Short-run Driver Response to a Gasoline Price Spike: Evidence from San Diego, CA

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Drivers' response to an unexpected gasoline price spike is examined using daily data from San Diego County. Elasticities of demand are calculated for the very short run and are compared to prior short run and long run elasticity estimates. Public transportation use is also examined and a cross-price elasticity for bus travel is estimated. The immediate effects of a gasoline price spike are found to be close to zero, but results are broadly consistent with prior short-run estimates after 10 days.

INTRODUCTION

In October 2012 California suffered a series of supply shocks in the gasoline market. There were two major events. The first was a fire at a Chevron refinery in Richmond (near San Francisco) that dramatically reduced its capacity. The Richmond facility has a capacity of 243,000 barrels per day, and typically refines over 8% of the total gasoline output supplied to the Petroleum Administration for Defense District 5, of which California is a part. The second shock was a power outage that shut down an ExxonMobil refinery in Torrance (near Los Angeles). The Torrance refinery has a capacity of 149,000 barrels per day.

The sudden decrease in supply caused a significant increase in retail gasoline prices. The October price spike was unprecedented, even given California's isolated and volatile gasoline market. Retail prices jumped about 57 cents within one week, about a 14% increase. This sudden price spike is comparable only to the results seen after natural disasters like Hurricane Katrina or superstorm Sandy.

How do drivers respond to an unexpected and significant gasoline price increase? We examine this question using data from San Diego County.

CALIFORNIA GASOLINE PRICES

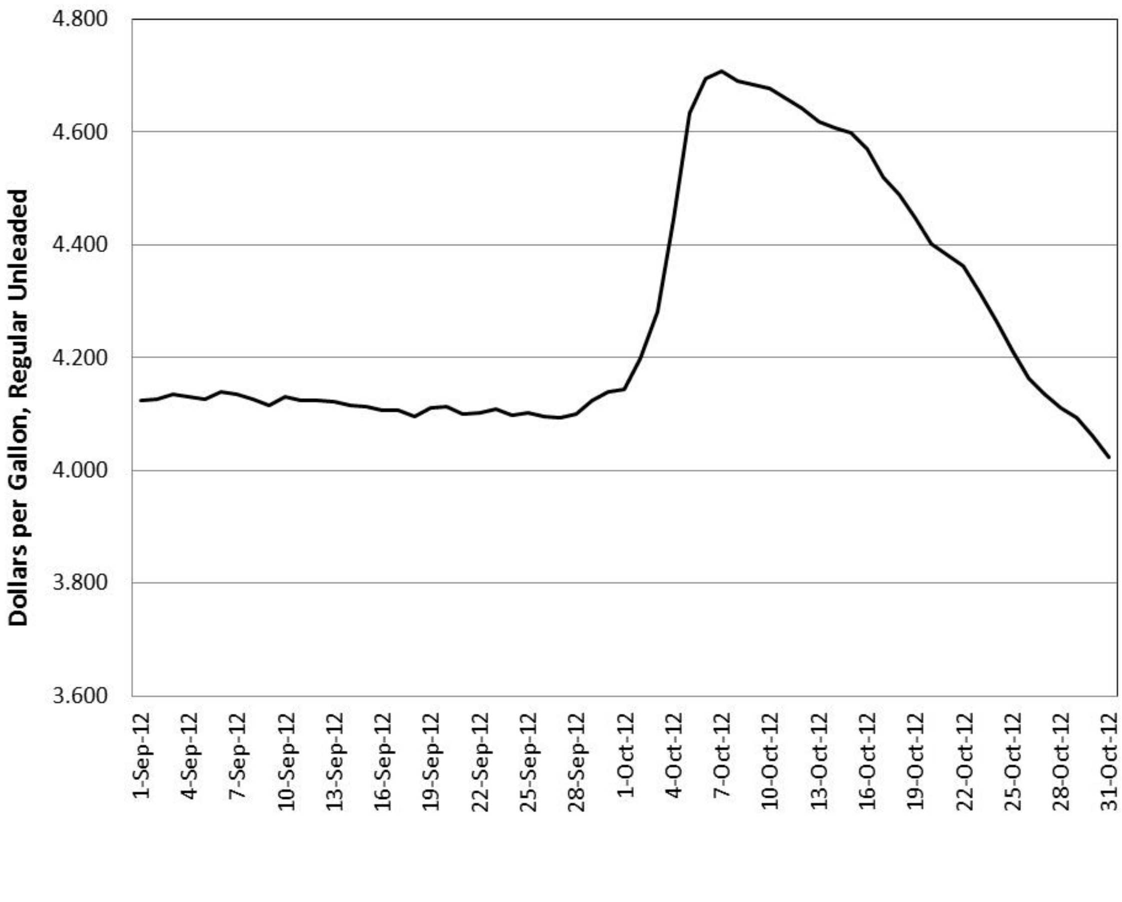
California gasoline prices are typically at least 30 cents per gallon higher than the national average. Higher state gasoline taxes account for about 20 cents of that gap, and a large portion of the remainder is explained by California's air quality regulations that require a higher quality gasoline to reduce air pollution. The special blend used in California is not used in other nearby states so production shortfalls cannot easily be offset by bringing in refined gasoline from elsewhere.

