for E10, which simply means that slightly less than 50 percent of flex motorists will fill up with E85 at cost-per-mile price parity.

At cost-per-mile parity, Pouliot and Babcock (2014) estimate that approximately 750 million gallons of ethanol would be consumed in E85, which would be adequate to meet EPA's proposed ethanol mandates for 2017. The results shown in Figure 3b indicate that price parity would result in far lower sales. Rescaling the results in Pouliot and Babcock (2014) using our findings, we find that nationwide, approximately 405 million gallons of ethanol (i.e.,  $750 \times 0.27 / 0.50$ ) would be consumed in E85 at cost-per-mile parity. To generate consumption levels of 750 million gallons would require a price ratio of approximately 0.60. At current E10 retail prices of \$2.20 per gallon, Pouliot and Babcock's (2014) results suggest that a retail price of \$1.72 per gallon for E85 would be sufficiently low to sell 750 million gallons. However, the results in Figure 3b indicate that an E85 price of \$1.32 per gallon would be needed to sell 750 million gallons. Assuming that the ethanol mandate is binding and a perfect RIN pass-through, to lower the E85 price from \$1.72 to \$1.32 per gallon would require an increase in the ethanol RIN price of approximately 51 cents, which represents an increase in the annual cost of compliance of approximately \$7.7 billion. This illustrates the magnitude of the increase in compliance cost caused by US consumers not buying E85 when it lowers the cost per mile of driving.

## **X. Summary and Conclusion**

In this study, we conducted a survey of motorists at retail fuel stations offering E85 to estimate the distribution of preferences for E85 relative to E10 among flex motorists. Knowledge of US motorists' preferences for E85 is crucial for the evaluation of the RFS in particular given that the implied mandated ethanol volumes now exceed the volumes that can easily be blended in regular gasoline. The EPA and other stakeholders expect that increased consumption of E85 will make compliance with the ethanol blending mandates possible. The estimates of motorists' preferences for E85 relative to E10 in this study can be used to better measure the cost of compliance for increased volumes of biofuels in US motor fuels.

With the collaboration of two E85 retailers, we conducted an intercept survey at E85 stations to collect both revealed fuel preferences and stated fuel opinions from motorists with FFVs. We visited E85

stations in the urban areas of Colorado Springs, Des Moines, Little Rock, Tulsa, Los Angeles and Sacramento. We collected both RP and SP choice data giving us a greater range of relative fuel prices and hence more precise estimation of preferences. The hypothetical choice offered to motorists in the collection of the SP data was specifically designed to induce switching and hence we obtained more balanced answers in the SP data. We combined the RP and the SP data together to correct the rare choice bias and obtain more precise estimates of willingness to pay for E85.

We find much stronger preferences for E85 in California than in the other states covered by our survey. When the nominal E85 price per gallon was about 80 percent of the nominal E10 price per gallon, less than half of flex motorists outside of California chose E85, whereas nearly 90 percent of flex motorists in California chose E85. Part of this difference is accounted for by greater self-selection of California drivers into our survey because there are fewer E85 stations in California than in the other surveyed states. After correcting for self-selection, our results indicate that motorists in the Los Angeles and Sacramento areas either have a genuine greater willingness to pay more for E85 as a substitute for E10 or that the California retailer's marketing techniques to promote biofuels to local flex motorists have been successful.

In the four states excluding California, we find a mean willingness to pay for E85 between 51 and 63 percent of the price of E10. In California, we find a mean willingness to pay for E85 between 68 and 116 percent of the price of E10. Estimates from the SP-off-RP models are similar to the estimates from the RP-only models but the standard errors are lower because the SP data feature greater variation in 'observed' fuel prices. In particular, the estimated standard errors of the price variable coefficients are about 70 percent smaller in the SP-off-RP models than they are in the RP-only models.

We estimate models where the motorists respond to the absolute difference in fuel prices (the E85 premium) as well as models where the motorists respond to the relative difference in fuel prices (the E85 ratio). We find practically no difference in how well these two models fit the data. Thus we cannot say whether motorists are responding to the E85 ratio or the E85 premium when they make their fuel choices.

We find that vehicle ownership, vehicle type, the presence of an FFV badge on vehicles, gender, age, miles traveled, motorist opinions about which fuel is better for the environment, the engine, the economy, national security, and which fuel yields more miles per gallon do not statistically affect the mean willingness to pay. We did not find differences in willingness to pay between states other than California. We do find an unexplained difference in willingness to pay between the mean motorists in California and those in other states. This is a key result, and it means that, all else equal, the probability

that a motorist chooses E85 is not significantly different in Des Moines than it is in Colorado Springs, Little Rock, or Tulsa, despite the fact that the general opinion of ethanol among flex motorists in our sample is much higher in Des Moines than the other regions. Extrapolating to other regions of the United States, this result indicates that we may be able to apply estimation results from one state to project national demand, though we would need to make adjustments for California.

## References

- Adamowicz, W., J. Louviere, and M. Williams. 1994. Combining revealed and stated preference methods for valuing environmental amenities. *Journal of Environmental Economics and Management*, 26(3), 271-292.
- Aguilar, F., Z. Cai, P. Mohebalian, and W. Thompson. 2015. Exploring the drivers' side of the "blend wall". US consumer preferences for ethanol blend fuels. *Energy Economics*, 49, 217-226.
- Anderson, S. T. and J. M. Sallee. 2011. Using loopholes to reveal the marginal cost of regulation: The case of fuel-economy standards. *The American Economic Review*, 101(4), 1375-1409.
- Anderson, S. 2012. The demand for ethanol as a gasoline substitute. *Journal of Environmental Economics and Management*, 63(2), 151-168.
- Ben-Akiva, M. and T. Morikawa. 1990. Estimation of switching models from revealed preferences and stated intentions. *Transportation Research Part A: General*, 24(6), 485-495.
- Corts, K. 2010. Building out alternative fuel retail infrastructure: Government fleet spillovers in E85. *Journal of Environmental Economics and Management*, 59(3), 219-234.
- Domencich, T. and D. McFadden. 1975. Urban Travel Demand-A Behavioral Analysis (No. Monograph).
- Hensher, D. 2010. Hypothetical bias, choice experiments and willingness to pay. *Transportation Research Part B*, 44: 735-752.
- Hensher, D. and M. Bradley. 1993. Using stated response choice data to enrich revealed preference discrete choice models. *Marketing Letters*, 4(2), 139-151.
- Hensher, D., J. Louviere, and J. Swait. 1999. Combining sources of preference data. *Journal of Econometrics*, 89(1), 197-221.
- Houde, J. 2012. Spatial differentiation and vertical mergers in retail markets for gasoline. *The American Economic Review*, 102(5), 2147-2182.
- Imbens, G.W., 1992. An efficient method of moments estimator for discrete choice models with choice-based sampling. *Econometrica: Journal of the Econometric Society*, 1187-1214.
- Imbens, G.W. and T. Lancaster. 1996. Efficient estimation and stratified sampling. *Journal of Econometrics*, 74(2), 289-318.
- Jensen, K., C. Clark, B. English, R. Menard, D. Skahan, and A. Marra. 2010. Willingness to pay for E85 from corn, switchgrass, and wood residues. *Energy Economics*, 32(6), 1253-1262.
- Knittel, C.R., Meiselman, B.S. and Stock, J.H., 2015. The pass-through of RIN prices to wholesale and retail fuels under the renewable fuel standard (No. w21343). National Bureau of Economic Research.

- Manski, C. and S. Lerman. 1977. The estimation of choice probabilities from choice based samples. *Econometrica: Journal of the Econometric Society*, 1977-1988.
- Manski, C.F. and D. McFadden. 1981. Alternative estimators and sample designs for discrete choice analysis. *Structural analysis of discrete data with econometric applications*, 2-50.
- Petrolia, D., S. Bhattacharjee, D. Hudson, and C. Herndon. 2010. Do Americans want ethanol? A comparative contingent-valuation study of willingness to pay for E-10 and E-85. *Energy Economics*, 32(1), 121-128.
- Pouliot, S. and B. A. Babcock. 2014. The demand for E85: Geographical location and retail capacity constraints. *Energy Economics*, 45, 134-143.
- Pouliot, S., and B. A. Babcock. 2016. Compliance path and impact of ethanol mandates on retail fuel market in the short run. *American Journal of Agricultural Economics*, 98(3), 744-764.
- Rubin, J. 1996. A model of intertemporal emission trading, banking and borrowing. *Journal of Environmental Economics and Management*, 31(3), 269-286.
- Salvo, A. and C. Huse. 2013. Build it, but will they come? Evidence from consumer choice between gasoline and sugarcane ethanol. *Journal of Environmental Economics and Management*, 66(2), 251-179.
- Train, K. and W. Wilson. 2008. Estimation on stated-preference experiments constructed from revealed-preference choices. *Transportation Research Part B: Methodological*, 42(3), 191-203.
- Train, K. and W. Wilson. 2009. Monte Carlo analysis of SP-off-RP data. *Journal of Choice Modelling*, 2(1), 101-117.
- Wolff, H. 2014. Value of time: Speeding behavior and gasoline prices. *Journal of Environmental Economics and Management*, 67(1), 71-88.

