Reference Dependence in the Demand for Gasoline*

Laurence Levin†
Matthew S. Lewis‡
Frank A. Wolak§

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Abstract

Recent behavioral models of reference-dependent or context-dependent preferences have posited that consumers form reference points or consideration sets based on expectations. We investigate this hypothesis empirically within the retail gasoline market. Given that gasoline consumers have been shown to form price expectations based on past price levels, reference- or context-dependence would likely cause gasoline demand to become more price-sensitive when prices are high relative to the recent past (i.e., higher than expected). Consistent with these predictions, we find that gasoline demand in the U.S. is up to three times more elastic when prices rise above their average over the previous year than when prices fall below this average. Reference-price effects vary substantially across cities with different demographic and commuting patterns, and cities that have less elastic demand for gasoline are shown to exhibit greater asymmetry in demand responsiveness. These findings provide valuable new evidence to support recent developments in the behavioral literature and also broaden our understanding of the factors affecting temporal and geographic heterogeneity in the price responsiveness of gasoline demand and the influence of price volatility on overall gasoline consumption. *JEL* Codes: Q41, D03.

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†VISA Decision Sciences, 901 Metro Center Boulevard, Mail Stop: M3-2B Foster City, CA 94404-2775, llevin@visa.com

‡Corresponding Author: John E. Walker Department of Economics, Clemson University, 228 Sirrine Hall, Box 341309, Clemson, SC 29634-1309, mslewis@clemson.edu

§Program on Energy and Sustainable Development and Department of Economics, Stanford University, Stanford, CA 94305-6072, wolak@zia.stanford.edu.

1 Introduction

Economists and psychologists have long considered the importance of reference dependence (Savage, 1954; Kahneman and Tversky, 1979) and evidence from numerous experimental and empirical studies has suggested that reference points can help to explain a variety of common behavioral phenomena.[1] More recently, models of reference- or context-dependent preferences by Kőszegi and Rabin (2006) and Bordalo, Gennaioli and Shleifer (2013) have attempted to rationalize a number of different behavioral biases within a single generalized framework. In both cases, expectations are assumed to determine the reference point or influence the context relative to which decisions are made. Consequently, the Kőszegi and Rabin (2006) model as well as some formulations of the Bordalo et al. (2013) framework suggest that reference- or context-dependence will cause consumers to be more responsive to price when prices are higher than expected levels and less responsive when prices are lower than expected.

Gasoline markets offer an ideal setting for studying reference dependence because large, unexpected price movements are common, consumers purchase frequently and at transparent prices, and we observe factors that directly influence consumers' expectations. Evidence has shown that gasoline consumers overwhelmingly rely on past prices when forming expectations of the prices they will encounter in the future (Anderson, Kellogg and Sallee, 2013). If these expectations serve as a reference point, then the demand for gasoline at a given price will depend also on the price levels experienced in the recent past. More specifically, based on Kőszegi and Rabin (2006) and Bordalo et al. (2013), consumers' gasoline demand is likely to be be more price sensitive when gasoline prices have increased relative to recent levels and less price sensitive when prices have decreased.

Using daily, city-level data on prices and city-level gasoline purchases on Visa cards in 177 cities across the United States between 2006 and 2014, we investigate the empirical validity of these hypotheses by examining how purchases of gasoline respond to both current prices and prices in the recent past. The results suggest that longer-run gasoline demand response tends to exhibit an elasticity of around -0.25 to -0.30. However, when

[1] See Section 2.2 of DellaVigna (2009) for a review of this literature.

prices increase above their average level over the previous year, demand responds more strongly, with an elasticity of -0.43, whereas when prices fall below their average over the previous year demand responds with an elasticity of only -0.14. Similar asymmetric patterns are found when considering recent prices over different time horizons.

These asymmetric patterns in gasoline demand response have not been documented in the previous literature and reveal a number interesting insights. One important consequence is that empirical studies of gasoline demand that do not account for these asymmetries are likely to obtain substantially more elastic estimates for sample periods when prices are rising more than falling, generating potentially misleading conclusions. Another important implication is that a temporary positive shock to prices will generate a greater reduction in quantity demanded than would an equal-sized temporary negative price shock. As a result, greater volatility in prices can generate lower total gasoline consumption over time even with no change in the average price of gasoline.

In an attempt to quantify the effect of price volatility on demand, we construct a counterfactual in which the log price of gasoline in each city is held constant over the entire sample period at the city-specific sample average value. Based on our parameter estimates, average gasoline consumption under constant prices would have been 1.6% higher than the observed level. To match observed consumption levels, the constant price in the counterfactual would have to have been around 6.7% (or 20 cents per gallon) higher than the true sample average.

Examining geographic heterogeneity in demand response reveals that cities with higher average per capita vehicle miles traveled (VMT) or a higher share commuting over 30 minutes to work exhibit significantly more elastic longer-run demand response. Demand also responds more elastically in cities with a lower share of people driving alone to work and a lower share with income less than twice the poverty level. These findings provide additional evidence (based on different data) for some of the relationships identified by previous studies of gasoline demand heterogeneity, including Wadud et al. (2010) and Small and Van Dender (2007), but offer contradictory evidence for others, such as Gillingham's 2014 finding that higher-income households are more elastic.

Incorporating reference dependence into our analysis of geographic demand heterogeneity produces the striking result that each of the characteristics associated with lower demand elasticity are also associated with substantially more severe reference dependence. Moreover, the geographic differences in reference dependence can be quite large. As an example, a city with a 16 percentage point (2 standard deviations) higher share of people commuting over 30 minutes to work is predicted to have 50% less asymmetry in response elasticity to positive and negative price changes.