California, along with the rest of the nation, has experienced a recent increase in the volatility of gas prices. National average gasoline prices rose nearly 50 cents a gallon in the first two months of 2013 alone, after a slow decline in late 2012, when seasonally adjusted energy prices fell.

The price of gasoline has a large impact on family budgets since gasoline purchases represent a large portion of monthly spending for many families. Transportation and transportation services comprise a large fraction of the national economy, so insights on how consumers react to sudden gas price changes are important to policy makers and forecasters in this increasingly volatile market.

In this study we concentrate on data from San Diego County. Using daily data, the average price of regular unleaded gas in September 2012 was $4.116 per gallon. The daily average price over the month was quite steady, with a maximum of $4.140 and a minimum of $4.094. In October the average price jumped to $4.414 per gallon. The peak daily average price was $4.708, reached on October 7. The minimum in October was $4.024. Figure 1 shows the average daily regular unleaded retail gasoline price for September and October of 2012 for San Diego County. In this study we examine how drivers in San Diego County responded in the short run to this sudden spike in gasoline prices.

FIGURE 1
AVERAGE UNLEADED RETAIL GAS PRICE, SAN DIEGO COUNTY, SEPT-OCT 2012



PRIOR LITERATURE

There are many papers that have estimated short-run and long-run price elasticities for gasoline, including several meta-studies that summarize a large number of prior results. Espey (1996) examined 101 different studies in a meta-analysis and finds that the short-run average price elasticity of demand for gasoline is -0.26. She defines the short run to be one year or less. In the long-run (longer than 1 year) she finds an average price elasticity of demand of -0.58.

More recent work suggests that short-run price elasticities are lower now, and have decreased over time. For example, Hughes, Knittel, and Sperling (2008) examine data over time to analyze short-run changes in elasticity. By comparing two different time periods, they find that the short-run gasoline price elasticity decreased from a range of -0.21 to -0.34 in the late 1970s to between -0.034 and -0.077 in the early 2000s. Some of this decrease is explained by changes in consumer behavior, partly driven by real income growth and preferences for suburban living, which increases the need to commute. Other factors influencing elasticity include technology advancement and government policies to increase fuel efficiency, such as the national Corporate Average Fuel Economy program, which have increased the productivity of each gallon purchased.

A 2008 Congressional Budget Office study reported a short-run retail price elasticity of about -0.06. In the long run, however, consumers would be expected to respond more to a price increase because they would have more time to make choices that take longer to implement, such as buying a more fuel-efficient car. The CBO reports estimates of about -0.40 for the long run elasticity of demand for gasoline, but this would not be fully realized unless prices remained higher for a long time – up to 15 years – as the stock of consumer vehicles gradually is replaced with more efficient substitutes.

