

# **Gasoline price volatility and the elasticity of demand for gasoline<sup>1</sup>**

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## **Abstract**

We examine how gasoline price volatility impacts consumers' price elasticity of demand for gasoline. Results show that volatility in prices decreases consumer demand for gasoline in the intermediate run. We also find that consumers appear to be less elastic in response to changes in gasoline price when gasoline price volatility is medium or high, compared to when it is low. Moreover, we find that when we control for variance in our econometric model, gasoline price elasticity of demand is lower in magnitude in the long run.

**Keywords:** gasoline demand elasticity, gasoline price volatility

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## **1. Introduction**

Gasoline-powered passenger vehicles create numerous negative externalities including local air pollution, global climate change, accidents, congestion, and dependence on foreign oil. These externalities can be addressed by policy makers through a variety of actions aimed at reducing demand for gasoline or reducing pollution from automobiles. The latter could be addressed with state vehicle smog standards, industry standards, and efforts to reduce vehicle speeds and congestion. The former is typically addressed with gasoline or carbon taxes or automobile industry production standards for fuel efficiency.

A big concern among policy makers in terms of reduction of demand for gasoline is the inelastic demand for gasoline that consumers exhibit. The literature shows increasingly inelastic demand for gasoline with respect to price in both the short and long run and recent studies have shown that short-run price elasticity of demand has decreased in absolute value by up to an order of magnitude in the past decade, meaning that consumers have become significantly less responsive to changes in gasoline price.

In this study, we examine how gasoline price volatility impacts consumers' demand for gasoline and the price elasticity of demand for gasoline. We hypothesize that gasoline price volatility may matter econometrically in that volatility should be included in models of gasoline demand and gasoline demand elasticity, and also that gasoline price volatility matters behaviorally in that volatility impacts consumers' demand for gasoline and their responsiveness to changes in gasoline price. In particular, we hypothesize that as prices become more volatile, consumers will be less responsive to changes in gasoline price since the price changes so much. We find that an increase in gasoline price volatility decreases consumer demand for gasoline in the intermediate run. We also find

that in an atmosphere of high gasoline price volatility, consumers exhibit less elastic demand for gasoline than in times of lower price volatility in both the short and long run. Retail gasoline prices have displayed higher than normal volatility in recent years. For example, gasoline hit its highest real price in 30 years at just over \$3.99 per gallon of unleaded regular grade gasoline in May of 2008 and dipped as low as \$1.74 per gallon just 7 months later (US Energy Information Administration 2012). While there have been extensive studies in which price elasticity of demand for gasoline has been estimated, it is unclear how volatility in gasoline prices impacts consumer demand and elasticity. Specifically, it is unclear whether a change in gasoline prices in a volatile market induces consumers to change their short- or long-run gasoline consumption behavior in a different manner than a change in gasoline prices in a less volatile market. We test this by modeling gasoline demand elasticity with respect to instantaneous prices while controlling for the variance in prices over the previous 12 months. Interaction terms are used to test the impact of volatility on gasoline price elasticity.

Three conclusions stem from our analysis. First, results show that volatility in prices decreases consumer demand for gasoline in the intermediate run. All else equal, when gasoline prices are volatile, consumers buy less gasoline. We see a less robust and significant consumer response in the short run, indicating that consumer response to volatile prices may be delayed. Second, we find that consumers appear to be less elastic in response to changes in gasoline price when gasoline price volatility is medium or high, compared to when it is low. In other words, when consumers recognize that volatility of gasoline prices has been, on average, high over the past year, they are less likely to shift their behavior in response to changes in gasoline prices. Third, we find that when we

control for variance in our econometric model, gasoline price elasticity of demand is lower in magnitude in the long run.

## 2. Background

There is a significant literature in which the price elasticity of demand for gasoline is estimated using a variety of models and with seemingly large differences in findings. Reasons for this variation include differences in functional form, model assumptions, specification and measurement of variables, and econometric estimation technique. Several meta-studies (including Espey 1998, Dahl and Sterner 1991) summarize large numbers of studies, analyzing the variation in gasoline price elasticity of demand by regressing these estimates on different series of explanatory variables, which are features of the model and its structure.

Dahl and Sterner (1991) base a meta-analysis on a study of 97 prior estimates of the price elasticity of gasoline demand based on data before 1989. They stratify their analysis based on ten distinct models and find that estimates tend to be more uniform when they fall within a specific cluster. They find a range of short- to intermediate-run price elasticities to be -0.22 to -0.31 and long-run elasticities to be -0.8 to -1.01.

Espey (1998) bases a meta-study on hundreds of prior estimates from data between 1929 and 1993. Short- to intermediate-run price elasticity is estimated to be within the range of 0 to -1.36 with a mean of -0.26 and long-run price elasticity to be within the range of 0 to -2.72 with a mean of -0.58 and a median of -0.43. In terms of short- versus long-run estimates, Espey argues that models which include some measure of vehicle ownership and fuel efficiency capture the “shortest” short-run elasticities as they control for changes in vehicle ownership and fuel economy over the longer run.

Further, because static models produce more elastic short-run estimates and less elastic long-run estimates than dynamic models, Espey notes that they are likely producing intermediate-run elasticities.

