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"DOING MY PART" TO SAVE THE GLOBAL COMMONS? Environmental Awareness and Voluntary Fuel Economization in Gasoline Markets

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ABSTRACT: Information about collectively created problems, such as air pollution, may elicit voluntary changes to consumer behavior that at least partially offset the cause of the problem. We show that increases in information about climate change are associated with statistically and economically significant decreases in expenditure on gasoline, controlling for gasoline prices and income. We simultaneously provide updated estimates of the short-run price and income elasticities of demand for gasoline in the United States, utilizing recent weekly gasoline consumption and price data and spatially-delineated supply side disruptions due to hurricanes as an instrument for price.

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1. Introduction

Climate change and energy dependence are key issues in both modern policymaking and environmental economics. Central to these issues is the consumption of energy—in particular gasoline—and how consumption patterns change in response to information, prices, and government policies. In 2008, the consumption of motor gasoline declined by 3.4 percent compared to 2007. Notably, this was the first annual decline in gasoline consumption in the United States since 1991 (EIA, 2009). Some of this decrease can be attributed to a movement along the demand curve as the retail price of gasoline rose precipitously during 2008 (figure 1); some of it may be attributable to a weakening economy contracting income and shifting demand inwards (Energy Information Administration, 2009). However, prices and income alone do not explain all of the fall in gasoline consumption. In this paper, we consider the role that environmental awareness may have on consumer behavior at the pump.

From 1997 to 2008, there was a (noisy) upward trend in the flow of climate change information through major media outlets. It is possible that, as agents ingested this climate change information, they became more aware of the potential seriousness of climate change. This increase in environmental awareness could lead to a voluntary reduction in gasoline consumption as consumers try to do their part to reduce their emissions of greenhouse gases. Individual consumers can economize their fuel consumption via two margins: driving less and by driving more fuel-efficient vehicles. Regardless of the relative importance of these two avenues for fuel economization, our empirical analysis finds that as consumers became more informed on climate change, they voluntarily reduced their carbon footprint by purchasing less gasoline (relative to what they would have given prices and income).

We do not claim that the climate change problem can be solved by these voluntary actions to economize fuel consumption. Economic theory has established that public goods are underprovided when contributions are voluntary. Despite the uncertainty surrounding climate change, reductions in greenhouse gas emissions can be considered to be a public good. Hence, when people reduce their consumption of gasoline in order to do their part to combat climate change, these reductions are too small relative to the Pareto optimum. This has led to a dismissal of voluntary schemes from the serious policymaking arena. In the process of relegating voluntary schemes, it is tempting to consider any voluntary reductions in gasoline consumption as negligible. They are not.

In this paper, we develop a metric of consumers' environmental awareness and implement this variable as a determinant in estimates of the demand for gasoline in the United States. We find that increases in environmental awareness were associated with statistically and economically significant decreases in expenditure on gasoline. Extrapolating our estimates to an out-of-sample forecast, we predict that a change to full awareness of climate change from perfect ignorance would result in a 20 percent decrease in weekly per capita expenditure on gasoline. This finding is a significant contribution to the literature on optimal climate change policy, behavioral responses to climate change, empirical findings of voluntary contributions to public goods problems, and the estimation of the demand for gasoline.

In the process of establishing the observed connection between climate change information in the media and gasoline consumption behavior, we provide new estimates of the national short-run price and income elasticities of demand for gasoline utilizing recent, high-frequency gasoline consumption data and data on spatially-delineated supply side disruptions due to hurricanes. Our estimates of short run price elasticity range from -0.16 to -0.18, while our short-run income elasticity estimates range from 0.08 to 0.31. The lower estimates of both price and income elasticity come from OLS regressions and the higher estimates come from two-stage least squares regressions using data on hurricanes and lagged oil prices as instrumental variables.

2. Background

In the summer of 2008, the real price of gasoline in the United States increased to levels not seen since the late 1970s, as shown in figure 1. Up until 2008, annual consumption of gasoline consistently had increased every year since the early 1990s, despite the increases in the real price of gasoline that began in late 1990s (EIA, 2009; see figure 1). In the year 2008, however, the United States witnessed the first year-to-year decrease in gasoline consumption since 1991 (EIA, 2009). Economists typically attribute this decrease in consumption to the high price of gasoline combined with an economic recession—in other words, a combination of a substitution effect induced by increased gasoline prices and an income effect caused by the economic downturn (EIA, 2009). The magnitude of these effects depends on the price elasticity of demand and the income elasticity of demand. Indeed, the recent volatility of gasoline prices offers economists an opportunity to update calculations of price and income elasticity of demand for gasoline using data that were previously out of sample. Awareness of the possible links between the environment and energy use may also affect consumer demand, a prospect we test and find support for in this paper.

