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Reference Dependence in the Demand for Gasoline[*]

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Abstract

Consistent with the predictions of recent behavioral models of reference- or context-dependent preferences, 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. In cities where residents drive more, gasoline demand is less elastic but exhibits greater reference dependence. We also demonstrate that the asymmetric demand response generated by reference dependence can cause total gasoline consumption over a period of time to be lower when prices are more volatile than when prices exhibit the same average level but are more stable. *JEL* Codes: Q41, D9.

Keywords: reference dependence, gasoline demand, asymmetric demand response, reference price

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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 the current price level when forming expectations of the prices they will encounter in the future (Anderson, Kellogg and Sallee, 2013). If these expectations subsequently 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 through their influence on expectations of today's price. More specifically, based on Kőszegi and Rabin (2006) and Bordalo et al. (2013), consumers' gasoline demand is likely to be more elastic when gasoline prices have increased relative to recent levels and

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

less elastic when prices have decreased.[2]

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 gasoline demand response tends to exhibit an elasticity of around -0.25 to -0.30. However, when 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. A variety of alternative specifications confirm the substantial effect that reference prices have on the elasticity of consumer demand and rule out alternative explanations, such as the possibility that demand is simply more elastic when price levels are high than when they are low.

These asymmetric patterns in short run 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 (temporary) reduction in quantity demanded than the quantity increase from 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

[2]It should be noted that our analysis focuses on whether consumers' gasoline usage exhibits reference dependence. Therefore, we model the overall demand for gasoline rather than the demand faced by any particular station. An extensive literature has explored the nature of gas station competition and the role of consumer price search, as surveyed by Eckert (2013) and Noel (2016). Ultimately, however, the decision of where to buy gas has little impact on overall gasoline usage.

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 a significantly more elastic demand response. Demand also responds more elastically in cities with a lower share of people driving alone to work or a higher share of households with income below 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 price elastic.

Incorporating reference dependence into our analysis of geographic demand heterogeneity produces the striking result that each of the driving-related 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 its price elasticity above vs. below the reference price level.

Several previous studies, including Gately (1992), Dargay and Gately (1995), and Gately and Huntington (2002), have empirically examined longer-run asymmetric energy demand response or imperfect price-reversibility using annual data to evaluate the importance of large irreversible investments such as the development of more fuel efficient technologies following higher oil prices in the 1970s. In contrast, our study investigates an entirely different source of asymmetric demand response—reference dependence—that occurs over the short to medium run (i.e., weeks and months) where vehicle technologies and other investments are likely fixed. Additionally, these previous studies estimate gasoline demand using annual time series data with little acknowledgment or attempt to address the substantial endogeneity challenges inherent in such an exercise, while our study uses daily panel data and a two-way fixed effects approach help to mitigate endogeneity concerns to identify asymmetric demand response and the role of reference prices. Our detailed panel data also allow us to examine geographic heterogeneity in the asymmetry of demand response and relate it to relevant demographic characteristics.

The analysis reveals that observed asymmetries in demand reflect actual reference-dependent responses in fuel usage and are not simply the result of very short run responses in the timing of purchase that occur in the days immediately following a price change. Gasoline sales temporarily respond with a greater elasticity, consistent with the adjustments to purchase timing highlighted by Levin et al. (2017). However, these very short run responses are largely symmetric or, if anything, more pronounced following price decreases than price increases. After 3 to 5 days, these temporarily high response elasticities subside, and demand becomes less responsive when prices are below where they have been in previous months.

These new results both enhance our understanding of 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 grade (higher octane) to regular grade (lower octane) gasoline to an extent that cannot be explained by income effects. Similarly, they conclude that observed grade-substitution patterns are consistent with the models of Kőszegi and Rabin (2006) and Bordalo et al. (2013) when longer-run expectations are incorporated.

The demand responses identified in our analysis, however, are distinctly different from the behavior highlighted by Hastings and Shapiro (2013). Rather than examining quantity responses, they use consumers' choice of octane level to demonstrate that money spent on gasoline is not fungible with money spent on other goods.[3] Consumers are shown to substitute between grades more frequently in response to a change in income generated by a change in the gasoline price than to an equivalent change in income available to spend on other goods. Such non-fungibility may also cause consumers' demand for gasoline to respond more elastically to both increases and decreases in gasoline price than to other changes in the budget constraint, but cannot explain why we observe demand responding more elastically to prices above the reference level but less elastically below. In this sense, our results identify a new asymmetry in an arguably more consequential dimension of the gasoline purchase decision. In addition, 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,

[3] In Hastings and Shapiro (2013) the purchase quantity is assumed to be exogenous and independent of the choice of octane level.

Shumway and Stoffman (2010) have explored heterogeneity in the intensity of behavioral biases in other settings and have offered 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, and therefore less reference dependent, our results offer additional support for this proposition. Alternatively, considering the predictions of Kőszegi and Rabin (2006) and Bordalo et al. (2013), one might instead expect that consumers who purchase more gasoline or are more responsive to current prices would be more cognizant of past price levels and, therefore, exhibit stronger reference dependence. This prediction 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 an average of the posted prices collected from over 100,000 stations nationwide through information sharing agreements and fleet credit card transactions.[4]

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 and debit cards at

[4]Prices reflect averages across observed stations. Quantity-weighted average purchase prices are unavailable.

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. One significant advantage is the much lower level of aggregation which reduces bias in the elasticity estimates 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, for all the analysis in this study we measure gasoline consumption using the total volume of gasoline purchased at the pump with 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 has 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 gasoline 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 equilibrium 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.

We exclude cycling cities from our main analysis because consumers in cities with large predictable price fluctuations are likely to develop distinctly different purchasing patterns. Once consumers understand the cyclical pricing movements, their demand for gasoline on a given day may depend on the position of prices within the cycle. Moreover, since these cyclical price movements have an asymmetric pattern of rising quickly and falling slowly, this could generate an asymmetric response in gasoline purchases that is very different from what would arise in a non-cycling market. Therefore, to simplify the empirical setting and isolate the asymmetric responses in gasoline consumption that can result from reference dependence, our primary analysis considers cities exhibiting more typical pricing patterns, but we also present results based on all cities for completeness.