Other studies have examined the impact of changing gasoline prices on vehicle traffic or vehicle miles travelled. Goodwin, Dargay and Hanly (2004) find that if the real price of fuel permanently increases by 1%, the volume of traffic will decrease about 0.1% within a year, up to an eventual reduction of about 0.3% within about five years. Graham and Glaister (2002) report that the short-run elasticity of traffic with respect to price is about -0.15 and the long-run value is about -0.30.

As these studies report, demand is less inelastic in the long run. Driver response in the long run to higher gasoline prices can take the form of a new more fuel-efficient car or moving to a location closer to work. These are generally not feasible options in the short run, but some lifestyle changes can be made in the short run, such as forming carpools, using public transportation, or consolidating tasks to reduce the number of miles driven.

Few studies examine the very short run, which is the focus of this paper. We use daily price and traffic volume data to estimate driver response within the first one or two weeks after a price spike. In the very short run, some discretionary trips can potentially be rescheduled or eliminated, and public transportation can be used as a substitute to driving. We examine the extent to which these options reduce driving and calculate appropriate price elasticities to measure driver responsiveness to unexpected higher gas prices.

MODEL AND DATA

We wish to examine how drivers respond to a sudden and sizable increase in fuel cost. The standard economic prediction is that higher gas prices would lead to reduced gas use and a possible shift to substitutes. The effect is likely to be small, however, since demand for gasoline is very price inelastic, especially in the short run.

Gasoline use by freeway drivers can be reduced by making fewer trips. We measure this effect with highway traffic vehicle counts in San Diego, California, detected by electronic traffic sensors and reported by the California Department of Transportation (CalTrans). Public transportation may be a substitute to car travel, so bus ridership before and after the price spike was examined for all routes served by the San Diego Metropolitan Transit System (MTS).

The data used in this study can be thought of as the result of a natural market experiment. The price spike has generated data that would not have been easy to obtain otherwise, and the time span is so short that it is not necessary to control for changes in population, income, or other demand- or supply-side variables.

We use the following data: (1) Daily average gas price for San Diego County for September-October 2012; (2) Daily vehicle counts recorded by all California Department of Transportation (CalTrans)

District 11 (San Diego County) highway traffic sensors for September-October 2012; (3) Daily bus ridership data for all routes served by the San Diego Metropolitan Transit System for September-October 2012. The values of all three variables were also obtained for September and October 2011 to help control for any short-run month-to-month variation.

RESULTS

Embedded sensors in San Diego County freeways record traffic volume. Daily traffic counts from between729 and 1244 individual sensors was obtained for each day from September 1 to October 31, 2012, collected from all of the 13 different freeways in CalTrans District 11 (San Diego County). Traffic volume varies by day of the week (Saturday and Sunday are well below average, for example) so sensor data for September and October was paired by sensor and by day of week. The first Monday in September was matched with the first Monday in October, for example. Two holidays were removed: Labor Day in September and Columbus Day in October.

A paired t-test was performed using the 30,974 unique day/sensor pairs, comparing the September (*S*) volume to October (*O*). Each difference, *D*, is defined as

$$D_{ij} = S_{ij} - O_{ij}$$

where the subscripts *i* and *j* denote the day and sensor number, respectively. Index *i* ranges from 1 to 26, and *j* ranges from 1 to between 729 and 1244.

The mean difference should be positive if October traffic volume is lower than in September, as we predict. Table 1 shows the paired two sample test result.

TABLE 1
2012 TRAFFIC VOLUMES

	September	October	Difference	T Statistic
Mean	44030.3881	43202.8846	827.5036	42.7201
Variance	1289496040	1242788149		
Observations	30974	30974		

The observed mean difference is small but highly statistically significant (t = 42.72). The October reduction by an average of 827.5 vehicles per sensor per day represents a 1.88% reduction from September. When aggregated by day, the October daily volume was less than in September on 24 of the 26 paired days examined, as shown in Figure 2.