Several recent studies suggest that short-run elasticities are decreasing over time. Hughes et al. (2008) analyze data over two distinct time periods to demonstrate changes in short-run elasticities over time. They find that the majority of literature overestimates gasoline demand elasticities for the past decade. In a comparison study using data from two different time periods, they show that the short-run gasoline price elasticity shifted down considerably from a range of -0.21 to -0.34 in the late 1970s to -0.034 to -0.077 in the early 2000s. They argue that the change in price elasticity of demand likely stems from structural and behavioral changes in the U.S. since the 1970s which might include the implementation of Corporate Average Fuel Economy program (CAFÉ), changing land-use patterns, growth in per capita and household income and an increase in public transportation. Hughes et al. (2008) suggest that it is likely that long-run elasticities have decreased over time also. In contrast, Espey (1998) argues that short-run elasticities have declined over time, but long-run elasticities have increased over time.

Table 1 displays the results of these studies and seven other previous studies estimating the price elasticity of demand for gasoline using data between the years 1929 and 2006. The table includes estimates from the use of a wide range of models and the meta-analysis ranges include studies using both cross-sectional and time-series data.<sup>2</sup> Further, although Espey (1998) argues that a static model likely produces “intermediate-

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<sup>2</sup> Some authors have found that analysis using cross-sectional data give higher estimates in both the short and long run (Goodwin 1992, Dahl 1986, Dahl and Sterner 1991) and others have found that cross-sectional analysis produces higher price elasticities in the short run, but comparable estimates in the long run (Espey 1998).

run” estimates, authors typically include the results of a static model in either short- or long-run analysis.<sup>3</sup>

We build on this body of literature by not only estimating gasoline price elasticity of demand for the United States for years through 2012, but also by including an analysis of the impact of volatility in gasoline prices on consumer behavior as it is reflected through the demand for gasoline.

### 3. Model

#### 3.1 Basic Static Model

Following the literature (see Basso and Oum 2007), one can express gasoline demand  $D$ , as a function of gasoline prices  $P$ , income  $I$ , and other determinants  $X$  of gasoline demand. This model can be written as:

$$D = f(P, I, X). \quad (1)$$

The simplest way to estimate equation (1) is with a “static” reduced-form demand model, where demand for gasoline is a function of price and income. We use a double log model, which has been shown in meta-study analysis to be more appropriate model than the linear model for gasoline consumption (Dahl 1986, Espey 1998).<sup>4</sup> The basic double-log model assumes that the elasticity is constant over each analysis period:

$$\ln D_t = \beta_0 + \beta_1 \ln P_t + \beta_2 \ln Y_t + \varepsilon_t, \quad (2)$$

where  $D_t$  is per capita gasoline demand in gallons at time  $t$ ,  $P_t$  is the real price of gasoline,  $Y_t$  is per capita disposable income, and  $\varepsilon_t$  is a mean zero error term.

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<sup>3</sup> For example, Goodwin (1992) included static estimates in either the range for short-run or long-run elasticities depending on each author’s classification (Basso and Oum 2007).

<sup>4</sup> Regressions using linear and semi-log models with the dataset used in this study produce similar results for price and income elasticity once coefficients are interpreted properly.

The interpretation of the coefficients of the static model is not entirely clear. We would expect that the price elasticity to be:

$$\frac{\partial \ln D_t}{\partial \ln P_t} = \beta_1 \quad (3)$$

A naïve assumption about the coefficient  $\beta_1$  is that it is an estimate of long-run elasticity and that observed price and demand are in equilibrium. A static specification will not take into account the fact that behavioral change in response to changes in price may take time to come about. For example, delays in movement towards equilibrium may be due to vehicle stock turnover rates, imperfections in alternative fuel markets, and stickiness in changes to population demographics, including relocation. Thus, elasticity estimates from a static model only account for adjustments in the current time period and may actually produce short- or intermediate-run estimates.

### *3.2 Examining the impact of price volatility using alternative specifications*

We hypothesize that gasoline price volatility may matter econometrically in that volatility should be included in models of gasoline demand and gasoline demand elasticity, and also that gasoline price volatility matters behaviorally in that volatility impacts consumers' demand for gasoline and their responsiveness to changes in gasoline price. In particular, we hypothesize that as prices become more volatile, consumers will be less responsive to changes in gasoline price since the price changes so much.

To examine the impact of volatility of price on gasoline demand, we can add a variance term  $v_t$  into the demand equation:

$$\ln D_t = \beta_0 + \beta_1 \ln P_t + \beta_2 \ln Y_t + \beta_3 v_t + \varepsilon_t. \quad (4)$$

The elasticity estimated in equation (4) can be compared to that estimated in equation (3).

A higher magnitude of elasticity in equation (4) could indicate that medium- to long- run gas price elasticity of demand is being overestimated in models that do not control for variance of gasoline prices.<sup>5</sup>

To examine the effects of different levels of price volatility on the price elasticity of demand by interacting the log of gasoline price with dummy variables indicating high, medium, or low levels of price variance respectively:

$$\ln D_t = \beta_0 + \beta_1 \ln P_t \cdot I\{\text{high\_variance}\} + \beta_2 \ln P_t \cdot I\{\text{mid\_variance}\} + \beta_3 \ln P_t \cdot I\{\text{low\_variance}\} + \beta_4 \ln Y_t + \beta_5 v_t + \varepsilon_t . \quad (5)$$

These alternative specifications can also be applied to the dynamic model discussed below.

### 3.3 Dynamic Model

The use of a dynamic model allows us to better separate short- and long-run responses in consumer demand to a change in price. Moreover, a dynamic model allows us to account for a lag in consumer response that the static model does not. Lags in consumer response may be due to intermediate- or longer-run changes in consumer behavior, such as a shift to a more fuel efficient vehicle or form of transport. Thus, observed gasoline consumption may be a function of current gasoline price and consumer income levels, but also of gasoline consumption, gasoline prices and/or consumer income in previous periods.

