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The demand for ethanol as a gasoline substitute

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ABSTRACT

This paper estimates household preferences for ethanol (E85) as a gasoline (E10) substitute. I develop a theoretical model linking the shape of the ethanol demand curve to the underlying distribution among households of willingness to pay for ethanol. I estimate the model using instrumental variables techniques and data from many retail fueling stations. I find that a \$0.10-per-gallon increase in ethanol's price relative to gasoline leads to a 12–16% decrease in the quantity of ethanol demanded. My findings imply that preferences for ethanol are heterogeneous and that a substantial fraction of households are willing to pay a premium for the fuel. This reduces substantially the simulated efficiency cost of an ethanol content standard, since some households choose ethanol without large subsidies, mitigating deadweight losses.

1. Introduction

Policies to reduce oil consumption increasingly promote ethanol and other biofuels through subsidies, mandates, and funding for research. Proponents argue that substituting toward biofuels will enhance energy security, reduce carbon dioxide emissions, improve air and water quality, and benefit farmers. Many recent policies mandate, either explicitly or implicitly, a minimum market share for ethanol. A prime example is the U.S. Renewable Fuels Standard (RFS), which will increase ethanol use to about 16% of fuel consumption in the coming years. Despite this attention from policymakers, relatively little is known about household preferences for biofuels or the effect that ethanol mandates will have on gasoline markets. This information is critical for designing, implementing, and evaluating policies to promote ethanol and other biofuels.

I address this research need by estimating demand for ethanol (E85) as a gasoline (E10) substitute. I find that a \$0.10-per-gallon increase in the price of ethanol relative to gasoline leads to a 12–16% decline in the quantity of ethanol demanded. These are the first available estimates in the literature for the price responsiveness of household ethanol demand, which is a key parameter for studies that analyze a retail ethanol subsidy or mandate. Price responses are substantially smaller than they would be if fuel-switching behavior were concentrated around a single price, however, and ethanol typically sells for a premium in my sample. These findings imply that a substantial fraction of households are willing to pay a premium and that preferences for ethanol among these households are actually quite diffuse.

These results have economically significant implications for policy. Previous analyses assume that households are identical, treating ethanol and gasoline as perfect substitutes after adjusting for ethanol's lower mileage [1].

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This assumption can yield misleading results if some households are willing to pay a premium for ethanol, perhaps because they value the fuel's perceived environmental and social benefits. In simulations, I find that accounting for households that prefer ethanol can substantially reduce the welfare cost of a minimum market-share requirement, since households with strong preferences choose ethanol without large price subsidies, mitigating deadweight losses.

I begin my analysis by developing a model of household utility in which inputs of ethanol and gasoline combine linearly to produce household transportation services; ethanol and gasoline are also allowed to affect utility directly. The key parameter in this model is the household's willingness to pay a premium for ethanol, or the household's ethanol preference. When this parameter varies continuously among households, aggregate demand for ethanol is a smooth function of ethanol's price premium. Thus, the model formalizes the precise, theoretical link between the distribution of preferences for ethanol and the shape of the aggregate demand curve, allowing me to recover micro-preferences from aggregate data.

I estimate the model using a unique dataset that contains nearly 5000 monthly observations for ethanol prices and sales volumes at over 200 individual retail fueling stations in Minnesota during 1997–2006. These data provide a rare opportunity to document household preferences for biofuels in the United States. I use these data to estimate demand for ethanol as a function of relative fuel prices.

I use the distribution of preferences implied by my econometric estimates to simulate the effects of minimum market-share requirement for ethanol. I find that a requirement consistent with the federal RFS would cost roughly $1.8 billion annually in lost surplus. At the level of the standard, marginal abatement costs are about $71 per metric ton of carbon dioxide emissions avoided or about $0.59 per gallon of oil saved. When I ignore ethanol preferences, as in previous studies, marginal costs increase by nearly two-thirds. Nevertheless, marginal abatement costs still exceed most estimates for the external damages associated with carbon emissions and petroleum dependence, although these inferences are sensitive to assumptions about ethanol and gasoline supply costs.

While an immense literature estimates demand for gasoline, the vast majority of studies focus on the response of overall fuel demand to changes in fuel price levels. Because households have relatively few transportation alternatives, fuel demand in the short run is price inelastic.[1] This paper in contrast focuses on fuel-switching behavior and how demand for ethanol as a gasoline substitute responds to changes in relative fuel prices. Because households that purchase ethanol in my sample are able to substitute easily between ethanol and gasoline, demand for ethanol is highly responsive to prices: my estimates imply an own-price elasticity of negative 3.2–3.8 and a gasoline-price elasticity of 2.3–3.2.

My findings are consistent with Salvo and Huse [11], which estimates demand for sugarcane ethanol, regular gasoline, and midgrade gasoline using a multinomial probit model and micro-data on individual fueling choices in Brazil.[2] Like me, they find that fuel-switching behavior extends over a wide range of prices, with some consumers willing to pay a large premium for ethanol (and others demanding a discount). They find own-price elasticities of 2–3 in magnitude. My findings also contribute to a broader literature on fuel choice, including Greene [16], which estimates demand for regular and premium gasoline in both leaded and unleaded varieties using a multinomial logit model and micro-data on individual fueling choices, as well as Phillips and Schutte [17], which estimates demand for full-service and self-serve gasoline using aggregate cross-sectional data from several dozen U.S. cities. These studies find own-price and cross-price elasticities that exceed 10 in absolute value. I improve on this vein of the fuel demand literature by formalizing fuel-switching behavior in terms of the underlying distribution of household preferences for alternative fuels and by using panel data and instrumental variables (IV) techniques to identify demand more credibly.

2. Industry background

Ethanol is an alcohol fuel that in the United States derives primarily from corn. Gasoline blenders mix ethanol with gasoline to comply with federal air quality regulations, to produce mid-grade and premium fuels, and to satisfy the federal RFS. Virtually all gasoline vehicles can burn fuel blends that contain 10% ethanol or less. Blenders added about 5 billion gallons of ethanol to gasoline in 2006, or about 3.5% of gasoline consumption by volume; blending has since increased to 12 billion gallons or 9.4% of consumption by volume in 2010 (my calculations based on U.S. Energy Information Administration data). Ethanol is heavily subsidized, with direct federal and state payments to ethanol producers, a federal tax subsidy of $0.45 per gallon for blenders, and a tariff of $0.54 per gallon that applies to all but a nominal quantity of imports.

The market for ethanol as a direct gasoline substitute is comparatively small but growing rapidly. Stimulated by rising gasoline prices and supported by federal, state, and local subsidies for alternative-fuel vehicles and infrastructure, the number of fueling stations offering E85—an alternative retail fuel blend containing 85% ethanol and 15% gasoline by volume—more than doubled during 2006–2009 to over 1900 stations nationwide. I estimate demand for this

[1] For recent surveys and meta-analyses, see Goodwin et al. [2], Graham and Glaister [3], Greening et al. [4], Espey [5,6], Goodwin [7], and Dahl and Sterner [8]. These papers report short-run price elasticities of about 0 to −0.5 with a central tendency of about −0.25. Recent studies indicate that the price response has since declined to less than 0.1 in magnitude [9,10].

[2] The remaining empirical literature is sparse. Rask [12] estimates demand for ethanol as a 10% blending component in gasoline; he does not estimate household demand. Alves and Bueno [13] estimate aggregate demand for gasoline in Brazil, where ethanol has a large market share [14]; they do not estimate price responses for ethanol. Salvo and Huse [15] find that the correlation between ethanol and gasoline prices in Brazil increased in the mid 2000s after the introduction of flexible-fuel vehicles; they do not estimate demand.

ethanol-blended fuel in my empirical application below. Only flexible-fuel vehicles are certified to run on fuel blends containing more than 10% ethanol. These vehicles have larger fuel injectors and fuel-system components that are more resistant to corrosion, allowing the vehicles to burn both E85 and gasoline (or any mixture thereof).[3]

Pure gasoline contains 1.41 times more energy per gallon than E85, implying lower mileage for drivers that choose E85, and actual differences in mileage align closely with this difference in energy content.[4] Gasoline blended with 10% ethanol (commonly known as E10) contains 1.36 times more energy per gallon than E85. Thus, in my empirical application based on data from Minnesota, which mandates that all conventional gasoline be E10, I divide E85 quantities by 1.36, and I multiply E85 prices by 1.36, to express these values in "gasoline-equivalent" (or technically, E10-equivalent) energy-adjusted units.

The federal RFS sets a minimum quantity of renewable fuel each year, increasing gradually to 36 billion gallons in 2022, which is about 25% of current gasoline consumption by volume. Thus, compliance with the RFS will require that many households own flexible-fuel vehicles and choose E85 or other fuel blends containing high concentrations of ethanol. The RFS limits corn ethanol's role to 15 billion gallons annually; the remaining 21 billion gallons in 2022 must come from advanced biofuels that more effectively curtail greenhouse gas emissions. One attractive option is cellulosic ethanol produced from corn stover and other agricultural wastes, or from dedicated bioenergy feedstocks, such as switchgrass and miscanthus. Below I simulate the effects of a minimum market-share requirement for E85 that is modeled on the federal RFS for 2022.

The RFS is likely to reduce net oil consumption and greenhouse gas emissions. It has been estimated that replacing one gallon of gasoline with pure, corn-based ethanol or cellulosic ethanol would reduce net petroleum consumption by roughly 0.95 gallons, after accounting for upstream petroleum inputs and ethanol's lower energy content [19]. Corn-based ethanol's net energy and climate benefits are less impressive. Because its production relies heavily on fossil-fuel energy, corn ethanol only reduces net carbon dioxide emissions by about 15%. Because cellulosic ethanol production uses less fossil-fuel energy, its environmental performance is much better, reducing net carbon dioxide emissions by about 90% [19].