## Tables

**Table 1.** Observed E85 and E10 prices and shares of motorists who choose E85 by station, region, and retailer

Urban area and station	Number of observations	Avg. E85 price (\$/gal)	Avg. E10 price (\$/gal)	Avg. E85 premium (E85 - E10)	Avg. E85 ratio (E85/E10)	Share of motorists using E85
Col. Springs 1	11	2.00	2.00	0.00	1.00	9.1%
Col. Springs 2	33	2.00	2.02	-0.02	0.99	30.3%
Col. Springs 3	54	2.00	2.06	-0.06	0.97	13.0%
<b>Total</b>	<b>98</b>	<b>2.00</b>	<b>2.04</b>	<b>-0.04</b>	<b>0.98</b>	<b>18.4%</b>
Des Moines 1	117	2.16	2.72	-0.56	0.79	46.2%
Des Moines 2	50	2.30	2.64	-0.35	0.87	28.0%
Des Moines 3	27	2.32	2.81	-0.49	0.82	51.9%
Des Moines 4	114	2.29	2.69	-0.39	0.85	40.4%
<b>Total</b>	<b>308</b>	<b>2.25</b>	<b>2.70</b>	<b>-0.46</b>	<b>0.83</b>	<b>41.6%</b>
Little Rock 1	26	1.84	2.18	-0.34	0.84	34.6%
Little Rock 2	23	1.83	2.13	-0.30	0.86	34.8%
Little Rock 3	60	1.83	2.18	-0.35	0.84	31.7%
<b>Total</b>	<b>109</b>	<b>1.83</b>	<b>2.17</b>	<b>-0.34</b>	<b>0.84</b>	<b>33.0%</b>
Tulsa 1	58	1.80	2.09	-0.29	0.86	41.4%
Tulsa 2	12	1.80	2.10	-0.30	0.86	66.7%
Tulsa 3	65	1.80	2.04	-0.24	0.88	18.5%
<b>Total</b>	<b>135</b>	<b>1.80</b>	<b>2.07</b>	<b>-0.27</b>	<b>0.87</b>	<b>32.6%</b>
<b>Retailer Y total</b>	<b>650</b>	<b>2.05</b>	<b>2.38</b>	<b>-0.34</b>	<b>0.86</b>	<b>34.8%</b>
Los Angeles 1	85	2.61	3.20	-0.59	0.82	95.3%
Los Angeles 2	52	2.63	3.10	-0.47	0.85	84.6%
<b>Total</b>	<b>137</b>	<b>2.62</b>	<b>3.16</b>	<b>-0.54</b>	<b>0.83</b>	<b>91.2%</b>
Sacramento 1	43	2.57	3.23	-0.66	0.79	81.4%
Sacramento 2	51	2.48	2.92	-0.44	0.85	88.2%
<b>Total</b>	<b>94</b>	<b>2.52</b>	<b>3.06</b>	<b>-0.54</b>	<b>0.82</b>	<b>85.1%</b>
<b>Retailer B total</b>	<b>231</b>	<b>2.58</b>	<b>3.12</b>	<b>-0.54</b>	<b>0.83</b>	<b>88.7%</b>
<b>Sample total</b>	<b>881</b>	<b>2.19</b>	<b>2.58</b>	<b>-0.39</b>	<b>0.85</b>	<b>48.9%</b>

Data are from 17 stations in six urban areas: Colorado Springs, CO; Des Moines, IA; Little Rock, AR; Tulsa, OK; Los Angeles, CA; and Sacramento, CA. We cooperated with Retailer Y in AR, CO, IA, and OK and with Retailer Z in CA. We conducted surveys around IA over the course of two months before spending one week at each other area. Prices are in nominal, non-energy-adjusted terms and are averaged over the observations in the sample for each station/region/retailer. The E85 premium is the E85 price minus the E10 price. The E85 ratio is the E85 price divided by the E10 price.

**Table 2.** Estimated distribution parameters and model fit statistics for the sample with 479 observations

<b>E85 premium models</b>										
	<b>Model 1-A</b>		<b>Model 1-B</b>		<b>Model 1-C</b>		<b>Model 1-D</b>		<b>Model 1-E</b>	
	<b>Mean</b>	<b>SE</b>								
Loc. Ret. Y	-1.885*	1.031	-1.782	1.122	-1.857**	0.904	-1.869**	0.701	-1.701**	0.666
Loc. Ret. Z	-1.121	0.874	-1.016	0.799	-1.213	0.912	-1.235*	0.720	-1.074*	0.609
Scale	0.370*	0.196	0.465	0.308	0.368**	0.158	0.413**	0.094	0.487**	0.131
N	479		479		958		479		479	
Pseudo R <sup>2</sup>	0.312		0.263		0.104		0.114		0.086	
Correct E85	0.276		0.345		0.310		0.103		0.103	
Correct E10	0.998		0.996		0.996		1.000		1.000	
Correct total	0.954		0.956		0.954		0.946		0.946	
<b>E85 ratio models</b>										
	<b>Model 2-A</b>		<b>Model 2-B</b>		<b>Model 2-C</b>		<b>Model 2-D</b>		<b>Model 2-E</b>	
	<b>Mean</b>	<b>SE</b>								
Scale Ret. Y	0.510**	0.169	0.525**	0.191	0.450**	0.172	0.440**	0.118	0.475**	0.116
Scale Ret. Z	0.682**	0.189	0.704**	0.181	0.624**	0.231	0.605**	0.174	0.651**	0.155
Shape	7.844**	3.831	6.222	3.831	6.117**	2.690	5.373**	1.015	4.557**	1.013
N	479		479		958		479		479	
Pseudo R <sup>2</sup>	0.307		0.258		0.101		0.111		0.081	
Correct E85	0.276		0.241		0.241		0.138		0.103	
Correct E10	0.998		0.996		1.000		1.000		1.000	
Correct total	0.954		0.950		0.954		0.948		0.946	

\* Significant at 90 percent; \*\* Significant at 95 percent. The model samples are: A) MLE with the RP data only; B) finite-sample correction on the estimates in A); C) traditional augmentation of RP with SP data; D) SP-off-RP method for data augmentation; and E) finite-sample correction on the estimates in D).

**Table 3.** Estimated distribution parameters and model fit statistics for the sample with 670 observations

<b>E85 premium models</b>										
	<b>Model 3-A</b>		<b>Model 3-B</b>		<b>Model 3-C</b>		<b>Model 3-D</b>		<b>Model 3-E</b>	
	<b>Mean</b>	<b>SE</b>								
Loc. Ret. Y	-1.214*	0.678	-1.198*	0.67	-3.119	2.757	-1.126**	0.502	-1.109**	0.485
Loc. Ret. Z	0.388	0.661	0.377	0.661	2.115	2.560	-0.091	0.463	-0.095	0.453
Scale	0.556**	0.184	0.587**	0.205	1.766*	1.064	0.465**	0.033	0.491**	0.037
N	670		670		1,340		670		670	
Pseudo R <sup>2</sup>	0.323		0.321		0.168		0.200		0.200	
Correct E85	0.586		0.582		0.398		0.514		0.509	
Correct E10	0.922		0.920		0.902		0.927		0.929	
Correct total	0.812		0.809		0.747		0.791		0.791	
<b>E85 ratio models</b>										
	<b>Model 4-A</b>		<b>Model 4-B</b>		<b>Model 4-C</b>		<b>Model 4-D</b>		<b>Model 4-E</b>	
	<b>Mean</b>	<b>SE</b>								
Scale Ret. Y	0.629**	0.152	0.633**	0.152	0.305	0.300	0.583**	0.148	0.588**	0.144
Scale Ret. Z	1.155**	0.274	1.150**	0.272	2.257	1.995	1.026**	0.230	1.024**	0.225
Shape	4.990**	1.588	4.724**	1.588	1.479*	0.815	4.372**	0.399	4.148**	0.399
N	670		670		1,340		670		670	
Pseudo R <sup>2</sup>	0.323		0.322		0.167		0.193		0.192	
Correct E85	0.582		0.582		0.400		0.500		0.500	
Correct E10	0.922		0.922		0.908		0.942		0.942	
Correct total	0.810		0.810		0.752		0.797		0.797	

\* Significant at 90 percent; \*\* Significant at 95 percent. The model samples are: A) MLE with the RP data only; B) finite-sample correction on the estimates in A); C) traditional augmentation of RP with SP data; D) SP-off-RP method for data augmentation; and E) finite-sample correction on the estimates in D).