These new results both enhance our understanding of the geographic and temporal variation in gasoline demand response and provide new empirical evidence to the evolving literature on reference dependence. Most notably, the influence of past price levels on demand responsiveness appears to directly support the central premise adopted by Kőszegi and Rabin (2006) and Bordalo et al. (2013) regarding importance of expectations. Our findings also complement those of Hastings and Shapiro (2013) who show that when gasoline prices increase consumers substitute from premium to regular grade gasoline to an extent that can not be explained by income effects. They conclude that observed grade-substitution patterns can be rationalized by the models of Kőszegi and Rabin (2006) and Bordalo et al. (2013) when longer-run expectations are incorporated. In contrast to our analysis, however, Hastings and Shapiro (2013) do not examine heterogeneity across consumers in the importance of expectations.

Studies including Genesove and Mayer (2001), Dhar and Zhu (2006) and Seru, Shumway and Stoffman (2010) explore heterogeneity in the intensity of behavioral biases in other settings and offer suggestive empirical evidence that such biases, including reference dependence, are more pronounced for unsophisticated agents than for those who are more experienced or engaged. To the extent that consumers who drive more and have longer commutes can be viewed as more experienced gasoline buyers, our results offer additional support for this proposition. Considering the predictions of Kőszegi and Rabin (2006) and Bordalo et al. (2013), one might also expect that consumers who purchase more gasoline or are more responsive to current prices would be more cognisant of past price levels and, therefore, exhibit stronger reference dependence. This interpretation, however, is not supported by our empirical findings.

2 Data

Our analysis examines daily gasoline price and expenditure data from 177 metropolitan (or micropolitan) areas across the United States from November 1, 2006 through November 30, 2014. Average daily prices for unleaded regular gasoline are obtained from the American Automobile Association (AAA) who publish the data on their *Gas Prices* website (`https://gasprices.aaa.com`). These average prices are provided to AAA by the Oil Price Information Service (OPIS) which generates averages based on prices collected from over 100,000 stations nationwide though information sharing agreements and fleet credit card transactions.

Data on gasoline expenditures come from the financial services company Visa Inc. We observe the total dollar amount of all purchases made on Visa credit or debit cards at at gas stations within each metropolitan area on each day. To control for fluctuations over time in the population of active Visa card users in each city, our analysis focuses on per capita consumption. The population of Visa card users in each city in a given month is measured as the total number of Visa cards that were used for any transaction in that metropolitan area within the month.

Levin, Lewis and Wolak (2017) also use Visa gasoline expenditure data (though for a shorter sample period) and discuss in detail both the advantages and disadvantages involved. The primary advantage is the much lower level of aggregation which reduces bias and makes it easier to control for unobserved demand shocks. Expenditures recorded at the actual point of sale are also likely to be much more geographically and temporally accurate than other measures of gasoline sales volume which are typically constructed based on the disappearance of refined products from primary suppliers like refineries and pipelines. One disadvantage is that the Visa data only reports total expenditures at gas stations, so our measure of the quantity of gasoline purchased is constructed as the total expenditure divided by the average gasoline price in that city on that day. In addition, total expenditures at gas stations can include non-gasoline purchases which would inflate our measure of quantity purchased and potentially bias estimates of gasoline demand elasticity. Fortunately, like Levin et al. (2017), we are able to avoid this potential bias by using only pay-at-pump transaction expenditures where non-gasoline items are entirely absent. Therefore, our measure of gasoline consumption reflects the total volume of gasoline purchased at the pump using Visa credit or debit cards within a given city on a given day.

Due to the nature of the data, we are analyzing the price responsiveness of gasoline demand based on a subset of the overall gasoline buyers. Estimates of demand elasticity may be affected if gasoline price changes impact the share of buyers that choose to purchase at the pump with a Visa card rather than using some other form of payment. Supplementary evidence presented by Levin et al. (2017) suggests that when gasoline prices increase consumers are somewhat more likely to purchase gasoline using credit or debit rather than cash and may also be more likely to purchase at the pump if higher gas prices cause them to make fewer in-store purchases. Consequently, demand elasticity estimates based on pay-at-pump transactions may, if anything, represent a slight underestimate (in absolute value) of the demand responsiveness of credit card users. To the extent that cash buyers exhibit a systematically different purchase behavior this is also not captured in our estimates. However, since three-quarters of all gasoline purchases are made with credit or debit cards (NACS, 2018), our estimates reflect the demand responsiveness of the majority of gasoline consumers.

Though average prices are reported by AAA for 285 cities, we deliberately focus our investigation on the 177 cities that do not exhibit evidence of Edgeworth cyclical pricing behavior. As as been well documented (Lewis, 2009; Lewis and Noel, 2011; Zimmerman, Yun and Taylor, 2013), a subset of cities throughout the United States have consistently exhibited cyclical price patterns in which retail prices frequently jump 10 to 20 cents per gallon in one day and then fall steadily over the course of a week or two before jumping again and repeating the cycle. This cyclical competitive equilibria produces volatile yet regular price fluctuations that are not driven by underlying cost changes and are very different from the normally stable and smoothly adjusting prices observed in other cities. Since consumers may develop distinctly different purchasing patterns in cities with large predictable price fluctuations, we restrict our gasoline demand analysis to cities exhibiting more typical pricing patterns.

Using the full 285 city AAA data sample, we identify cities with price cycles using a simple method proposed by Lewis (2009) and adopted in a number of subsequent studies. Since the cycles are characterized by large rapid price increases followed by many days of smaller price decreases, the median daily change in a city's average price over the sample period tends to be distinctly negative in cycling cities while being very close to zero in non-cycling cities. We define any city with a median daily price change below -0.15 cents per gallon to be a cycling city and exclude them from our analysis.[2] The 177 non-cycling cities selected for analysis are still quite diverse in terms of both size and geographic location, with 41 states represented.