3. Theoretical model

To motivate the empirical analysis below, I develop a discrete-choice model of household demand for a renewable fuel (ethanol) as a fossil fuel (gasoline) substitute. Households use inputs of ethanol and gasoline to generate utility from miles but may also derive utility (or disutility) directly from either fuel. The model implies that households will choose ethanol only when their willingness to pay for ethanol as a gasoline substitute exceeds ethanol's price premium. Given a distribution over willingness to pay, discrete fuel choice at the household level then leads naturally to an expression for ethanol's aggregate market share and total sales quantity as a function of price. Thus, the model formalizes the precise theoretical link between the distribution of household preferences and the shape of the aggregate demand function, which facilitates estimation using aggregate data. Below I describe the model and briefly preview my estimation approach.

3.1. Individual behavior

Among households that own flexible-fuel vehicles, I assume that utility is given by

$$v((q_e+q_g)mpg)+\theta_e q_e+\theta_g q_g+x, \tag{1}$$

where q_e and q_g are fuel quantities supplied by ethanol and gasoline (in gasoline-equivalent gallons); mpg is the fuel economy of the vehicle (in miles per gallon); $m \equiv (q_e+q_g)mpg$ is the number of miles the household drives; $v(m)$ is utility from driving, which is increasing and concave in miles; θ_e and θ_g are the direct utility benefits (or disutility costs, if negative) associated with ethanol and gasoline consumption; and x is the consumption of all other goods measured in dollars. This utility function, which is linearly separable in miles and the direct utility benefits of fuel consumption, leads to a discrete choice of fuel type at the household level, facilitating an explicit aggregation of households, as I show below.

Ethanol and gasoline are perfect substitutes in producing miles. Thus, when a household only cares about miles, it will choose the fuel with the lowest price. In general, however, households may also derive utility (or disutility) directly from fuel consumption itself, as reflected by the parameters θ_e and θ_g. These parameters capture the fact that many households claim to internalize ethanol's perceived environmental and social benefits [20,21]. For example, if a household feels guilty about its greenhouse gas emissions and perceives ethanol to be a relatively clean fuel, then $\theta_g<\theta_e<0$. Alternatively, if a household cares nothing about the environment but feels guilty when contributing to oil dependence while gaining satisfaction from supporting domestic farmers, then $\theta_e>0>\theta_g$. More generally, these parameters capture other direct utility costs and benefits as well, such as time costs associated with more frequent refueling or diminished driving range

[3] The federal Alternative Motor Fuels Act of 1988 created strong incentives under the Corporate Average Fuel Economy (CAFE) standards program for automakers with binding CAFE constraints to produce flexible-fuel vehicles [18]. Automakers produced about 5 million of these vehicles between 2000 and 2006, and production continues apace.

[4] Using Environmental Protection Agency (EPA) estimates, I calculated the ratio of gasoline to E85 mileage for each flexible-fuel vehicle model offered between 2000 and 2006. I then calculated the sales-weighted mean and standard deviation of this ratio, using nationwide sales data from the U.S. Department of Transportation. The ratio varies only slightly across models, with a mean of 1.36 and standard deviation of 0.05.

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due to ethanol's lower mileage. I refer to the difference in these direct utility effects, given by $\theta_e - \theta_g$, as a household's ethanol preference or willingness to pay for ethanol as a gasoline substitute.

The household's budget constraint is given by

$$p_e q_e + p_g q_g + x \le y, \tag{2}$$

where p_e and p_g are the prices of ethanol and gasoline (in gasoline-equivalent units), y is household income, and I have normalized the price of the composite good to $1.

Given these assumptions, the household will choose ethanol exclusively when the per-mile net utility cost of ethanol is less than the per-mile net utility cost of gasoline:

$$\frac{p_e - \theta_e}{mpg} \le \frac{p_g - \theta_g}{mpg}. \tag{3}$$

This decision rule simplifies to choosing ethanol when

$$p_e - p_g \le \theta_e - \theta_g, \tag{4}$$

where the left-hand side is the market price premium for ethanol and the right-hand side is the consumer's willingness to pay for ethanol as a gasoline substitute. Thus, the household chooses ethanol if the household's per-gallon willingness to pay for ethanol as a gasoline substitute exceeds ethanol's price premium.

While relative fuel prices determine the type of fuel that a household chooses, miles driven and derived demand for fuel depend on absolute price levels. Conditional on choosing ethanol, the household's optimal choice of miles is given by

$$m^* = v'^{-1}\left(\frac{p_e - \theta_e}{mpg}\right), \tag{5}$$

while demand for miles among households that choose gasoline is given by an analogous expression. The household's derived demand for fuel is then m^*/mpg.

3.2. Aggregate behavior

To move formally from individual to aggregate demand, first assume that there are N households in a given market that each own a single flexible-fuel vehicle. Next, assume that an individual household's demand for miles is perfectly inelastic in the short run. This assumption, which facilitates a convenient expression for aggregate demand, is approximately consistent with recent empirical evidence indicating that price elasticities for miles and fuel are less than 0.1 in magnitude during my study period [9,10]. I later relax this assumption in my estimation. Next, define a household's demand for fuel as $q \equiv m/mpg$, the household's willingness to pay for ethanol as $\theta \equiv \theta_e - \theta_g$ (which could be negative), and the price premium for ethanol as $p \equiv p_e - p_g$ (which also could be negative if ethanol sells at a discount). Finally, assume that fuel demand q and willingness to pay for ethanol θ are jointly distributed among households according to the probability density function (pdf) given by $f(q,\theta)$.

Given these assumptions, ethanol demand is simply the total number of flexible-fuel owners multiplied by average fuel consumption among those that choose ethanol:

$$Q_e = N \int_p^{\infty} \left[\int q f(q,\theta)\, dq \right] d\theta = N \int_p^{\infty} \mathbb{E}[q|\theta] f(\theta)\, d\theta, \tag{6}$$

where $\mathbb{E}[q|\theta]$ is mean fuel demand conditional on willingness to pay θ and I have used the fact that the joint density is the product of the conditional and marginal densities: $f(q,\theta) \equiv f(q|\theta) \cdot f(\theta)$.

This expression for aggregate demand can be simplified further to facilitate estimation using aggregate data. Dividing and multiplying by unconditional mean fuel demand $\mathbb{E}[q]$ inside and outside of the integral yields

$$Q_e = N \cdot \mathbb{E}[q] \cdot \int_p^{\infty} \frac{\mathbb{E}[q|\theta]}{\mathbb{E}[q]} f(\theta)\, d\theta = N \cdot \mathbb{E}[q] \cdot \int_p^{\infty} h(\theta)\, d\theta, \tag{7}$$

where $h(\theta) \equiv \mathbb{E}[q|\theta]/\mathbb{E}[q] \cdot f(\theta)$. Note by inspection that $h(\theta) \ge 0$ and that $h(\theta)$ integrates to one, which implies that $h(\theta)$ itself is a proper pdf. Thus, we can interpret $h(\theta)$ simply as the marginal pdf of willingness to pay for ethanol among households, where households are weighted according to their fuel consumption. Equivalently, we can interpret $h(\theta)$ as the pdf of willingness to pay for ethanol among all "gallons of fuel" to be consumed in aggregate.

Thus, ethanol's market share is given by

$$S_e = \int_p^{\infty} h(\theta)\, d\theta = 1 - H(p), \tag{8}$$

Table 1
Summary statistics.

Variable	Mean	Std. dev.	Min.	Max.
Retail E85 sales volume (gallons)	2463.41	2922.85	5.07	27752.02
Retail E85 price	2.37	0.47	1.00	4.03
Retail E10 price	1.98	0.43	1.10	3.00
Retail E85 price premium	0.39	0.18	−0.38	1.50
Wholesale E85 cost	1.76	0.73	0.67	3.94
Wholesale E10 cost	1.39	0.45	0.44	2.33
Wholesale E85 cost premium	0.37	0.40	−0.52	1.74
Retail E85 station age (months)	29.08	24.27	1.00	110.00
Number flexible-fuel vehicles in county	3252.61	4804.87	0.00	24453.00
Number E85 stations in county	3.72	2.75	1.00	13.00
Number fueling stations in county	96.69	110.68	4.00	357.00
Distance to Benson refinery (miles)	112.47	43.89	4.63	242.18

Note: Table is based on estimation sample of 4825 monthly reports from 232 fueling stations in Minnesota between October 1997 and November 2006. Prices are in 2006 dollars. All fuel prices and quantities are in E10-equivalent units. See text for details.

where $H(\theta)$ is the cumulative distribution function (cdf) of willingness to pay θ among households weighted by their fuel consumption, and aggregate ethanol demand is given by

$$Q_e = N \cdot \mathbb{E}[q] \cdot \int_p^\infty h(\theta)\, d\theta = N \cdot \mathbb{E}[q] \cdot [1-H(p)]. \tag{9}$$

Analogous expressions can be derived for gasoline demand and market share using similar arguments.

These derivations simply show that there is a direct mapping from the cdf of willingness to pay for ethanol as a gasoline substitute among households (weighted by their fuel consumption) to the shape of the aggregate demand curve for ethanol. Aggregate demand is proportional to ethanol's market share, which is equivalent to one minus the cdf of willingness to pay. Thus, where demand is steeply sloped, the cdf is steeply sloped as well (i.e., the pdf is high), indicating a high local concentration of households with similar willingness to pay; where demand is gradually sloped, the cdf is gradually sloped also (i.e., the pdf is low), indicating fewer households with willingness to pay in that region.