**Table 4.** Breakdown of mean willingness distribution for the sample with 479 observations (Model 1-D)

	Retailer Y		Retailer Z		Difference		
	Mean	SE	Mean	SE	Mean	SE	T-stat
Intercept	-1.893**	0.620	-1.893**	0.620			
Vehicle ownership	-0.010	0.147	-0.074	0.174	0.064	0.218	0.292
Vehicle type	-0.050	0.121	-0.035	0.133	-0.015	0.077	-0.198
Badge	0.069	0.116	0.052	0.095	0.017	0.076	0.225
Gender	-0.113	0.174	-0.068	0.145	-0.045	0.217	-0.207
Age	-0.291	0.245	-0.295	0.251	0.004	0.134	0.029
Miles traveled per year	-0.286	0.231	-0.283	0.244	-0.004	0.293	-0.012
Eth. Better for environment	-0.336	0.402	-0.302	0.391	-0.034	0.458	-0.075
Eth. Better for engine	0.269	0.287	0.235	0.272	0.033	0.231	0.144
Eth. Better for economy	0.495	0.357	0.464	0.365	0.032	0.340	0.093
Eth. Better for nat. security	0.062	0.149	0.054	0.122	0.008	0.085	0.095
Eth. More fuel efficient	0.168	0.263	0.124	0.234	0.044	0.238	0.185
Total (no retailer fixed effect)	-1.917**	0.610	-2.020**	0.768	0.104	0.876	0.118
Retailer fixed effect	0.175	0.188	0.799**	0.320	-0.624	0.341	-1.830*
Total	-1.742**	0.587	-1.222*	0.716	-0.521	0.903	-0.577

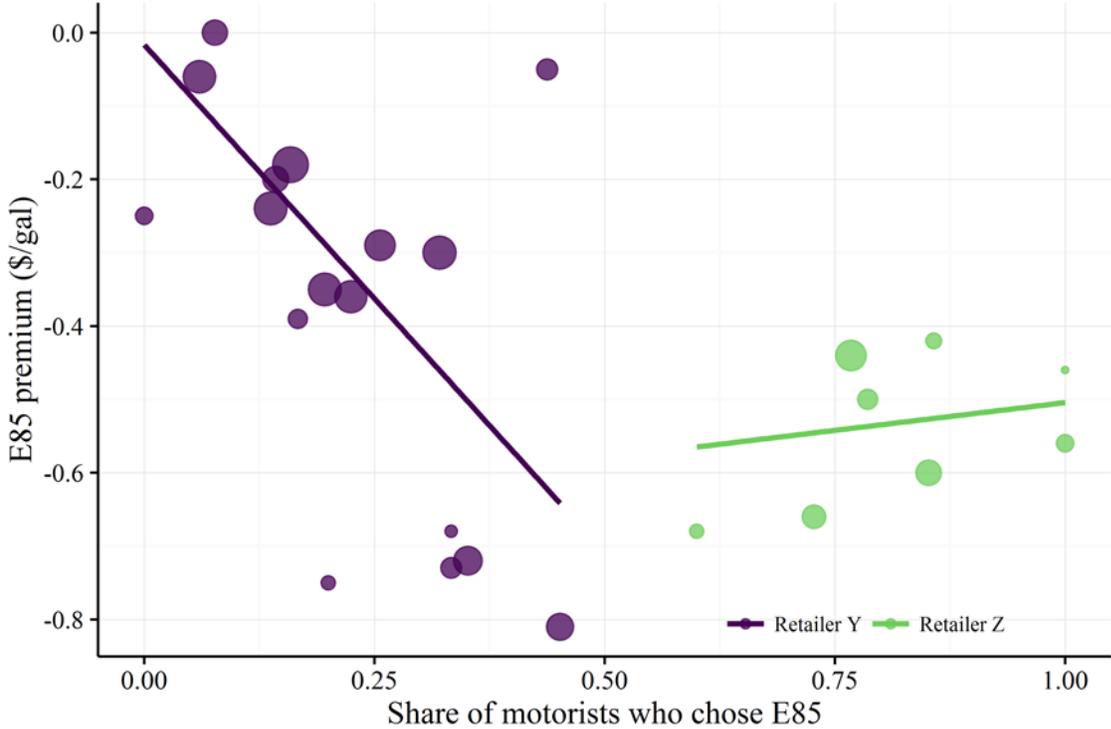
\* Significant at 90 percent; \*\* Significant at 95 percent. The values are in dollars per gallon. Standard errors are calculated using the delta-method.

**Table 5.** Breakdown of mean willingness distribution for the sample with 670 observations (Model 3-D)

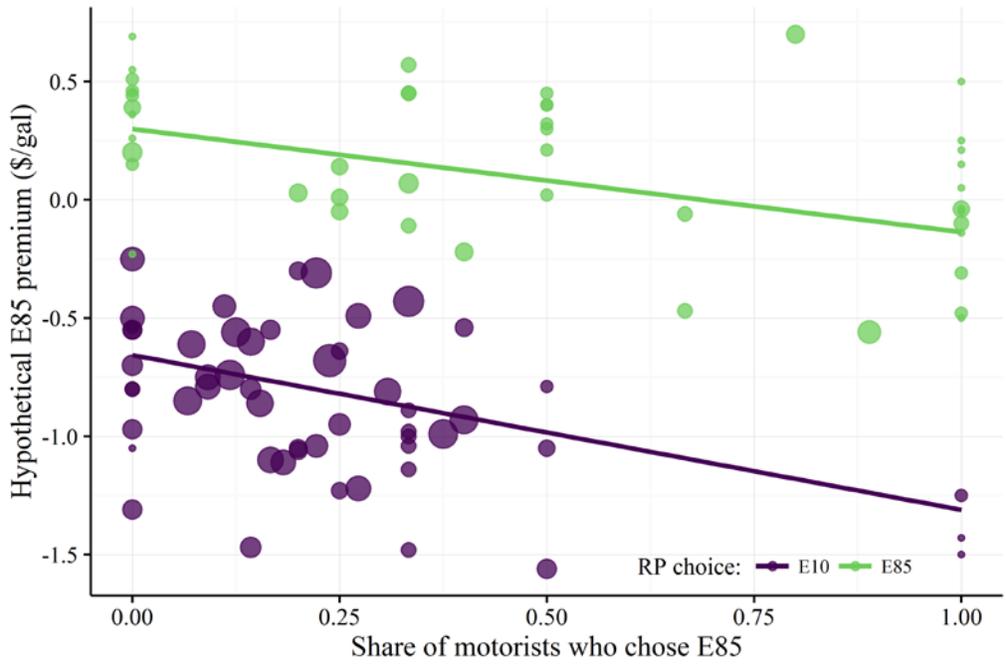
	Retailer Y		Retailer Z		Difference		
	Mean	SE	Mean	SE	Mean	SE	T-stat
Intercept	-1.789**	0.351	-1.789**	0.351			
Vehicle ownership	0.034	0.298	-0.013	0.042	0.046	0.299	0.155
Vehicle type	-0.023	0.124	-0.046	0.126	0.022	0.139	0.162
Badge	0.148	0.121	0.143	0.122	0.005	0.145	0.034
Gender	-0.003	0.037	-0.003	0.035	0.000	0.006	-0.018
Age	0.042	0.151	0.039	0.141	0.003	0.021	0.128
Miles traveled per year	-0.121	0.108	-0.104	0.102	-0.017	0.119	-0.144
Eth. Better for environment	-0.124	0.204	-0.082	0.165	-0.042	0.182	-0.233
Eth. Better for engine	0.035	0.243	0.145	0.228	-0.110	0.295	-0.373
Eth. Better for economy	0.328	0.243	0.350	0.245	-0.022	0.270	-0.081
Eth. Better for nat. security	0.087	0.102	0.066	0.088	0.022	0.079	0.274
Eth. More fuel efficient	0.177	0.159	0.166	0.170	0.011	0.156	0.071
Total (no retailer fixed effect)	-1.212**	0.531	-1.129**	0.465	-0.083	0.694	-0.119
Retailer fixed effect	0.082	0.128	1.065**	0.157	-0.983**	0.187	-5.267
Total	-1.130**	0.513	-0.065	0.465	-1.065	0.697	-1.528

\* Significant at 90 percent; \*\* Significant at 95 percent. The values are in dollars per gallon. Standard errors are calculated using the delta-method.

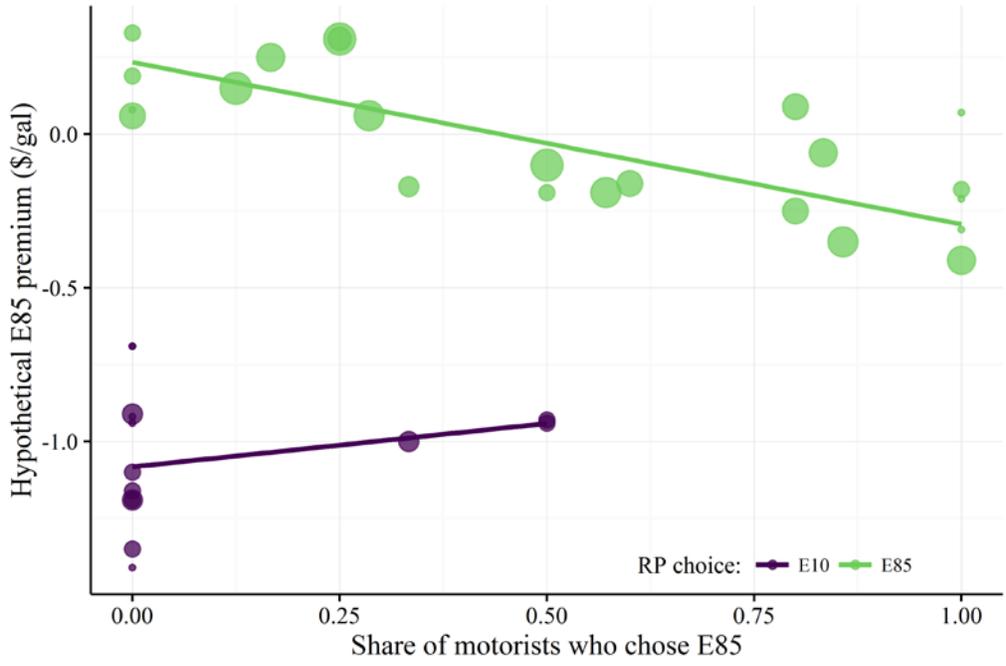
Figures



**Figure 1.** E85 premium and share of motorists who chose E85 in the sample with 670 observations  
Note: The sizes of the dots represent the relative number of observations at each pair of E85 premium and share of motorists. The lines are weighted linear regressions.