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<sup>5</sup> A volatility-price interaction term could also be added, however we found that significance in the non-interacted terms dropped out when an interaction was added, likely due to the much higher variance in price volatility than gas price.

There are several approaches to dynamic models (see Dahl and Sterner 1991 for a detailed description), with varying lag specification nested within in the following:

$$\ln D_t = \beta_0 + \sum_{i=0}^m \beta_{Pi} \ln P_{t-i} + \sum_{i=0}^n \beta_{Yi} \ln Y_{t-i} + \sum_{i=0}^q \beta_{Di} \ln D_{t-i} + \varepsilon_t \quad (6)$$

The most popular (and easiest to interpret) dynamic lag model used in the gas price elasticity literature (Basso and Oum 2007) is the partial adjustment model:

$$\ln D_t = \beta_0 + \beta_1 \ln P_t + \beta_2 \ln Y_t + \beta_3 \ln D_{t-1} + \varepsilon_t \quad (7)$$

Here,  $\beta_1$  is the short-run price elasticity of demand for gasoline, and  $\frac{\beta_1}{1-\beta_3}$  is the long-run gas price elasticity. When monthly time series data are used, it is important to note that the “long-run” estimates may reflect a short- or intermediate-run equilibrium, depending on the time necessary for the adjustment to equilibrium.<sup>6</sup> In the dynamic model, the parameter estimates will have valid t-statistics if the dynamics are correctly specified and if the residual is serially uncorrelated.

## 4. Data

### 4.1 Description of Data

We use a monthly dataset for the years 1990 through March 2012. Data on US population and per capita disposable income are from the Bureau of Economic Accounts National Income and Product Account (NIPA) tables. Gasoline price data and gasoline supply data are from the Energy Information Administration (EIA) data for retail

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<sup>6</sup> In equation (8), the speed of adjustment can be estimated using  $\frac{1}{1-\beta_3}$ .

unleaded regular gasoline prices and for US product supplied of finished motor gasoline,<sup>7</sup> respectively. Gasoline price variance is calculated from weekly gasoline price data. Values of per capita gasoline demand in our analyses are derived from US gasoline supply divided by US population. Gasoline price data and per capita disposable income are adjusted to real dollars using a GDP deflator (in January 2008 USD). High, mid, and low gasoline price volatility are calculated by evenly dividing price variance among three groups by percentiles. For example the gasoline price volatility is considered high if the variance is in the top 33.33%, low if it is in the lowest 33.33%, and medium if it is in between.<sup>8</sup>

Figure 1 shows per capita gasoline demand plotted against real gasoline prices and per capita personal disposable income. In the past decade, US real gas prices moved from the relatively steady gasoline prices of the late 1980s and 1990s to a period of rising and highly volatile gasoline prices in the 2000s. We see a downward trend in per capita gasoline demand in the last six years – which occurs as per capita income slows down, but continues to grow. This downward trend is the first since the early 1980s.<sup>9</sup> In the 1980s there was a clear and sustained hike in the real price of gasoline and a slight dip in real per capita disposable income; the combination of these provide an easy explanation for the downward dip in demand. The recent downward dip in demand, however, is occurring as per capita disposable income continues to grow while peaks in gasoline prices are not sustained, although there is a general trend upward. This indicates that

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<sup>7</sup> According to the EIA, “product supplied” approximately represents consumption of gasoline. Product supplied is, in general, the sum of production, imports and other receipts minus exports, stock change and refinery inputs.

<sup>8</sup> Our results are robust to a 25/50/25 percentile split as well.

<sup>9</sup> Data for years prior to 1990 are not shown here, since we were unable to obtain the weekly data needed to calculate the gasoline price variance prior to 1990.

there may be variables other than price and income that are impacting demand and that these variables might be important in understanding gasoline price elasticity estimates.

Figure 2 shows real gasoline price and the variance in gasoline price, calculated using weekly price data over the previous 12 months for each month in the dataset. During the first half of the 2000s, increasing gasoline prices exhibited much less volatility than in the second half. Notably, the peak price volatility occurs just after the start of the recent economic recession.

Figure 3 shows gasoline price variance with horizontal lines indicating the cutoff points used in this analysis for low, medium, and high variance. Aside from a small spike in volatility in the early 1990s, we see fairly low volatility in the 1990s, followed by a decade of medium and high price volatility.<sup>10</sup>

#### *4.2 Addressing time-series properties of the data*

Because we are using time series data, we have to account for the possibility of non-stationarity of our variables. Regression of non-stationary variables on other non-stationary variables might produce significant coefficients based on the correlation between trends rather than the correlation of the underlying variables (Granger and Newbold 1974, Dahl 1991) and may lead to overestimation of elasticities (Basso and Oum 2007).