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.[5] 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 a 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

[5]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.

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; Levin et al., 2017).

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 difficulty controlling for the endogeneity of price when using highly aggregated data. Nearly all 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. Any unexpected city-specific gasoline demand shocks not captured by these fixed effects are likely to be relatively small. In addition, local gasoline supply curves tend to be fairly elastic in the short run because the local storage and distribution infrastructure can be used to arbitrage day-to-day demand fluctuations. As a result, any bias arising from the endogeneity of price is likely to be minimal. In contrast, temporary regional gasoline supply shocks resulting from refinery outages or pipeline disruptions regularly generate significant variation in relative prices across cities that facilitate the empirical identification of local gasoline demand.[6] The primary advantages of using daily data, therefore, are the ability to obtain more robust estimates of short run (or medium run) responses and the ability to flexibly incorporate potential reference dependence. Daily data also allows us to study very short-run demand responses occurring in the days immediately following a price change. However, these responses are not the primary focus of the analysis, nor do they drive the demand elasticities and reference dependence that we estimate.

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, because 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.[7] When estimating this baseline model using OLS we obtain:

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

[6]For a more extensive discussion of identification see Levin et al. (2017).

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

implying an elasticity of gasoline demand of $-.27$.[8]

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 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. Such factors will have been determined based on past expectations of today's price, and those expectations are likely to have been informed by price levels that prevailed at the time. As a result, current gasoline demand may be influenced by both current and past gasoline price levels. In the empirical literature, these dynamic effects are often incorporated into the estimation of gasoline demand by adopting either a lagged dependent variable model or a more flexible distributed lag model (Dahl and Sterner, 1991).

To allow for the possibility of lagged demand response in our setting, we consider a distributed lag demand model:

$$ln(Q_{jd}) = \sum_{l=0}^{L} \delta_l ln(p_{j,d-l}) + \alpha_j + \lambda_d + \tau_{jM} + \zeta_{jR} + \epsilon_{jd}, \tag{2}$$

where demand today responds to a permanent price change occurring l days ago with an elasticity equal to the sum of the subsequent lagged price coefficients $\sum_{t=0}^{l} \delta_t$.[9] Rather than estimate this model directly, we use an equivalent specification that is instead written as a

[8]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.

[9]For comparison purposes, we also estimate a lagged dependent variable specification in Appendix A.

function of the log price in period $d - L$ and subsequent changes in the log price[10]:

$$\begin{aligned} ln(Q_{jd}) &= \delta_0 \Delta ln(p_{j,d}) + (\delta_0 + \delta_1)\Delta ln(p_{j,d-1}) + (\delta_0 + \delta_1 + \delta_2)\Delta ln(p_{j,d-2}) + ... \\ &\quad +(\delta_0 + \delta_1 + ... + \delta_{L-1})\Delta ln(p_{j,d-L+1}) + (\delta_0 + \delta_1 + ... + \delta_L) ln(p_{j,d-L}) \\ &\quad +\alpha_j + \lambda_d + \tau_{jM} + \zeta_{jR} + \epsilon_{jd} \\ &= \sum_{l=0}^{L-1} \gamma_l \Delta ln(p_{j,d-l}) + \gamma_L ln(p_{j,d-L}) + \alpha_j + \lambda_d + \tau_{jM} + \zeta_{jR} + \epsilon_{jd}, \end{aligned} \tag{3}$$

where $\gamma_l = \sum_{t=0}^{l} \delta_t$. This parameterization is easier to interpret, with each coefficient γ_l now representing the elasticity of the response in today's consumption to a permanent price change occurring l days ago. However, rather than estimate separate γ coefficients for every day, we restrict the model somewhat by assuming a common γ within certain time windows. Specifically, the γ coefficient is assumed to be the same for any price change occurring between 5 and 30 days ago, as well as from 31–60 days ago, 61–90, 91–120, 181–240, and 241–360 days ago. Separate daily γ coefficients are estimated for price changes occurring within each of the most recent five days to allow for potential adjustments in the timing of purchase. The resulting estimates are reported in Equation 4.[11]

$$\begin{aligned} ln(Q_{jd}) &= \underset{(0.13)}{-0.42} \Delta ln(p_{jd}) + \underset{(0.09)}{-0.56} \Delta ln(p_{j,d-1}) + \underset{(0.10)}{-0.41} \Delta ln(p_{j,d-2}) \\ &\quad + \underset{(0.09)}{-0.36} \Delta ln(p_{j,d-3}) + \underset{(0.08)}{-0.31} \Delta ln(p_{j,d-4}) + \sum_{l=5}^{30} \underset{(0.03)}{-0.23} \Delta ln(p_{j,d-l}) \\ &\quad + \sum_{l=31}^{60} \underset{(0.04)}{-0.27} \Delta ln(p_{j,d-l}) + \sum_{l=61}^{90} \underset{(0.06)}{-0.27} \Delta ln(p_{j,d-l}) + \sum_{l=91}^{120} \underset{(0.07)}{-0.31} \Delta ln(p_{j,d-l}) \\ &\quad + \sum_{l=121}^{180} \underset{(0.07)}{-0.32} \Delta ln(p_{j,d-l}) + \sum_{l=181}^{240} \underset{(0.09)}{-0.29} \Delta ln(p_{j,d-l}) + \sum_{l=241}^{359} \underset{(0.11)}{-0.24} \Delta ln(p_{j,d-l}) \\ &\quad + \underset{(0.13)}{-0.19} ln(p_{j,d-360}) + \alpha_j + \lambda_d + \tau_{jM} + \zeta_{jR} + \epsilon_{jd}. \end{aligned} \tag{4}$$

[10]Here the change in log price is defined as: $\Delta ln(p_{j,d}) = ln(p_{j,d}) - ln(p_{j,d-1})$.

[11]The standard errors reported in parenthesis below the coefficient estimate have been clustered by city to allow for correlation in errors within a city over time and also by day to allow correlation across cities within each day.