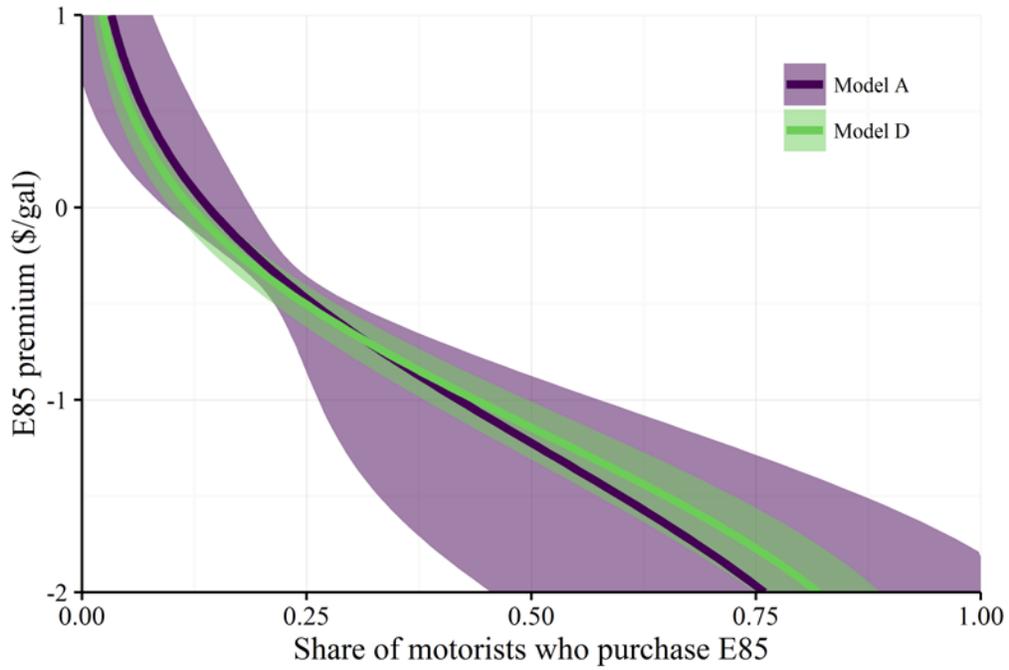
a) Hypothetical E85 premium and share of motorists who chose E85 at Retailer Y in the sample with 670 observations



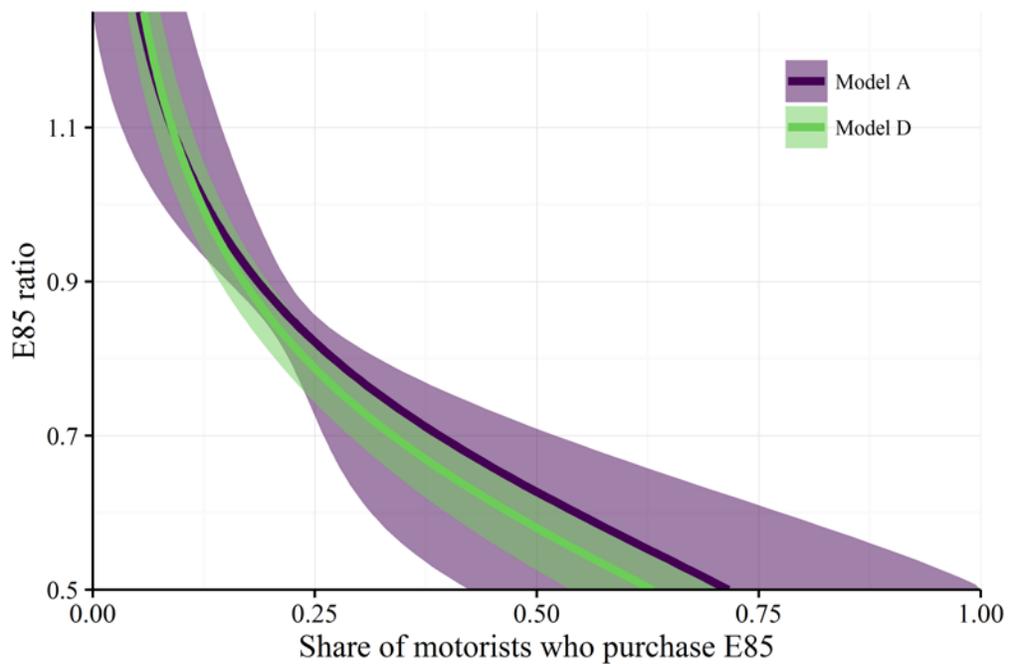
b) Hypothetical E85 premium and share of motorists who chose E85 at Retailer Z in the sample with 670 observations

**Figure 2.** Hypothetical E85 premium and share of motorists who chose E85 in the sample with 670 observations

Note: The sizes of the dots represent the relative number of observations at each pair of E85 premium and share of motorists. The lines are weighted linear regressions.



a) Probability of E85 purchase as a function of E85 premium



b) Probability of E85 purchase as a function of E85 ratio

**Figure 3.** Probability of E85 purchase at Retailer Y estimated with sample of 670 observations

Note: The shaded areas are 95-percent confidence intervals.

## Appendix A: The Intercept Survey

The survey uses 7 different forms, though each observation is collected entirely using one form contained on a single (double-sided) piece of paper. One of the 7 forms is a 1-page, station-level form where the interviewer can record pertinent information about the fueling station.

The next six forms are slightly different versions of the 2-page, motorist-level form. The versions are labeled A1, A2, A3, B1, B2, and B3. The forms only differ in the stated preference question (Question II). In versions with the letter A, the motorist is asked if she would still make the same fuel choice if her choice of fuel was more expensive. In versions with the letter B, the motorist is asked if she would still make the same fuel choice if the other fuel was less expensive. In versions with the number 1, the hypothetical price is \$0.25/gal different from the actual price. In versions with the number 2, the hypothetical price is \$0.50/gal different from the actual price. In versions with the number 3, the hypothetical price is \$0.75/gal different from the actual price. To summarize, the stated preference question asks if the motorist would still make the same choice if:

Version	1	2	3
A	The price of the fuel chosen was \$0.25/gal higher	The price of the fuel chosen was \$0.50/gal higher	The price of the fuel chosen was \$0.75/gal higher
B	The price of the fuel not chosen was \$0.25/gal lower	The price of the fuel not chosen was \$0.50/gal lower	The price of the fuel not chosen was \$0.75/gal lower

**Instructions to the Interviewer:** The motorist-level forms are completed in three stages, and there are three parts to the form that coincide with these stages. The first part of the form can (and should) be completed while you are waiting for a flex-fuel vehicle to pull alongside one of the station's pumps. This part requires recording the fuel prices and performing addition or subtraction so that you are able to generate the appropriate stated-preference question (Question II) quickly and accurately once you observe the motorist's fuel choice.

Fill out part 2 of the form while the motorist is preparing to fuel. Make sure to note the motorist's fuel choice. If the motorist chooses E85, the hypothetical alternative fuel in Question II should be the least expensive gasoline option (i.e., regular grade). Remember to record the volume of fuel purchased and the expenditure once the motorist has finished.

**Survey Form:** Station-level

**Instructions to the Interviewer:** Fill out this form once for each station visit. Answer questions 1-11 upon arriving at the station, and answer question 12 when you conclude the visit.

1. Date and start time of visit: \_\_\_\_\_
2. Interviewer name: \_\_\_\_\_
3. Station name and brand: \_\_\_\_\_
4. Station address: \_\_\_\_\_
5. Initial per gallon E85 price: \_\_\_\_\_
6. Gas option 1 – grade, ethanol %, and price: \_\_\_\_\_
7. Gas option 2 – grade, ethanol %, and price: \_\_\_\_\_
8. Gas option 3 – grade, ethanol %, and price: \_\_\_\_\_
9. Number of gasoline nozzles: \_\_\_\_\_
10. Number of E85 nozzles: \_\_\_\_\_
11. Presence of E85 price signage \_\_\_\_\_
12. Date and end time of visit: \_\_\_\_\_

**Before You Begin:** Each station visit is assigned a 7-digit code for bookkeeping. The code is generated by concatenating today’s date (MMDD) followed by your initials (First, Last) followed by the number of stations you have visited today. For example, if the date is October 15 (1015), your name is Kenneth Liao (KL), and this is the second station you have visited today (2), then the code would be, “1015KL2”.

Write the 7-digit code for this station visit: \_\_\_\_\_

You must write this code on each of the motorist forms you complete during this station visit.

When you are ready to begin, target the next FFV to pull alongside any of the station’s pumps. When you finish one survey, target the next FFV to pull alongside any of the station’s pumps. Do not survey flex motorists who are already at a pump when you arrive, and do not survey flex motorists who pull alongside a pump while you are surveying someone else. There are six versions of the motorist-level form: A1, A2, A3, B1, B2, and B3. Pick one version at random to start, and then proceed to use each version in sequence and repeat.

**Write other notes (if any) about the station visit here:**

Part 1: (Fill out this table while waiting for a flex-fuel vehicle to pull alongside one of the station's pumps.)

		<b>E85 Price</b>	<b>Gas 1 Price</b>	<b>Gas 2 Price</b>
<b>7-digit Station-Visit Code</b>	<b>Actual Prices:</b>	Box 1	Box 2	Box 3
	<b>Hypothetical Prices:</b> (Add \$0.25)	(Box 1 + \$0.25) 4	(Box 2 + \$0.25) 5	(Box 3 + \$0.25) 6

Part 2: (Fill out this table while the motorist is preparing to fuel and/or after the motorist has finished.)