In estimates of the elasticity of gasoline demand, it is common to find that  $D$ ,  $Y$ , and  $P$  in equation (2) above are all nonstationary and I(1) series. If all variables in the model are integrated of the same order, then a linear combination of non-stationary

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<sup>10</sup> Although the data are not shown here, it is worth noting that earlier periods, such as the late 1970s and early 1980s supported increasing high gasoline prices with a much lower degree of price volatility than in the recent decades.

variables may be stationary ( $I(0)$ ), such that co-integration exists. If the residuals in the models above are stationary, then equations (2)-(5) can be estimated to determine the intermediate- or long-run relationship between the variables. It is important to note, however, that even if an  $I(0)$  combination of  $I(1)$  variables does exist, OLS estimation of these variables still runs the risk of residual autocorrelation, making inference on the coefficients inappropriate (Wadud et al. 2007, Patterson 2000).<sup>11</sup>

## 5. Results and Discussion

To test each variable for its stationarity properties, both an Augmented Dickey-Fuller Test (ADF) and a Dickey-Fuller Generalized Linear Square Unit Root Test (DF-GLS) were used. The DF-GLS test (Elliot et al. 1996) is an updated version of the standard ADF test (Dickey and Fuller 1979) where the data are GLS de-trended prior to testing for stationarity. The DF-GLS test is thought to reject the presence of unit roots less liberally than the ADF and Phillips and Perron (PP) tests (Phillips and Perron 1988) that have been popular in the gasoline demand literature to date (Maddala and Kim 1998, Wadud et al. 2009), and thus may provide a stronger argument for stationarity.

Table 2 reports ADF and DF-GLS test statistics. Gasoline price and disposable income are stationary  $I(1)$ , while the gasoline demand is  $I(0)$  in the ADF test and  $I(1)$  in the DF-GLS test and the variance is  $I(0)$  in the ADF test but  $I(1)$  in the DF-GLS test. Based on the varying test results, it is unclear if our model can be assumed to be cointegrating. Further, the residuals in the basic static model are only border-line

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<sup>11</sup> In estimating demand functions, one may also worry that prices are endogenous since prices and quantities are jointly determined (Lin 2011, Goldberger 1991). However, identifying appropriate instrumental variables for gasoline demand is difficult (Hughes et al. 2008). Hughes et al. (2008) present results using crude oil production disruptions as instrumental variables, but do not focus their discussion of gasoline price elasticities on these estimates.

stationary, thus we should proceed to discuss the results of this model with caution, as we cannot state, with certainty, that our parameters are consistent (Stock 1987).<sup>12</sup> We also present results from a dynamic model, which does not require co-integration.

Table 3 shows results from the basic model (equation (2)), with various additional specifications as presented in equations (4) and (5).<sup>13</sup> The coefficient on log of price represents the intermediate- or long-run gasoline price elasticity of demand. The coefficient of gasoline price variance in specification (2) is negative and significant, indicating that, as gasoline price variance increases, demand for gasoline decreases.

Specification (3) in Table 3 shows the effects of different levels of price volatility on the price elasticity of demand when gasoline price variance is high, medium, or low. We see that elasticity is lowest when gasoline price variance is highest. This result indicates that consumers are less likely to make changes in their driving behavior when they expect gasoline prices to fluctuate.

Table 4 shows results from the estimation of the dynamic model. We tested the dynamic model using different lag structures and including various numbers of lags for demand, price and income. We chose to present results from a dynamic model with 3 demand lags and zero price and income lags for several reasons. First, for models with various specifications of lagged price and income and just one demand lag, we found that our residuals were not “well behaving”.<sup>14</sup> Second, the coefficient on the lags of price and

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<sup>12</sup> It is also for these reasons that an error correction model would not be appropriate for our data.

<sup>13</sup> Because autocorrelation was present in the residuals based on a Breusch-Godfrey test for residual autocorrelation, we present results using Newey-West standard errors (Newey and West 1987).

<sup>14</sup>  $p = 0.000$  for Breusch-Godfrey test for residual autocorrelation and presence of unit root, based on a DFGLS test.

income were not statistically significant in most cases.<sup>15</sup> Third, a model with three demand lags not only had well-behaving residuals, but also had a higher adjusted R-squared than the other models. Fourth, the estimates of both price and income elasticity remained fairly robust to all lag-specification changes. Fifth, a dynamic model with demand lags, but without other lagged variables provides an easier interpretation of long-run elasticities.<sup>16</sup>

In Table 4, the coefficient on log of price is negative and significant in all specifications, as in the static model, and represents the short-run consumer price elasticity of demand for gasoline. As expected, consumers are less price elastic in the short run than in the longer run, as represented by the basic static model above.

Specification (3) of Table 4 shows the effect of volatility on gasoline price elasticity when gasoline price variance is high, medium, or low. We find the results to be consistent with those estimated in the static model above. We see that elasticity is lowest when the gasoline price variance is highest. Thus, in both the short run and intermediate run, consumers respond less to changes in gasoline price if the price volatility over the past year has been high.

As the previous literature has found that short-run gasoline price elasticity is decreasing over time (Hughes et al. 2008), and as the gasoline price volatility is increasing over time as well, we ran our dynamic model over several time periods to test the hypothesis that less elastic demand in an atmosphere of greater price volatility is not

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<sup>15</sup> Estimating equation (7) with zero lags of demand and income and one lag of gas price, the coefficient on lagged gas price (-0.071) was significant at 5%. The coefficient on gas price with no lag (-0.20) was not significant, indicating the possibility of a lagged consumer response to changes in gas price.

<sup>16</sup> Results were also robust to the addition of more demand lags, but beyond 3 lags, the coefficients on the lagged parameters were generally not significant. The exception to this was the 12-month lag. A model using a 12-month lag could be explored in further work.

merely reflecting a decrease in elasticity over time. Breaking up the years also allows us to control for changes in elasticity due only to changes in price or income.

Tables 5, 6 and 7 show results from the dynamic model in the periods 1990–2007 (the time period prior to the recent economic recession), 2008–2012 (the recent period of high gasoline price volatility), and 2000–2006 (a period of relatively lower volatility comparable to the “recent” years used in Hughes et al. 2008)<sup>17</sup>, respectively. While the level of gasoline price elasticity changes depending on the time period, we find that in each case when the price elasticity is estimated at different levels of price volatility, the gas price elasticity is lowest when volatility is greatest.