Note that logged aggregate ethanol demand is then given by

$$\ln(Q_e) = \ln(N) + \ln\, \mathbb{E}[q] + \ln(1-H(p)), \tag{10}$$

which suggests that a researcher armed with market-level data could regress ethanol's logged sales quantity (or logged market share) on the ethanol premium to recover the distribution of willingness to pay for ethanol from the shape of the ethanol demand curve. This is precisely my strategy below, where I estimate demand for ethanol (E85) as a gasoline (E10) substitute using data on prices and quantities from Minnesota. Thus, the model allows me to extract information about micro-preferences from aggregate data.

Finally, the presence of the fuel demand term $\ln\, \mathbb{E}[q]$ merits further discussion. Under the assumption that household energy demand is perfectly inelastic in the short run (which is approximately consistent with recent empirical studies) this term is captured by market-level fixed effects and other controls. Percent changes in the quantity of ethanol demanded then coincide one-for-one with percent changes in ethanol's market share. In practice, overall fuel demand might decrease slightly as fuel prices rise. Thus, I relax the assumption of perfectly inelastic fuel demand as a robustness check in my econometric estimation.

4. Data and summary statistics

I estimate Eq. (10) above using monthly data for ethanol (E85) prices and sales volumes at a large number of fueling stations in Minnesota, gasoline (E10) prices in those same areas, and several ancillary variables. Table 1 presents summary statistics.

4.1. Data sources

These data come from several sources. My data for E85 prices and sales volumes come from a Minnesota Department of Commerce and American Lung Association of Minnesota monthly survey of retail E85 stations in Minnesota. Stations that received state funding to help defray E85 infrastructure costs are required to respond, while other stations may participate on a voluntary basis. The earliest stations began reporting in October 1997, and the data include records through November 2006.[5]

[5] I omit a handful of state-operated stations from my analysis, because they are only open to government fleets. While government fleets are able to purchase E85 from privately operated stations, private flexible-fuel vehicles outnumber government flexible-fuel vehicles 100–1 in the Midwest [22].

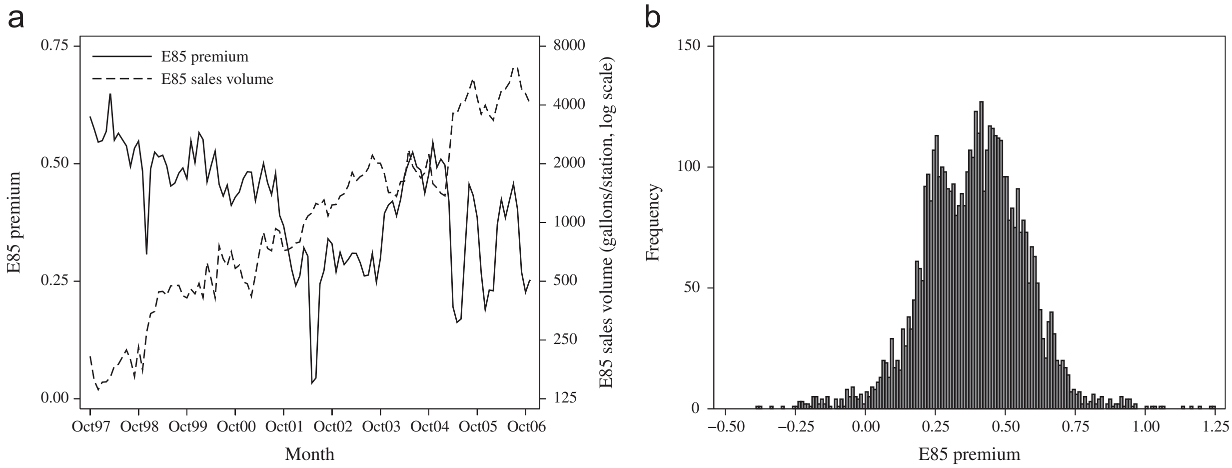

Fig. 1. Relative retail prices and E85 sales volumes. Note: The E85 sales volume in (a) is the monthly average volume of E85 sales among reporting E85 stations in Minnesota; the E85 premium is the volume-weighted sample-mean price of E85 minus the volume-weighted sample-mean price of E10. (b) is the empirical distribution of the E85 price premium (i.e., E85 price minus E10 price) in the estimation sample. All prices and quantities are in E10-equivalent units.

Stations report volume-weighted prices derived from monthly sales volumes and revenues. Retail prices include all federal, state, and local fuel taxes. The data also record, for every station that sold E85 in Minnesota, the date the station first started (and in some cases stopped) selling the fuel, as well as the county in which each station is located. I use this information to calculate the total number of E85 stations in each county in each month and the length of time that each station has been selling E85, both of which I include as control variables. I match these retail E85 data to county-average prices for regular unleaded gasoline (always E10 in Minnesota) from Oil Price Information Service (OPIS). I divide E85 quantities by 1.36 and multiply E85 prices by 1.36 to convert these values to E10-equivalent units. I convert all prices to real 2006 prices using the monthly consumer price index from the U.S. Department of Labor.

My data report geographic coordinates for many E85 stations. Using these coordinates, I attempted to assign brand affiliations to the stations in my sample.[6] I am able to identify 86% of stations, which account for 95% of the observations in my sample. I use the brand affiliations (if any) of these stations to construct price instruments, as discussed below.

Fig. 1(a) plots relative retail prices over time. The average E85 price premium (i.e., E85 price minus E10 price) varies considerably during the sample period without any obvious long-run trend. Average E85 sales increase steadily over time, however, which is consistent with a growing stock of flexible-fuel vehicles. Fig. 1(b) shows that the E85 premium ranges from \$0 to \$0.75 per gallon over time and across stations in my sample; thus, my estimates will reflect price responses only within this region of the demand function.

To generate measures of underlying costs, I obtain wholesale ethanol price data from a trade publication called *Ethanol and Biodiesel News* (previously known as *Renewable Fuels News* and *Oxy-Fuel News* before that). These data measure weekly rack prices for ethanol at fuel terminals in Minneapolis and Fargo.[7] I obtain wholesale finished gasoline (E10) price data from the U.S. Energy Information Administration (EIA). These data measure the volume-weighted monthly average rack price in Minnesota. I calculate wholesale E85 costs as a weighted average of these two wholesale price series.[8] Costs for E10 simply equal the wholesale gasoline (E10) price. I use these wholesale cost variables to construct my price instruments.

In addition to these price variables, I obtain data on flexible-fuel vehicle registrations from the Minnesota Department of Public Safety Division of Driver and Vehicle Services. These data record vehicle identification numbers (VINs), original sales dates, and owner zip codes for all vehicles registered in Minnesota as of the summer of 2007. I identify 154,000 flexible-fuel vehicles in the database by cross-referencing VINs with lists of flexible-fuel vehicle models and VIN identifiers from the National Ethanol Vehicle Coalition and from a private firm that collects data on the auto industry. These vehicles represent about 3.3% of the 4.6 million light-duty vehicles registered in Minnesota in 2007. I then use original sales dates

[6] After locating the coordinates in Google Maps, I searched for the nearest fueling station and recorded its name. I attempted to corroborate this information using a MN Department of Commerce list of E85 stations operating in Minnesota as of late 2006, a similar list from the National Ethanol Vehicle Coalition, and the U.S. Department of Energy's database of alternative-fuel stations.

[7] I assign to each county (and thereby each station) the wholesale price from whichever city is nearest; about four-fifths of stations are nearest to Minneapolis. I calculate the monthly average and then subtract the federal ethanol blending subsidy, which fell from \$0.54 per gallon to \$0.51 per gallon during my study period.

[8] I first calculate 0.83 times the ethanol price plus 0.17 times the wholesale gasoline (E10) price. Since finished gasoline in Minnesota already contains 10% ethanol by volume, these weights yield the cost of an 85% ethanol blend by volume. I then multiply by 1.36 to convert to E10-equivalent costs.

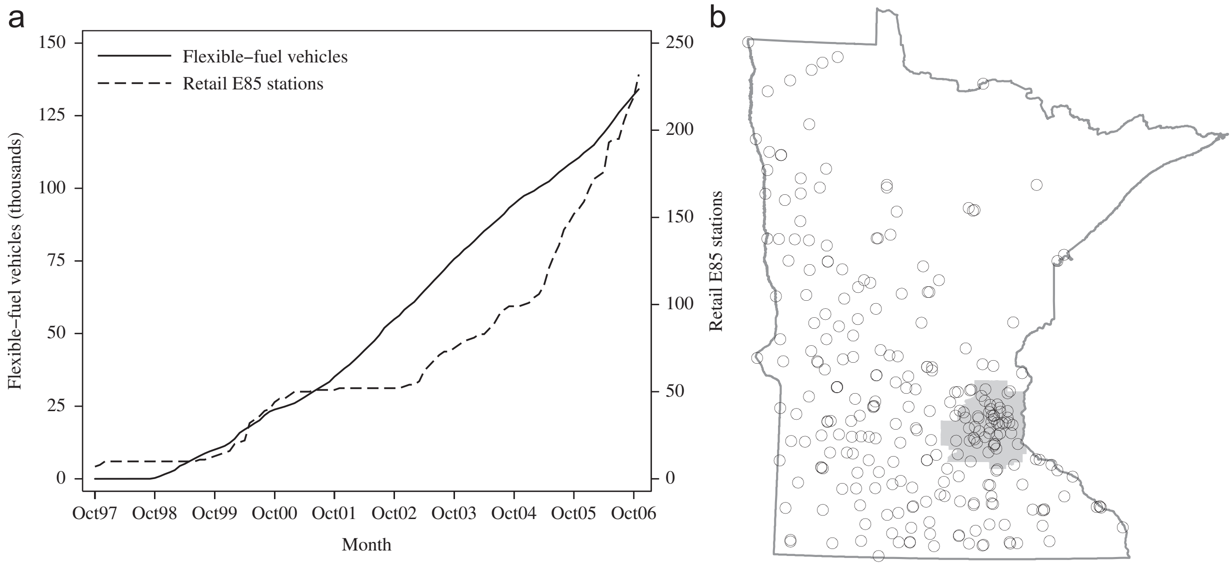

Fig. 2. Flexible-fuel vehicles and retail E85 stations. Note: (a) shows the growth in the number of retail E85 stations and the stock of flexible-fuel vehicles in Minnesota. (b) shows the locations of Minnesota's 264 retail E85 stations as of August 2006. Minnesota measures 400 miles from north to south and about 250 miles along its southern border. The shaded region is the seven-county metropolitan area of Minneapolis and St. Paul.

to reconstruct a monthly time series for the stock of flexible-fuel vehicles in each county, which I include as a control variable.[9]

Fig. 2(a) charts the growth in the number of retail E85 stations and flexible-fuel vehicles. The flexible-fuel stock grows at a roughly constant rate during the sample period, which is consistent with CAFE standards that generated strong incentives for some manufacturers to produce a limited number of flexible-fuel vehicles each year [18]. Growth in the number of E85 stations is also strong over time, though less consistent.