To check whether such a decrease from September to October is typical, traffic data from the same two months in 2011 was examined using the same non-holiday paired comparison. Although mean daily traffic volume in 2011 is similar to 2012, no September to October difference in traffic volume was found (t = 0.37). The 2011 results are shown in Table 2 and Figure 3.

TABLE 2
2011 TRAFFIC VOLUMES

	September	October	Difference	T Statistic
Mean	42881.4708	42873.4364	8.0345	0.3737
Variance	1304497890	1277284429		
Observations	31106	31106		

FIGURE 2
VEHICLES/DAY DIFFERENCE, ALL FREEWAY SENSORS AGGREGATED PER DAY, SEPTEMBER – OCTOBER 2012

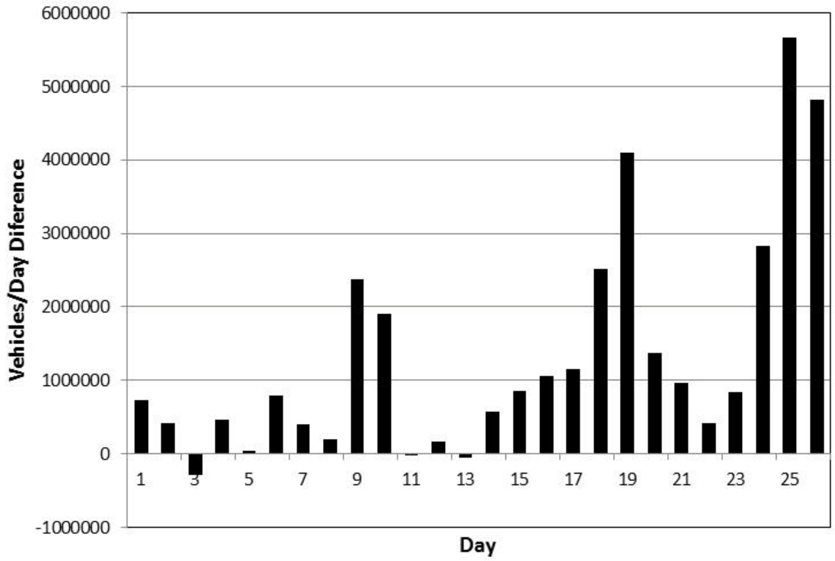
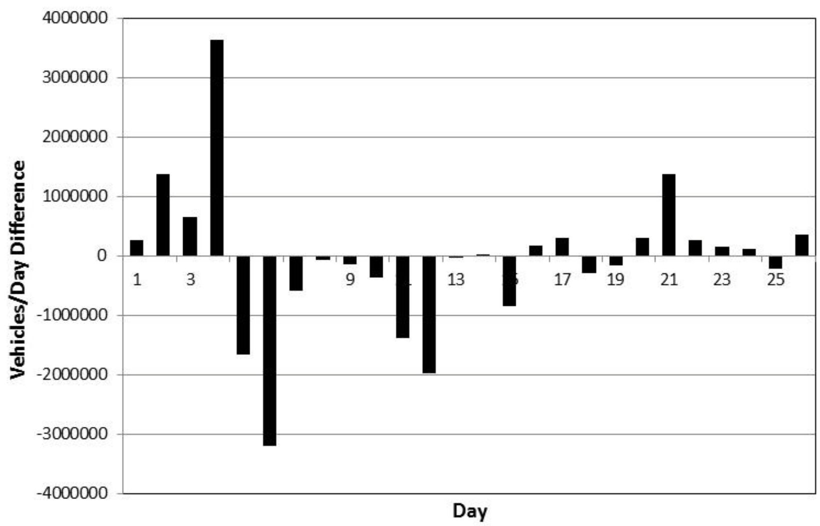


FIGURE 3
VEHICLES/DAY DIFFERENCE, ALL FREEWAY SENSORS AGGREGATED PER DAY, SEPTEMBER – OCTOBER 2011



BUS RIDERSHIP

If public transportation is a substitute for driving then an increase in gasoline price should increase mass transit ridership. There are 98 regular bus routes serving the San Diego area provided by the Metropolitan Transit System (MTS). Daily ridership data was obtained for all routes in September and October for 2011 and 2012.