Table 8 summarizes the coefficients on the log of gasoline price in the various models presented here both with and without control for variance. Although the differences are slight in most cases, we see that controlling for variance results in a less elastic consumer in the long run and a more elastic consumer in the short run.<sup>18</sup> This could indicate that models that do not control for price variance are over-estimating elasticity in the long run and under-estimating elasticity in the short run. This could be especially true in periods of high price volatility, such as the years 2008-2012, where we see the most notable difference in elasticity coefficients.

Table 9 summarizes the gasoline price elasticity when prices over the past year have been highly volatile over the past 52 weeks compared to mid and low periods of volatility. In the short run, intermediate run and long run, we find that consumers are less responsive to gasoline prices in times of high variance than in times of mid or low variance.

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<sup>17</sup> We included the year 2000 in the analysis, whereas Hughes et al. (2008) analyze elasticity for the years 2001–2006. We include 2000 to allow for the inclusion of data that fall into the “low” volatility category.

<sup>18</sup> With the exception of the years 2000-2006.

## **6. Summary and Conclusion**

In this paper, we find three major results. First, in an atmosphere of volatile gasoline prices, as the volatility of prices increases, the magnitude of consumers' demand for gasoline decreases in the intermediate run. Second, consumers become less responsive to changes in gasoline prices when prices are volatile, indicating that gasoline price volatility has an impact on gasoline price elasticity of demand. Third, when a control for variance is included in an econometric model, the estimated gasoline price elasticity of demand is slightly lower in magnitude (in absolute value) in the long run and slightly higher in magnitude (in absolute value) in the short run. This indicates that models that do not control for gasoline price volatility may be over-estimating gasoline price elasticities in the long run and under-estimating gas price elasticities in the short run.

During the years 2008-2012 representing the recent “recession”, leveling per capita income and high gasoline prices have led to more elastic behavior, but, even with more elastic behavior, consumers are less elastic with higher volatility.

This study provides strong evidence that gasoline price volatility should not be ignored when estimating gasoline price elasticity. Our results that gasoline price volatility affects gasoline demand and gasoline demand elasticities have important implications for government policies that may have an impact on the volatility of gasoline prices.