Several interesting patterns emerge from the estimates in Equation 4. First, the gasoline sales respond much more strongly in the first 2 to 3 days following a price change, likely reflecting a purchase timing effect more than a change in driving behavior. When consumers encounter a higher-than expected price they may try to postpone purchase as long as possible in hopes of finding a station that still has a lower price. Alternatively, if they encounter an unexpectedly low price, they may stop and fill their tank earlier than they otherwise would have. The second important pattern revealed in Equation 4 is that, after the first 5 days, none of the coefficients on the subsequent lagged price changes are statistically different from each other or from to the -.27 elasticity value identified using the static demand model in Equation 1.[12] In other words, gasoline demand responds fairly completely to a price change within the first 5 days and remains relatively unchanged thereafter.[13] Incorporating lagged prices into the (symmetric) demand model offers little additional explanatory power over 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.[14] Different types of reference points have been considered in different applications, often inspired by abstract behavioral concepts such as endowment effects

[12]None of the time window coefficients (excluding the first 4 days) are statistically different from the -.27 elasticity value identified in Equation 1. An F-test of the joint equality of these 7 lagged price change coefficients across the time windows results in a p-value of .0372, which we believe is not overwhelming evidence against the null hypothesis given the relatively large sample size of over 500,000 observations. When specified as a more standard distributed lag model in levels (similar to Equation 2), the corresponding estimates would produce a coefficient of -.27 on the current log price and coefficients not statistically different from zero on all lagged log prices of more than 4 days.

[13]Similar estimates are obtained when both cycling and non-cycling cities are included in the sample, although the response within the first few days is substantially more elastic because day-to-day price movements in cycling cities are more predictable over the very short run.

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

or status-quo bias. Kőszegi and Rabin (2006) offer perhaps the most complete model of 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.[15] 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,

[15] 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.

causing demand to become more elastic. Similarly, demand can become less elastic when actual prices are below expectations.[16]

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 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.

Reference-dependent or context-dependent utility may also impact the behavior of gasoline consumers in other ways. In particular, price fluctuations and past price expectations have been shown to impact how extensively consumers search around for a lower-priced station (Lewis, 2011; Lewis and Marvel, 2011). Such changes in search can cause input cost fluctuations to be passed through to pump prices more quickly when prices rise relative to recent levels. The focus of our study, however, is the potential reference dependence exhibited in the response of gasoline usage to current and past prices, independent of the processes that generate those prices.

As discussed in the previous section, 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). Alternatively, in the very short run, consumers may respond to an unexpected price movement by strategically timing their purchase, leveraging

[16]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.

their gas tank as temporary storage. These mechanisms may shift and rotate the demand curve, reducing or increasing the price elasticity in the short run, but these mechanisms 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 that our high-frequency data is ideally suited to 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 found that there is generally no better predictor of future gasoline prices than the current price level.[17] 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, we assume that historical prices provide a reasonable approximation of the expectations consumers' held in the past about what today's gasoline price level would be.

Although past price levels in this environment reflect both the consumer's *status quo* (what they paid in the past) as well as their past expectations of the current price, (Kőszegi and Rabin, 2006) conclude from the existing empirical literature that "equating the reference point with expectations generally makes better predictions." We therefore

[17]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.

interpret our empirical results under the assumption that focal points arise from expectations.[18] However, our analysis focuses on characterizing the influence of past prices on demand, so the results can be equally useful under alternative interpretations of what past prices represent.

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:

$$\begin{aligned} ln(Q_{jd}) &= \beta_1 ln(p_{jd}^{expected}) + \beta_2 \left[ln\left(\frac{p_{jd}}{p_{jd}^{expected}}\right)\right]^+ + \beta_3 \left[ln\left(\frac{p_{jd}}{p_{jd}^{expected}}\right)\right]^- \\ &\quad +\alpha_j + \lambda_d + \tau_{jM} + \zeta_{jR} + \epsilon_{jd} \end{aligned} \tag{5}$$

where:

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

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.

At different points in time during the recent past consumers will have had different expectations about today's price, and, as in Kőszegi and Rabin (2006), consumers' utility today may be influenced by each of these different expectations. We incorporate this notion in our analysis by using the geometric mean of prices observed in the recent past as a

[18]Within the broader literature on reference pricing, including Winer (1986), Kalyanaram and Winer (1995), and Mazumdar et al. (2005), consumers are almost always assumed to form reference prices based on past price observations, and even prior to the formalizations by Kőszegi and Rabin (2006) and Bordalo et al. (2013) such assumptions have typically been justified by the idea that past prices contribute to the formation of expectations regarding future transactions.

measure of the reference level. In other words, the average of recent log prices serves as the reference level for the current log price. Using this definition of the reference price, Equation 5 becomes[19]:

$$
\begin{aligned}
ln(Q_{jd}) \quad = \quad & \beta_1 \frac{1}{L} \sum_{l=1}^{L} ln(p_{j,d-l}) + \beta_2 \max \left(ln(p_{jd}) - \frac{1}{L} \sum_{l=1}^{L} ln(p_{j,d-l}), 0 \right) \\
& + \beta_3 \min \left(ln(p_{jd}) - \frac{1}{L} \sum_{l=1}^{L} ln(p_{j,d-l}), 0 \right) + \alpha_j + \lambda_d + \tau_{jM} + \zeta_{jR} + \epsilon_{jd}. \quad (6)
\end{aligned}
$$

This specification represents an asymmetric version of a restricted distributed lag demand model. If demand were to respond symmetrically to past price levels (i.e., $\beta_2 = \beta_3$), Equation 6 would simplify to a version of the model of Equation 2 in which $\delta_0 = \beta_1$ and $\delta_1 = \delta_2 = ... = \delta_L = \frac{\beta_1 - \beta_2}{L}$.[20]