As noted above, I calculate the total number of E85 stations in each county in each month, and I include this variable as a control. Fig. 2(b) maps the locations for all 264 such stations in Minnesota as of August 2006 based on a separate list of station addresses from the Minnesota Department of Commerce. I also calculate the total number of fueling stations (selling gasoline only or both fuels) in each county based on a snapshot of station addresses in 2006 from the Minnesota Department of Commerce Weights and Measures Division. Table 1 shows that there are more than 25 fueling stations total for every E85 station on average in my sample. While competition in fuel markets is typically fierce, most E85 retailers operate as local monopolists in the much narrower E85 market. I use both measures of competition to construct my price instruments.

My analysis covers the time period from October 1997 through November 2006. During this time the number of privately operated E85 stations in Minnesota grew from less than 10 to nearly 250. Based on reported open and close dates, there were about 7500 potential monthly observations at these stations. Approximately 64% of these observations are covered by the Minnesota survey. The remaining 36% are missing, reflecting stations that rarely or never participate in the survey, as well as stations that fail to report in just some months. This results in an estimation sample of 4825 observations at 232 stations, implying an average panel size of about 21 months.

My data are subject to several potential layers of selection. First, my data come from fueling stations in Minnesota, which may not be representative. Second, retailers of E85 might locate in areas where preferences are strongest. Third, most flexible-fuel vehicles are large, American-made cars and trucks. Finally, drivers that choose to own a flexible-fuel vehicle may have stronger preferences than average. For these reasons, sales volumes in my data will tend to overstate average preferences.[10] To the extent that selection is driven by differences in average preferences across markets, however, my estimated price responses will be unaffected, given my inclusion of station fixed effects.

[9] I am unable to determine whether some vehicles are flexible-fuel vehicles due to missing or invalid VINs, and a small percentage of flexible-fuel vehicles are excluded due to missing sales dates or zip codes outside of Minnesota. I am also unable to account for attrition or movements of vehicles in and out of Minnesota and across county lines prior to 2007. Owner addresses also might differ from where vehicles are driven. For these various reasons I measure flexible-fuel stocks with error.

[10] In addition, not all stations participate in the survey, not all participating stations report every month, and stations appear and disappear as they open and close. I tested specifically for biases related to an unbalanced panel and non-random reporting, finding no evidence for either [23,24].

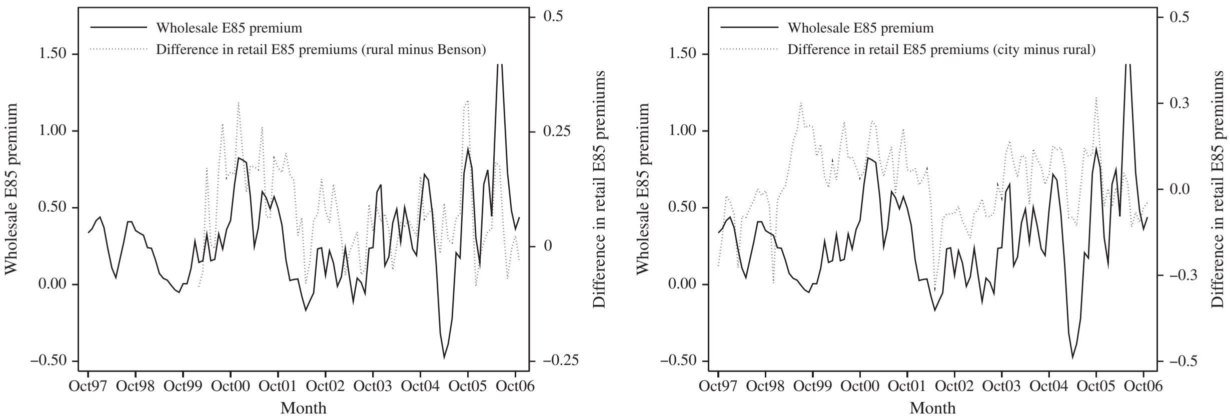

Fig. 3. Relative wholesale prices and relative retail fuel prices. Note: (a) shows the retail E85 premium in rural counties far from Benson (more than 50 miles away) minus the retail E85 premium in rural counties near to Benson (within 50 miles). (b) shows the retail E85 premium for Twin Cities counties minus the retail E85 premium in rural counties. Both figures also plot the wholesale E85 cost premium. All prices are in E10-equivalent units.

4.2. *Retail pricing behavior*

I spoke with industry representatives and inspected retail pricing behavior closely to identify price variation that is arguably exogenous to demand.[11] Retailers generally set prices using rule-of-thumb strategies, which vary over time and across retailers. Most retailers price E85 at a fixed nominal discount below gasoline in volumetric terms, which typically amounts to a premium in energy-adjusted terms; the discounts and patterns I see in the data are consistent with anecdotal reports. Retailers update premiums mainly to adjust for broad shifts in relative fuel costs; they do not deliberately adjust premiums in response to local, short-term shifts in demand, limiting the potential for price endogeneity.

The sizes of these premiums depend on underlying fuel costs as determined in the broader wholesale fuels market. Average premiums generally increase when wholesale costs for E85 rise relative to gasoline, and premiums shrink when costs fall. The economic causality is markedly one sided: events specific to the tiny E85 market have zero bearing on prices for crude oil, gasoline, or even ethanol, whose primary role is as a gasoline additive.

The key to my identification strategy is that these changes in market spot prices affect individual retailers in my sample differently. One reason is that retailers have different relationships with their suppliers. As of 2006, about one third of E85 retailers in Minnesota bought finished fuel from an ethanol refinery in Benson, which is a small town in the southwestern part of the state. Throughout the entire sample period, this refinery supplied E85 to retailers at a fixed discount (in volumetric terms) below the wholesale spot price of gasoline. The retailers, in turn, agreed to pass this same discount along to consumers at their stations. As a result, premiums for E85 are mechanically less sensitive to relative fuel costs at these stations. This pricing behavior is apparent in Fig. 3(a). When wholesale E85 costs increase relative to E10, stations located in counties far from Benson (which are less likely to have contracts with the refinery) tend to raise their retail E85 prices more than stations located near Benson.

A second reason that costs affect individual retailers differently is variation in local competition. Retailers facing greater competition from other E85 retailers will tend to price at marginal cost, whereas retailers in less competitive areas can price according to willingness to pay (i.e., the price of gasoline). This pattern is evident in Fig. 3(b). When wholesale E85 costs decline relative to E10, stations located in the Twin Cities metropolitan area (where competition is strong) tend to cut their retail E85 prices more than stations located in rural areas (where competition is weak). In the next section, I exploit this variation in pricing behavior across stations to identify demand, generating a series of price instruments by interacting wholesale fuel costs with distance to the Benson refinery, measures of competition, and station brand dummies.

5. Econometric estimation and results

5.1. *Econometric model*

I estimate logged aggregate demand for E85 (as an E10 substitute) of the following form:

$$\ln quantity_{it} = \alpha \ln p_{e_{it}} + \beta(p_{e_{it}} - p_{g_{it}}) + \gamma' \boldsymbol{X}_{it} + \delta_i + \varepsilon_t + \omega_i \cdot t + u_{it}, \tag{11}$$

[11] I spoke with representatives from the largest retail chains in Minnesota, as well as several independently owned and operated stations, representatives from two ethanol refineries that directly supply about one-third of E85 stations, several industry analysts, and the administrators of the Minnesota survey.

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where $quantity_{it}$ is the volume of E85 sold at fueling station i in month t (in E10-equivalent units); $p_{e_{it}}$ is the retail price of E85 and $p_{g_{it}}$ is the retail price of E10 (both in E10-equivalent units); $\boldsymbol{X}_{it}$ is a vector of time-varying county and station characteristics; δ_i is a fueling station effect that is constant across all time periods; ε_t is a month effect that is constant across all fueling stations; $\omega_i \cdot t$ is a station-specific time trend; u_{it} is an unobserved station-month demand shifter; and the remaining elements are coefficients and vectors of coefficients to be estimated.

Note that regression (11) is the empirical analog of logged aggregate demand in theoretical equation (10) above. The main parameter of interest in this model is β, which is the slope of the demand curve with respect to the E85 premium. When β is large in magnitude, demand is sensitive to prices, implying that many households have similar willingness to pay; when β is small, willingness to pay varies more substantially across households. Given my inclusion of time and station controls, the slope is identified based on within-market variation in willingness to pay for E85 due to differences in age, education, patriotism, concern about the environment, support for domestic farmers, or other factors; between-market variation in average willingness to pay is captured by the time and station controls.