A paired comparison of average daily ridership by route from September to October should generate a negative difference if ridership increased. The 2012 data show a mean difference of -143.2 riders per route, which is an 8.96% overall increase (see Table 3). This increase in ridership is statistically significant (t = -6.05). The same pattern was not observed in 2011, in fact the sign of the difference was positive (t = 1.696). The 2011 results are in Table 4. Figures 4 and 5 show the differences graphically.

TABLE 3
2012 BUS RIDERSHIP

	September	October	Difference	T Stat
Mean	1598.3830	1741.5800	-143.1970	-6.0491
Variance	3821417.25	4400641.39		
Observations	98	98		

TABLE 4
2011 BUS RIDERSHIP

	September	October	Difference	T Stat
Mean	1639.3850	1615.9456	23.4394	1.6958
Variance	3958461.96	3844000.76		
Observations	98	98		

FIGURE 4
BUS RIDERSHIP CHANGE BY ROUTE, SEPTEMBER – OCTOBER 2012

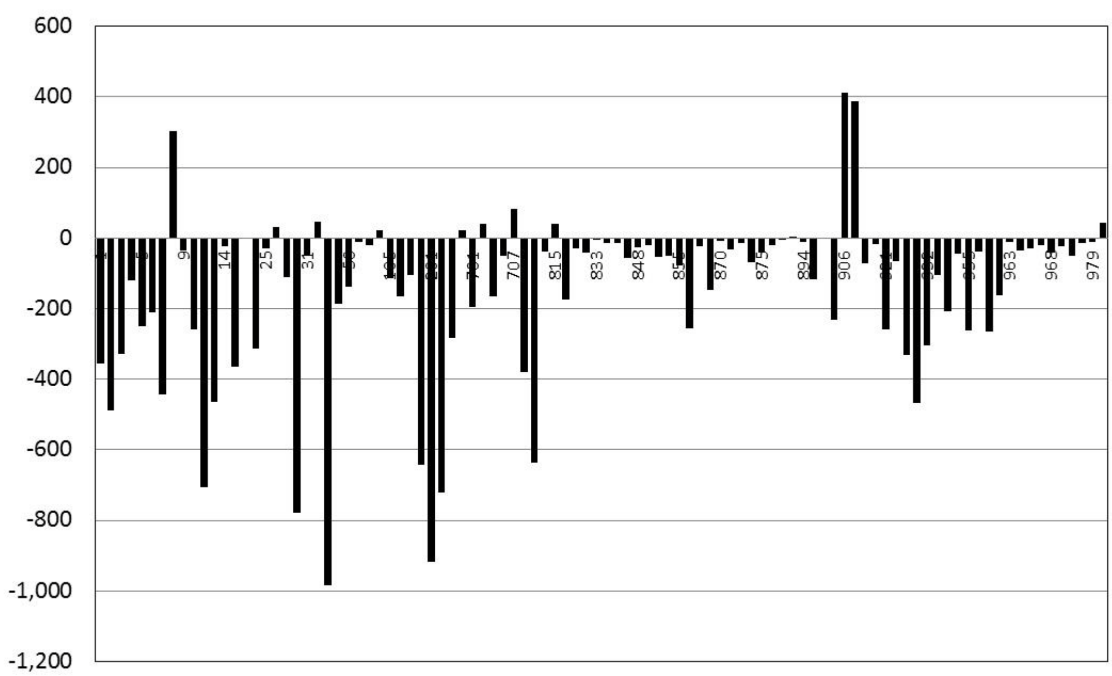
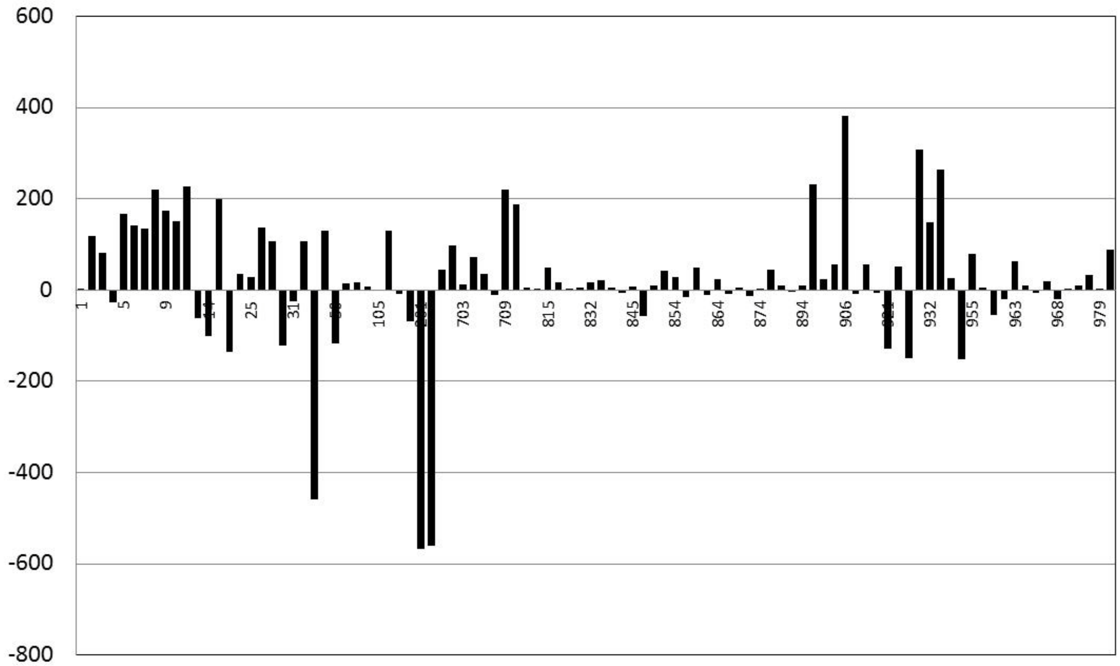