2.1 Environmental awareness and the demand for gasoline

Concerns for the environment may elicit voluntary behavior changes in energy producers and consumers. We argue that the extent of this phenomenon is already large enough to be observable in the available data. In its *Annual Energy Outlook*, the Energy Information Administration noted, “Even without the enactment of Federal laws and policies limiting U.S. [greenhouse gas] emissions, regulators and the investment community are beginning to push energy companies to shift their investments towards less [greenhouse gas]-intensive technologies” (Energy Information Administration, 2009, p. 3). The report goes on to note that to some degree concerns about climate change may already be affecting decisions made by producers in energy markets. We consider whether those same concerns are also affecting decisions made by consumers.

The voluntary adoption of environmentally friendly consumption patterns is, of course, not unprecedented. Individuals across the world voluntarily recycle household waste, sometimes even going to great lengths and costs to separate and rinse the refuse prior to recycling it. In some cases (although probably not recycling), the voluntary adoption of environmentally-friendly consumption patterns results in lower costs for the consumer. One such case is that of compact fluorescent bulbs in Hungary in the 1990s, where a combination of low prices for compact fluorescent bulbs due to fierce market competition among lighting manufacturers, a marketing campaign performed by manufacturers that increased awareness of potential savings from a marketing campaign performed by manufacturers, and an increase in energy prices led to more rapid adoption of compact fluorescent bulbs (Ürge-Vorsatz and Hauff, 2001). Conversely, some environmentally friendly actions appear to be undertaken despite an increase in costs.

For example, some model year 2008 hybrid vehicles sold in the United States would require the purchasers to drive the hybrid 15,000 miles per year for more than a decade at gas prices of $3.61 per gallon or more in order to recover the hybrid premium, or the additional amount a hybrid purchaser must pay in order to buy a car with two powertrains and other complexities (Valcourt, 2008).

Of course, cost savings is not the only reason some people purchase hybrids, recycle, or engage in other environmentally friendly actions. Many other possible motivations exist, such as concerns about air pollution or preserving nature, desire to breathe cleaner air or reduce cancer rates, beliefs that failure to appear green will result in ostracization, or the desire to feel as part of a club of environmentalists, to name just a few.[3] Indeed, we contend that the present social norms in the United States encourage conspicuous consumption of environmentally-friendly goods. To some degree, this is demonstrated by the distinctive shape of the most popular hybrid vehicles, which makes others aware that the driver of the hybrid is "doing his part" to preserve the environment.

To what extent, however, are concerns about global warming and greenhouse gas emissions affecting decisions made by consumers of energy in the United States? To help answer this question, we attempt to measure consumer awareness of climate change as a proxy of environmental awareness and then test whether this metric is a significant determinant of gasoline demand. Our results indicate that, all else constant, as environmental awareness increases, demand for gasoline decreases. This finding should be considered by policymakers. If environmental awareness increases in the future, less-drastic policies may be sufficient to produce a targeted level of gasoline consumption.

[3] For an interesting discussion of the motivations of environmentalists, especially the characterization of environmentalism as a religion, see Nelson (2004).

There is an important role in policymaking for a fuller consideration of the effect of environmental awareness on the behavior of consumers of fossil fuels.

2.2 Literature on the demand for gasoline

Price elasticity of demand for gasoline is perhaps one of the more useful elasticity estimates economists can provide policymakers, both because gasoline taxes represent a large revenue source for governments and because policymakers occasionally try to create rules and laws that are designed to decrease pollution caused by gasoline consumption. Previous estimates of the elasticity of demand for gasoline have varied depending upon the estimation technique used, the time period and frequency of the data used, and the region from which the data were collected. In a review of studies of price and income elasticity estimates, Dahl and Sterner (1991) noted that studies occasionally arrive at conflicting results, which is “quite natural since the studies surveyed are based on different models, types of data, countries, time periods, different functional forms and econometric techniques” (Dahl and Sterner, 1991, p.1). The authors reviewed 97 different gasoline demand studies that implement a variety of estimation techniques, data types, and data intervals. They found the average short run price elasticity across the studies to be -0.26, while the average long run price elasticity was -0.86. Dahl and Sterner calculated average income elasticity to be 0.48 in the short run and 1.21 in the long run. In comparing their survey to previous surveys done (Dahl, 1986; Bohi and Zimmerman, 1984; and Bohi, 1981), Dahl and Sterner noted that “representative elasticities for the short run do not vary greatly.” The authors did find, however, considerable variability in long-run estimates of both price and income elasticity. Goodwin (1992) similarly reviewed a multitude of price elasticity estimates produced in the 1980s and early 1990s, and, unsurprisingly, arrived at similar averages. Goodwin separated the studies into those that explicitly measured short run and long run elasticities and those that did not explicitly consider the time dimension, and then further broke down the studies into those that used time series data and those that used cross-sectional data. The resulting mean short-run price elasticities were -0.27 for time series and -0.28 for cross-sectional data; mean long-run elasticities were -0.71 in time series and -0.84 for cross-sectional; and the mean time-ambiguous elasticity estimates were -0.53 for time series and -0.18 for cross sectional (Goodwin, 1992; Graham and Glaiser, 2002). Goodwin concluded that long-run estimates tend to range from 1.5 to 3 times greater than short-run estimates, and that the data type—cross sectional or time series—only marginally affects those estimates. By contrast, Dahl (1995), in a review of 18 studies of demand for gasoline in the United States, found that studies that implement static models tended to find lower long-run price and income elasticities with more recent data, whereas dynamic models (defined as those that include at least one lagged independent variable) appeared to find similar estimates regardless of the time period of data observations.

