Online Appendix

“High Frequency Evidence on the Demand for Gasoline”

by Laurence Levin, Matthew S. Lewis, and Frank A. Wolak

B Exploring Potential Biases due to Substitution from Regular Grade to Premium Grade Gasoline

Our data include daily total revenues at gas stations aggregated to the city level and a city-level average of regular grade gasoline prices. Our measure of the quantity purchased in a city on a given day is generated by dividing the aggregate gasoline station revenue by the average price. One concern with this approach arises from the fact that roughly 15% of gasoline purchases are purchases of mid-grade or premium grade gasoline which sells at a higher prices than regular grade. As a result, dividing total revenues (from sales of all grades) by the price of regular grade gasoline generates a slight overestimate of the number of total gallons purchased. If the relative shares of premium, mid-grade, and regular gasoline remains fairly constant over time the presence of premium and mid-grade purchases would not bias our elasticity estimates, as all identification is based on relative changes in prices and quantities over time. However, Hastings and Shapiro (2013) present evidence that gasoline consumers substitute from premium to regular grade fuel when gasoline prices increase. If the relative purchase shares of regular and premium gasoline fluctuate with price this substitution could bias our elasticity estimate. The following calculation approximates the potential size of such a bias.

Assuming that premium gasoline sells at a γ% premium over the regular grade price, the true quantity of gasoline purchased can be represented by:

$$Q_{true} = \frac{S_{reg} * R}{P_{reg}} + \frac{(1 - S_{reg}) * R}{P_{reg} * (1 + \gamma)},$$

where S_{reg} is the share of all gasoline purchased that is of regular grade and $(1 - S_{reg})$ represents the share of premium grade purchases, P_{reg} represents the price of regular grade gasoline, R is the total observed revenues from all gasoline sales. (For simplicity I am considering just regular and premium grades.)

The measure of quantity we use in the paper does not adjust for the price difference between premium and regular grade sales, so our measure can be expressed as:

$$Q_{measured} = \frac{R}{P_{reg}} \equiv \frac{S_{reg} * R}{P_{reg}} + \frac{(1 - S_{reg}) * R}{P_{reg}}.$$

As a result, the bias in our measure of quantity will simply be:

$$Bias_Q = Q_{true} - Q_{measured} = \frac{(1 - S_{reg}) * R}{P_{reg}} - \frac{(1 - S_{reg}) * R}{P_{reg} * (1 + \gamma)} = \frac{\gamma}{1 + \gamma}(1 - S_{reg}) * \frac{R}{P_{reg}},$$

where $\frac{\gamma}{1+\gamma}$ reflects the percentage discount at which regular grade sells relative to premium grade, and $\frac{\gamma}{1+\gamma}(1 - S_{reg})$ then represents the percent to which our quantity measure is biased (upward) from the true quantity as a result of assuming that all gasoline is sold at the regular-grade price.

Once again, if γ and S_{reg} are constant over time our demand elasticity estimates will not be affected by this bias. On the other hand, if the share of consumers buying regular grade gasoline (S_{reg}) increases when prices rise (as Hastings and Shapiro (2013) suggest) then some of the decrease in quantity we observe could be a result of people substituting to cheaper regular grade gasoline rather than people reducing gasoline consumption altogether. The magnitude of this effect, however, is almost sure to be rather small. Hastings and Shapiro (2013) estimate that a \$1.00 increase in the gasoline price is associated with a 1.4 percentage point increase in the share of people buying regular grade gasoline. Given that prices average around \$3.00 per gallon during our sample and the baseline share of people buying regular grade gasoline is around 85%, this would imply a *price elasticity of substitution to regular grade gasoline* of around 0.0005.

Measuring gasoline price in cents per gallon and assuming a mark-up on premium gasoline of around 10% over regular, this implies that:

$$\frac{\partial PercentBias_Q}{\partial P_{reg}} = \frac{\gamma}{1+\gamma}(-\frac{\partial S_{reg}}{\partial P_{reg}}) = 0.1 * (-0.014) = -0.0014,$$

which in the absence of any actual demand response and at an average gasoline price of \$3.00 would generate a false elasticity of demand of around $-0.0014 * 3 = -0.0042$. Given that our demand elasticity estimates are two orders of magnitude larger than this, any substitution from premium to regular gasoline associated with price changes will have a negligible impact on our analysis.