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Figure 1

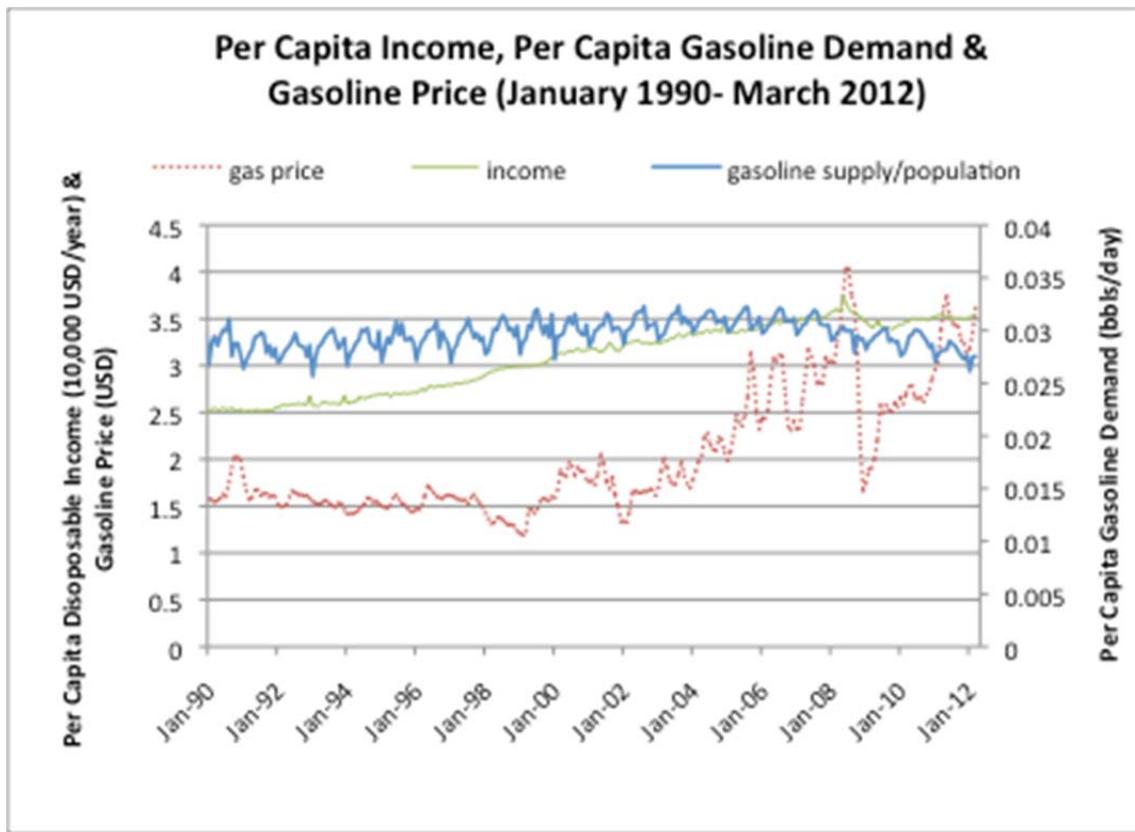


Figure 2

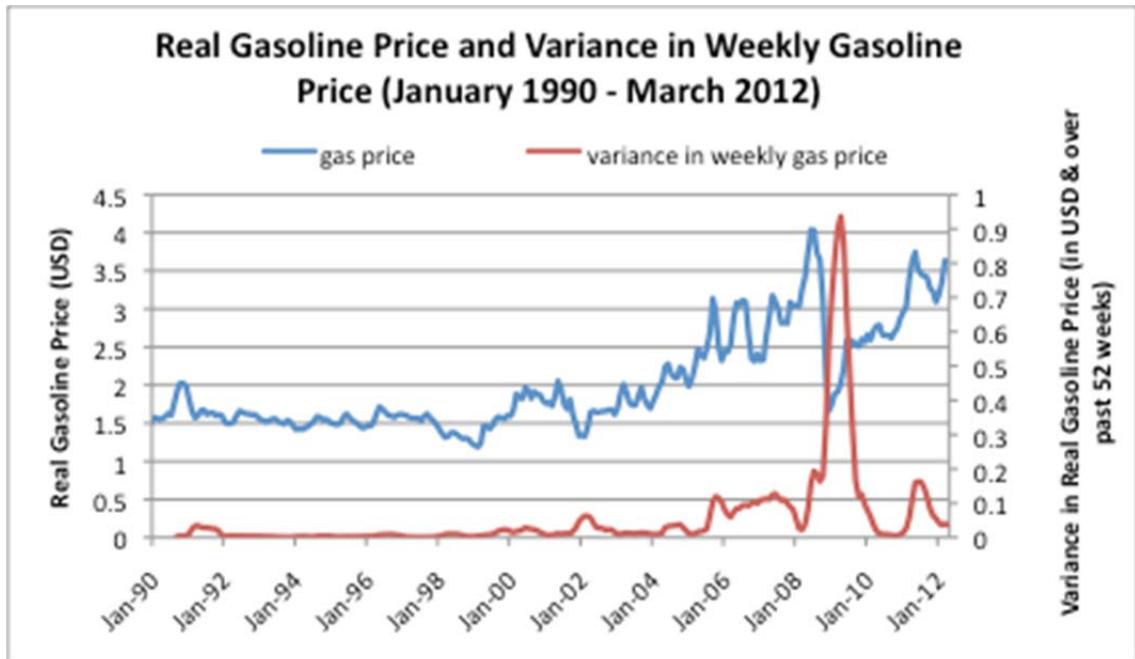


Figure 3

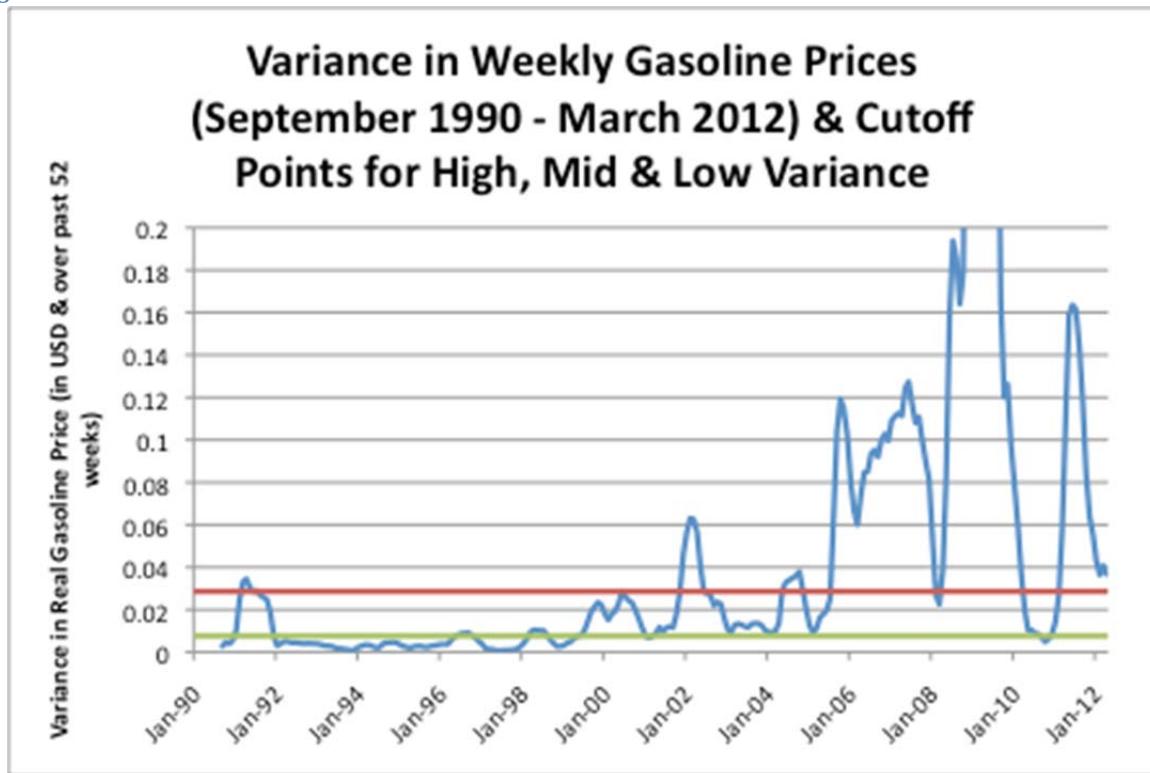


Table 1

Previous Estimates of Short-Run (SR) and Long-Run (LR) Price Elasticities of Demand for Gasoline					
	data range	SR		LR	
		mean	range	mean	range
Dahl and Sterner, 1991	meta analysis (pre 1989)	-0.26	-0.22 to -0.31	-0.86	-0.80 to -1.01
Espey, 1998	meta analysis (1929 - 1993)	-0.26	0 to -1.36	-0.58	0 to -2.72
Goodwin, 1992	meta analysis (pre 1987)	-0.27		-0.71	
- Time series		-0.28		-0.84	
- Cross Section		-0.25	-0.01 to -0.57	-0.64	0 to -1.81
Goodwin et al., 2004	meta analysis (1929 - 1991)		-0.2 to -0.5		-0.23 to -0.8
Graham and Gleister, 2002	meta analysis (pre 1994)	-0.25	0.59 to -2.13	-0.77	0.85 to -22.0
Graham and Gleister, 2004	meta analysis (pre 1994)				
Hanley et al., 2002	meta analysis (1929 - 1991)	-0.25	-0.01 to -0.57	-0.64	0 to -1.81
Wadud et al., 2009	1978 - 2004		-.065 to -.091		-.102 to -.118
Small and Van Dender, 2007	1966 - 2001		-0.09		-0.16
	1997 - 2001		-0.07		-0.16
Hughes et al., 2008	1975 - 1980	-0.21 to -0.34			
	2001 - 2006	-0.034 to -0.077			

**Table 2**

Dickey Fuller and Augmented Dickey Fuller Test Statistics for Levels and First Differences (1990 - 2012)			
	ADF		DF-GLS (lags)
	level	1st diff	level
Log Per Capita Gasoline Demand	-6.216^^	-22.848^^	-0.683
Log Real Gasoline Price	-0.875	-10.019^^	-1.107
Log Real Per Capita Disposable Income	-1.211	-21.194^^	-1.065
Gasoline Price Variance over Past 52 Weeks	-2.001	-5.118^^	-3.206^^

Critical value for test statistic: ^less than 0.05, ^^less than 0.01  
Elliot, Rothenberg, and Stock critical values were used for DF-GLS  
DF-GLS critical value for 8 lags were used, based on an intermediate value of the lag lengths suggested by the Schwarz Information Criteria, Modified Akaike Information Criteria, and Ng-Perron sequential tests.

**Table 3**

Basic OLS model			
Dependent variable: log of per capita gasoline demand			
	(1)	(2)	(3)