Graham and Glaister (2002) performed a more recent survey of elasticity estimates of demand for gasoline. The range of estimates reported in Graham and Glaister remains similar to previous reviews: long run estimates were typically between -0.6 and -0.8, while short run estimates tended to fall between -0.2 and -0.3. Graham and Glaister also reported a long-run income elasticity range between 1.1 and 1.3 and short-run estimates between 0.35 and 0.55.

Espey (1998) conducted a meta-analysis of “277 estimates of long-run price elasticity, 245 estimates of long-run income elasticity, 363 estimates of short- or medium-run price elasticity, and 345 estimates of short- or medium-run income elasticity” in order to determine if any factors systematically affect those elasticity estimates, such as the inclusion of vehicle stock or characteristic variables; periodicity of the data; the time period from which data were taken; whether studies were regional, national, or transnational; differences in dynamic structures of studies’ models; and whether studies used linear, multiplicative, or indirect estimation of demand (Espey, 1998, p. 274 and pp. 293–294). Espey concluded that studies that exclude vehicle ownership generally produce more price- and income- elastic estimates. Espey also found that differences in lag structures of dynamic models tend not to affect estimates, except in the case of a quarterly lag compared to models with annual lags. Although she finds that using state or regional level data does not significantly alter estimates compared to national level data, Espey notes that elasticity estimates tend to vary across countries or when other countries are pooled with the United States. This finding is consistent with two other studies that examined elasticities in multiple countries in Europe, both of which used consistent models and specifications for all countries and found that both short-run and long-run price elasticities differ significantly across countries (Drollas, 1984; Sterner et al, 1992). Finally, Espey concluded that differing estimates produced using older data compared to newer data suggest “the need for updated studies and for care to be taken in extrapolating into the future” with elasticity estimates from old data (Espey, 1998, p. 294).

A more recent study on the demand for gasoline has perhaps confirmed Espey’s intimation about relying on old data. Hughes et al. (2006) noted that a variety of factors could have altered the nature of gasoline demand in the United States over the last few decades, including changing land use patterns, the federally mandated Corporate Average Fuel Economy (CAFE) program, higher per-capita incomes and more multiple-income households, and availability of automobile transportation substitutes such as mass transit (Hughes et al, 2006). As an example, the authors pointed out that the trend of flight to the suburbs likely resulted in increased driving per household (Hughes et al, 2006; Kahn, 2000). Hughes et al found strong evidence that the elasticity of demand has indeed changed over time. They estimate the short-run price elasticity of demand for gasoline to fall in the range of -0.034 and -0.077 using data from years 2001 to 2006. Using the same model and data type, Hughes et al estimated the short-run price elasticity was between -0.21 and -0.34 in the period from 1975 to 1980. Given the evidence that elasticities may change over time, our paper contributes to the literature by providing updated short run price and income elasticity estimates levels using data from 1997 through most of 2008.

2.3 Policy relevance of elasticity estimates

Heedless of Espey's advice regarding old data, some government agencies have relied on older estimates of price elasticity of demand even in recent publications. For example, in 2008, the U.S. Environmental Protection Agency (EPA) issued a regulation addressing emissions from petroleum refineries (EPA, 2008). As part of its rulemaking process, EPA performed a Regulatory Impact Analysis that relied upon an estimate of the price elasticity of demand for gasoline of -0.69 for some of its calculations (EPA, 2008, p. 5-3). Notably, although the rule was promulgated in 2008, the elasticity estimate was taken from another EPA publication written in 1995, which in turn took its elasticity estimate from an EPA publication from 1993.[4] It is worth noting that the 2008 EPA publication did not address the possibility of price elasticity changing over time.