3 Identifying and Estimating Gasoline Demand

The vast literature estimating gasoline demand has been summarized by a number of survey articles over the years, including Dahl and Sterner (1991); Goodwin (1992); Espey (1998); Basso and Oum (2007). Though many different empirical approaches have been used, the majority of studies (including recently Hughes, Knittel and Sperling, 2008; Li, Linn and Muehlegger, 2014) estimate gasoline demand using a simple log-linear model of quantity as function of the gasoline price and other variables included to control for temporal or cross-sectional shifts in demand. This functional form is convenient because the coefficient on log price can be directly interpreted as an estimate of demand elasticity. While a variety of other specifications have been considered, they tend to produce reasonably similar elasticity estimates (see Sterner and Dahl, 1992; Espey, 1998).

An important factor that has been shown to influence estimated elasticities is the level of geographic and temporal data aggregation. Studies often use monthly, quarterly, or annual aggregate proxies of gasoline usage and average prices, sometimes relying on a single national time series. Levin, Lewis and Wolak (2017) demonstrate that highly aggregated data tend to produce less elastic estimates of gasoline demand and identify several different sources of potential aggregation bias. Some of this bias arises from difficultly controlling for the endogeneity of price when using highly aggregated data. Nearly all

[2] This cutoff is similar to that used in other studies, and changes in the cutoff do not substantially affect the set of cities or the results of our demand analysis.

studies lack the data necessary to construct credible instrumental variables for use in demand estimation. As a result, the most common approach is to estimate demand using OLS while including additional control variables that help explain shifts in demand in order to minimize correlation between prices and unexplained demand shocks. Specifications using various macroeconomic variables to control for shifts in gasoline demand tend to generate highly inelastic estimates of demand. In contrast, studies working with more detailed panel data that use both cross-sectional and time-period fixed effects to control for demand shifts (such as Levin et al., 2017) generally reveal much more elastic estimates of demand. Davis and Kilian (2011) implement an instrumental variables estimation using state gasoline tax rate changes to instrument for changes in state-level gasoline prices and obtain an estimate of gasoline demand elasticity of $-.46$ (s.e.$=.23$) which is much closer to the OLS estimate from Levin et al. (2017) of $-.30$ (s.e. $=.03$) than to estimates from more aggregated studies like Hughes et al. (2008) ($-.04$ with s.e.$=.01$).

In this study we will adopt an approach similar to Levin et al. (2017) utilizing daily city-level panel data with extensive temporal and cross-sectional fixed effects to control for unobserved changes in demand. We begin by considering a static log-linear model of demand that relates total per capita gasoline consumption (Q_{jd}) in a city j on a day d to the average gasoline price (p_{jd}). In addition to city fixed effects (α_j) and day-of-sample fixed effects (λ_d) we also include city-specific month-of-year fixed effects (τ_{jM}) for city j in calendar month M to allow seasonal fluctuations in demand to vary across cities. Finally, since the impact of the 2008–2010 recession on gasoline demand may have differed in magnitude in different areas, a city-specific recession period indicator (ζ_{jR}) is also included.[3] When estimating this baseline model using OLS we obtain:

$$ln(Q_{jd}) = \underset{(0.04)}{-0.27}\, ln(p_{jd}) + \alpha_j + \lambda_d + \tau_{jM} + \zeta_{jR} + \epsilon_{jd}, \tag{1}$$

implying an elasticity of gasoline demand of $-.27$.[4]

The model estimated above is fairly restrictive in that it assumes demand responds immediately and with a constant elasticity to all changes in price. It is certainly possible

[3]The recession period has been defined as December 2007 through January 2010.

[4]The robust standard error (reported in parenthesis below the coefficient estimate) has been clustered by city to allow for correlation in errors within a city over time and also clustered by day to allow correlation across cities within each day.

that the initial demand response following a price change could differ somewhat from the longer-run response. For example, some factors that influence gasoline consumption, such as travel commitments, the type of automobile owned, or commute length, may take longer to adjust. Dynamic specifications of gasoline demand that include lagged prices are often estimated to allow for such differences.

The following more flexible specification allows the elasticity of demand response to differ depending on how how long it has been since the price change occurred. More specifically, it can identify the elasticity of demand during the first 60 days following a price change, as well as separate elasticities for the responses occurring between 60 and 120 days, between 120 and 240 days, between 240 and 360 days, and after 360 days.

$$\begin{aligned} ln(Q_{jd}) &= \underset{(0.04)}{-0.26}\, ln(\frac{p_{jd}}{p_{j,d-60}}) + \underset{(0.06)}{-0.29}\, ln(\frac{p_{j,d-60}}{p_{j,d-120}}) + \underset{(0.08)}{-0.31}\, ln(\frac{p_{j,d-120}}{p_{j,d-240}}) \\ &\quad + \underset{(0.10)}{-0.25}\ ln(\frac{p_{j,d-240}}{p_{j,d-360}}) + \underset{(0.13)}{-0.21}\, ln(p_{j,d-360}) \\ &\quad + \alpha_j + \lambda_d + \tau_{jM} + \zeta_{jR} + \epsilon_{jd}. \end{aligned} \quad (2)$$

Interestingly, the demand elasticity estimates reported in Equation 2 are all relatively similar to each other and to the estimate from the static model in Equation 1. Though the estimated demand response after 360 days is somewhat smaller it is also less precise. Overall, there are no statistically significant differences in elasticity estimates across the lag lengths. The findings imply that gasoline demand responds fairly completely to a price change within the first 60 days and remains relatively unchanged thereafter. As a result, demand response is captured relatively well using the simple static demand model in Equation 1.