C Exploring the Bias in Estimated Gasoline Demand Elasticity Resulting from Non-Gasoline Purchases

As is discussed in Section 2, measuring quantity using the total revenues earned by gas stations in a city on a particular day divided by the city's average price of gasoline will result in upward bias since around 21% of these revenues come from non-gasoline items. More importantly for our demand analysis, the estimated response of gasoline consumption to changes in prices will also biased upward (in absolute value). In our analysis we attempt to avoid this issue by using only pay-at-pump transactions in our quantity calculations. However, it is also possible to derive a reasonably accurate approximation of the magnitude of the bias that would result from using all transactions to calculate the quantity of gasoline sold. In this section we will derive the expected bias and show that it is fairly similar to the difference in estimated elasticities found when using only pay-at-pump transactions as opposed to all transactions.

Dividing total revenues by price results in a quantity measure $\tilde{Q} = Q + \frac{K}{P}$, where Q represents the true quantity of gasoline sold, K represents the revenues from all non-gasoline sales, and P is the price of gasoline. Using this representation, the response of our measure of Q to a change in price will be:

$$\frac{\partial \tilde{Q}}{\partial P} = \frac{\partial Q}{\partial P} - \frac{K(P)}{P^2} + \frac{1}{P}\frac{\partial K(P)}{\partial P}.$$

Here we have allowed for the possibility that the demand for non-gasoline items may also be influenced by changes in the price of gasoline. As a result, the elasticity of our measure of Q with respect to price will be:

$$\begin{aligned}
\tilde{\epsilon} = \frac{\partial \tilde{Q}}{\partial P}\frac{P}{\tilde{Q}} &= \frac{\partial Q}{\partial P}\frac{P}{Q + \frac{K}{P}} - \frac{K(P)}{P^2}\frac{P}{Q + \frac{K}{P}} + \frac{1}{P}\frac{\partial K(P)}{\partial P}\frac{P}{Q + \frac{K}{P}} \\
&= \frac{\partial Q}{\partial P}\frac{P}{Q}\frac{Q}{Q + \frac{K}{P}} - \frac{\frac{K}{P}}{Q + \frac{K}{P}} + \frac{\partial K(P)}{\partial P}\frac{P}{K}\frac{\frac{K}{P}}{Q + \frac{K}{P}} \\
&= \epsilon_g \sigma_g - (1 - \sigma_g) + (1 - \sigma_g) * \epsilon_k \\
&= \epsilon_g \sigma_g + (1 - \sigma_g)(\epsilon_k - 1),
\end{aligned}$$

where $\epsilon_g = \frac{\partial Q}{\partial P}\frac{P}{Q}$ represents the true elasticity of demand for gasoline, $\epsilon_k = \frac{\partial K(P)}{\partial P}\frac{P}{K}$ represent the elasticity of non-gasoline revenues with respect to the price of gasoline, and $\sigma_g = \frac{PQ}{PQ+K}$ represents the share of total revenues coming from gasoline sales. Alternatively, the true elasticity of demand for gasoline can be expressed as a function of our all-transactions elasticity estimate:

$$\epsilon_g = \frac{\tilde{\epsilon}}{\sigma_g} + \frac{1 - \sigma_g}{\sigma_g}(\epsilon_k - 1).$$

Based on this result, we can approximate the expected bias using estimates of parameters from previous studies. In a survey of gas station consumers, NACS (2014) estimates that around 27% of gas stations transactions are in cash, and only 44% of customers enter the store during their visit.[26] Assuming that all cash paying customers enter the store, at most 17% of all customers (or 39% of those entering the store) are potentially making non-gasoline purchases with a credit card. Data from the U.S. Economic Census suggests that 21% of all gas station revenues come from non-gasoline items. Supposing that gasoline revenues can be attributed proportionally across all payer types and non-gasoline revenues attributed proportionally across customers entering the store, this would suggest that non-gasoline purchases represent roughly 6% of non-cash customers' total spending.[27]

There are no direct estimates of how the demand for non-gasoline items at the station responds to changes in the price of gasoline, but Gicheva, Hastings and Villas-Boas (2007) have examined how gasoline prices impact consumer spending more generally. They estimate that consumers reduce spending on *food away from home* by 45-56% when gas prices increase by 100%. However, they also find that grocery spending actually increases as consumers cook at home more and that consumers substitute from more expensive to less expensive items within each category. In some ways, food and drink from a gasoline convenience store can be considered part of the food away from home category, but packaged items from the convenience store could also be considered as similar to grocery items (or less expensive options compared with other food away from home). As a result, it could be that spending in convenience stores decreases when gas prices rise, but probably not to the same extent as other food away from home.