FIGURE 5
BUS RIDERSHIP CHANGE BY ROUTE, SEPTEMBER – OCTOBER 2011



ELASTICITIES

In the models below we estimate elasticites with respect to vehicle traffic counts, but these will be a close approximation to the gasoline price elasticity if the vehicle mix remains constant over the time period being examined. However, it may actually underestimate the true gasoline price elasticity. It is likely that higher short-run fuel prices will lead some drivers to use less gasoline even if they drive the same number of miles. This is possible by driving slower, maintaining their vehicle better, or selecting the family compact car instead of the SUV for an errand.

Static Model

There are two common models used to estimate gasoline elasticities, a static model and a dynamic model (Lin and Prince, 2010). The static model examines gasoline demand (or vehicle traffic counts as a proxy) as a function of gas prices (P), income (Y), and other determinants of gasoline demand (X):

$$D = f(P, Y, X)$$

In our very-short run model we assume that Income and other variables are constant, so the static model collapses to a function of price alone. Since time is the variable of interest, lags are introduced to see how recent past prices influence gasoline use.

Consider the following model, which uses vehicle traffic volume to measure drivers' response to higher gasoline prices, where n represents a time lag in days:

$$\log VehCount_t = b_0 + b_1 (\log\_GasPrice)_{t-n} + b_2 (Sat) + b_3 (Sun)$$

Sat and *Sun* are dummy variables for Saturday and Sunday, and *VehCount* is the average daily vehicle traffic count, aggregated over all traffic sensors in the county. The double log model has been found in prior studies to be more appropriate than a linear model for gasoline demand (Espey 1998). The coefficient b_1 thus represents the elasticity of vehicle volume with respect to gas price.