3.1 Demand with Reference Prices

In the wake of Savage (1954) and Kahneman and Tversky (1979) economists have uncovered extensive evidence of reference dependence in wide variety of experimental and empirical settings.[5] Different types of reference points have been considered in different applications, often inspired by abstract behavioral concepts such as endowment effects or status-quo bias. Kőszegi and Rabin (2006) offer perhaps the most complete model of

[5] See Section 2.2 of DellaVigna (2009) for a review of this literature.

reference-dependent preferences based on the idea that reference points are determined by the expectations that individuals held in the recent past. They argue that this framework can rationalize endowment effects, status-quo biases, and other types of reference points to the extent that agents' expectations are informed by these factors. Subsequent experimental (Abeler et al., 2011; Marzilli Ericson and Fuster, 2011) and empirical (Crawford and Meng, 2011; Card and Dahl, 2011) studies have provided evidence supporting the idea that expectations serve as a reference point.

It would be quite reasonable for consumers' expectations about future gasoline prices to impact their gasoline purchasing behavior. Given that gasoline prices tend to be highly volatile, consumers frequently end up paying prices that differ substantially from what they would have predicted several months prior. The model of Kőszegi and Rabin (2006) allows consumers' purchase decisions today to be influenced not only by the price of gasoline today but also by any deviation from the price they expected (in the recent past) to be paying for gasoline today. When combined with a gain-loss utility function (i.e. loss aversion) this assumption generates an asymmetry in the response of consumers to positive and negative deviations from past price expectations.

Bordalo, Gennaioli and Shleifer (2013) provide an alternative salience-based framework that also incorporates expectations. If the appropriate choice context is specified, this model can similarly rationalize asymmetry in the responsiveness of gasoline demand around past price levels.[6] When the price of a product is higher than it was expected to be, price becomes more salient to consumers than the other non-price characteristics of the product and, as a result, consumers become more price sensitive. Similarly, consumers can become less price sensitive when actual prices are below expectations.[7]

As Hastings and Shapiro (2013) point out, changes in the specification of the choice context (or consideration set) within the Bordalo et al. (2013) model often result in different predictions. While some specifications predict that deviations in price from expected

[6]In Bordalo et al. (2013), the salience of an attribute (e.g., price) is determined by how far its value is from the mean value within the choice context (or consideration set). When both actual and expected prices are included in the choice context, lower expected prices can increase this distance and cause the price attribute to be relatively more salient.

[7]These general properties are discussed by Bordalo et al. (2013) following their Definition 2, but the specific context that most closely matches our situation is the setting proposed in their Section IV.B.

levels will generate asymmetric changes in demand responsiveness, other specifications suggest that both positive and negative deviations from expectations will (symmetrically) increase price salience and price responsiveness. Consequently, investigating these relationships empirically can reveal the types of choice contexts that most accurately capture consumer behavior within the Bordalo et al. (2013) model.

It is important to highlight that past price expectations can also influence demand if consumers rely on expected gasoline prices when making fixed investments that will impact their gasoline demand in the longer run (e.g. making travel plans, buying a car, deciding where to live and work). These mechanisms may shift and rotate demand, reducing elasticity in the short run, but they are unlikely to create a kink in demand around past price expectations. As a result, finding that past price expectations influence demand may reflect fixed investments, but finding a substantial and distinct asymmetry in the response of demand to deviations from past price expectations is more likely associated with reference dependence.

While the Kőszegi and Rabin (2006) and Bordalo et al. (2013) models specify that reference points arise based on expectations from the recent past, the time frame over which expectations are relevant depends on the setting to which it is applied. This raises an additional empirical question which we can explore. How recent of expectations do gasoline consumers use to formulate reference points?

Empirically examining reference dependence in gasoline demand heavily relies on observing or estimating consumers' past price expectations. Previous studies including Anderson, Kellogg and Sallee (2013) and Alquist and Kilian (2008) have clearly demonstrated there is generally no better predictor of future gasoline prices that the current price level.[8] Moreover, Anderson et al. (2013) use survey data to show that consumers tend to expect future gasoline prices to be about the same as the current price. Relying on these results, our empirical analysis will assume that past price expectations can be reasonably approximated using historical price information.[9]

[8] While Alquist and Kilian (2008) focus on predicting crude oil prices rather than gasoline, oil prices explain nearly all longer run variation in gasoline prices so these findings are highly related.

[9] This assumption has also been relied on quite heavily by researchers studying the demand for energy-consuming durable goods like automobiles. While vehicle choice might reasonably be affected by expected

To capture the fact that deviations from reference prices are likely to influence demand asymmetrically, we specify the following generalization of the log-linear demand model from Equation 1:

$$\begin{aligned} ln(Q_{jd}) &= \beta_1 ln(p_{jd}^{expected}) + \beta_2 \left[ln \left(\frac{p_{jd}}{p_{jd}^{expected}} \right) \right]^+ + \beta_3 \left[ln \left(\frac{p_{jd}}{p_{jd}^{expected}} \right) \right]^- \\ & \quad + \alpha_j + \lambda_d + \tau_{jM} + \zeta_{jR} + \epsilon_{jd} \end{aligned} \tag{3}$$

where:

$$X^+ = \begin{cases} X & : X > 0 \\ 0 & : X \leq 0 \end{cases} \quad and \quad X^- = \begin{cases} 0 & : X > 0 \\ X & : X \leq 0 \end{cases} \quad .$$

If deviations from past price expectations have no impact on demand, then β_1, β_2, and β_3 will all be equal and all expected price terms will drop out leaving the original log-linear model of Equation 1. On the other hand, a β_2 that is substantially larger in magnitude than β_3 would be consistent with consumers having reference-dependent preferences and responding much more elastically to losses (i.e. higher prices) than to gains.