Vehicle Type	Vehicle Make	Vehicle Model	LP State	FFV Badge	Yellow Gas Cap	Motorist Sex	Volume & Expenditure	Fuel Choice
Sedan / Truck SUV / Van				Y / N	Y / N	M / F		E85 / Gas

Part 3: (Fill out this part of the form with assistance from the motorist.)

“Hi, I am doing research for Iowa State University, and I am interested in your opinion on the different fuels. I have a few short questions to ask you while you are fueling, will you help me by answering?”

“Great! Are you 18 or older?” (If ‘No’ then STOP) (Yes) (No)

I. Is this your personal vehicle? (Yes) (No) \_\_\_\_\_

(If company car) Are you: (a) financially responsible for your fuel choice or (b) fully reimbursed regardless?

Only ask these questions if the motorist did **NOT** choose E85:

- a. Is your vehicle a flex-fuel vehicle capable of using E85? (Yes) (No) (Don't know)
- b. (If 'Yes' to Q1) Have you ever fueled this vehicle with E85? (Yes) (No) (Don't know)
- c. Did you know that this station supplies E85 fuel? (Yes) (No)

Only ask these questions if the motorist **DID** choose E85:

- d. Did you choose to fuel at this station because it offers E85? (Yes) (No)
- e. (If 'Yes' to Q4) How far out of your way did you have to drive? (minutes or miles) \_\_\_\_\_

Ask this question to all motorists: (Use the values from Parts 1 and 2 to generate this question.)

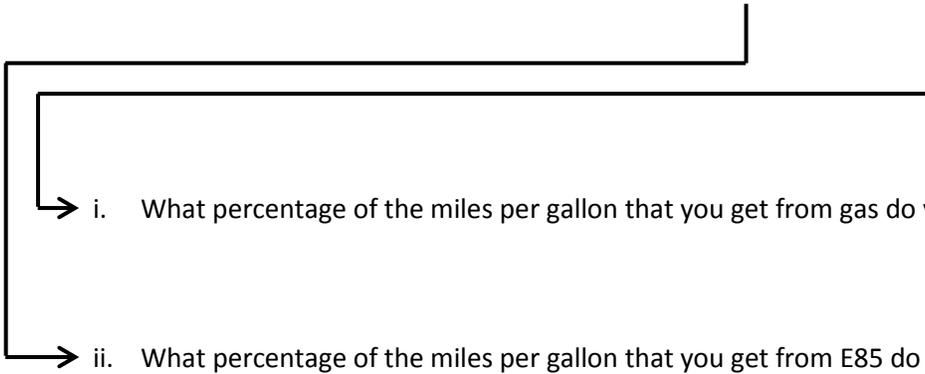
- II. If the price of (fuel chosen) \_\_\_\_\_ had been (\$0.25/gal more expensive) \_\_\_\_\_, would you still have purchased (fuel chosen) \_\_\_\_\_? (Yes) (No)

**Ask these questions to all motorists**

- III. How many times do you fuel per month? \_\_\_\_\_
- IV. (FFVs\*) Out of those, how many times do you use E85? \_\_\_\_\_
- V. On average, how many miles do you drive per year? \_\_\_\_\_
- VI. How old are you? \_\_\_\_\_

“Thanks, we’re almost done. For these last questions, please answer, ‘Ethanol’, ‘Gasoline’, or ‘No Difference’.”

- VII. Which fuel is better for the environment? (Eth) (Gas) (ND) (DK)
- VIII. Which fuel is better for your engine? (Eth) (Gas) (ND) (DK)
- IX. Which fuel is better for the economy? (Eth) (Gas) (ND) (DK)
- X. Which fuel is better for national security? (Eth) (Gas) (ND) (DK)
- XI. Which fuel yields more miles per gallon? (Eth) (Gas) (ND) (DK)

- 
- i. What percentage of the miles per gallon that you get from gas do you get from E85? \_\_\_\_\_% (DK)
- ii. What percentage of the miles per gallon that you get from E85 do you get from gas? \_\_\_\_\_% (DK)

“Thank you for your participation. Have a nice day.”

## **Appendix B: Survey Data and Summary Tables**

As described in Section II, we record other observable characteristics about motorists in addition to their fuel choices before approaching with the intercept survey. The motorists' characteristics recorded are: the vehicle make, model, and type (car, truck, SUV, or van), the state on the license plate, whether the vehicle has an FFV badge, whether the vehicle has a yellow gas cap, and the gender of the motorist. Table B.1 contains summary statistics for these data. We ended up not using the vehicle license plate data in our regressions. Instead we use dummy variables for each of the states where we survey. There was little variation in license plate states within a state so there is near collinearity with the state dummy variables.

For the vehicle make, the largest share of the vehicles in the sample were Chevrolet, at 46 percent. The most common Chevrolet models were the Silverado, Impala, Tahoe, Suburban, HHR, Equinox and Malibu. The next most common vehicle make was Ford with 18 percent of the sample and common models F150, Explorer, Focus, Fusion, and Taurus. Third in our sample was Dodge with 14 percent and common models Grand Caravan, Ram, and Durango. GMC and Chrysler were tied for fourth, making up 7 percent of our sample each, and the final 8 percent of the sample represented all of the other vehicle makes.

As for vehicle type, trucks and SUVs each made up about 30 percent of our sample, cars were 25 percent, and vans were the remainder. We were surprised that our sample contained about twice as many men as women. Our initial expectation was that the population of flex motorists would be about half men and half women. It is possible that the types of vehicles that tend to be FFVs (large American-made cars and trucks) are more often driven by men than women. Lastly about 67 percent of the FFVs in our sample had FFV badges, and about 94 percent had some sort of yellow E85 indicator inside the gas door. The noteworthy exceptions are the flexible-fuel Toyotas (Tundra and Sequoia) and Nissans (Titan and Armada), which have badges on the backs, but no yellow gas caps. Other makes and models were also missing the yellow cap/ring/sticker on rare occasions.

Table B.1 shows that of the 881 flex motorists who completed our survey, 727 (83 percent) responded that they were refueling their personal FFV. Another 80 motorists (9 percent) were refueling company FFVs, 27 (3 percent) were refueling government FFVs, and the remaining 47 motorists (5 percent) were refueling other non-personal vehicles like rentals or FFVs that belonged to friends or family.

**Table B.1:** Summary of characteristics of motorists in the sample

Vehicle make	Chevrolet	45.9%
	Ford	18.2%
	Dodge	14.0%
	GMC	7.2%
	Chrysler	7.2%
	Other	7.7%
Vehicle type	Truck	30.4%
	SUV	29.7%
	Car	25.5%
	Van	14.3%
Motorist gender	Male	66.4%
	Female	33.6%
FFV badge	Yes	67.0%
	No	33.0%
Yellow cap/sticker	Yes	94.4%
	No	5.6%
Vehicle ownership (stated)	Personal	82.5%
	Company	9.1%
	Government	3.1%
	Other	5.3%
Age (stated)	Min	18
	1st Qu.	33
	Median	43
	Mean	44.1
	3rd Qu.	54
	Max	88
Miles per year (stated)	Min	500
	1st Qu.	12,000
	Median	17,000
	Mean	21,780
	3rd Qu.	27,000
	Max	120,000

Summary statistics are for 881 observations of flex motorists refueling at E85 stations in the areas: Little Rock, AR; Los Angeles, CA; Sacramento, CA; Colorado Springs, CO; Ames/Des Moines, IA; and Tulsa, OK. Vehicle type 'Car' includes coupes, convertibles, sedans, hatchbacks, and station wagons.

In the sample, the range of ages span 18 to 88, and the median age is 43. In some cases, motorists declined to give their age. In these cases the interviewer would move on, and write in an estimate after the interview was completed. However, we decided to exclude these observations from the sample along with the other incomplete observations. Similarly, on rare occasions motorists were unable to answer the question about how intensively they used their vehicle. In most cases, motorists

were able to offer an approximation of how many miles they drove per year or per month or per week. Sometimes the motorists would check the odometer and say something like, “Well I’ve driven [odometer reading] miles in [number of years of car ownership] years.” Most of the cases where the motorist was unable to answer was when they were not driving their personal vehicle and were unsure how to respond. Again we excluded these incomplete observations from the sample.

Next, to the motorists who chose E10, we asked questions to measure their knowledge and awareness of E85. The results are in Table B.2. Of the 450 flex motorists in our sample who refueled with E10, 385 (86 percent) indicated that they were aware that their vehicle was in fact a flexible-fuel vehicle capable of using E85. Of the 385 E10 users who were aware of their vehicles’ capabilities, 145 (38 percent) responded that they had refueled with E85 at least once, while the majority had never tried it. This might be explained by E85 having been historically more expensive than E10 in energy-equivalent terms. Finally, 280 of the 385 responded that they were aware that the station sold E85, and of the remaining 105 who answered they did not know, 80 previously responded that they had never used E85. In general, these are motorists who happen to own FFVs, but know almost nothing about E85. They do not know what it is, they have never used it, and they certainly do not think to look for it.

**Table B.2:** Responses to questions to flex motorists who refueled with E10

	Yes	No / Don't know	Total
Is your vehicle an FFV?	385 (86%)	65 (14%)	450
Have you ever fueled with E85?	145 (38%)	240 (62%)	385
Did you know this station sells E85?	280 (73%)	105 (27%)	385

We wanted to see if the 450 E10 motorists were responding to the relative fuel prices. To the motorists who responded that their vehicle was an FFV, we asked the follow-up questions shown. Between the 65 motorists who did not know their vehicle was an FFV and the 105 motorists who did not know the station sold E85, there were 170 motorists in our sample who we assume would not have chosen E85 regardless of the relative prices. Only 145/450 (32 percent) of the flex motorists in our sample who refueled with E10 had ever refueled with E85.