The log-linear relationship between E85 quantity and the E85 premium in this equation is consistent with an exponential distribution for willingness to pay.[12] If we take this distributional assumption literally and assume it holds globally, then the standard deviation in willingness to pay is identified directly by the slope and is given by $\sigma = -1/\beta$. Mean willingness to pay is then given by $\mu + \sigma$, where the parameter μ is a preference shifter that may vary across markets. My inclusion of station-level fixed effects and time controls allows the preference shifter μ (and therefore mean preferences) to vary flexibly and independently of the standard deviation across markets. Thus, I am able to estimate the variance in willingness to pay separately from the mean(s) (see the Appendix posted to JEEM's online repository of supplementary material, which makes these points formally, http://www2.econ.iastate.edu/jeem/supplement.htm).

In practice, I do not assume that the log-linear functional form and the exponential distribution it implies hold globally. Rather, my only assumption is that the exponential distribution is a good approximation locally amongst households whose willingness to pay falls within the range of E85 price premiums observed historically. This is a reasonable assumption in my data. Because E85 prices almost always exceed E10 prices in my sample, only those households with high willingness to pay will have chosen to participate in the E85 market. Thus, only the right-most tail of the preference distribution is empirically relevant. As it happens, the exponential distribution is shaped very much like the truncated right tail of a more conventional, bell-shaped distribution, such as a normal or logistic.

Besides having a sensible shape, this local approximation is also quite flexible. The slope parameter captures the steepness of the right tail, while my inclusion of station fixed effects allows the tail to shift either left or right to reflect differences in average preferences across markets. In short, my price data trace out the right tail of the preference distribution, and the exponential distribution is shaped like a right tail. Moreover, given the flexibility of my model, this local approximation will be quite good, with both the steepness and position of the right tail separately identified. That the exponential distribution may fit poorly outside the right tail has no bearing on the validity of my econometric estimates, since there is no price variation outside of this range.

While my empirical model has several advantages, it is limited in its ability to make out-of-sample predictions. Given the relatively narrow range of prices observed in my data, similar limitations would also apply if I instead assumed a normal or logistic distribution for willingness to pay. Nevertheless, these other functional forms would likely perform better in an out-of-sample prediction, particularly among households in the left tail, since the exponential distribution is right-skewed everywhere with no left tail at all. Fortunately, my policy simulation below does not imply an out-of-sample prediction. Thus, my functional form assumption is unlikely to be a strong driver of the results in this paper.

The theoretical model developed above assumes that household fuel demand is perfectly inelastic; I have the ability to relax this assumption in the econometric model by including logged E85 price as an additional control.[13] To see why this control might be important, suppose that prices for both fuels increase by the same amount. While the E85 premium is unchanged, so that the set of households choosing E85 remains fixed, price levels are higher, so that all households (including those that choose E85) curtail their fuel consumption. Thus, β captures fuel-switching behavior as a function of relative prices (the extensive margin) while α captures energy conservation among households that continue to choose E85 as a function of E85's price (the intensive margin). Since α captures the price elasticity of fuel demand conditional on fuel choice, its value should be consistent with previous estimates in the literature for the price elasticity of overall fuel demand.

In my baseline estimates, I impose $\alpha = 0$ for consistency with my theoretical model. As noted above, this choice is consistent with recent empirical estimates, which suggest that the short-run price elasticity of overall fuel demand is less than 0.1 in magnitude [9,10]. Thus, any specification bias introduced by this choice is likely small. As I show below, my

[12] An alternative approach would have been to regress the logged ratio of E85 and gasoline market shares on the E85 premium, which would have been consistent with a logistic distribution for willingness to pay. Unfortunately, I do not observe gasoline quantities below the state level, which means I am unable to calculate local market shares. In addition, I am unable to calculate E85 quantities for alternative levels of aggregation (e.g., zip code or county), because I do not observe prices and sales volumes for every E85 station. Retailers of E85 are isolated, however, with stations located 8 miles from their nearest competitors on average. Thus, it is valid to treat the stations themselves as distinct E85 markets.

[13] This approach implicitly assumes that the price elasticity of fuel demand is uncorrelated with willingness to pay for E85, so that the demand-weighted distribution of willingness to pay remains roughly constant as price levels increase. In practice, minor violations of this assumption are unlikely to pose a problem for identification, given that fuel demand is inelastic.

estimates are robust to imposing other reasonable values for α; choosing $\alpha=0$ leads to a conservatively high estimate for the slope β (and conservatively low estimate for preference heterogeneity).[14]

Returning to the econometric model, the station effects, time dummies, and station trends control for between-market shifts in average willingness to pay for E85 as an E10 substitute, as described above. In addition, these controls capture differences in station characteristics (such as brand name, location, and amenities), local demographics (such as age and occupation), and driving patterns (such vehicle efficiency and distance to work) that affect the overall scale of fuel demand. Finally, the month controls capture seasonality in demand, including the well-known surge in driving that occurs each summer.

The vector of time-varying station characteristics $\boldsymbol{X}_{it}$ includes the log of the county's flexible-fuel vehicle stock. The vector also includes the log of the total number of retail stations that offer E85 in the same county. While a negative coefficient would imply that new stations draw customers away from existing stations, a zero coefficient might only suggest that new stations locate where competition is weak. Finally, the vector includes dummy variables indicating the length of time that a station has been offering E85. Sales will likely grow as buyers learn about the new opportunity to purchase ethanol.

5.2. Identification

I estimate the econometric model in (11) using ordinary least squares (OLS) and two-stage least squares (2SLS). OLS estimates are potentially biased if unmodeled shifts in demand correlate with fuel prices. This is a standard endogeneity problem in estimating demand functions. 2SLS attempts to identify demand using variation in prices that derives from shifts in supply.

There are several reasons to suspect that OLS estimates for β will not be severely biased in my application. First, while unmodeled shifts in E85-specific demand would tend to increase E85 premiums and generate bias, shifts in overall fuel demand would tend to increase prices for both fuels. Second, station owners set prices using rule-of-thumb strategies based on underlying fuel costs, which mitigates E85-specific demand shifts correlating with station-level price changes. Third, I include a rich set of time and station controls to capture aggregate demand shifts. These controls are important, since even if individual retailers are price takers in wholesale markets, market-wide demand shocks could influence wholesale prices, meaning that wholesale costs are not exogenous in an econometric sense [25]. A classic example is the surge in travel demand that drives up fuel prices each summer. Finally, I control for local demand shifts that evolve gradually using station-specific trends. Nevertheless, one might worry about short-term, station-level, E85-specific demand shocks correlating with local price premiums and biasing OLS estimates.

Thus, to identify demand more credibly, I also estimate the model using 2SLS. I generate a series of price instruments by interacting wholesale E85 costs and wholesale E10 costs with each of the following: (1) dummy variables for the 14 identifiable retail brands in my sample (28 instruments total), (2) the logged distance from each station's county center to the Benson refinery, which proxies for having a contract with the refinery (two instruments total), and (3) the logged numbers of E85 and fueling stations per square mile operating in the same county (four instruments total). As described above, I am able to document a variety of contractual relationships between retail E85 stations and their wholesale suppliers, as well as variation in local competition, that lead retail prices at individual stations to respond differently to changes in underlying wholesale costs. My instruments are designed explicitly to exploit this variation in pricing behavior.

Identification using 2SLS rests on two assumptions. First, the "instrument relevance" assumption requires that the instruments, given by vector $\boldsymbol{Z}_{it}$, be correlated with the E85 premium, conditional on controls: $\mathbb{E}[p_{e_{it}}-p_{g_{it}}|\boldsymbol{Z}_{it},\boldsymbol{X}_{it},\delta_i,\varepsilon_t,\omega_i\cdot t]\neq 0$. Above, I motivate this assumption by describing how individual retailers respond differently to changes in underlying wholesale costs; below, I test this assumption directly, finding that the instruments do indeed explain a statistically significant amount of price variation in my sample. Second, the "instrument exogeneity" assumption (or exclusion restriction) requires that the instruments be uncorrelated with demand, conditional on controls: $\mathbb{E}[u_{it}|\boldsymbol{Z}_{it},\boldsymbol{X}_{it},\delta_i,\ \varepsilon_t,\omega_i\cdot t]=0$. While this assumption cannot be tested directly, economic intuition suggests that my instruments are plausibly exogenous.

When assessing the exogeneity of the instruments, it is useful to remember that I include a rich set of time and station controls. Thus, by construction the error term in my model represents local, short-run shifts in E85 demand. It is highly unlikely that local, short-run demand shifts in a given area would correlate strongly with fuel costs in the broader wholesale market, given the many low-cost opportunities for wholesale price arbitrage over time and across geography. At the same time, these local, short-run shifts are unlikely to correlate with a station's brand name, location, or number of competitors, since firms make entry and exit decisions based not on short-run anomalies but rather on average expected profits over the long run, which are captured by my time and station controls. Thus, there is no obvious economic reason to suspect that interactions between wholesale costs and brand, location, or competition would be correlated with local, short-run shifts in demand. For such endogeneity to arise, it would take deviations in the wholesale cost of E85 (or E10)

[14] Because logged E85 prices are highly correlated with the E85 premium, standard errors on these variables are quite large when both are included. Thus, by imposing a reasonable value for α rather than estimating this parameter directly, I can substantially reduce the risk of statistical sampling error in my estimates.

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Table 2
Main estimation results.