The horizon over which consumers use past prices to formulate their expectations is unknown, so we estimate the model using different measures of $p_{jd}^{expcted}$ based on average prices over the past 60 days, 120 days, 240 days, 360 days, or 720 days. Results are reported in Table 1. Standard error estimates have been clustered by city and also by day-of-sample to allow for potential correlation in errors across cities within a given day as well as temporal correlation within each city. Regardless of how expectations are measured, the coefficient estimates on positive deviations from expected price are significantly larger in magnitude than those for negative price deviations. Consumers appear to respond much more elastically when prices are higher than in the recent past and respond less elastically when prices are lower.

The influence of past prices on demand appears to be fairly long-lasting. If anything, the asymmetric response to positive and negative deviations becomes more pronounced when expectations are represented using longer-run average prices. Since the sample period is shorter for the specification using a 720-day average due to lack of previous price

fuel costs over the life of the vehicle, virtually all researchers use current gasoline prices when calculating the expected cost of driving for each vehicle.

Table 1: Gasoline Demand Elasticity with Reference Dependence over Different Time Horizons

	(1) 720 Days	(2) 360 Days	(3) 240 Days	(4) 120 Days	(5) 60 Days
$ln(\frac{\text{price}}{\text{mean price over previous X days}})^{+}$	-0.478	-0.427	-0.353	-0.308	-0.328
	(0.062)	(0.053)	(0.050)	(0.044)	(0.048)
$ln(\frac{\text{price}}{\text{mean price over previous X days}})^{-}$	-0.192	-0.138	-0.201	-0.203	-0.203
	(0.044)	(0.047)	(0.047)	(0.041)	(0.043)
ln(mean price over previous X days)	-0.068	-0.234	-0.276	-0.311	-0.281
	(0.238)	(0.146)	(0.117)	(0.084)	(0.065)
N	472306	516138	516258	516378	516438
R^2	0.918	0.909	0.909	0.909	0.909

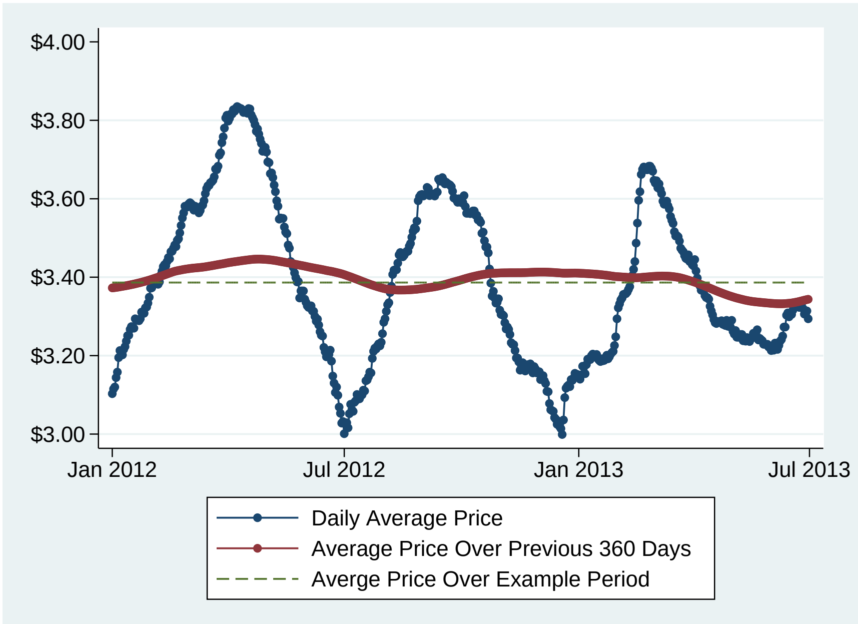
Robust standard errors (in parentheses) incorporate two-way clustering on city and day of sample.
Dependent Variable is ln(Quantity of Gasoline per Capita Purchased at the Pump)

observations, we largely focus on specifications using the 360-day average price for the remainder of our analysis.

Exploring alternative models confirms the critical role that past price levels play in determining when consumers will respond more elastically. For example, the patterns revealed in Table 1 do not appear to arise from consumers simply responding more elastically when prices are high than when they are low. As a robustness check we estimate a specification allowing each coefficient in Equation 1 to have different values when prices are in different quartiles of the city-specific mean price distribution. The results (reported in Table A1) reveal that quartile-specific elasticities still exhibit substantial asymmetry around the average price over the previous year. Consumers may respond somewhat more elastically at higher price levels in general, but these responses are still strongly affected by relative deviations from prices in the recent past.

One interesting implication of the asymmetric response of gasoline demand to price movements around a reference price is that additional price volatility itself can lead to lower gasoline consumption. Since the quantity demanded will fall more when prices rise than it will rise when prices decline, equal deviations above and below the reference price will result in less gasoline consumption than if prices had stayed stable at the reference price.

Figure 1: Daily Average Retail Gasoline Prices in Charlottesville, VA



To illustrate this, consider the gasoline prices observed in Charlottesville, VA from January 2012 through June 2013. As is demonstrated in Figure 1, prices fluctuated fairly regularly around an average level of $\$3.39$ during this period, but the 360-day trailing average of prices remained quite stable at a level very close to the period's average price. Based on the coefficient estimates from Column 2 of Table 1, our model predicts that total gasoline consumption over the period would have been 0.7% higher if prices had stayed steady at $\$3.39$ rather than fluctuating as they did. This drop in demand resulting from price volatility over the period is of the same magnitude as one would expect to result from a permanent 3% (or 10 cents/gallon) increase in the price level.