Out of the 450 flex motorists in our sample who chose E10, 65 did not know they were refueling an FFV capable of using E85, and another 105 were not aware that the station sold E85. The implication is that these 170 motorists would not have chosen E85 no matter how low the relative price of E85 would have been. These motorists represent a segment of the population of flex motorists who were

not aware of the station’s or the vehicle’s capabilities, though they were not necessarily unwilling to use E85 in the future.

We asked the flex motorists who chose E85 whether they chose to refuel at the station because of E85, and, if so, how far out of their way they drove. Summary data for these questions are shown in Table B.3. Out of the 431 motorists who chose E85, 402 (93 percent) said that they chose to refuel at the station because it offered E85. And out of those 402 motorists, 191 (48 percent) said that they did not drive out of their way at all. It seems that most motorists drive past a number of fuel stations in their normal routine, and while they may choose to refuel at a particular station due to the station’s unique amenities (e.g., whether it offers E85), most motorists do not consider the station they choose to be ‘out of their way’.<sup>21</sup> We use the responses to how far motorists drove to inform about how the general population of flex motorists differs from our sample population. Specifically, we assume that the remaining 211 observations of flex motorists who chose E85 and drove out of their way for it are oversampled. We construct our estimates of the population shares by removing those 211 observations from our sample.

**Table B.3:** Responses to questions to flex motorists who refueled with E85

Did you choose to fuel at this station because it offers E85?	Yes	402 (93.3%)
	No	29 (6.7%)
	<b>Total</b>	<b>436</b>
How far out of your way did you drive? (miles)	Not at all (zero mi.)	191 (47.5%)
	(0,1] miles	44 (10.9%)
	(1,3] miles	73 (18.2%)
	(3,5] miles	42 (10.4%)
	(5,10] miles	38 (9.5%)
	More than 10 miles	14 (3.5%)
	<b>Total</b>	<b>402</b>

Statistics are for the 431 observations of flex motorists in our sample who chose to refuel with E85. In total, 402/431 (93%) said they came for the E85, but of those 402 motorists, 191 said that they did not drive out of their way at all. We remove the remaining 211 motorists who drove out of their way for E85 from the sample to create a sample that is more representative of the population.

<sup>21</sup> In retrospect, a better way to ask this question may have been something along the lines of, “If every gas station in the area offered E85, would you still have chosen to refuel at this station?”

Responses to the questions we have discussed to this point do not differ significantly by state/region. The measurable differences in the data across regions are in the fuel prices and observed choices, as shown in Table 1, but also in the fuel opinion questions shown in Table B.4 and Table B.5. Table B.4 shows the responses to the fuel opinion questions by region from only the 450 motorists who refueled with E10, and Table B.5 shows the responses from only the 431 motorists who chose E85. In the three questions about which fuel is better for the environment, the engine, and the economy, the differences in opinions across regions are especially apparent. In general, a greater share of flex motorists we surveyed in Iowa and California believe that ethanol is better for the environment, for a vehicle's engine, and for the economy, while the average motorist in Arkansas and Oklahoma has a much less favorable opinion of ethanol in these same areas, and the average motorist in Colorado is somewhere in between.

We separate the responses by fuel choice so we can compare the opinions across regions separately from fuel choices across regions. Table B.4 shows that even among only the motorists who choose E10, motorists have a much higher opinion of ethanol in Iowa than they do elsewhere when it comes to the environment and the economy, and the other factors. In Iowa, 78 percent of E10-using flex motorists responded that ethanol was better for the environment, and 71 percent responded that ethanol was better for the economy. On the other hand, in Oklahoma, 42 percent of E10-using flex motorists responded that ethanol was better for the environment, and 25 percent responded that ethanol was better for the economy. Note that of the 231 observations we collected at Retailer Z's California locations, only 26 chose E10. Also note that we collected fuel opinion data for all of the flex motorists in our sample, even those who did not know they had an FFV or did not know anything about ethanol or E85.

Table B.6 likewise shows that even among only the motorists in our sample who chose E85, average opinions of ethanol are much higher in Iowa and California than in Arkansas, Colorado, and Oklahoma. At the extremes are Iowa and Oklahoma. Among the flex motorists who chose to refuel with E85, 84 percent in Iowa responded that ethanol was better for the environment, compared to 43 percent in Oklahoma. And 87 percent of E85-using Iowa motorists responded that ethanol was better for the economy compared to 55 percent in Oklahoma. We model the opinions as explanatory variables in our empirical model. The opinions are especially informative when we compare the Iowa data with the data from Arkansas and Oklahoma. Retailer Y operated all the stations in these regions and the E85/E10 price ratios were quite similar. By contrast, opinions of ethanol were drastically different.

**Table B.4:** Responses to fuel opinion questions by region from flex motorists who refueled with E10

	Region	Observations	Ethanol	Gasoline	No difference	Don't know
Which fuel is better for the environment?	Little Rock	73	52%	18%	14%	16%
	Los Angeles	12	50%	25%	8%	17%
	Sacramento	14	64%	7%	7%	21%
	Colorado Springs	80	64%	5%	13%	19%
	Ames/Des Moines	180	77%	6%	11%	6%
	Tulsa	91	42%	19%	25%	14%
	<b>Total</b>	<b>450</b>	<b>62%</b>	<b>11%</b>	<b>14%</b>	<b>12%</b>
Which fuel is better for your engine?	Little Rock	73	18%	52%	14%	16%
	Los Angeles	12	0%	42%	25%	33%
	Sacramento	14	14%	43%	7%	36%
	Colorado Springs	80	24%	48%	15%	14%
	Ames/Des Moines	180	25%	42%	18%	14%
	Tulsa	91	13%	69%	9%	9%
	<b>Total</b>	<b>450</b>	<b>20%</b>	<b>50%</b>	<b>15%</b>	<b>15%</b>
Which fuel is better for the economy?	Little Rock	73	33%	45%	4%	18%
	Los Angeles	12	25%	50%	0%	25%
	Sacramento	14	43%	14%	14%	29%
	Colorado Springs	80	44%	30%	11%	15%
	Ames/Des Moines	180	71%	12%	10%	8%
	Tulsa	91	25%	44%	15%	15%
	<b>Total</b>	<b>450</b>	<b>48%</b>	<b>28%</b>	<b>10%</b>	<b>13%</b>
Which fuel is better for national security?	Little Rock	73	32%	29%	12%	27%
	Los Angeles	12	25%	33%	0%	42%
	Sacramento	14	21%	21%	14%	43%
	Colorado Springs	80	34%	31%	24%	11%
	Ames/Des Moines	180	51%	13%	11%	25%
	Tulsa	91	21%	29%	30%	21%
	<b>Total</b>	<b>450</b>	<b>37%</b>	<b>23%</b>	<b>17%</b>	<b>23%</b>
Which fuel yields more miles per gallon?	Little Rock	73	12%	66%	7%	15%
	Los Angeles	12	8%	50%	0%	42%
	Sacramento	14	7%	50%	0%	43%
	Colorado Springs	80	16%	60%	5%	19%
	Ames/Des Moines	180	8%	76%	4%	12%
	Tulsa	91	10%	67%	3%	20%
	<b>Total</b>	<b>450</b>	<b>10%</b>	<b>68%</b>	<b>4%</b>	<b>17%</b>

Summary statistics are for survey data collected from 450 flex motorists who refueled with E10.

**Table B.5:** Responses to fuel opinion questions by region from flex motorists who refueled with E85

	Region	Observations	Ethanol	Gasoline	No difference	Don't know
Which fuel is better for the environment?	Little Rock	36	67%	6%	19%	8%
	Los Angeles	125	82%	0%	6%	13%
	Sacramento	80	85%	0%	9%	6%
	Colorado Springs	18	67%	6%	11%	17%
	Ames/Des Moines	128	84%	1%	11%	5%
	Tulsa	44	43%	9%	30%	18%
	<b>Total</b>	<b>431</b>	<b>77%</b>	<b>2%</b>	<b>12%</b>	<b>10%</b>
Which fuel is better for your engine?	Little Rock	36	44%	28%	17%	11%
	Los Angeles	125	64%	8%	10%	18%
	Sacramento	80	55%	14%	21%	10%
	Colorado Springs	18	39%	33%	6%	22%
	Ames/Des Moines	128	41%	31%	17%	10%
	Tulsa	44	32%	34%	16%	18%
	<b>Total</b>	<b>431</b>	<b>50%</b>	<b>21%</b>	<b>15%</b>	<b>14%</b>
Which fuel is better for the economy?	Little Rock	36	56%	19%	17%	8%
	Los Angeles	125	78%	8%	6%	8%
	Sacramento	80	66%	18%	10%	6%
	Colorado Springs	18	44%	33%	17%	6%
	Ames/Des Moines	128	88%	4%	4%	5%
	Tulsa	44	55%	20%	16%	9%
	<b>Total</b>	<b>431</b>	<b>73%</b>	<b>12%</b>	<b>9%</b>	<b>7%</b>
Which fuel is better for national security?	Little Rock	36	44%	28%	11%	17%
	Los Angeles	125	45%	10%	6%	39%
	Sacramento	80	44%	6%	15%	35%
	Colorado Springs	18	28%	11%	28%	33%
	Ames/Des Moines	128	70%	7%	5%	17%
	Tulsa	44	30%	23%	20%	27%
	<b>Total</b>	<b>431</b>	<b>50%</b>	<b>11%</b>	<b>10%</b>	<b>29%</b>
Which fuel yields more miles per gallon?	Little Rock	36	28%	56%	8%	8%
	Los Angeles	125	30%	40%	14%	16%
	Sacramento	80	15%	55%	18%	13%
	Colorado Springs	18	17%	61%	6%	17%
	Ames/Des Moines	128	20%	66%	5%	10%
	Tulsa	44	23%	52%	5%	20%
	<b>Total</b>	<b>431</b>	<b>23%</b>	<b>54%</b>	<b>10%</b>	<b>13%</b>

Summary statistics are for survey data collected from 431 flex motorists who refueled with E85.