Within this framework, the elasticity with which demand responds to a change in the current price is captured by either β_2 or β_3, depending on whether the current price is above or below the reference price. Therefore, we will measure the degree of reference dependence using the difference between these coefficients $(\beta_2 - \beta_3)$. The coefficient on the reference price (β_1) represents the elasticity with which demand responds to a change in the reference price level while holding constant the difference between the current price and the reference price. In other words, this reflects how demand responds to an equal-sized shift in both the current price and the average price during the entire reference period. In a sense, the β_1 coefficient captures consumers' longer-run demand elasticity with respect to a

[19]Equation 6 can be equivalently written in terms of the geometric mean of prices as:

$$
\begin{aligned}
ln(Q_{jd}) \quad = \quad & \beta_1 ln \left(\prod_{l=1}^{L} (p_{j,d-l})^{\frac{1}{L}} \right) + \beta_2 \max \left(ln \left(\frac{p_{jd}}{\prod_{l=1}^{L} (p_{j,d-l})^{\frac{1}{L}}} \right), 0 \right) \\
& + \beta_3 \min \left(ln \left(\frac{p_{jd}}{\prod_{l=1}^{L} (p_{j,d-l})^{\frac{1}{L}}} \right), 0 \right) + \alpha_j + \lambda_d + \tau_{jM} + \zeta_{jR} + \epsilon_{jd}.
\end{aligned}
$$

[20]As we discuss below and present in Appendix Table A4, the reference price structure of Equation 6 can be combined with the more flexible distributed lag structure of Equation 4 to separately account for both reference dependence and delayed response.

change in overall price level, while the β_2 and β_3 coefficients capture how demand responds to more a recent change in price (relative to the typical price level observed during the reference period).[21]

The horizon over which consumers' past expectations influence utility is unknown, so we estimate the model using different values of L, producing different measures of $p_{jd}^{expected}$ based on average prices over the past 3 days, 30 days, 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. As long as expectations are measured over horizons longer than 3 days, 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 past months and respond less elastically when prices are lower.

Interestingly, the level of prices over the previous 3 days appears to have a different impact on the elasticity of price response. Because gasoline consumers can strategically shift the timing of their gasoline purchases by several days without adjusting actual usage, the behavior generating asymmetric response in the very short run is likely to be fundamentally different. Lewis (2011) and Lewis and Marvel (2011) find evidence that consumers search longer to find a station with a better price when prices have increased relative to recent levels and search less when prices have decreased. In our data, consumers appear to respond most strongly when prices fall relative to previous days, filling up their tank early to take advantage of lower prices. Of course, adjusting search intensity, topping off a tank, or delaying purchase can only shift demand by a few days. A separate mechanism, such as

[21]The β_1 coefficient in Equation 6 captures the same type of longer-run demand response as the coefficient on $ln(p)$ in Equation 1, and, consequently, the estimates of β_1 presented below correspond closely with the estimate obtained from Equation 1.

reference dependence, must be responsible for the persistent impact that prices from earlier weeks and months have on overall consumption.

The broader influence of past prices on demand appears to be fairly long-lasting. In many cases, 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 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. We demonstrate this by estimating a specification allowing each coefficient in Equation 5 to have different values when prices are in different quartiles of the city-specific mean price distribution.[22] The results (reported in Table A1) show 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. Specifying demand to be linear in levels rather than in logs also produces similar results. The implied elasticities from the linear models (reported in Table A2) are somewhat smaller in magnitude but exhibit a similar degree of asymmetry in the responses to deviations from past price levels.[23]

[22]We construct a set of 4 price-quartile indicator variables designating where each price observation lies within the distribution of prices observed for that city over the sample period. Then the 3 explanatory variables in Equation 5 are interacted with each of the quartile indicators to generate quartile-specific demand elasticity estimates.

[23]The linear equivalent of Equation 5 is specified as:

$$Q_{jd} = \beta_1 p_{jd}^{expected} + \beta_2 (p_{jd} - p_{jd}^{expected})^+ + \beta_3 (p_{jd} - p_{jd}^{expected})^- + \alpha_j + \lambda_d + \tau_{jM} + \zeta_{jR} + \epsilon_{jd}.$$

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

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	720 Days	360 Days	240 Days	120 Days	60 Days	30 Days	3 Days
$ln(\frac{\text{price}}{\text{mean price over previous X days}})^{+}$	-0.470	-0.427	-0.355	-0.310	-0.330	-0.420	-0.437
	(0.062)	(0.053)	(0.050)	(0.044)	(0.048)	(0.062)	(0.193)
$ln(\frac{\text{price}}{\text{mean price over previous X days}})^{-}$	-0.190	-0.132	-0.200	-0.198	-0.201	-0.130	-0.691
	(0.044)	(0.047)	(0.047)	(0.042)	(0.043)	(0.057)	(0.171)
$ln(\text{mean price over previous X days})$	-0.051	-0.223	-0.265	-0.309	-0.280	-0.269	-0.265
	(0.233)	(0.144)	(0.115)	(0.083)	(0.065)	(0.054)	(0.047)
N	472254	516138	516258	516378	516438	516468	516494
R^2	0.918	0.909	0.909	0.909	0.909	0.909	0.909
Asymmetry in Response Elasticity	-0.280	-0.295	-0.155	-0.112	-0.129	-0.290	0.254
Test of Symmetric Response (P-value)	<0.001	<0.001	0.024	0.058	0.046	0.001	0.398

Notes: 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). Mean prices reflect geometric means as presented in Equation 6.

While our analysis focuses on a subsample of 177 cities that do not exhibit Edgeworth price cycles (as discussed in Section 2), Appendix Table A3 reports corresponding estimates from the full sample of 285 cities. Demand is estimated to be somewhat more elastic than in the non-cycling subsample, but continues to respond asymmetrically when prices are above vs. below the reference price level. Notably, the inclusion of cycling cities in the sample leads to substantially larger estimates of demand response in the three days immediately following a price change. This is consistent with consumers in these additional cities more easily adjusting the timing of gasoline purchases in response to predictable within-week cyclical price fluctuations.