To get a broader understanding of the impact of price volatility on demand we also construct a counterfactual in which the log price of gasoline in each city is held constant over the entire sample period at the city-specific sample average value. In the constant price world, the price is always equal to the average over the previous year which is always equal to the sample average. Hence, our estimate of the average daily percentage difference between observed and counterfactual consumption is:

$$\frac{1}{DJ}\sum_{d=0}^{D}\sum_{j=0}^{J}\left(\hat{\beta}_1 ln\left(\frac{p_{jd}^{expected}}{\overline{p}_j}\right)+\hat{\beta}_2\left[ln\left(\frac{p_{jd}}{p_{jd}^{expected}}\right)\right]^{+}+\hat{\beta}_3\left[ln\left(\frac{p_{jd}}{p_{jd}^{expected}}\right)\right]^{-}\right),$$

where $\overline{p}_j$ is the sample average price in city j, and D and J represent the total number of days and cities in the sample, respectively. Based on our parameter estimates, average gasoline consumption with constant prices would have been 1.6% higher than the observed level. To match true consumption levels observed with price volatility, the constant price in the counterfactual would have to have been around 6.7% (or 20 cents per gallon) higher than the true sample average. In other words, the average reduction in consumption generated by price volatility is similar to the long-run demand effect of the federal gasoline tax of 18.4 cents per gallon. Moreover, empirical studies of gasoline demand that don't account for this effect are likely to confound responses to price volatility with responses to correlated movements in the price level and draw misleading conclusions about the underlying elasticity of demand.

4 Geographic Variation in Gasoline Demand Elasticity

The results in the previous section clearly identify an asymmetry in gasoline demand response, but reveal little about the underlying factors giving rise to this behavior. Fortunately, with our detailed panel data it is possible to examine more carefully geographic heterogeneity in demand elasticity and asymmetric response and study how these relate to various regional characteristics.

A number of studies have examined how gasoline demand elasticity varies across geographic areas or consumer groups but have not considered the presence or degree of asymmetry in demand response. Moreover, previous studies have been limited by substantial geographic or temporal data aggregation, typically relying either on regional averages observed annually or monthly (as in Small and Van Dender (2007)) or on individual level survey data that is cross-sectional or observed over only a few quarters or years (as in Wadud et al. (2010) or Gillingham (2014)).

Table 2: City Characteristics

(a) Summary Statistics

	Mean	Std. Dev.	5th Percentile	95th Percentile
share commuting over 30 min	0.254	0.078	0.129	0.393
share driving alone	0.808	0.061	0.713	0.866
daily VMT per 100 people	0.267	0.067	0.176	0.392
share over twice poverty level	0.705	0.069	0.580	0.805
N	177			

(b) How Commuting Characteristics are Related

		Share Commuting over 30 Minutes to Work	
		Top Quintile	Bottom Quintile
Share Driving Alone to Work	Top Quintile	Birmingham, AL Baton Rouge, LA Raleigh-Durham, NC	Fargo, ND Sioux Falls, SD Waterloo, IA
	Bottom Quintile	Los Angeles, CA Oakland, CA Newark, NJ	Juneau, AK Santa Barbara, CA Flagstaff, AZ

Using our daily city-level data we explore heterogeneity in the elasticity of demand across cities by allowing the price-related coefficients in Equations 1 and 3 to vary as a linear function of city characteristics. Information on driving patterns and household income are collected from the 2010 U.S. Census for the metropolitan and micropolitan statistical areas represented in our sample. In addition, data on the average per capita daily vehicle miles traveled (VMT) in each area are obtained from the Federal Highway Administration's Highway Statistics 2012. We have deliberately chosen to use cross-sectional measures that capture exogenous and persistent differences across cities in income and travel behavior rather than using time-varying panel data where fluctuations in driving behavior could partially reflect responses to gasoline price changes. Summary statistics are reported in Table 2a. To better illustrate the types of cities that have particularly extreme commuting patterns, Table 2b lists cities that lie within either the upper or lower quintile of values for both the share commuting over 30 minutes to work and the share driving alone to work.

Table 3: Gasoline Demand Elasticity and City Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
ln(price)	-0.271	-0.097	-1.070	-0.137	-0.632	-1.159
	(0.047)	(0.059)	(0.207)	(0.067)	(0.122)	(0.231)
ln(price) $\times$ share commuting over 30 min		-0.671				-0.493
		(0.130)				(0.144)
ln(price) $\times$ share driving alone			0.967			0.946
			(0.243)			(0.270)
ln(price) $\times$ daily VMT per 100 people				-0.350		-0.386
				(0.149)		(0.148)
ln(price) $\times$ share over twice poverty level					0.519	0.544
					(0.153)	(0.146)
N	516497	516497	516497	472712	516497	472712

Robust standard errors (in parentheses) incorporate two-way clustering on city and day of sample.
Dependent Variable is ln(Quantity of Gasoline per Capita Purchased at the Pump)

To understand generally how demand elasticities vary with city characteristics we first estimate the traditional log-log demand model while interacting log price with the variables in Table 2a, both individually and together in one specification. The results reported in Table 3 reveal that consumers' demand for gasoline tends to be more elastic on average in cities where a higher share of workers commute longer than 30 minutes to work and in cities where the average number of miles driven per day is greater. Both of these measures tend to be higher in large metro areas. In contrast, demand is less elastic in cities where a high share of commuters drive alone to work, which is often the case when public transportation options are limited and few people live close enough to work to walk or bike. Cities in which more households have income greater than twice the poverty level also tend to have less elastic demand for gasoline.[10]

Interestingly, some of these results are noticeably different from Gillingham (2014) who examines heterogeneity in the elasticity of demand for vehicle travel using smog check odometer readings of cars in California. Gillingham reports that households with higher VMT and households in areas with longer average commute times tend to have less-elastic demand, while our results suggest these groups respond more elastically to gasoline price

[10]A similar relationship is identified when using alternative measures such as the median income level.

changes. In addition, cities with more low-income households exhibit more elastic demand in our analysis which is consistent with the findings of Wadud et al. (2010) and Small and Van Dender (2007) but not with Gillingham (2014) who finds higher-income households to be somewhat more elastic. Such differences could arise if demand in California (examined by Gillingham (2014)) were sufficiently different from the rest of the U.S. It is also possible that the higher degree of temporal aggregation in Gillingham's data make it more difficult to control for contemporaneous macroeconomic fluctuations that may influence gasoline demand differently in different regions of the state, as shown in Levin et al. (2017).