Variable	Fixed effects		First differences	
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS
E85 price − E10 price ($\hat{\beta}$)	−1.322	−1.622	−0.910	−1.352
	(0.093)	(0.217)	(0.104)	(0.243)
ln(number flex-fuel vehicles)	0.043	0.052	0.094	0.095
	(0.025)	(0.026)	(0.023)	(0.023)
ln(number E85 stations)	−0.098	−0.094	−0.023	0.012
	(0.075)	(0.073)	(0.093)	(0.094)
Month 1 of operation	−0.654	−0.645	−0.694	−0.699
	(0.100)	(0.100)	(0.112)	(0.113)
Month 2 of operation	−0.087	−0.084	−0.108	−0.112
	(0.078)	(0.078)	(0.083)	(0.084)
Month 3 of operation	−0.003	0.005	−0.037	−0.036
	(0.067)	(0.068)	(0.058)	(0.059)
Month 4 of operation	−0.019	−0.014	−0.036	−0.034
	(0.045)	(0.047)	(0.032)	(0.033)
Heterogeneity in WTP ($\hat{\sigma} = -1/\hat{\beta}$)	0.756	0.617	1.099	0.739
	(0.053)	(0.082)	(0.125)	(0.133)
Number of observations	4825	4825	4148	4148
Number of stations	232	232	202	202
R-squared	0.20		0.14	
Residuals AR(1)	0.415	0.453	−0.255	−0.246
	(0.029)	(0.026)	(0.026)	(0.026)
F-statistic (weak instruments)		12.15		76.02
(Chi-square p-value)		(0.00)		(0.00)
Hansen's J-statistic (overidentification)		49.124		37.780
(Chi-square p-value)		(0.035)		(0.260)

Note: Dependent variable is logged monthly E85 sales volume; results implicitly impose a short-run fuel demand elasticity of $\alpha = 0$. Clustered standard errors (in parentheses) are robust to arbitrary heteroskedasticity and serial correlation within stations; the standard error on $\hat{\sigma}$ was calculated using the delta method. All regressions control for station effects (either through fixed-effects or first-differences estimation), month dummy variables, and station-specific linear time trends; R-squared is the fraction of remaining variation explained by the variables above. Residuals AR(1) is the coefficient from the least-squares regression of the residuals on their lagged values. F-statistic (for weak instruments) tests the null hypothesis that the excluded instruments have no explanatory power in the first-stage regression; robust p-values are in parentheses. Hansen's J-statistic (for overidentification) tests the null hypothesis that the instruments are jointly uncorrelated with the errors; robust p-values are in parentheses. See text for details.

around its trend to be correlated systematically with local, short-run demand shifts at particular types of stations. For example, if every time the wholesale cost of E85 was high, there were a coinciding demand shift at BP-branded stations near Benson facing robust competition, then my instruments might violate the exogeneity assumption. While I cannot rule out such systematic correlations, they seem unlikely.

While the above discussion focuses on standard simultaneous equations bias, the instruments also correct for potential endogeneity related to measurement error in E10 prices. Recall that I only observe county-average E10 prices. If consumers instead respond to E10 prices at a more local level, then E10 prices are measured with error. By construction, local E10 prices (and therefore the measurement error) are not correlated with the county averages that I include in my regression. Note, however, that local E10 prices (and therefore the measurement error) are likely correlated with local E85 prices, which I use to construct the E85 premium. Thus, in effect, my OLS estimates may be subject to classical errors-in-variables attenuation bias, which is remedied through 2SLS regression [26].

5.3. Estimation results

Table 2 presents my main OLS and 2SLS estimation results, which impose $\alpha = 0$; I present results that relax this assumption below. I control for station effects using both fixed-effects and first-difference estimators, which have different efficiency properties in the presence of serial correlation and different probability limits in the presence of dynamic price responses [24].[15]

[15] The fixed-effects estimator transforms each variable by subtracting its mean value (at the same station); the estimator then applies OLS or 2SLS to the mean-differenced data. The first-difference estimator transforms each variable by subtracting its lagged value (at the same station); the estimator then applies OLS or 2SLS to the first-differenced data. See Wooldridge [26].

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Demand for E85 is sensitive to changes in relative fuel prices. The coefficient of $\hat{\beta} = -1.322$ on the E85 premium in regression (1), which is based on the OLS fixed-effects estimator, implies that a \$0.10-per-gallon increase in the E85 premium leads to a 13.2% decrease in the quantity of E85 demanded. The corresponding coefficient of $\hat{\beta} = -1.622$ in regression (2), which is based on the 2SLS fixed-effects estimator, implies that \$0.10-per-gallon increase in the E85 premium leads to a 16.2% decrease in the quantity of E85 demanded. These results imply that the OLS estimator is biased toward zero by about 20%, which is consistent with the standard intuition as well as possible measurement error in E10 prices.

The corresponding coefficients based on the first-difference estimator in regressions (3) and (4) are about 0.3 smaller in magnitude. Why? One plausible explanation is that demand does not respond fully to changes in relative fuel prices within the first month, in which case the fixed-effects and first-difference estimators may give different results. The first-difference estimator exploits the correlation between price and quantity changes in adjacent time periods only, while the fixed-effects estimator relates average sales volumes to average prices in all time periods. For this reason, the fixed-effects estimator may be more robust to delayed price responses.

The instruments appear to be performing well. The first-stage *F*-statistics are highly significant: they indicate that the instruments are strong predictors of relative fuel prices, conditional on covariates. Hansen's *J*-statistic for overidentification is insignificant in the first-difference 2SLS model: I am unable to reject the null hypothesis that the instruments are jointly uncorrelated with the error term in first-differences. Hanson's *J*-statistic is statistically significant in the fixed-effects 2SLS model, however, which may indicate that one or more of the instruments is endogenous in levels. It is equally plausible, however, that price responses simply vary somewhat across markets, in which case 2SLS estimates will tend to reflect price responses for markets in which the instruments induce the most price variation. Since I constructed my instruments by interacting wholesale fuel costs with market-specific variables (e.g., brand name and location), different combinations of instruments would then be expected to yield different results. This is not an endogeneity problem; rather, this is a straightforward application of the local average treatment effect (LATE) interpretation for IV regression to demand estimation [27].

The coefficients on flexible-fuel vehicle stocks indicate that a 1% increase in the number of vehicles leads to a 0.05–0.10% increase in E85 sales volumes. I had expected to find coefficients closer to 1, indicating that E85 sales increase proportionally with the density of potential buyers. Recall, however, that I constructed this variable based on a snapshot of registered vehicles in 2007. Thus, I suspect that these estimates are biased toward zero as a result of measurement error, which is exacerbated in panel data models [28].

The coefficients in the next row indicate that a 1% increase in the number of E85 stations per county leads to a 0–0.10% reduction in sales volumes at individual stations; these coefficients are not statistically different from zero. Conditional on where new sellers choose to locate, they only draw a small fraction of customers away from existing stations. This result is not surprising, given the small number of E85 stations statewide and the fact that infrastructure subsides targeted areas where the fuel was not already available.

The last set of coefficients indicates that E85 buyers learn quickly about new opportunities to purchase the fuel. Sales volumes are about $\exp(-0.70)-1 \approx 50\%$ lower during a station's first month selling E85 but quickly increase to long-run levels within a month or two. This rapid increase indicates that market participants are well-informed about E85's availability.

Table 3 explores the sensitivity of these results to imposing different values for the short-run price elasticity of overall fuel demand α (in the first five rows) and estimating α freely (in the last row). The table omits estimates for the covariates, since they change little. A clear pattern emerges: as the imposed value of α rises in magnitude, the estimated response to the E85 premium, given by β, declines in magnitude. This is not surprising: logged E85 prices and the E85 premium are highly positively correlated; hence, the offsetting effects. Nevertheless, my estimates for β are relatively stable across models that impose different values for α. At sample-mean fuel prices, these estimates imply an own-price elasticity of negative 3.2–3.8 and a gasoline-price elasticity of 2.3–3.2; I obtained similar results when modeling a log–log functional form relationship between quantity and fuel prices.

When I estimate α freely using OLS (columns 1 and 3), its sign and magnitude are within the range of estimates in the literature, which is comforting. Its confidence interval is large, however, containing both zero and one, while β is also estimated imprecisely. When I estimate α freely using 2SLS treating both price variables as endogenous (columns 2 and 4), these problems worsen: contrary to previous studies, my fixed-effects estimates imply that overall fuel demand is highly price-elastic, while my first-difference estimates have the wrong sign. The confidence intervals on these estimates are very large, however, and I am unable to reject $\alpha = 0$ or any of the other reasonable values I impose in Table 3. Thus, the bias-efficiency tradeoff appears to weigh heavily in favor of imposing a reasonable value for α and exploring the sensitivity of the results to this choice.

5.4. Preferences for ethanol

My results indicate that preferences for E85 are quite heterogeneous. If we take the exponential distributional assumption literally, then my slope estimates identify the standard deviation in willingness to pay as $\sigma = -1/\beta$. According to my main estimation results in Table 2, which impose a zero short-run price elasticity of fuel demand, I estimate $\hat{\sigma} = 1/1.622 \approx 0.617$ based on my 2SLS fixed-effects estimates and $\hat{\sigma} = 1/1.352 \approx 0.739$ based on my 2SLS first-difference estimates. In both cases, I strongly reject the null hypothesis of homogeneity in willingness to pay, given by $H_0 : \sigma = 0$. These estimates likely represent lower bounds on heterogeneity: estimated price responses decline in magnitude, meaning

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Table 3
Sensitivity of $\hat{\beta}$ to different choices for α.