In P	-0.089** (0.017)	-0.090** (0.016)	
In P (if variance is high)			-0.088** (0.016)
In P (if variance is mid)			-0.091** (0.018)
In P (if variance is low)			-0.118** (0.020)
In Y	0.193** (0.019)	0.211** (0.017)	0.187** (0.017)
variance		-0.059** (0.012)	-0.063** (0.014)
In P * variance			
Constant	1.696** (0.163)	1.535** (0.151)	1.753** (0.144)
Observations	259	259	259
DF-GLS test statistic for residual error	-1.744^	-1.773^	-2.020^^

Newey-West standard errors in parentheses  
Standard errors: \*\* p<0.01, \* p<0.05  
Regression controls for fixed month effects, coefficients not shown  
Critical value for test statistic: ^> 1% critical value, ^^>5% critical value, ^ > 10% critical value. DFGLS test conducted with 2 lags and Elliot, Rothenberg, and Stock critical values, and no trend.

Table 4

Basic dynamic model			
Dependent variable: log of per capita gasoline demand			
	(1)	(2)	(3)
In P	-0.027** (0.006)	-0.028** (0.006)	
In P (if variance is high)			-0.030** (0.006)
In P (if variance is mid)			-0.035** (0.007)
In P (if variance is low)			-0.036** (0.008)
In Y	0.036** (0.010)	0.042** (0.011)	0.043** (0.011)
variance		-0.011 (0.007)	-0.016* (0.008)
In P * variance			
In D (t-1)	0.152** (0.058)	0.146* (0.058)	0.142* (0.058)
In D (t-2)	0.328** (0.054)	0.324** (0.054)	0.323** (0.054)
In D (t-3)	0.418** (0.057)	0.413** (0.057)	0.412** (0.057)
Constant	0.042 (0.091)	0.037 (0.091)	0.051 (0.105)
Observations	256	256	256
Adjusted R-squared	0.905	0.905	0.905
Adjusted In P	-0.265	-0.239	see table 11
Time for adjustment (in months)	9.804	8.547	8.130
DF-GLS test statistic for residual error	-2.153^^	-2.284^^	-2.626^^^
Breusch-Godfrey LM test for residual autocorrelation (Prob > chi2)	0.506	0.467	0.529
Newey-West standard errors in parentheses			
Standard errors: ** p<0.01, * p<0.05			
Regression controls for fixed month effects, coefficients not shown			
Critical value for test statistic: ^^^ > 1% critical value, ^^ >5% critical value, ^ > 10% critical value. DFGLS test conducted with 5 lags and Elliot, Rothenberg, and Stock critical values, and no trend.			