Overall, the findings of the reference price model demonstrate an asymmetry in demand response that cannot be captured by partial adjustment models or distributed lag models. This can be confirmed by reincorporating the more flexible distributed lag structure used in Equation 4 into the reference dependence model in Equation 5. Estimates from the combined model are reported in column 2 of Appendix Table A4. The estimated lagged price change coefficients in Table A4 differ from those estimated in Equation 4 because the added reference price terms already contain a restricted distributed lag structure.[24] Nevertheless, the degree of reference dependence in Table A4 is nearly identical to that reported in Table 1, generating an asymmetry in demand elasticity of around .29. Incorporating reference dependence delivers an empirical model that can rather parsimoniously capture the complex dynamics of gasoline demand response. Even a highly flexible distributed lag model with 360 lagged price parameters does not deliver a significantly better fit of observed

While average gasoline consumption per capita varies substantially across cities, the linear demand model assumes that a change in price results in the same change in gallons consumed per capita in all cities. This seems unlikely and may partially explain why estimated price coefficients in the linear model are smaller in magnitude and less precisely estimated than in the log-linear model.

[24]In particular, Equation 5 is an asymmetric form of a distributed lag model in which all lagged price changes have the same coefficient.

gasoline demand than the 3-parameter reference dependence model of Equation 6.[25]

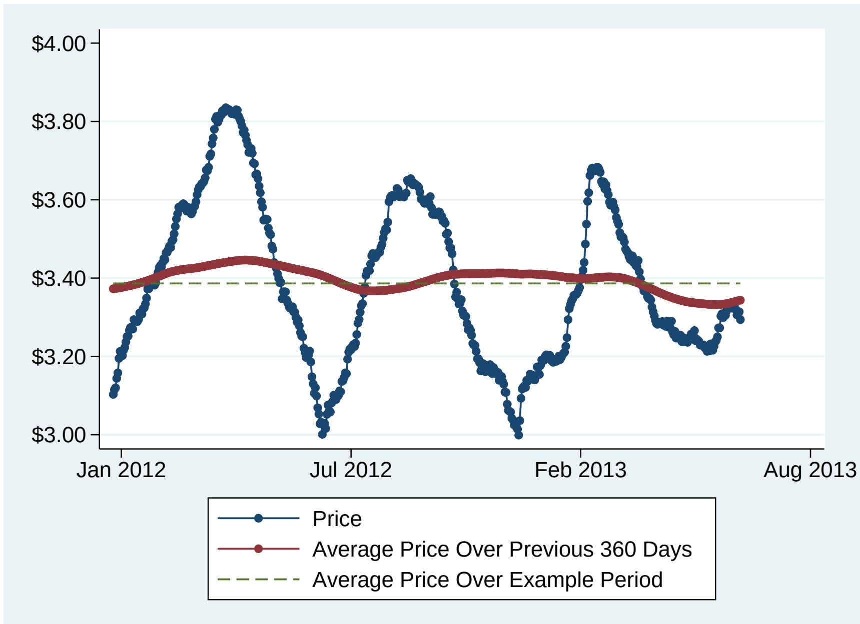
3.2 Effects of Price Volatility on Gasoline Demand

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. 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 in Charlottesville over this 18-month 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 8-year 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

[25]When performing a Vuong (1989) non-nested test comparing our model to the general distributed lag model of Equation 2 with $L = 360$ coefficients, the null hypothesis that the simple reference dependence model of Equation 6 with three coefficients provides a fit that is as good as the distributed lag model cannot be rejected at significance levels lower than 3%. With a sample size of 500,000 observations, we take this as strong evidence of that our reference dependence model offers a substantial restriction of the parameter space without sacrificing explanatory power.

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



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.[26] 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 slightly larger than the long-run demand effect of the federal

[26]The impact of price volatility on demand varies substantially across cities. In cities with the most price volatility demand would have been 1.9% higher with stable prices, while in cities with the least price volatility demand would only have been 1.2% higher with stable prices.

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 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 more carefully examine 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)).

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 5 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. The variables include the share of workers not working from home that drive alone to work, the share of workers not working from home who commute over 30 minutes via nonpublic transit, and the share of the population with household income over twice the poverty level. 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.

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.[27] Some care must be taken in interpreting these results, as there may be underlying factors influencing both the demographics of a city and the elasticity of gasoline demand within the city. Nevertheless, the findings help to illustrate what types of cities tend to have more elastic gasoline demand.

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

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 per capita VMT/100	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

Interestingly, several 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 changes.[28] 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

[28]One potential explanation consistent with our finding would be that an increase in the gasoline price has larger income effects on commuters who spend more in total on gasoline.

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 per capita VMT/100				-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

Notes: 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).

Small and Van Dender (2007) but not with Gillingham (2014) who finds higher-income households to be somewhat more elastic. However, Gillingham (2014) models aggregate VMT over a multi-year period (typically 6 years) as a function of the corresponding average price over that period, which is unlikely to capture the same short run responses that we identify using daily data.

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 5. 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 character-