To examine geographic differences in the degree of reference dependence in gasoline demand we interact our city characteristics with each of the three price-related variables in Equation 3. For simplicity we focus only on specifications using the average price over the previous year as the reference price. Estimates from these specifications are reported in Table 4. Our baseline model with reference dependence (in Table 1) revealed that demand responses to positive deviations from the reference price are more elastic than responses to negative deviations from the reference price. As a result, any of the characteristics considered in Table 4 can be interpreted to be associated with greater reference dependence when coefficients on positive price-deviation interactions are smaller than those for negative price-deviation interactions, because increases in the characteristic variable would then create a larger difference in the elasticity of response to positive versus negative deviations from the reference price. For example, using estimates from Column 6, a 12 percentage point (or roughly 2 standard deviation) increase in the share of people driving alone to work would imply a reduction of 0.08 in the coefficient on positive price deviations and an increase of 0.06 in the coefficient on negative deviations, causing the asymmetry in the elasticity of demand response to increase by 0.14.[11] In contrast, a 2 standard deviation increase (of 0.16) in the share of people commuting more than 30 minutes to work would result in a reduction of 0.21 in the asymmetry of response elasticity for positive versus negative deviations. Both of these changes are quite large relative to the average level of asymmetry, which according to the estimate from Table 1, Column 2 is around 0.29.

Across all specifications in Table 4 the degree of reference dependence is found to

[11]The change is calculated as: 0.491*0.12 - (-0.641)*0.12 = 0.14.

Table 4: Gasoline Demand Elasticity and City Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
$ln\left(\frac{P_{it}}{\overline{P}_{it}^{360}}\right)^{+}$	-0.427	-0.748	0.184	-0.573	-0.470	-0.253
	(0.053)	(0.064)	(0.188)	(0.079)	(0.151)	(0.175)
$ln\left(\frac{P_{it}}{\overline{P}_{it}^{360}}\right)^{-}$	-0.138	-0.034	-0.429	-0.021	-0.340	-0.508
	(0.047)	(0.053)	(0.169)	(0.064)	(0.096)	(0.186)
$ln(\overline{P}_{it}^{360})$	-0.234	0.147	-1.895	0.022	-0.929	-2.024
	(0.146)	(0.158)	(0.430)	(0.178)	(0.295)	(0.473)
$ln\left(\frac{P_{it}}{\overline{P}_{it}^{360}}\right)^{+} \times$ share commuting over 30 min		1.518				1.160
		(0.192)				(0.192)
$ln\left(\frac{P_{it}}{\overline{P}_{it}^{360}}\right)^{-} \times$ share commuting over 30 min		-0.366				-0.170
		(0.113)				(0.120)
$ln(\overline{P}_{it}^{360})\times$ share commuting over 30 min		-1.678				-1.373
		(0.242)				(0.274)
$ln\left(\frac{P_{it}}{\overline{P}_{it}^{360}}\right)^{+} \times$ share driving alone			-0.697			-0.641
			(0.232)			(0.179)
$ln\left(\frac{P_{it}}{\overline{P}_{it}^{360}}\right)^{-} \times$ share driving alone			0.408			0.491
			(0.196)			(0.216)
$ln(\overline{P}_{it}^{360})\times$ share driving alone			1.934			1.836
			(0.476)			(0.506)
$ln\left(\frac{P_{it}}{\overline{P}_{it}^{360}}\right)^{+} \times$ daily VMT per 100 people				0.735		0.395
				(0.217)		(0.168)
$ln\left(\frac{P_{it}}{\overline{P}_{it}^{360}}\right)^{-} \times$ daily VMT per 100 people				-0.400		-0.485
				(0.119)		(0.124)
$ln(\overline{P}_{it}^{360})\times$ daily VMT per 100 people				-0.729		-0.628
				(0.288)		(0.274)
$ln\left(\frac{P_{it}}{\overline{P}_{it}^{360}}\right)^{+} \times$ share over twice poverty level					0.058	0.082
					(0.204)	(0.178)
$ln\left(\frac{P_{it}}{\overline{P}_{it}^{360}}\right)^{-} \times$ share over twice poverty level					0.273	0.266
					(0.112)	(0.111)
$ln(\overline{P}_{it}^{360})\times$ share over twice poverty level					0.924	1.001
					(0.311)	(0.291)
N	516138	516138	516138	472353	516138	472353

Robust standard errors (in parentheses) incorporate two-way clustering on city and day of sample.
Dependent Variable is ln(Quantity of Gasoline per Capita Purchased at the Pump)

be higher in cities where: more people have incomes above twice the poverty level, more people drive alone to work, fewer people commute over 30 minutes to work, and average per capita vehicle miles traveled are lower. Interestingly, each of these characteristics are also associated with lower levels of gasoline demand elasticity according to estimates in Table 1. In other words, cities that exhibit lower levels of demand elasticity also tend to exhibit a grater degree of reference dependence.