Coefficient (**value of** α)	Fixed effects		First differences	
	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS
$\hat{\beta}$ ($\alpha=-0.00$)	−1.322	−1.622	−0.910	−1.352
	(0.093)	(0.217)	(0.104)	(0.243)
$\hat{\beta}$ ($\alpha=-0.05$)	−1.300	−1.600	−0.888	−1.332
	(0.092)	(0.216)	(0.103)	(0.244)
$\hat{\beta}$ ($\alpha=-0.10$)	−1.278	−1.579	−0.866	−1.313
	(0.092)	(0.216)	(0.103)	(0.244)
$\hat{\beta}$ ($\alpha=-0.25$)	−1.213	−1.514	−0.801	−1.253
	(0.092)	(0.215)	(0.103)	(0.244)
$\hat{\beta}$ ($\alpha=-0.50$)	−1.103	−1.407	−0.692	−1.154
	(0.092)	(0.213)	(0.102)	(0.245)
$\hat{\beta}$ (α estimated freely)	−1.109	−0.521	−0.757	−1.854
	(0.278)	(1.183)	(0.273)	(0.602)
$\hat{\alpha}$ (α estimated freely)	−0.487	−2.558	−0.352	1.265
	(0.565)	(2.609)	(0.596)	(1.479)

Note: Table replicates the results in Table 2 above while imposing different values for α (in the first five rows) and estimating α freely (in the last row). Clustered standard errors (in parentheses) are robust to arbitrary heteroskedasticity and serial correlation within stations. See text and the previous table for details.

estimated preference heterogeneity increases in magnitude, as I impose larger values for the short-run price elasticity of fuel demand.

Still taking the exponential distributional assumption literally, mean willingness to pay is given by $\sigma+\mu$. While my econometric estimates identify the variance in willingness to pay, they do not directly reveal the mean, since the preference shifter μ is perfectly collinear with the overall scale of fuel demand, which is captured by the station fixed effects (see the online appendix). Thus, I calibrate the mean by matching observed and predicted E85 market shares at the state level using Eq. (8). Assuming that the slope of demand is given by my 2SLS fixed effects estimates, I calculate mean willingness to pay as $\hat{\mu}+\hat{\sigma}=-\$1.04+\$0.62=-\$0.42$ per gallon.[16] Following expression (8) above, the distribution of willingness to pay is then equivalent to (one minus) market share as a function of price, which is given by the demand function in Fig. 4(a).

These inferences merit a strong note of caution. The log-linear functional form and the exponential distribution it implies are sensible assumptions when modeling the right tail of the distribution of preferences but are unlikely to hold in the left tail where E85 sells at a discount. Thus, my demand estimates should not be used for large out-of-sample predictions, particularly among households that prefer E10. Similarly, the parameter estimates above should not be interpreted literally as giving the mean and standard deviation in willingness to pay across all households, since such an interpretation implicitly extrapolates the exponential distribution far outside the range of E85 premiums observed in my data. Rather, my econometric estimates and back-of-the-envelope calibration yield the demand function and distribution of willingness to pay over the range of E85 price premiums that have been observed historically, from roughly \$0 to \$0.75 per gallon (see Fig. 4a). According to my estimates, willingness to pay for E85 averages about \$0.30 per gallon among households within this range, while about 20% of households overall are willing to pay a premium for the fuel.

Thus far, I have focused on social and environmental considerations or legitimate differences in utility (e.g., the time cost of more frequent refueling) as the primary source of observed heterogeneity in willingness to pay for E85. There are two other possible interpretations.

First, consumers might make mistakes in fuel choice. For example, they might not understand that E85's mileage is lower, or they may inaccurately calculate relative mileage. Systematic mistakes that are common to all households would mainly affect my calibration for the position of demand, while mistakes that are idiosyncratic to individual households would lead to smaller estimated price responses. Thus, while my estimates would accurately reflect behavioral

[16] The average vehicle logged 935.73 miles per month in 2001 (as reported by U.S. FHWA), the average flexible-fuel vehicle gets 17.95 miles per gallon (my calculations based on EPA data), and there are an average of 3252.61 flexible-fuel vehicles per county in my sample, which implies 169,559 potential gallons per county. In practice, there are an average of 3.72 stations per county in my sample with average monthly sales of 2463.41 gallons, which implies 9163.89 gallons per county. Thus, E85's market share is approximately $9164/169,559=5.4\%$. Since only $3.72/96.69=3.85\%$ of stations sold E85, however, many flexible-fuel owners arguably lacked access to the fuel. Based on Greene [29], which estimates the value of fuel availability using stated preference data, I calculate that 3.85% availability is equivalent to paying an extra \$0.37 per gallon (in 2006 dollars). Thus, given an E85 market share of 5.4%, an effective E85 premium of $\$0.39+\$0.37=\$0.76$ per gallon, and $\hat{\sigma}=0.617$, I calibrate $\hat{\mu}=-1.04$.

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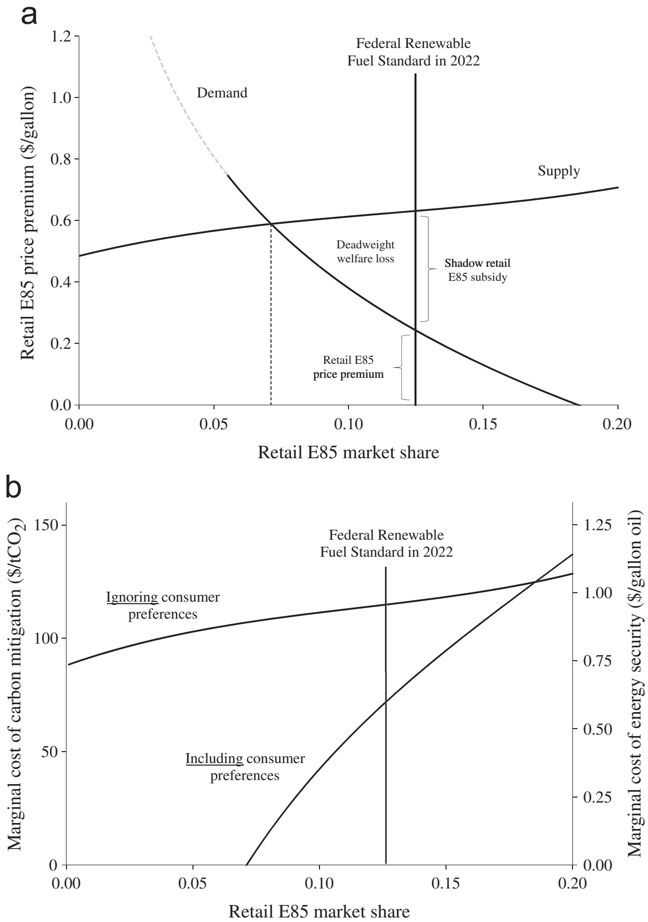

Fig. 4. Policy simulation results. Note: (a) on top shows the market for E85 as an E10 substitute. The vertical axis measures E85's price and cost relative to E10; the horizontal axis measures E85's market share. The dashed portion of the demand curve indicates an out-of-sample prediction; the solid portion indicates a within-sample prediction. (b) at bottom traces out marginal abatement costs as a function of the minimum market-share requirement. The left axis measures costs per metric ton of carbon dioxide avoided; the right axis measures costs per gallon of oil saved. See text for details.

responses, they would in such cases overstate the "true" mean and variance in willingness to pay. Similar criticisms could be leveled at virtually any empirical demand estimate, however, if we are willing to relax the assumption of revealed preference.

Second, observed heterogeneity might derive in part from variation in E85's relative convenience across households or over time for the same household (e.g., due to the timing of refueling). Such variation would likely diminish as the E85 market expands, meaning my demand estimates might not be valid for simulating the effects of policies designed explicitly to promote ethanol.

This interpretation is unlikely to be a major concern for four reasons. One, temporary variation in E85's relative convenience (e.g., due to the timing of refueling) is only likely to affect first-difference estimates, which is consistent with my finding that fixed-effects estimates are larger in magnitude. Two, any between-market variation in convenience or search costs (e.g., a sign prominently displaying E85's price) will be captured by my time and station controls. Three, within-market variation is only a problem if households literally weigh E85's price against travel or hassle costs when deciding whether to visit a station specifically to purchase E85. If households simply visit inconvenient stations less frequently, observe prices, and then make their fuel choices, then variation in convenience will be captured fully by my station effects. Finally, because E85 and other fueling stations tend to cluster in the same locations, there is little scope for within-market variation in E85's relative convenience to contaminate my slope estimates.[17]

[17] Within a five-mile radius around each E85 station, half of the nearby fueling stations are within 0.5 miles and two-thirds are within 1 mile. At a time cost of $15 per hour, travel speed of 30 miles per hour, E85 cost of $2.37 per gallon, fuel economy of 18 miles per gallon, and refueling rate of 15 gallons, traveling one mile round-trip out of the way for E85 (the median) would add only $0.04 to the effective E10-equivalent per-gallon price of E85.

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6. Policy simulation

I use my estimates to simulate the effects of a minimum market share requirement for ethanol, which I have modeled on the federal RFS. The simulation model is necessarily stylized and intended to highlight the importance of accurately modeling preferences. I assume in my simulations that the baseline fuel is an ethanol–gasoline blend containing 10% ethanol by volume (E10), while the renewable fuel is an ethanol–gasoline blend containing 85% ethanol (E85). Thus, increasing the market share for E85 relative to E10 increases the overall level of ethanol blending in the fuel supply. I assume that total fuel demand is fixed at 155 billion E10-equivalent gallons based EIA projections for 2022 [30], facilitating a simple and highly intuitive graphical analysis. Given these assumptions, the federal RFS for 2022 would require that ethanol comprise 16% of the overall fuel supply by energy content, which implies a 12.5% market share for E85.

I assume in my simulations that every car is a flexible-fuel vehicle and that preferences for E85 follow my 2SLS fixed-effects estimates in Table 2, which yields a conservatively flat demand function. Again, while my econometric estimates reveal the slope of demand, they do not give its position. Thus, I calibrate this value by matching observed and predicted statewide market shares as described in detail in the previous section. For comparison to previous analyses, I also simulate the standard's effects assuming that all households have zero willingness to pay a premium (i.e., a horizontal demand function through zero).