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	-0.737	0.161	-0.571	-0.459	-0.258
	(0.053)	(0.063)	(0.183)	(0.079)	(0.148)	(0.173)
$ln\left(\frac{P_{it}}{\overline{P}_{it}^{360}}\right)^{-}$	-0.132	-0.046	-0.360	-0.014	-0.316	-0.442
	(0.047)	(0.053)	(0.163)	(0.064)	(0.094)	(0.178)
$ln(\overline{P}_{it}^{360})$	-0.223	0.133	-1.840	0.017	-0.893	-1.978
	(0.144)	(0.155)	(0.418)	(0.174)	(0.286)	(0.457)
$ln\left(\frac{P_{it}}{\overline{P}_{it}^{360}}\right)^{+} \times$ share commuting over 30 min		1.482				1.131
		(0.188)				(0.187)
$ln\left(\frac{P_{it}}{\overline{P}_{it}^{360}}\right)^{-} \times$ share commuting over 30 min		-0.299				-0.105
		(0.113)				(0.120)
$ln(\overline{P}_{it}^{360}) \times$ share commuting over 30 min		-1.604				-1.312
		(0.232)				(0.264)
$ln\left(\frac{P_{it}}{\overline{P}_{it}^{360}}\right)^{+} \times$ share driving alone			-0.668			-0.605
			(0.226)			(0.176)
$ln\left(\frac{P_{it}}{\overline{P}_{it}^{360}}\right)^{-} \times$ share driving alone			0.333			0.425
			(0.190)			(0.206)
$ln(\overline{P}_{it}^{360}) \times$ share driving alone			1.874			1.779
			(0.460)			(0.488)
$ln\left(\frac{P_{it}}{\overline{P}_{it}^{360}}\right)^{+} \times$ daily per capita VMT/100				0.735		0.401
				(0.212)		(0.164)
$ln\left(\frac{P_{it}}{\overline{P}_{it}^{360}}\right)^{-} \times$ daily per capita VMT/100				-0.401		-0.492
				(0.116)		(0.122)
$ln(\overline{P}_{it}^{360}) \times$ daily per capita VMT/100				-0.698		-0.601
				(0.277)		(0.265)
$ln\left(\frac{P_{it}}{\overline{P}_{it}^{360}}\right)^{+} \times$ share over twice poverty level					0.041	0.058
					(0.200)	(0.175)
$ln\left(\frac{P_{it}}{\overline{P}_{it}^{360}}\right)^{-} \times$ share over twice poverty level					0.247	0.237
					(0.111)	(0.110)
$ln(\overline{P}_{it}^{360}) \times$ share over twice poverty level					0.895	0.970
					(0.299)	(0.281)
N	516,138	516,138	516,138	472,353	516,138	472,353

Notes: Robust standard errors (in parentheses) incorporate two-way clustering on city and day of sample. The dependent variable is ln(Quantity of Gasoline per Capita Purchased at the Pump). In all specifications the reference price is represented by $\overline{P}_{it}^{360}$, the geometric mean of the price over the previous 360 days.

istics 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.[29] 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.

Using the estimates from Column 6 of Table 4, a city's predicted elasticity of demand with respect to each of the three price variables can be calculated as a linear function of the city's 4 observed characteristics. Figure 2 presents scatter plots that reveal how these predicted elasticities vary across cities depending on city characteristics. Blue circles represent estimated elasticities of response to a change in price when the current price is above the reference level, i.e., the marginal effect of $ln(\frac{P_{it}}{\overline{P}_{it}^{360}})^+$.[30] Red triangles represent estimated elasticities of response to a change in price when the current price is below the reference level, i.e., the marginal effect of $ln(\frac{P_{it}}{\overline{P}_{it}^{360}})^-$. The difference between the red and blue elasticities reveals the degree of reference dependence. The green squares in Figure 2 represent the marginal effect of a change in $ln(\overline{P}_{it}^{360})$ given a particular level of $ln(\frac{P_{it}}{\overline{P}_{it}^{360}})$.

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

[30]We use $\overline{P}_{it}^{360}$ to represent the reference price, which in these specifications is the geometric mean of the price over the previous 360 days.