Similarly, a 2003 Congressional Budget Office study assumed that the elasticity of vehicle-miles traveled with respect to fuel price, which may be considered as one of the main components of the short-run price elasticity of gasoline, is -0.2, while using a long-run price elasticity of -0.39 (Congressional Budget Office, 2003).[5] This short-run assumption is based off of a review of literature published in 1997 while the long-run estimate is based on a simulation and compared to "more recent estimates of long-run elasticities" (Congressional Budget Office, 2003, p. 12). These estimates apparently included the aforementioned Dahl and Thomas (1991) study and a Department of Energy review of gas emissions studies published in 1996 (Congressional Budget Office, 2003, p. 12, footnote 22; Department of Energy, 1996). While this Congressional Budget Office study did make an attempt to consider more recent estimates, the studies considered are nevertheless relatively dated. Our study could usefully inform policymakers by producing elasticity estimates that rely on very recent data and include some data from gasoline price spike of 2008.

[4] The 1995 publication, *Regulatory Impact Analysis for the Petroleum Refinery NESHAP, Revised Draft for Promulgation* (available online at: http://yosemite.epa.gov/ee/epa/riafile.nsf/Attachment+Names/A.95.29%20petroria.htm/$File/A.95.29%20petroria.htm?OpenElement), referred to a 1993 publication, the *Industry Profile for the Petroleum Refinery NESHAP*, as the source of its estimate of price elasticity of demand for gasoline (EPA, 1995, section 6.2.8.1). Unfortunately, we were unable to retrieve the 1993 publication online, but given the date of its publication, it is safe to assume the data it relied upon were primarily from the 1980s or earlier.

[5] The CBO study actually assumes that the "elasticity of vehicle-miles traveled" is -0.2. This is a main component of short-run price elasticity because, as the CBO study states, in the short run, "consumers respond to a change in the price of gasoline primarily by adjusting their driving behavior. […] In the short run, the elasticity of vehicle-miles traveled predominates. In the long run, the elasticity of fuel economy plays a larger role as more consumers purchase new vehicles."

3. Model

We begin by developing a theoretical model for the gasoline consumption behavior of individuals. We then transform that theoretical model into a structural econometric model whose reduced-form parameters can be estimated with high-frequency aggregated data. To fully flush out the regressors representing beliefs over climate change, we then develop a submodel of beliefs as a function of news coverage. We address the endogeneity of price with a two-stage least squares procedure: an initial reduced-form regression of gasoline price on supply shocks and a second stage structural estimation with the predicted price of gasoline from the first stage substituting for the observed price as a regressor.

3.1 Modeling gasoline consumption behavior

The individual's problem is to maximize their objective, a Stone-Geary utility function in gas and all other goods, subject to their budget constraint:[6]

$$\max_{x,y} E_S \left(y - \underline{y} - z\psi - s\beta\right)\left(x - \underline{x}\right)^{\frac{\eta}{1-\eta}} \quad st \quad m \geq px + y \tag{1}$$

Where:

x = quantity of gas

y = quantity of (and expenditure on, due to y being the numeraire) all other goods

E_s = expectation at time t with respect to beliefs over the seriousness of climate change

\underbar{x} = minimum "necessary" amount of gas

η = gas' expenditure share of "disposable" income (i.e., not spent on necessities)

zψ = demographics affecting demand (e.g., age)

[6] See von Haefen (2002) for a systematic development of similar such "incomplete" demand systems.

s = seriousness of climate change

β = damage parameter transforming seriousness of climate change into damages

m = income (deflated by the numeraire's price index)

p = price of gas (deflated by the numeraire's price index)

Solving for the optimal gas expenditure on LHS with primitive parameters broken out into bracketed terms from observable variables:

$$px = [-\eta \underline{y}] + [-(1-\eta)\underline{x}]p + [\eta]m + [-\eta\beta]E(s) + [-\eta\psi]z \tag{2}$$

We can cleanly aggregate over the N people in the region (the unit of observation in our data) and divide through by that population to put in per-capita terms:[7]

$$\frac{p\sum_{i=1}^{N} x_i}{N} = [-\eta \underline{y}] + [-(1-\eta)\underline{x}]p + [\eta]\frac{\sum_{i=1}^{N} m_i}{N} + [-\eta\beta]E(s) + [-\eta\psi]\frac{\sum_{i=1}^{N} z_i}{N} \tag{3}$$

Note that each primitive parameter can be easily recovered from the bracketed terms. This structural equation becomes an estimable equation by including a disturbance term on the end to capture noise in the measurement of average expenditure on gas. That same disturbance term also implicitly contains the supply-side relationship between the quantity of gas and its price. In order to obtained unbiased estimates of the parameters, we employ a standard remedy to handle this endogeneity problem: instrumental variables. We use shocks to supply in the form of hurricanes and (lagged) oil prices to instrument for price in a standard two-stage least squares procedure.