Considering these findings, suppose the share of total credit card customer revenues coming from gasoline sales (σ_g) is 94% $(= 1 - .06)$, and the elasticity of non-gasoline revenues with respect to the price of gasoline (ϵ_k) is 33%. Then, based on the bias derived above and the demand elasticity estimated using all purchases in our data, the true gasoline demand elasticity can be approximated as:

$$\epsilon_g = \frac{\tilde{\epsilon}}{.94} - .064 * (-1.33) = 1.064\tilde{\epsilon} + .085.$$

Interestingly, the bias-adjusted elasticity estimates implied by this relationship are relatively similar

[26] Survey data from previous years could not be used because the question determining the share of customers entering the store was not included.

[27] The 6% results from multiplying the fraction those visiting the store that do not pay cash times the share of revenues that are non-gasoline (39% $\times$ 21%) and then dividing this by the the overall share of non-cash customers times the share of revenues from gasoline (73% $\times$ 79%).

in magnitude to the elasticities obtained by estimating demand using only pay-at-pump transactions (reported in Table 1). For example, applying this bias-adjustment to the elasticity estimate of $-.328$ from the traditional demand model estimated using all transactions (Column 4) would imply a *true* elasticity of gasoline of $\epsilon_g = 1.064(-.328) + .085 = -.264$, which is very close to the coefficient of $-.259$ that we obtain when estimating the same model using only pay-at-pump transactions (Column 1). The estimate from our probability of purchase model (Column 6) would imply a bias-adjusted elasticity estimate of around $-.336$ which is also much closer to (though not as low as) the estimate of $-.288$ obtained using only pay-at-pump transactions (Column 3).

We conclude from the calculations above that biases resulting from the presence of non-gasoline purchases in our data are non-negligible in magnitude but are nowhere near large enough to explain the differences between our elasticity estimates and those obtained by other recent studies. Moreover, our ability to estimate demand using only pay-at-pump purchases appears to eliminate, or perhaps over-correct for, any bias resulting from non-gasoline purchases.

D Instrumental Variables Estimates

Table D1 reports the instrumental variables estimation results for both the basic model (Column 1) and the restricted and unrestricted versions of the consumer purchase model (Columns 2 & 3) presented in Section 3. All specifications are estimated using only pay-at-pump purchases. In an attempt to utilize exogenous variation refinery market conditions to identify supply-driven price fluctuations we use the log of the current ”spot market” price of gasoline in the region as an instrument for local retail prices. While using measures of refinery outages directly as instruments might seem like attractive alternative, the relationship between outages and gasoline prices is complex and difficult to capture in a model because the impact depends also on the level of inventories in the market, the ease of importing from alternative sources, the available capacity at other refineries in the area, etc. Using spot market prices reveals the net impact of these outages on gasoline markets. Input prices further upstream are also not likely to be useful instruments here, as oil prices do not exhibit the regional variation necessary to identify fluctuations in relative gasoline prices across different parts of the country.

We use the spot market gasoline price data reported by the Department of Energy's Energy Information Administration for either New York Harbor, the Gulf Coast, or Los Angeles depending on which of these large refining centers is most closely integrated into the city's gasoline supply network. Petroleum Area Defense District (PADD) geographic definitions are used to classify this supply network integration. The New York Harbor spot price is used as an instrument for cities in the New England and Central Atlantic portions of PADD 1; the Gulf Coast spot price is used for cities in the Lower Atlantic region of PADD 1 and for cities in PADDs 2, 3, and 4; and the Los Angeles spot price is used for PADD 5 cities. Resulting estimates are directly comparable to the OLS estimates from Columns 4 through 6 of Table 1.

Table D1: IV Estimates of Baseline Empirical Model of Demand

Dependent Variable = ln(quantity$_{jd}$)

		Pay-at-Pump Only	
	(1)	(2)	(3)
ln(price$_{jd}$)	-0.357	-0.431	-0.323
	(0.050)	(0.085)	(0.017)
ln(# of transactions$_{jd}$)		1	0.996
			(0.002)
ln(predicted probability of purchase$_{jd}$)		-1	-0.003
			(0.009)

Note: Day-of-sample fixed effects and city fixed effects are included in all specifications. Log retail gasoline prices in each city are instrumented for using the log of the spot price of gasoline from the either New York Harbor, the Gulf Coast, or Los Angeles depending on which of these refining centers is most closely linked with the city's supply infrastructure. Standard errors in Columns 1 & 4 are robust and clustered to allow serial correlation within city. Standard errors for the remaining specifications are generated using a nonparametric bootstrap that allows errors to be serially correlated within a city and jointly distributed with the error term in the first-stage regression.

E Replication of Hughes, Knittel and Sperling (2008) Model and Comparison to Visa Data

Once aggregated to a national time series our elasticity estimates are fairly close to those of Hughes, Knittel and Sperling (2008) who estimate an identical specification using data from 2000–2006. Although our data is from a later period, we can generate a more accurate comparison by replicating the same specification using their data sources but for our later time period. As in their study, gasoline consumption is measured using the EIA's monthly nationwide estimate of motor gasoline "product supplied". Price is measured using the U.S. city average price for unleaded regular gasoline as reported in the U.S. Bureau of Labor Statistics' CPI-Average Price Data and is converted to constant 2005 dollars using the GDP implicit price deflator.