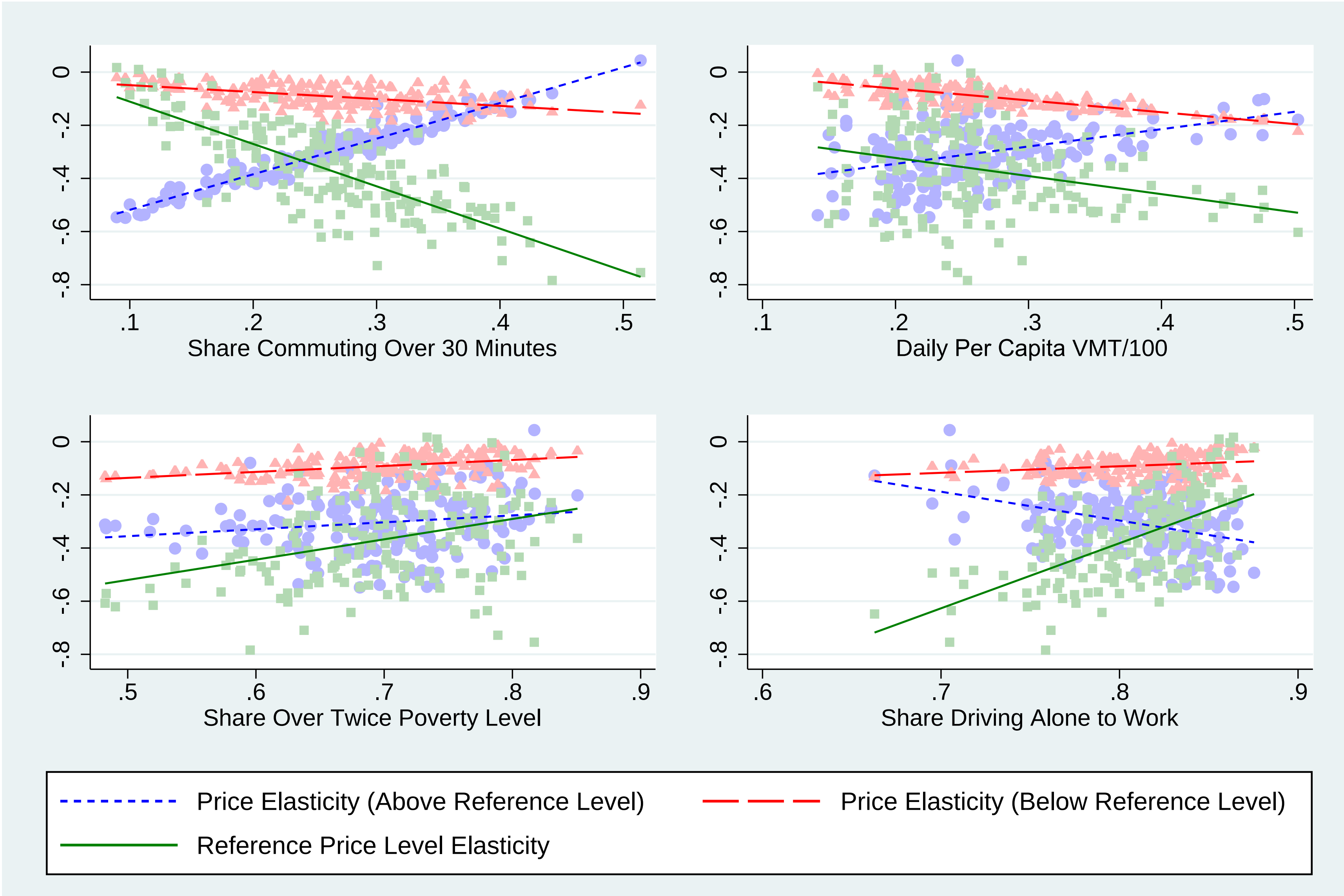


Figure 2: How Price Elasticities Vary with City Characteristics. *Notes:* Each scatter point represents the estimated elasticity of the specified type for a particular city based on the empirical specification presented in Table 4, Column 6. Linear fitted value lines are included to reveal how the corresponding elasticity varies with the chosen city characteristic.

Therefore, these estimates capture the elaticity of response to an equal-sized change in both $ln(\overline{P}_{it}^{360})$ and $ln(P_{it})$. As discussed in Section 3.1 (following Equation 6), such elasticities could be interpreted to reflect the longer-run response of demand to a price level that has been present throughout the previous year. In contrast, the blue and red elasticities reflect how demand responds in the shorter-run to price changes that occur relative to the average level over the previous year.

Across all specifications in Table 4, the degree of reference dependence is found to be higher in cities where: more people drive alone to work, fewer people commute over 30 minutes to work, and average per capita vehicle miles traveled are lower.[31] Interestingly, each of these characteristics are also associated with lower levels of gasoline demand elasticity according to estimates in Table 1. Figure 2 depicts in more detail how elasticities vary with driving characteristics. In cities where people are driving more (long commutes, high VMT) and have more commuting options (fewer people driving alone to work), demand is relatively elastic in the long run but responds more inelastically to shorter-run movements in price—both above and below the reference level. On the other hand, in cities were people drive less and more people drive alone to work, demand is generally inelastic but responds more elastically when prices are above their reference level.

5 Discussion

Our empirical analysis establishes robust evidence of reference dependence in the demand for gasoline. Moreover, the patterns we document provide a clearer foundation for un-

[31]A rough measure of the degree of reference dependence is measured by the difference between the red line and blue in line Figure 2 for a given value of the variable on the horizontal axis. The lower left panel of Figure 2 shows that the degree of reference dependence does not vary significantly with the share of people having incomes above twice the poverty level, though cities with a larger share of low-income residents continue to exhibit more elastic demand.

derstanding geographic and temporal variation in gasoline demand response and offer 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,[32] 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, 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 the expectations derived from these past prices. For example, consumers who drive more and purchase more gasoline may have a stronger recollection of past price levels. In this

[32]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.

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. Our empirical results suggest that more elastic drivers may 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.[33] 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

[33] 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).

further below the actual gasoline price and increases price salience. Alternative choice contexts or consideration sets that do not meet this criteria do not appear to be empirically supported within the gasoline market.

6 Conclusion

We present new evidence that past prices strongly and asymmetrically influence the elasticity of 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. Past prices continue to influence demand months into the future, indicating an asymmetric response in actual gasoline consumption rather than a very short run adjustment in the timing of gasoline purchase. These results offer a new perspective on how gasoline consumers respond to price fluctuations and suggest that higher levels of price volatility can lead to lower total consumption over the same time period. In addition, 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, cities where residents tend to drive more generally have less elastic demand for gasoline but exhibit greater reference dependence, with a demand that responds much more elastically when current prices are higher than they had been during the preceding year. In the gasoline market, at least, price expectations appear to more strongly influence the responsiveness of relatively inelastic customers.

While previous work (e.g., Gately, 1992) has demonstrated that technological advancements in vehicle fuel efficiency cause gasoline demand to respond asymmetrically or exhibit imperfect price-reversibility over the long run, our research reveals an asymmetric response of gasoline demand in the short to medium run that is more consistent with consumer reference dependence. When considered within the behavioral frameworks recently proposed by Kőszegi and Rabin (2006) and Bordalo et al. (2013), the empirical evidence offered here can help researchers to identify particular specifications or parameterizations that more accurately capture observed behavior. In addition, our findings suggest that additional theoretical investigation of the behavioral links between reference dependence and demand elasticity could be particularly valuable.

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Appendix A: Lagged Dependent Variable Specification

Here we consider a lagged dependent variable specification of our baseline demand model from Equation 1. The lagged dependent variable specification is commonly used in the literature on gasoline demand (e.g., Hughes et al., 2008) and can be rationalized by a partial adjustment model in which demand responds to a price change by adjusting a percentage of the way toward the new equilibrium consumption level each period. Incorporating partial adjustment into our model of daily demand produces the following:

$$ln(Q_{jd}) = \underset{(0.022)}{-0.115}\, ln(p_{jd}) + \underset{(0.026)}{0.605}\, ln(Q_{j,d-1}) + \alpha_j + \lambda_d + \tau_{jM} + \zeta_{jR} + \epsilon_{jd}, \qquad \text{(A-1)}$$

The coefficient estimates indicate a fully adjusted response elasticity of $-0.291 = \frac{-.115}{1-0.605}$, with consumption responding with an elasticity of -0.115 on the day of the price change and continuing to respond by eliminating an additional 40% of the remaining deviation on each subsequent day. In other words, five days after a price change consumption is predicted to have almost fully adjusted, with a response elasticity of $-.267 = -.291 * (1 - 0.605^5)$. However, this model assumes that the influence of past prices on demand takes exhibits a particular geometric decay pattern which may not be realistic in our setting. Therefore, in the paper we adopt a more flexible distributed lag specification to model the influence of past prices on demand.