[7] See Blundell and Stoker (2002) for a review of analyses on aggregate data that are consistent with an aggregation up from microeconomic agent behavior.

3.2 Modeling hurricane impacts on gasoline prices

We treat the peak of a hurricane's impact as the point where the hurricane passes closest to the population-weighted centroid of each PADD region.[8] At a given location of impact, we would expect that the supply-side shock to price would be an increasing function of the hurricane's winds.[9] Across locations, a hurricane's disruption of the gasoline supply decreases convexly in distance from the hurricane. After the event, the effects of the shock tail off. Likewise, the impact on prices due to anticipation accelerates as we approach the point in time when the hurricane produces its maximum impact. Because the first stage need not be structural, we can capture these stylized facts by specifying a reduced form model of price:

$$p_{it} = \alpha_{0i} 1\{i\} + \alpha_1 o_{t-1} + \alpha_2 w_{ih} + \alpha_3 \left(\frac{1}{d_{hi}} \right) + \alpha_4 \frac{1\{\tau_{ih} - t\}}{(\tau_{ih} - t) + 1} + \alpha_5 \frac{1\{t - \tau_{ih}\}}{(t - \tau_{ih}) + 1} + \varepsilon_{it} \tag{4}$$

Where:

p_{it} = price of gas at time t in location i

α_{0i} = region-specific fixed effect

o_{t-1} = lagged price of oil on world market

w_{ih} = wind speed (in KpH) of hurricane h when it is closest to location i

d_{hi} = distance (in kilometers) from hurricane h to location i

$\tau_{ih} - t$ = time (in days) before hurricane h reaches its closest point relative to location i

[8] Our reduced-form model appears to treat a hurricane as a point event, rather than a path of destruction of varying strengths and shifting expectations. However, by making the impact of the point event propagate over time and space (at a diminishing rate), we capture a comfortable majority of the impact. A more realistic model would require many additional complications with little return to such added realism.

[9] Wind speed is the basis by which an Atlantic weather system gets classified as a tropical depression, tropical storm, or Category 1 through 5 hurricane.

t - τ_{ih} = time (in days) since hurricane h reached its closest point relative to location i

The price of oil captures long-run trends in gas prices due to two important supply factors: scarcity of reserves and extraction/refining technology. For every hurricane included in the first stage model, we give it a two-week window on either side of the point in time at which it is closest to the PADD's population-weighted centroid.[10]

3.3 Model of Bayesian Updating of Climate Change Beliefs

Information at time t arrives in the form of the presence or absence of "climate change" or "global warming" in a headline, following a Bernoulli process:

$$\Pr(a_t = 1) = s \tag{5}$$

The beliefs over the serious of climate change, s, are represented by a Beta distribution:

$$pdf(s) = \frac{s^{k-1}(1-s)^{q-1}}{Beta(k,q)} \tag{6}$$

where k and q are parameters describing the distribution of beliefs. The conjugacy of the distribution on prior beliefs and the likelihood of the headline generating process makes the Bayesian updating of beliefs (i.e., new beliefs as a function of old beliefs and new data from headlines) closed within the family of Beta distributions. Thus, the updating of beliefs is a simple dynamic process for both of the parameters that describe individuals' beliefs on climate change:

$$k_{t+1} = k_t + a_t \qquad q_{t+1} = q_t + 1 - a_t \tag{7}$$

Hence, k will equal the count of time periods in which "climate change" or "global warming" actually appeared as headline and q is the number of time periods in which it

[10] In the rare case when multiple hurricanes would overlap, we used the data of the hurricane nearest future hurricane, if one was due in 2 weeks or less, rather than the data from a hurricane that had already hit.

did not. The first moment of this distribution, k/(k+q), is a very intuitive measure of awareness: the share of periods in which “climate change” or “global warming” appeared in the headlines.[11] With risk neutrality in the specification of our utility function, the expected beliefs in the damages from climate change is given by:

$$E_t(\beta s) = \beta\left[\frac{k_t}{k_t + q_t}\right] \tag{8}$$

4. Data

As our model depends on the shocks to the price of gasoline induced by hurricanes, which tend to last only a few days to a week, it was essential to observe prices and quantities of gasoline in as fine a temporal resolution as possible. The United States Energy Information Administration (EIA) provides weekly data on the retail prices of finished motor gasoline (gasoline) in seven different regions of the United States. These prices are the nominal price of gasoline (averaged across all grades), measured at 8:00 AM local time on Monday at approximately 900 locations across the country. The nominal prices of all formulations (conventional and reformulated) and grades (regular, mid, and premium) are collected by EIA, and the average nominal price in seven different regions is calculated, weighting by sales and volume data collected in other surveys. Each region, called a Petroleum Administration for Defense District (PADD), consists of a number of states in geographically similar situations. The states in each of the seven PADDs are listed in table 1. The Energy Information Administration also furnishes weekly data on the quantity of gasoline delivered to each PADD, which we use as the