Given that gasoline demand is price inelastic we expect b_1 to be between 0 and -1. Prior studies have shown that demand is more inelastic in the short run than in the long run. Very short run elasticities can be estimated by varying *n*, the time lag in days, in this model. We find a negative coefficient in every case, but close to zero in the first few periods. The coefficient value increases in magnitude monotonically as the time lag increases. Thus the elasticity of vehicle travel becomes less inelastic over time, consistent with prior studies of the long run vs. short run. The *p*-value also decreases monotonically, and elasticity estimates starting with the 7-day lag begin to be significant at the 0.10 level.

In the very short run the responsiveness of vehicle travel to higher gas prices is close to zero. Within ten days the elasticity approaches -0.30, consistent with prior estimates of the short run gasoline price elasticity. Results are shown in Table 5 and Figure 6.

TABLE 5
OLS, VARIOUS LAGS ON LOG (GASPRICE)
DEPENDENT VARIABLE: LOG (VEHCOUNT)

	Lag (days)	*Coefficient*	*Std. Error*	*t-ratio*	*p-value*	
log_GasPrice	0	-0.02613	0.106195	-0.2460	0.80657	
log_GasPrice-1	1	-0.05542	0.107818	-0.5140	0.60936	
log_GasPrice-2	2	-0.07256	0.105708	-0.6864	0.49544	
log_GasPrice-3	3	-0.09970	0.106866	-0.9329	0.35517	
log_GasPrice-4	4	-0.12638	0.107916	-1.1711	0.24701	
log_GasPrice-5	5	-0.14806	0.108726	-1.3618	0.17937	
log_GasPrice-6	6	-0.15436	0.107233	-1.4395	0.15637	
log_GasPrice-7	7	-0.18473	0.107523	-1.7181	0.09223	*
log_GasPrice-8	8	-0.21383	0.107463	-1.9898	0.05245	*
log_GasPrice-9	9	-0.27138	0.100838	-2.6913	0.00989	***
log_GasPrice-10	10	-0.30108	0.100152	-3.0062	0.00432	***

(The coefficients for the dummy variables *Sat* and *Sun* are significant at the 0.01 level in each of these models.)
* significant at the 10% level
** significant at the 5% level
*** significant at the 1% level

Dynamic Model

In a dynamic model, the impact of all prior time periods can be included in the estimate of the current elasticity. Consider a Koyck lag dynamic model, which includes a variable for the lagged dependent variable:

$$log\ VehCount_t = b_0 + b_1\ (log\_GasPrice)_{t-n} + b_2\ (Sat) + b_3\ (Sun) + b_4\ (log\ VehCount)_{t-(n+1)}$$

In this form the coefficient b_1 is the static price elasticity and $b_1/(1- b_4)$ is the dynamic elasticity which incorporates the effects of all prior periods. Assumed in this model is that the impact of prior periods decreases geometrically.