Appendix B: Additional Tables

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

	Coef.	S.E.
$ln(\frac{\text{price}}{\text{mean price over previous 360 days}})^+$:		
Quartile 1 (Lowest)	-0.456	(0.084)
Quartile 2	-0.459	(0.079)
Quartile 3	-0.615	(0.084)
Quartile 4 (Highest)	-0.456	(0.067)
$ln(\frac{\text{price}}{\text{mean price over previous 360 days}})^-$:		
Quartile 1	-0.177	(0.048)
Quartile 2	-0.071	(0.071)
Quartile 3	-0.094	(0.078)
Quartile 4	0.621	(0.270)
$ln(\text{mean price over previous 360 days})$:		
Quartile 1	-0.183	(0.144)
Quartile 2	-0.270	(0.141)
Quartile 3	-0.409	(0.160)
Quartile 4	-0.418	(0.166)
Quartile 2 Fixed Effect	0.088	(0.037)
Quartile 3 Fixed Effect	0.240	(0.082)
Quartile 4 Fixed Effect	0.254	(0.097)
N	516138	
R^2	0.910	

Notes: 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). Quartile indicator variables reveal the quartile in which each price observation lies within the distribution of prices observed for that city over the sample period. Estimates listed under each of the three price-related variables reflect the estimated coefficients of the interactions between that variable and each price-quartile indicator.

Table A2: Gasoline Demand Response (Linear Model) with Reference Dependence over Different Time Horizons

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	720 Days	360 Days	240 Days	120 Days	60 Days	30 Days	3 Days
$(\text{price} - \text{mean over previous X days})^+$	-0.060	-0.057	-0.047	-0.046	-0.051	-0.061	-0.065
	(0.009)	(0.009)	(0.008)	(0.008)	(0.009)	(0.013)	(0.043)
$(\text{price} - \text{mean over previous X days})^-$	-0.030	-0.024	-0.034	-0.031	-0.031	-0.024	-0.086
	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.011)	(0.027)
mean price over previous X days	-0.008	-0.047	-0.055	-0.055	-0.048	-0.045	-0.044
	(0.034)	(0.028)	(0.023)	(0.016)	(0.012)	(0.010)	(0.009)
Implied Demand Elasticities:							
$(\text{price - mean over previous X days})^+$	-0.327	-0.310	-0.256	-0.251	-0.278	-0.332	-0.354
$(\text{price - mean over previous X days})^-$	-0.164	-0.130	-0.185	-0.169	-0.169	-0.131	-0.469
mean price over previous X days	-0.044	-0.256	-0.300	-0.300	-0.262	-0.245	-0.240
N	472306	516138	516258	516378	516438	516468	516491
R^2	0.896	0.886	0.886	0.886	0.886	0.886	0.886

Notes: Robust standard errors (in parentheses) incorporate two-way clustering on city and day of sample. Dependent Variable is Quantity of Gasoline per Capita Purchased at the Pump. Implied elasticities are evaluated at the mean values of quantity per capita and price.

Table A3: Gasoline Demand Elasticity (in All Cities) with Reference Dependence over Different Time Horizons

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	720 Days	360 Days	240 Days	120 Days	60 Days	30 Days	3 Days
$ln(\frac{\text{price}}{\text{mean price over previous X days}})^{+}$	-0.538	-0.498	-0.433	-0.431	-0.475	-0.598	-1.193
	(0.050)	(0.043)	(0.042)	(0.040)	(0.043)	(0.054)	(0.130)
$ln(\frac{\text{price}}{\text{mean price over previous X days}})^{-}$	-0.293	-0.260	-0.335	-0.332	-0.352	-0.389	-1.766
	(0.040)	(0.042)	(0.044)	(0.039)	(0.041)	(0.055)	(0.182)
$ln(\text{mean price over previous X days})$	-0.051	-0.237	-0.282	-0.336	-0.317	-0.303	-0.317
	(0.202)	(0.127)	(0.102)	(0.075)	(0.058)	(0.047)	(0.039)
N	642467	702272	702512	702752	702872	702932	702984
R^2	0.908	0.899	0.899	0.899	0.899	0.899	0.899
Asymmetry in Response Elasticity	-0.245	-0.238	-0.098	-0.099	-0.123	-0.209	0.573
Test of Symmetric Response (P-value)	$<$0.001	$<$0.001	0.079	0.034	0.014	0.002	0.008

Notes: 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). Mean prices reflect geometric means as presented in Equation 6.

Table A4: Gasoline Demand Elasticity with Reference Dependence and Distributed Lags

	(1)	(2)
$ln(\frac{\text{price}_t}{\text{mean price over previous 360 days}})^+$	-0.427	-0.490
	(0.053)	(0.096)
$ln(\frac{\text{price}_t}{\text{mean price over previous 360 days}})^-$	-0.132	-0.201
	(0.047)	(0.100)
$ln(\text{mean price over previous 360 days})$	-0.223	-0.212
	(0.144)	(0.150)
$\Delta ln(\text{price}_t)$		-0.066
		(0.142)
$\Delta ln(\text{price}_{t-1})$		-0.209
		(0.108)
$\Delta ln(\text{price}_{t-2})$		-0.056
		(0.112)
$\Delta ln(\text{price}_{t-3})$		-0.005
		(0.107)
$\Delta ln(\text{price}_{t-4})$		0.045
		(0.105)
$\sum_{l=5}^{30} \Delta ln(\text{price}_l)$		0.110
		(0.074)
$\sum_{l=31}^{60} \Delta ln(\text{price}_l)$		0.053
		(0.066)
$\sum_{l=61}^{90} \Delta ln(\text{price}_l)$		0.039
		(0.055)
$\sum_{l=91}^{120} \Delta ln(\text{price}_l)$		-0.018
		(0.050)
$\sum_{l=121}^{180} \Delta ln(\text{price}_l)$		-0.046
		(0.044)
$\sum_{l=181}^{240} \Delta ln(\text{price}_l)$		-0.033
		(0.034)
$\sum_{l=241}^{360} \Delta ln(\text{price}_l)$		-0.020
		(0.025)
N	516138	516136
R^2	0.909	0.910

Notes: Column 1 estimates are from Table 1, Column 2. 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).