[11] We set the starting values for k_0 and q_0 at 0, which we find to be reasonable because climate change was not a mainstream issue before our sample period. Alternatively, those parameters could be estimated non-linearly.

best available proxy for quantity purchased by consumers. This measure of quantity includes all gasoline supplied, irrespective of end consumer. These data are publicly available at the Energy Information Administration's website.[12] We converted the prices to year 2000 dollars.

As a consequence of relying on weekly average prices and quantities in each PADD, other covariates which are normally measured at the state level were averaged to PADD levels as well. State level data on population were taken from the U.S. Census Bureau.[13] These population estimates are given yearly. We took state-level, quarterly data on personal income from the Bureau of Economic Analysis.[14] In order to match the data to the weekly frequency of prices and quantities, we linearly interpolated weekly estimates of population in each state each week and then aggregated the state data up to the PADD level. We also converted the personal income data from current dollars to year 2000 dollars. Summary statistics of real prices of gasoline as well as quantities delivered, populations, and personal incomes are shown in table 2.

Because we utilize the distance from each PADD to hurricanes, we estimated the population-weighted centroid of each PADD. By combining the population center of each state with the population of each state—both based on the 2000 census and available on the U.S. Census Bureau's website—we calculated the state population-weighted means of the latitudes and longitudes of all state population centers in each PADD, yielding one population-weighted centroid for each PADD.[15]

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[12] EIA's petroleum products data available at: http://tonto.eia.doe.gov/dnav/pet/pet_sum_top.asp
[13] http://www.census.gov/popest/states/
[14] http://www.bea.gov/regional/sqpi/
[15] Year 2000 state populations and population centers available from the U.S. Census Bureau at: http://www.census.gov/geo/www/cenpop/statecenters.txt

Data on the world price of oil were gathered from EIA's website.[16] Weekly observations were available for all weeks from the beginning of 1997. The EIA data consists of average, free-on-board nominal prices. We converted these prices to year 2000 dollars.

To construct a measure of beliefs on climate change, we searched the LexisNexis newspaper database for the terms "global warming" or "climate change" in the title of newspaper articles published in each state over the period from January 1, 1997, to August 1, 2008. Beginning in the second week of January 1997 up to the week of the observation, we created a running total of the number of weeks that at least one article had been published anywhere in the nation that included those search terms in the article title and divided this running total by the total number of weeks that had passed. This ratio is equivalent to the bracketed term of Equation 7. We thus arrive at our primary variable of interest: *environmental awareness*, which is observed weekly at the national level and may proxy for environmental awareness, which we define here to mean "cognizant of the possibility of anthropogenic changes of the environment." It does not necessarily show environmental activism, which we take to mean "actively pursuing a lifestyle that seeks to mitigate or reverse anthropogenic changes of the environment." Though the relation between environmental activism and energy consumption may present a ripe field for future research, we do not directly address it in this paper. Instead, we focus on the presence of information about the environment alone. Summary statistics on *environmental awareness* are also presented in table 2.

The first stage of our two-stage least squares regression approach entails estimating the impact of hurricanes on gasoline prices. The term 'hurricane' is slightly

[16] http://tonto.eia.doe.gov/dnav/pet/pet_pri_wco_k_w.htm

misleading, as the dataset we use includes lower category storms such as tropical storms as well as hurricanes. These non-hurricanes are included with good reason: Some of the costliest storms in terms of damage inflicted are tropical storms, as shown in table 3, which lists the thirty costliest storms in U.S. history. The U.S. National Oceanic and Atmospheric Administration's Hurricane Research Division provides data on the location and wind speed of tracked Atlantic storms on their website.[17] We use these data to estimate the average distance between each PADD population-weighted centroid and the (eye of) the nearest hurricane, if one existed that week, using the Haversine formula.[18] As previously mentioned, we calculated time (in days) up to two weeks before and after the achievement of closest distance to each PADD as another variable included in the first stage regression. We also noted the maximum wind speed of the nearest hurricane on the day of the week it was closest to each PADD population center, which we use to help estimate the impact of the hurricane on gas prices.