FIGURE 6
ELASTICITY OF TRAFFIC VOLUME VS. GAS PRICE OVER TIME

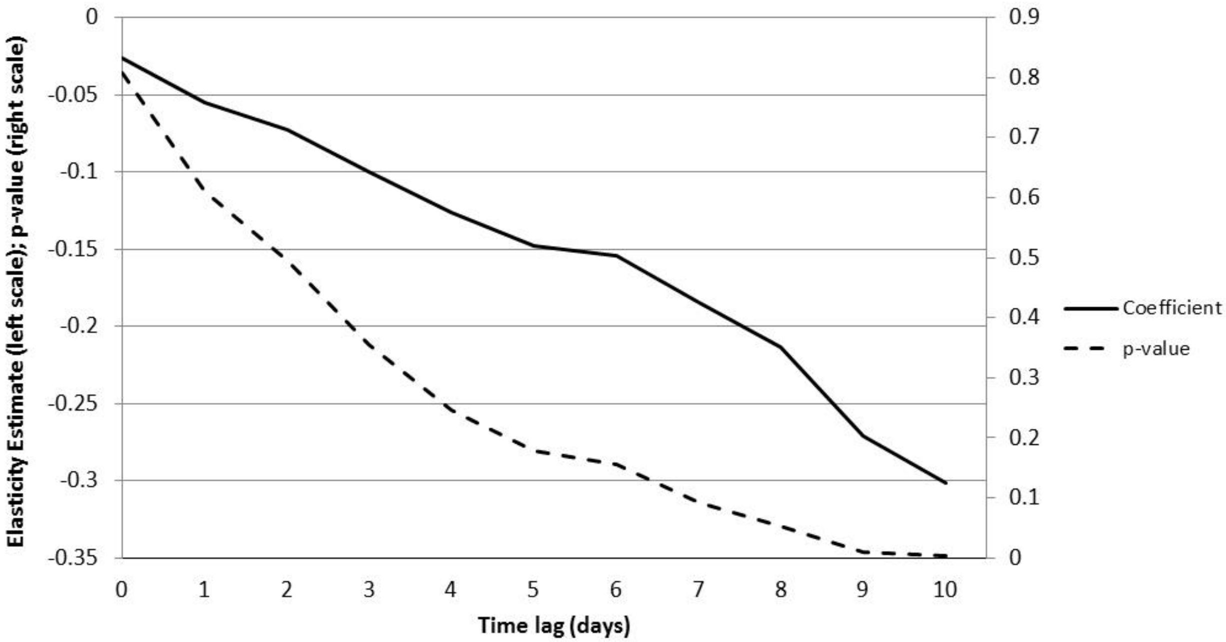


TABLE 6
DYNAMIC MODEL ELASTICITIES

lag, n	b_1	*p-value*		b_4	*p-value*		$b_1/(1-b_4)$
0	-0.01169	0.88972		0.22669	<0.00001	***	-0.01512
1	-0.02607	0.78282		0.17399	0.00032	***	-0.03156
2	-0.07249	0.50482		0.02326	0.62257		-0.07421
3	-0.11086	0.29102		-0.11170	0.02162	**	-0.09972
4	-0.15097	0.10285		-0.19910	0.00001	***	-0.12590
5	-0.14479	0.18496		-0.10040	0.19220		-0.13158
6	-0.13224	0.15439		0.28861	0.00003	***	-0.18589
7	-0.15948	0.09138	*	0.19855	0.00005	***	-0.19898
8	-0.21949	0.02760	**	0.14124	0.00689	***	-0.25559
9	-0.27778	0.01002	**	0.00695	0.88735		-0.27972

(The coefficients for the dummy variables *Sat* and *Sun* are significant at the 0.01 level in each of these models.)
* significant at the 10% level
** significant at the 5% level
*** significant at the 1% level

Results are similar to the static model in that the estimated elasticities are near zero in the first few days after the price spike, gradually increasing in magnitude as consumers have time to adjust their driving behavior. Estimated coefficients for b_1 and b_4 from the dynamic model are reported in Table 6. The estimated dynamic elasticity $b_1/(1- b_4)$ is still monotonic, changing from near zero in the first few days to about -0.28 after nine days.

CONCLUSION

In October 2012 a sudden gasoline price spike occurred in California. Southern California drivers responded by making fewer trips and by increasing their use of public transportation. An average gasoline price increase of 7.24% in October 2012 compared to September led to a 1.88% decrease in freeway vehicle traffic volume. These aggregate changes suggest a short-run price elasticity of -0.26, which is consistent with the short-run estimates of elasticity summarized by Espey (1996).

The 7.24% average gasoline price increase was accompanied by an 8.96% increase in bus ridership, suggesting a cross-price elasticity of 1.24 for public transportation. Changes in both vehicle traffic counts and bus ridership were significant over this period.

Driver response to higher gas prices was very small in the first few days after the price spike. This is to be expected since most drivers do not buy gasoline every day and the impact of a higher price may not be felt until their next stop at the pump. Price elasticities in the first few days after the spike were close to zero and not statistically significant. Over time the response increased and became significant by the 7^{th} day after the price increase. By the end of 10 days the elasticity value approaches -0.30, consistent with prior short-run elasticity estimates.

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