5 Discussion and Conclusion

Our empirical analysis establishes robust evidence of reference dependence in the demand for gasoline. Gasoline consumption is three times more price-responsive when prices increase relative to recent levels than when prices decrease relative to recent levels, supporting the idea that past prices serve as an important reference point. Across a broad panel of 177 cities, we find substantial variation in both the overall elasticity of demand for gasoline and the degree of reference dependence. Moreover, each of the city-level characteristics found to be associated with greater reference dependence are also shown to correlate with less elastic demand. In the gasoline market, at least, it appears that consumers who are more elastic also tend to exhibit less reference dependence on average. Documenting these patterns provides a clearer foundation for understanding geographic and temporal variation in gasoline demand and demand response, and also offers an opportunity to more thoroughly evaluate some of the potential explanations of reference dependence.

Many studies view loss aversion and other related phenomena as behavioral biases exhibited by relatively unsophisticated agents and suggest that such biases may be overcome by consumers with higher levels of experience or engagement. For example, investors commonly exhibit a reluctance to sell investments that have lost value,[12] and this tendency appears to be more pronounced for inexperienced investors. Barber et al. (2007) and Shapira and Venezia (2001) find this bias to be stronger amongst individual investors than amongst corporate or professional investors, and Dhar and Zhu (2006) and Seru et al. (2010) find that it declines with trading experience. Similarly, in the real estate market,

[12]Commonly referred to as the "disposition effect", this tendency was highlighted by Shefrin and Statman (1985) and has been empirically documented in the field by Odean (1998) and others.

Genesove and Mayer (2001) show that owner-occupants are significantly more averse to realizing a nominal loss when selling their property than are investor-owners. In the gasoline market, individuals with longer commutes and higher VMT could be reasonably viewed as more experienced or knowledgeable consumers. In this sense, our results are consistent with previous findings. Cities with more of these consumers tend to exhibit less reference dependence.

Kőszegi and Rabin (2006) and Bordalo et al. (2013) each offer generalized theoretical frameworks within which expectations based on past prices can influence the responsiveness of demand. In both settings, the influence of past prices on demand may depend on the degree to which different consumers recall past prices or the importance they place on such expectations. For example, consumers who drive more and purchase more gasoline may have a stronger recollection of past price levels. In this case, past price levels could be expected to more strongly impact the demand of consumers who drive more, which is not supported by our empirical findings. Another possibility is that highly inelastic gasoline consumers simply don't devote much attention to the prices they pay and don't keep a mental record of past price levels because price has little influence on their purchase decision. Our results also appear to contradict this narrative, as inelastic consumers tend to exhibit greater reference dependence.

The theoretical representations of Kőszegi and Rabin (2006) and Bordalo et al. (2013) also include a parameter or function that scales the degree of behavioral bias. In Kőszegi and Rabin (2006) this is the degree of nonlinearity in the assumed gain-loss function (μ), and in Bordalo et al. (2013) this is the severity of salient thinking (δ). Unfortunately, theory doesn't offer guidance on what might influence the severity of these relationships. As a result, it is possible that less elastic drivers just tend to have a lower level of susceptibility to such biases for reasons outside of the scope of these models.

Since the predictions of the Bordalo et al. (2013) model depend heavily on the specification of the choice context or consideration set, our empirical findings also shed light on the types of choice contexts that most accurately capture consumer behavior in this market. The model suggests that gasoline price salience and price responsiveness should depend on how far the gas price is from the average price within the consideration set (which also includes the expected price). For demand responsiveness to depend asymmetrically on price expectations, the choice context must be specified so that the gasoline price is always above the average price within the consideration set. In this case, a higher expected price increases the average price within the consideration set closer to the actual gasoline price and reduces price salience, whereas a lower expected price reduces the average price further below the actual gasoline price and increases price salience.[13] Alternative choice contexts that do not meet this criteria do not appear to be empirically supported within the gasoline market.

While we are unable to explicitly test between potential theoretical explanations, we present important new evidence that past prices strongly and asymmetrically influence the price sensitivity of gasoline demand in ways that can not be explained using standard neoclassical models. Moreover, our empirical findings reveal that price expectations more strongly influence the responsiveness of relatively inelastic customers, suggesting that additional theoretical investigation of the behavioral links between reference dependence and demand elasticity could be particularly valuable in advancing this research agenda.

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[13]This can be achieved, for example, by including less-attractive, lower-priced alternatives (such as not buying gas at all) within the consideration, similar to the example in Section IV.B. of Bordalo et al. (2013).

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Table A1: Reference-Dependent Gasoline Demand Elasticity
for Different Price Quantiles

	Coef.	S.E.
$ln(\frac{\text{price}}{\text{mean price over previous 360 days}})^{+}$:		
Quartile 1 (lowest)	-0.458	(0.089)
Quartile 2	-0.456	(0.078)
Quartile 3	-0.615	(0.083)
Quartile 4 (highest)	-0.460	(0.067)
$ln(\frac{\text{price}}{\text{mean price over previous 360 days}})^{-}$:		
Quartile 1	-0.187	(0.048)
Quartile 2	-0.083	(0.071)
Quartile 3	-0.106	(0.080)
Quartile 4	0.611	(0.248)
$ln(\text{mean price over previous 360 days})$:		
Quartile 1	-0.178	(0.150)
Quartile 2	-0.269	(0.143)
Quartile 3	-0.409	(0.162)
Quartile 4	-0.419	(0.167)
Quartile 2 Fixed Effect	0.092	(0.038)
Quartile 3 Fixed Effect	0.245	(0.083)
Quartile 4 Fixed Effect	0.262	(0.098)
N	516138	
R^2	0.910	

Note: Robust standard errors (in parentheses) incorporate two-way clustering on city and day of sample. Dependent Variable is ln(Quantity of Gasoline per Capita Purchased at the Pump).