We should note two limitations to our data. First, although it is high frequency, it is highly aggregated across the microeconomic decision makers and space. We do our best to circumvent this inconvenience; however, our results would be much richer with microdata. Unfortunately, those data does not appear to be publically available at such high frequencies. Second, we do not have high frequency and spatially delineated observations on the composition of the vehicle fleet. If such data were available, then we could separate out the effects of increased environmental awareness on reduced driving and purchasing more fuel-efficient vehicles. Our prior expectation is that increases in

[17] Hurricane data from NOAA Hurricane Research Division of AOML. See http://www.aoml.noaa.gov/hrd/hurdat/
[18] In those weeks where no storm was tracked, we used a value of 999,999 kilometers as the distance from the PADD population-weighted centroid to the nearest hurricane.

environmental awareness would increase the probability that a consumer would voluntarily pay more for a more fuel efficient model.

5. Results

We use a two-stage least squares (2SLS) approach to simultaneously estimate the effect of environmental awareness on gasoline expenditures and estimate the short-run price and income elasticities of demand for gasoline. The first stage distills the variation in price due to movements of the supply curve, isolating changes in price that are exogenous to demand so that the resulting reactions to price changes observed as decreases in quantity are due to movements along the demand curve. The first stage consisted of implementing our reduced-form model of the effect of hurricanes on gasoline prices as given in Equation 4, where we specified hurricanes as affecting price through their proximity to refineries, proximity to PADD population centers, and their windspeed. Additionally, we allowed for the possibility of an "anticipatory" price effect —or a change in price caused by the approach of a hurricane even though the hurricane may not yet have inflicted much damage—as well as a "recovery" period—the time after a hurricane has struck and dissipated, during which the damages wrought by the hurricane could still be reflected in prices. For robustness, we also perform and report OLS regressions of Equation 7, alongside the 2SLS regressions.

We use the results of OLS implementation of the first stage reduced form model of price, Equation 4, to obtain the predicted (exogenous) real price of gasoline which we use in the second stage. The structural model described in section 3 culminates in Equation 7, which is econometrically specified here as:

$$\textit{per capita expenditure}_{i,t} = b_0\, \textit{constant} + b_1\, \textit{predicted price}_{i,t} + b_2\, \textit{per capita income}_{,t} + b_3\, \textit{environmental awareness}_t + b_X\, \textit{padd}_i + \varepsilon_{i,t} \qquad (10)$$

where per capita expenditure on gasoline in PADD i in week t (*per capita expenditure*) is a function of the predicted price in PADD i in week t from the first stage regression (*predicted price*), real per capita income in PADD i in week t (*per capita income*), the ratio of the number of weeks in which an article published anywhere in the nation mentioned "climate change" or "global warming" in its headline to the total number of weeks gone by up to time t, PADD-level dummy variables (*padd*), and an error term (ε). Because the data are weekly and we include no lagged variables in the second stage, we are effectively estimating the week-to-week response to changes in price and income on gasoline expenditure. We do not control for the stock of vehicles because such data are unavailable at similar frequencies and regional aggregations. As a result, it is possible that some of the consumer response to changes in price, income, and environmental awareness reflects long run behavioral changes (e.g. buying an automobile with a different level of fuel efficiency). Thus, while admitting that our estimates probably cannot be viewed as purely short-run effects, we contend that these estimates probably are not dominated by long-run effects precisely because of the very short periodicity. Indeed, to our knowledge, no study has estimated gasoline demand elasticities using weekly data. Furthermore, any conflation of long- and short-run effects does not undermine our primary contribution, which is to test the effect of environmental awareness on gasoline demand.

The results of our second stage regressions are reported in table 5, alongside OLS estimates included for robustness. We focus our reporting and discussion of results into the following subsections: interpretation of the primary variable of interest, *environmental awareness*; and nationwide price and income elasticity estimates.