Table 5

Dynamic model ( 1990 - 2007 )			
Dependent variable: log of per capita gasoline demand			
	(1)	(2)	(3)
In P	-0.028** (0.006)	-0.028** (0.007)	
In P (if variance is high)			-0.024** (0.008)
In P (if variance is mid)			-0.030** (0.008)
In P (if variance is low)			-0.034** (0.010)
In Y	0.157** (0.024)	0.157** (0.025)	0.156** (0.025)
variance		0.003 (0.048)	-0.049 (0.077)
In D (t-1)	-0.095 (0.067)	-0.094 (0.068)	-0.095 (0.068)
In D (t-2)	0.138* (0.065)	0.139* (0.066)	0.134* (0.067)
In D (t-3)	0.268** (0.066)	0.269** (0.067)	0.265** (0.067)
Constant	0.939** (0.177)	0.937** (0.180)	0.977** (0.194)
Observations	205	205	205
Adjusted R-squared	0.920	0.919	0.919
Adjusted In P	-0.041	-0.041	see table 11
Time for adjustment (in months)	1.451	1.458	1.437
DF-GLS test statistic for residual error	-2.908***	-2.912***	-3.191***
Breusch-Godfrey LM test for residual autocorrelation (Prob > chi2)	0.271	0.276	0.232
Newey-West standard errors in parentheses			
Standard errors: ** p<0.01, * p<0.05			
Regression controls for fixed month effects, coefficients not shown			
Critical value for test statistic: *** > 1% critical value, ** >5% critical value, * > 10% critical value. DFGLS test conducted with 5 lags and Elliot, Rothenberg, and Stock critical values, and no trend.			

Table 6

Dynamic model ( 2008 - 2012 )			
Dependent variable: log of per capita gasoline demand			
	(1)	(2)	(3)
ln P	-0.052** (0.018)	-0.068** (0.020)	
ln P (if variance is high)			-0.086** (0.025)
ln P (if variance is mid)			-0.093** (0.030)
ln P (if variance is low)			-0.095** (0.031)
ln Y	0.184 (0.185)	0.153 (0.180)	0.254 (0.203)
variance		-0.018 (0.010)	-0.029 (0.014)
ln D (t-1)	0.138 (0.166)	0.077 (0.164)	0.053 (0.168)
ln D (t-2)	0.145 (0.160)	0.151 (0.155)	0.167 (0.159)
ln D (t-3)	0.462** (0.161)	0.507** (0.158)	0.535** (0.163)
Constant	-0.809 (1.784)	-0.467 (1.738)	-1.452 (1.962)
Observations	48	48	48
Adjusted R-squared	0.868	0.876	0.874
Adjusted ln P	-0.204	-0.257	see table 11
Time for adjustment (in months)	3.922	3.774	4.082
DF-GLS test statistic for residual error	-3.063^^^	-3.216^^^	-4.300^^^
Breusch-Godfrey LM test for residual autocorrelation (Prob > chi2)	0.127	0.185	0.466
Newey-West standard errors in parentheses			
Standard errors: ** p<0.01, * p<0.05			
Regression controls for fixed month effects, coefficients not shown			
Critical value for test statistic: ^^^ > 1% critical value, ^^ >5% critical value, ^ > 10% critical value. DFGLS test conducted with 2 lags and Elliot, Rothenberg, and Stock critical values, and no trend.			

Table 7

Dynamic model ( 2000 - 2006 )			
Dependent variable: log of per capita gasoline demand			
	(1)	(2)	(3)
ln P	-0.030** (0.009)	-0.029** (0.009)	
ln P (if variance is high)			-0.029** (0.009)
ln P (if variance is mid)			-0.028** (0.009)
ln P (if variance is low)			-0.040* (0.020)
ln Y	0.228** (0.052)	0.273** (0.061)	0.274** (0.062)
variance		-0.067 (0.048)	-0.058 (0.073)
ln D (t-1)	0.161 (0.111)	0.121 (0.114)	0.109 (0.118)
ln D (t-2)	-0.072 (0.107)	-0.110 (0.109)	-0.099 (0.112)
ln D (t-3)	0.247** (0.090)	0.214* (0.092)	0.204* (0.095)
Constant	0.205 (0.317)	0.175 (0.315)	0.205 (0.331)
Observations	81	81	81
Adjusted R-squared	0.900	0.901	0.899
Adjusted ln P	-0.452	-0.037	
Time for adjustment (in months)	1.506	1.290	1.272
DF-GLS test statistic for residual error	-4.251***	-4.235***	-4.462***
Breusch-Godfrey LM test for residual autocorrelation (Prob > chi2)	0.199	0.284	0.299
Newey-West standard errors in parentheses			
Standard errors: ** p<0.01, * p<0.05			
Regression controls for fixed month effects, coefficients not shown			
Critical value for test statistic: *** > 1% critical value, ** > 5% critical value, * > 10% critical value. DFGLS test conducted with 2 lags and Elliot, Rothenberg, and Stock critical values, and no trend.			

Table 8

<b>Summary of estimated elasticity of gasoline price demand with and without control for variance</b>		
	no control for variance	control for variance
<i>static (intermediate-run)</i>		
1990 - 2012	-0.089	-0.090
<i>dynamic (short-run)</i>		
1990 - 2012	-0.027	-0.028
1990 - 2007	-0.028	-0.028
2008 - 2012	-0.052	-0.068
2000 - 2006	-0.030	-0.029
<i>adjusted dynamic (long-run)*</i>		
1990 - 2012	-0.265	-0.239

\* the speed of adjustment to equilibrium is 9.8 months (no control for variance) or 8.5 months (control for variance), so this may be considered intermediate- or long-run.  
all estimates were shown to be statistically significant at 1%

Table 9

<b>Summary of estimated elasticity of gasoline price demand at high, mid, or low variance ( 1990 - 2012 )</b>			
	static model	dynamic model	
		short- run	long-run*
high variance	-0.088	-0.030	-0.244
mid variance	-0.091	-0.035	-0.285
low variance	-0.118	-0.036	-0.293

\* the speed of adjustment to equilibrium is 8.13 months, so this may be considered intermediate- or long-run.  
all estimates were shown to be statistically significant at 1%