For some of the flex motorists we surveyed, the question about national security elicited more confusion rather than an actual response. In 2006, national security and independence from foreign oil were touted as reasons to support the biofuels mandates, but the cause seems to have lost importance with flex motorists in 2015. As with the other questions, motorists in Iowa and California favor ethanol more than the motorists in the other urban areas, but there were also many more cases where the motorists answered, “No difference” or, “Don’t know”.

The last question of the survey asked which fuel yields more miles per gallon. In Iowa, about 67 percent of the flex motorists correctly answered E10 yielded more miles per gallon than E85. About 19 percent said that E85 yielded more miles per gallon than E10, 5 percent said there was no difference, and 10 percent answered that they did not know. In other regions, the percentage of motorists who correctly identify that E10 yielded more miles per gallon was even lower. In Colorado Springs, 61 percent answered correctly, and in Little Rock, Sacramento, and Tulsa, 56 percent, 55 percent, and 52 percent of motorists respectively correctly answered. Finally, in Los Angeles, just 40 percent of the flex motorists we surveyed responded that E10 yields more miles per gallon, 30 percent said E85 was better, 14 percent said there was no difference, and 16 percent answered that they did not know. Ignorance about the energy difference of the two fuels likely explains why some motorists drive miles out of their way or wait in line to refuel with E85. We also asked the motorists a follow up question to approximate the percentage the relative energy difference between the two fuels. Some motorists responded with an accurate answer saying that E85 gets about 75-80 percent of the miles per gallon of E10. Some approximated higher energy for E85 in the 90 percent range and some approximated the energy ratio to be as low as 50 percent. Responses were not always in the form of a simple percentage of energy content, but rather some motorists knew the miles per gallon of each, “I get 14 mpg with E85 and 18 mpg with E10,” and others knew how long a tank of each of the two fuels lasted.

Interestingly, many of the flex motorists who chose E85 demonstrated that they understood that E85 was more expensive on an energy-equivalent basis. Some chose E85 for reasons other than the price, while others simply did not bother to calculate the energy-equivalent fuel costs every time they filled up. Many flex motorists said something along the lines of, “I did the math once and figured that I need a \$0.60 per gallon discount on E85 for it to be worth it,” and now they make their fuel choice based on some rule-of-thumb or routine.

## Appendix C: Complete Estimation Results

**Table C.1.** Marginal effects for E85 premium models: Model 1-A through Model 1-E

	Model 1-A		Model 1-B		Model 1-C		Model 1-D		Model 1-E	
	Marg. Eff.	SE								
PREM	-0.117	0.063	-0.146	0.096	-0.121	0.054	-0.113	0.034	-0.151	0.055
GOV	0.108	0.058	0.152	0.088	0.111	0.059	0.108	0.069	0.158	0.106
COMP	-0.056	0.039	-0.062	0.060	-0.039	0.034	-0.039	0.029	-0.041	0.046
ONPV	0.039	0.034	0.056	0.052	0.020	0.041	0.007	0.041	0.026	0.064
VTTYPE_TRUCK	-0.008	0.028	-0.012	0.044	-0.012	0.028	-0.003	0.021	-0.007	0.033
VTTYPE_SUV	-0.007	0.027	-0.012	0.043	-0.016	0.028	-0.010	0.022	-0.015	0.035
VTTYPE_VAN	0.020	0.029	0.025	0.045	0.012	0.040	0.003	0.031	0.003	0.049
BADGE	-0.029	0.020	-0.039	0.031	-0.009	0.025	0.006	0.020	0.005	0.032
FEMALE	0.008	0.022	0.011	0.035	-0.021	0.031	-0.034	0.024	-0.042	0.039
AGE	-0.001	0.001	-0.001	0.001	-0.001	0.001	0.000	0.001	0.000	0.001
TMPY	-0.001	0.001	-0.001	0.001	-0.002	0.001	-0.001	0.001	-0.002	0.001
ENV_ETH	-0.019	0.040	-0.035	0.063	-0.020	0.044	-0.013	0.034	-0.031	0.053
ENV_GAS	-0.081	0.059	-0.094	0.091	-0.140	0.091	-0.102	0.056	-0.108	0.085
ENV_ND	-0.100	0.058	-0.127	0.089	-0.120	0.063	-0.086	0.043	-0.115	0.066
ENG_ETH	0.078	0.038	0.089	0.058	0.063	0.040	0.055	0.035	0.062	0.054
ENG_GAS	0.047	0.039	0.049	0.060	0.036	0.042	0.025	0.032	0.020	0.051
ENG_ND	-0.019	0.057	-0.013	0.089	-0.001	0.047	0.014	0.034	0.010	0.054
ECON_ETH	0.086	0.053	0.089	0.081	0.103	0.059	0.092	0.045	0.096	0.069
ECON_GAS	0.024	0.056	0.014	0.087	0.049	0.059	0.056	0.045	0.052	0.071
ECON_ND	0.132	0.058	0.150	0.087	0.130	0.064	0.098	0.051	0.106	0.078
NS_ETH	0.013	0.025	0.013	0.040	0.025	0.029	0.017	0.025	0.019	0.040
NS_GAS	0.042	0.031	0.048	0.047	0.048	0.035	0.036	0.030	0.045	0.047
NS_ND	-0.050	0.041	-0.061	0.065	-0.002	0.039	0.019	0.027	0.023	0.042
MPG_ETH	0.008	0.038	0.010	0.060	-0.004	0.044	-0.029	0.041	-0.032	0.064
MPG_GAS	0.036	0.033	0.039	0.052	0.036	0.036	0.014	0.027	0.013	0.043
MPG_ND	0.067	0.053	0.093	0.084	0.101	0.041	0.077	0.033	0.105	0.051
STNST_AR	0.031	0.036	0.041	0.056	0.035	0.029	0.019	0.026	0.028	0.041
STNST_CO	0.048	0.046	0.067	0.072	0.041	0.041	0.030	0.030	0.050	0.049
STNST_OK	0.066	0.036	0.087	0.056	0.060	0.033	0.048	0.024	0.067	0.038
STNST_CA	0.125	0.028	0.155	0.041	0.116	0.030	0.105	0.030	0.136	0.044

Sample size is 479 observations using the strictest sample-selection rule. All dummies equal zero is: personal vehicle, car type, no FFV badge, male, and “don’t know” to all opinion questions.

**Table C.2.** Marginal effects for E85 ratio models: Model 2-A through Model 2-E

	Model 2-A		Model 2-B		Model 2-C		Model 2-D		Model 2-E	
	Marg. Eff.	SE								
LOG_RATIO	-0.342	0.170	-0.424	0.257	-0.264	0.105	-0.247	0.059	-0.341	0.099
GOV	0.111	0.058	0.156	0.088	0.125	0.053	0.096	0.072	0.153	0.114
COMP	-0.061	0.039	-0.067	0.060	-0.039	0.032	-0.034	0.027	-0.037	0.043
ONPV	0.038	0.033	0.055	0.052	0.011	0.038	0.001	0.038	0.018	0.062
VTTYPE_TRUCK	-0.009	0.028	-0.014	0.044	-0.020	0.023	-0.019	0.020	-0.028	0.032
VTTYPE_SUV	-0.007	0.028	-0.011	0.043	-0.018	0.024	-0.017	0.020	-0.025	0.033
VTTYPE_VAN	0.019	0.029	0.024	0.045	-0.006	0.033	-0.011	0.029	-0.015	0.047
BADGE	-0.030	0.020	-0.039	0.031	-0.007	0.023	0.011	0.019	0.010	0.031
FEMALE	0.009	0.022	0.013	0.035	-0.028	0.026	-0.035	0.022	-0.045	0.036
AGE	-0.034	0.030	-0.043	0.046	-0.042	0.029	-0.026	0.025	-0.035	0.040
TMPY	-0.019	0.017	-0.022	0.027	-0.026	0.012	-0.011	0.011	-0.015	0.018
ENV_ETH	-0.017	0.040	-0.032	0.062	0.023	0.049	0.012	0.033	-0.002	0.055
ENV_GAS	-0.082	0.059	-0.095	0.090	-0.071	0.069	-0.079	0.054	-0.069	0.085
ENV_ND	-0.098	0.058	-0.124	0.088	-0.056	0.057	-0.054	0.040	-0.077	0.065
ENG_ETH	0.080	0.038	0.091	0.059	0.085	0.049	0.068	0.039	0.080	0.062
ENG_GAS	0.049	0.039	0.050	0.061	0.058	0.050	0.043	0.035	0.043	0.057
ENG_ND	-0.016	0.057	-0.010	0.089	0.040	0.048	0.036	0.036	0.040	0.059
ECON_ETH	0.084	0.053	0.086	0.080	0.073	0.052	0.048	0.033	0.048	0.052
ECON_GAS	0.025	0.056	0.015	0.086	0.027	0.053	0.012	0.035	0.002	0.057
ECON_ND	0.132	0.057	0.150	0.086	0.089	0.058	0.051	0.039	0.057	0.062
NS_ETH	0.014	0.026	0.013	0.040	0.018	0.026	0.007	0.023	0.005	0.037
NS_GAS	0.040	0.031	0.046	0.047	0.037	0.032	0.023	0.028	0.030	0.044
NS_ND	-0.053	0.042	-0.064	0.065	-0.003	0.036	0.001	0.027	0.001	0.043
MPG_ETH	0.009	0.039	0.010	0.061	-0.008	0.038	-0.003	0.039	-0.003	0.063
MPG_GAS	0.036	0.033	0.039	0.052	0.025	0.031	0.021	0.027	0.020	0.044
MPG_ND	0.059	0.052	0.080	0.082	0.078	0.038	0.077	0.033	0.107	0.052
STNST_AR	0.025	0.034	0.033	0.054	0.013	0.029	0.001	0.028	0.006	0.045
STNST_CO	0.055	0.048	0.074	0.074	0.021	0.033	0.025	0.025	0.041	0.042
STNST_OK	0.062	0.035	0.081	0.053	0.040	0.029	0.029	0.024	0.044	0.039
STNST_CA	0.134	0.029	0.166	0.042	0.116	0.031	0.101	0.027	0.136	0.041