On the supply side, I assume a horizontal supply curve for pure gasoline at $3.48 per gallon.[18] I assume that pure ethanol consumption beyond 15 billion gallons (the statutory limit on corn-based ethanol for the RFS) is supplied by cellulosic ethanol, which faces initial marginal costs of $2.73 per gallon and increasing marginal costs thereafter.[19] I calculate marginal costs for E85 and E10 as the weighted average of marginal costs for ethanol and gasoline; weights are given by the appropriate fuel blending ratios. I then convert these costs to E10-equivalent units.

Finally, I assume that replacing pure gasoline with pure cellulosic ethanol reduces life-cycle oil consumption by 95% and life-cycle carbon dioxide emissions by 90% on an energy-adjusted basis [19]. In absolute terms, one gallon of pure gasoline contains one gallon of oil and 8.788 kg of carbon dioxide [36]. Thus, if cellulosic ethanol is the marginal source of pure ethanol, these assumptions imply that replacing one gallon of E10 with one gallon of E85 reduces life-cycle oil consumption by 0.66 gallons and life-cycle carbon dioxide emissions by 5.5 kg on an energy-adjusted basis.

Fig. 4(a) shows the market for E85 as an E10 substitute. Note that the horizontal axis measures E85's aggregate market share, while the vertical axis measures the E85 premium (i.e., E85 price minus E10 price). Demand for E85 is downward-sloping according to my demand estimates. Marginal cost is upward-sloping due to cellulosic ethanol's increasing marginal production cost. In the absence of policy, E85's market share is 7% and the ethanol premium is $0.59 per gallon, which is given by the intersection of E85 demand and supply (both measured relative to E10). Any market share requirement below this level would not be binding. The price of E85 equals its marginal cost of $4.13 per gallon, while E10's price equals its marginal cost of $3.54 per gallon. Note that fuel taxes impose no pre-existing distortion whatsoever, since tax rates are assumed to be the same for both fuels and because I have assumed perfectly inelastic fuel demand overall.

Now consider a minimum market share requirement of 12.5%, which is consistent with the federal RFS. To attain this level of E85 consumption, the E85 price premium necessarily falls to $0.24 per gallon, which requires that fuel suppliers subsidize the fuel by $0.39 per gallon relative to E10. To support this shadow subsidy, however, all fuel is implicitly taxed by $0.05 per gallon, which equals the shadow subsidy multiplied by E85's market share. On balance, E85 is implicitly subsidized by $0.34 per gallon while E10 is taxed by $0.05 per gallon, with E85's price falling to $3.83 per gallon and E10's price rising to $3.59 per gallon. The policy results in a consumer surplus loss of $2.4 billion (about $0.016 per gallon of total fuel demand) and a producer surplus gain of $0.6 billion (about $0.004 per gallon) for an overall welfare loss of $1.8 billion (about $0.012 per gallon, equal to the area of the deadweight-loss triangle).[20]

Ignoring consumer preferences has a dramatic influence on these calculations. When demand is assumed to coincide precisely with the horizontal axis, as in previous studies, E85 is prohibitively costly in the unregulated equilibrium, and its market share is zero. Now, to attain 12.5% market share, E85's price premium must fall to zero, which requires that the fuel be subsidized relative to E10 by the full difference in marginal costs. In this case, the policy results in a welfare loss of $11.2 billion (about $0.072 per gallon of total fuel demand, equal to the entire area under the supply curve to the left of the standard).

Fig. 4(b) presents marginal abatement costs for greenhouse gas emissions ($/t$CO_2$) and oil dependence ($/gallon oil) as a function of E85's imposed market share. Marginal abatement costs increase with the stringency of the standard, since

[18] Retail prices averaged $2.85 per gallon during 2008–2010, including $0.52 for taxes and $0.17 for distribution and marketing (my calculations based on EIA data); I added $0.64 per gallon based on EIA's projected increase in imported crude oil prices for 2022 [30].

[19] Khanna et al. [31] present cellulosic biomass feedstock supply functions under six scenarios; I calculate the average. I assume a biomass-to-ethanol conversion yield of 87.3 gallons per metric ton (based on [32]); marginal feedstock costs start at $0.34 per gallon. I then add a constant $1.59 per gallon for ethanol refining (based on [33]), $0.15 for feedstock transport (based on [34]), $0.14 for ethanol transport by rail (based on [35]), $0.17 for retail distribution and marketing (equivalent to gasoline on a volumetric basis), and $0.34 for fuel taxes (equivalent to gasoline taxes of $0.52 per gallon on an energy-adjusted basis). Consistent with current legislation, I assume that federal ethanol blending subsidies are phased out completely before 2022.

[20] Note that welfare changes calculated by integrating the area under the aggregate demand curve are identical to what one would calculate based on Eq. (1) above. This follows from my assumptions that utility is linearly separable in the composite good and that overall fuel demand is perfectly inelastic.

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consumers have diminishing marginal willingness to pay and since E85 has increasing marginal production costs. For weak standards, ignoring consumer preferences would substantially overstate abatement costs, since marginal households strongly prefer E85. On the other hand, for stringent standards, it appears that ignoring preferences would likely understate abatement costs, since marginal households eventually prefer E10 instead. At the level of the federal RFS, ignoring preferences would lead one to overstate marginal abatement costs by more than two-thirds.

The RFS's marginal abatement costs nevertheless exceed most conventional estimates for social benefits. In terms of energy security, marginal welfare costs are $0.59 per gallon of oil saved. For comparison, a recent study by Harrington et al. [37] assumes external costs of $0.12 per gallon for petroleum dependence, though the studies they review estimate a range of $0.08–$0.50 per gallon. In terms of carbon mitigation, marginal welfare costs are $71 per metric ton of carbon dioxide emissions avoided. For comparison, a recent meta-analysis suggests that marginal damages are unlikely to exceed $15 per metric ton of carbon dioxide [38], although more pessimistic estimates put marginal damages at $85 per metric ton [39]. These estimates are sensitive to assumptions about ethanol's life-cycle emissions: if land-use changes eat into ethanol's climate benefits, as recent studies suggest is likely [40,41], costs would increase.

There are several other limitations to these results. First, my estimates reflect preferences among households in Minnesota that live near E85 stations and own flexible-fuel vehicles; relying on a more representative sample would likely shift the estimated E85 demand curve downward and increase simulated costs. Second, heterogeneity that derives from variation in E85's convenience or mistakes in fuel choice may be temporary or even illusory; addressing these issues would tend to tilt the E85 demand curve counter-clockwise and increase costs for weak standards. Third, my simulations ignore fuel conservation that would likely result from higher overall fuel prices; incorporating such effects would tend to reduce marginal abatement costs slightly. Fourth, my estimates are based on preferences for corn-based ethanol; preferences for cellulosic ethanol could be weaker or stronger, increasing or decreasing costs. Finally, as the E85 market expands, smaller, foreign cars will likely come equipped with flexible-fuel capacity; drivers of these vehicles may have different preferences than today's flexible-fuel owners.

On the supply side, my results are sensitive to assumptions about ethanol's marginal production cost relative to gasoline. If ethanol production costs are higher, or if gasoline prices are lower, then overall costs would tend to increase. Second, I do not consider preexisting distortions, such as the import tariff on sugarcane ethanol from Brazil, nor do I consider other general equilibrium effects, such as impacts on land use and food prices. Addressing these various issues would have an ambiguous effect on overall costs, but the key qualitative point remains: accounting for positive and heterogeneous willingness to pay for ethanol can (in this case) reduce simulated costs substantially.

7. Conclusion

I develop a model that explicitly links aggregate demand for ethanol in a market to the underlying distribution of household preferences for ethanol as a gasoline substitute. The model allows me to extract information about micro-preferences from aggregate data on ethanol quantities and relative fuel prices. I estimate the model using panel IV methods and data from a large number of retail fueling stations. Future research could apply this approach to estimate preferences for renewable fuels or other goods with close substitutes.

I find that demand for ethanol (E85) as a gasoline (E10) substitute is sensitive to relative fuel prices: a $0.10-per-gallon increase in ethanol's price relative to gasoline leads to a 12–16% decrease in the quantity of ethanol demanded. Price responses are considerably smaller, however, than they would be if households had identical willingness to pay for ethanol as a gasoline substitute, and my results imply that some households are willing to pay a sizeable premium for ethanol.

These results have economically significant implications for policy. Accounting for households that prefer ethanol cut the cost of an ethanol mandate substantially. While the typical household may demand a large subsidy, marginal households with stronger preferences choose ethanol with minimal price distortion, mitigating deadweight losses. Researchers should take care to distinguish between average and marginal households when assessing the impacts of policy; assuming identical preferences for all households can yield misleading results and (in this case) overstate costs.

A market share requirement at the level of the federal RFS nevertheless is costly relative to likely benefits. Marginal abatement costs for oil and carbon dioxide exceed most conventional estimates for marginal external damages, even after revising the analysis in ethanol's favor, although this conclusion is sensitive to assumptions about ethanol and gasoline supply costs in the coming decades. Moreover, to the extent that preferences for ethanol reflect pure altruism toward farmers, the environment, or national security, then the behavior I interpret as reducing costs is in fact only shifting costs, at least in part. Finally, some of the altruism may in fact be misplaced. If land-use changes associated with growing feedstocks negate ethanol's climate benefits, or if ethanol's other side effects are not managed carefully, then the policy could actually damage the environment. Policies that tax or regulate carbon dioxide emissions directly would tend to mitigate such side-effects.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found in the online version at doi: 10.1016/j.jeem.2011.08.002.

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