To check our ability to replicate the Hughes, Knittel and Sperling (2008) analysis we first estimate their baseline double-log specification (equivalent to Column 5 of Table 4 above) for the period 2001–2006. Results are reported in Table E1, Column 1. The estimate of price elasticity ($-.042$) is identical to that of Hughes, Knittel and Sperling (2008).[28] Estimating the same specification using data from 2006–2009 yields a price elasticity that is slightly positive and not significantly different from zero. This is very similar to our estimate from the same specification using aggregated Visa pay-at-pump purchase data (reported in Column 4) but is much less elastic than our estimate using all Visa purchases (Column 3). The use of an alternative data source may be partially responsible for differences between our elasticity estimates and those of previous studies, but overall the results above suggest that most of the difference likely a result of the level of data aggregation.

[28]Our estimate of the income elasticity is 0.32 as opposed to their estimate of 0.53. This discrepancy appears to have been caused by the fact that Hughes, Knittel and Sperling (2008) use previously published estimates of disposable personal income that have since been revised by the BEA. We utilize the updated estimates so that our income measures are consistent with those available for the 2006–2009 sample period.

Table E1: Elasticity Estimates from Replication of Hughes, Knittel and Sperling (2008)

Dependent Variable = ln(quantity per capita)

Date Range:	2000–2006	2006–2009	2006–2009	2006–2009
Data Source:	EIA/BLS	EIA/BLS	Visa/AAA (all purchases)	Visa/AAA (pay-at-pump)
	(1)	(2)	(3)	(4)
ln(price$_t$)	-0.042	0.026	-0.122	0.004
	(0.010)	(0.024)	(0.016)	(0.017)
ln(income$_t$)	0.321	-1.272	0.154	0.093
	(0.066)	(0.405)	(0.167)	(0.189)
Month-of-Year Fixed Effects	X	X	X	X

Note: Columns (1) and (2) use EIA data on "product supplied" to measure quantity and the CPI average price data for unleaded regular to measure price. Column (3) uses our Visa expenditure data to measure quantity and a weighted average of our AAA average price data to measure price. Standard errors are estimated using a Newey-West procedure and are robust to serial correlation.

F Additional Figures

Figure F1: Day-of-Week Averages of Daily Nationwide Gasoline Expenditures by Visa Customers in our 243 Cities

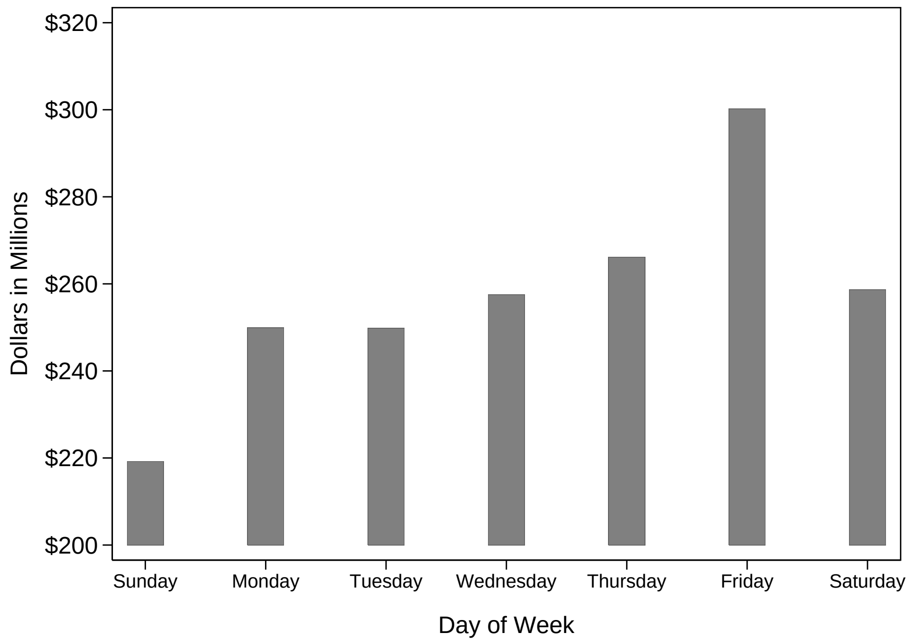

Figure F2: Day-of-Week Averages of Nationwide Gasoline Expenditures per Transaction by Visa Customers in our 243 Cities