Sample size is 479 observations using the strictest sample-selection rule. All dummies equal zero is: personal vehicle, car type, no FFV badge, male, and “don’t know” to all opinion questions.

**Table C.3.** Marginal effects for E85 premium models: Model 3-A through Model 1-E

	Model 3-A		Model 3-B		Model 3-C		Model 3-D		Model 3-E	
	Marg. Eff.	SE								
PREM	-0.246	0.080	-0.246	0.084	-0.078	0.047	-0.294	0.021	-0.296	0.022
GOV	0.388	0.078	0.374	0.083	0.489	0.082	0.463	0.095	0.443	0.101
COMP	-0.028	0.051	-0.027	0.054	0.011	0.047	-0.010	0.049	-0.008	0.052
ONPV	-0.020	0.067	-0.014	0.071	-0.062	0.067	-0.043	0.069	-0.035	0.073
VTTYPE_TRUCK	0.040	0.038	0.038	0.040	0.025	0.035	0.018	0.033	0.016	0.035
VTTYPE_SUV	-0.054	0.040	-0.053	0.042	-0.067	0.036	-0.039	0.034	-0.040	0.036
VTTYPE_VAN	-0.038	0.048	-0.037	0.050	-0.055	0.049	-0.057	0.048	-0.056	0.051
BADGE	0.033	0.031	0.033	0.033	0.073	0.030	0.073	0.029	0.072	0.030
FEMALE	0.039	0.033	0.039	0.035	0.036	0.031	0.006	0.032	0.006	0.034
AGE	0.001	0.001	0.001	0.001	0.000	0.001	0.000	0.001	0.000	0.001
TMPY	-0.001	0.001	-0.001	0.001	-0.002	0.001	-0.001	0.001	-0.001	0.001
ENV_ETH	-0.026	0.053	-0.027	0.057	-0.016	0.049	-0.010	0.046	-0.011	0.048
ENV_GAS	-0.142	0.085	-0.135	0.090	-0.150	0.083	-0.156	0.081	-0.145	0.085
ENV_ND	-0.038	0.064	-0.037	0.068	-0.015	0.057	-0.044	0.058	-0.043	0.061
ENG_ETH	0.132	0.046	0.131	0.048	0.162	0.045	0.115	0.044	0.115	0.046
ENG_GAS	-0.042	0.048	-0.043	0.050	-0.010	0.049	-0.025	0.044	-0.026	0.046
ENG_ND	0.039	0.052	0.039	0.055	0.074	0.049	0.046	0.046	0.045	0.049
ECON_ETH	0.163	0.055	0.160	0.058	0.174	0.055	0.150	0.051	0.147	0.054
ECON_GAS	0.020	0.065	0.019	0.069	0.056	0.062	0.041	0.057	0.039	0.061
ECON_ND	0.144	0.070	0.143	0.074	0.109	0.068	0.070	0.062	0.069	0.065
NS_ETH	0.034	0.037	0.032	0.039	0.054	0.035	0.040	0.035	0.038	0.037
NS_GAS	0.047	0.051	0.046	0.054	0.036	0.052	0.026	0.047	0.025	0.050
NS_ND	-0.029	0.053	-0.029	0.056	0.023	0.048	0.034	0.041	0.034	0.044
MPG_ETH	0.039	0.055	0.039	0.058	0.031	0.052	0.009	0.054	0.009	0.057
MPG_GAS	0.096	0.044	0.094	0.047	0.094	0.044	0.064	0.043	0.062	0.046
MPG_ND	0.158	0.069	0.158	0.073	0.160	0.060	0.113	0.053	0.113	0.056
STNST_AR	0.029	0.047	0.030	0.050	0.005	0.045	0.028	0.046	0.030	0.049
STNST_CO	0.019	0.064	0.024	0.068	-0.061	0.051	0.033	0.048	0.038	0.050
STNST_OK	0.107	0.048	0.107	0.051	0.061	0.042	0.095	0.039	0.096	0.042
STNST_CA	0.400	0.035	0.394	0.037	0.399	0.032	0.319	0.029	0.315	0.031

**Table C.4:** Marginal effects for E85 ratio Models 4

	Model 4-A		Model 4-B		Model 4-C		Model 4-D		Model 4-E	
	Marg. Eff.	SE								
Log(ratio)	-0.681	0.212	-0.681	0.224	-0.394	0.195	-0.602	0.059	-0.604	0.062
GOV	0.387	0.078	0.372	0.083	-0.210	0.114	0.469	0.106	0.448	0.113
COMP	-0.033	0.050	-0.032	0.053	0.450	0.082	-0.020	0.049	-0.019	0.051
ONPV	-0.022	0.067	-0.015	0.071	-0.024	0.050	-0.061	0.072	-0.052	0.076
VTTYPE_TRUCK	0.040	0.038	0.039	0.040	-0.048	0.065	0.015	0.034	0.014	0.036
VTTYPE_SUV	-0.052	0.040	-0.052	0.042	0.013	0.036	-0.048	0.034	-0.048	0.036
VTTYPE_VAN	-0.036	0.048	-0.036	0.051	-0.076	0.036	-0.050	0.048	-0.050	0.051
BADGE	0.034	0.031	0.034	0.032	-0.066	0.049	0.064	0.029	0.064	0.030
FEMALE	0.039	0.034	0.039	0.035	0.055	0.030	0.013	0.033	0.013	0.035
AGE	0.049	0.043	0.049	0.046	0.029	0.031	0.008	0.042	0.008	0.045
TMPY	-0.025	0.023	-0.025	0.024	0.004	0.042	-0.014	0.020	-0.013	0.021
ENV_ETH	-0.023	0.053	-0.024	0.056	-0.022	0.020	-0.015	0.045	-0.016	0.048
ENV_GAS	-0.141	0.085	-0.133	0.090	-0.036	0.046	-0.172	0.084	-0.158	0.089
ENV_ND	-0.038	0.064	-0.037	0.067	-0.216	0.095	-0.035	0.057	-0.035	0.060
ENG_ETH	0.129	0.046	0.128	0.048	-0.040	0.055	0.109	0.043	0.108	0.046
ENG_GAS	-0.045	0.048	-0.046	0.050	0.134	0.044	-0.045	0.043	-0.046	0.046
ENG_ND	0.038	0.052	0.037	0.055	-0.038	0.048	0.032	0.046	0.032	0.048
ECON_ETH	0.162	0.055	0.159	0.058	0.054	0.049	0.150	0.050	0.148	0.053
ECON_GAS	0.022	0.065	0.020	0.069	0.174	0.053	0.043	0.057	0.042	0.060
ECON_ND	0.145	0.070	0.143	0.074	0.055	0.060	0.083	0.061	0.082	0.065
NS_ETH	0.035	0.037	0.034	0.039	0.122	0.067	0.036	0.034	0.035	0.036
NS_GAS	0.046	0.051	0.045	0.054	0.033	0.035	0.027	0.048	0.026	0.051
NS_ND	-0.028	0.053	-0.028	0.056	0.006	0.052	0.024	0.042	0.024	0.045
MPG_ETH	0.037	0.055	0.037	0.058	-0.017	0.049	-0.004	0.054	-0.003	0.057
MPG_GAS	0.095	0.044	0.093	0.047	0.019	0.052	0.058	0.042	0.056	0.045
MPG_ND	0.157	0.069	0.156	0.073	0.071	0.043	0.113	0.052	0.114	0.055
STNST_AR	0.010	0.046	0.011	0.049	0.110	0.060	-0.020	0.048	-0.019	0.051
STNST_CO	0.026	0.065	0.031	0.069	-0.016	0.047	-0.015	0.050	-0.009	0.053
STNST_OK	0.091	0.046	0.091	0.049	-0.063	0.051	0.049	0.041	0.050	0.043
STNST_CA	0.414	0.034	0.408	0.036	0.059	0.042	0.324	0.030	0.320	0.032