5.1 Environmental awareness and gasoline expenditure

The primary variable of interest in this study is *environmental awareness*, our measure of environmental awareness in each PADD at the time of the observation. Table 5 allows an interpretation of the effect of this variable. In column 1, we have produced an estimate of the household gasoline expenditure function that depends only on price, income, and regionally constant conditions captured by the dummy variables, using OLS (that is, ignoring the results of our first stage and using the observed real price of gasoline as a RHS variable). In column 2, the results are again from an OLS regression, including the variable *environmental awareness*. Columns 3 and 4 replicate the regressions of columns 1 and 2 except that columns 3 and 4 are 2SLS regressions using the predicted price produced in the first-stage regressions rather than the observed real price. While we leave most discussion of the price and income coefficient estimates to the following subsection, we briefly discuss them here to help inform the discussion of the effect of environmental awareness. The coefficient estimate on *real price* is positive and statistically significant in all regressions; in column 1, the estimate is 25.16 cents and in column 2 it is nearly identical at 24.72 cents. Similarly, the 2SLS regressions shown in columns 3 and 4 yield coefficient estimates on *predicted price* of 25.04 and 25.50 cents. The positive sign is consistent with price inelastic demand. All four coefficient estimates are significant at the 1 percent level. These coefficient estimates indicate that weekly gasoline expenditure increased by around 25 cents as a result of a price increase of 1 cent per gallon. While this estimate would seem high, even for a very inelastically demanded good, if only household expenditure were included in our data, the fact remains that the best available proxy for gasoline consumed is gasoline supplied, which necessarily includes all end consumers. Thus, when considering that the quantity of gasoline consumed by firms is included in the data and may be substantially greater than that of households, the expenditure increase from a 1 cent price increase seems more feasible. As for income, the coefficient estimate on *per capita income* is positive in all four regressions and statistically significant in three out of four of the regressions reported in table 5. A positive income elasticity is also consistent with our expectation based on theory and previous literature on the topic.

The measure of environmental awareness, *environmental awareness*, is a significant factor in determining gasoline expenditure. Its coefficient estimates, given in columns 2 (OLS) and 4 (2SLS), are -993.7 and -864.9. Both are significant at the 1 percent level. These estimates give the marginal effect on gasoline expenditure of an increase in the probability that an article will be published in the next week that addresses climate change. The coefficient estimates correspond to a change in probability from 0 to 1, which is an out of sample extrapolation since the range of environmental awareness observed in the data is 0.5 to 1. Nevertheless, we interpret the coefficient estimate on *environmental awareness* of -993.7 to indicate that a change from 0 to 1 in the probability of observing an article on climate change leads to a weekly decrease in gasoline expenditure of $9.94, which is about a 20 percent decline relative to the mean of gasoline expenditure. A 1 percent increase in the probability, then, would lead to a decrease of $0.0994 in weekly gasoline expenditure, or a 0.2 percent decrease in expenditure evaluated at the mean.

Presumably, this result reflects decreased demand for gasoline due to environmental concerns—namely, due to changing beliefs about the seriousness of climate change. However, we should point out that this result could also be partially created by local vehicle usage laws, such as high-occupancy vehicle lanes on highways, or tax incentives for fuel-efficient vehicles. Nevertheless, the implication of the result is striking: Information alone may lead to greener actions on the part of consumers.

5.2 Price and income elasticity estimates

In table 5, the coefficient estimates on *predicted price* resulting from the 2SLS regressions are 25.04 cents and 25.50 cents, nearly identical to the estimates from the OLS regressions. All are significant at the 1 percent level. We interpret these estimates to mean that, ceteris paribus, a one cent increase in the price of gas results in about a 25 cent increase in weekly per capita expenditures on gasoline. The positive sign on the coefficient indicates that demand for gasoline in the United States is inelastic, as theory and literature predict, because when price goes up, expenditure also increases. We compute a nationwide price elasticity between -0.16 and -0.18 with these estimates, as we report in table 6. Relative to the existing literature using data from the 1990s and earlier containing estimates of the nationwide, short-run elasticity of demand for gasoline, our estimates are comparatively inelastic. Conversely, in comparison to Hughes et al (2006), who estimate the short-run elasticity to be between -0.03 and -0.07 during the years 2001–2006, our estimates are considerably more elastic. The difference between our estimates may be due to different time frames or to controlling for vehicle stock.

We also report income elasticity estimates in table 6. The estimates from the two OLS regressions are 0.08 and 0.20, and those from the two 2SLS regressions are 0.25 and

0.39. These estimates are fairly low compared to the existing literature, a result that could derive from at least a couple possible sources. First, as mentioned in section 4, personal income data are only available at quarterly intervals, and all weekly observations are simply linear interpolations. Thus, week-to-week changes in income simply reflect the average weekly change witnessed over 13 weeks. While this may suffice to serve as a control variable, allowing us to estimate the marginal effects of other variables holding income constant, it may overly smooth variation in *weekly* income. Second, as the periodicity of data examined shortens, income elasticity generally decreases. Because our data are weekly, we should expect a fairly low estimate of income elasticity compared to estimates that derive from lower frequency data.

6. Conclusion

We have shown that people voluntarily reduce their consumption of gasoline as they become more aware of climate change, controlling for growing incomes and exogenous changes in prices due to supply-side shocks. As time progresses, individuals will likely become even more aware of climate change and the voluntary component of emissions reductions will likely increase. Policymakers should take this into account so that they do not overshoot emission targets, particularly when one considers the colossal cost of abatement of climate change. In light of our findings, the acquisition and dissemination of information takes on an even more important role. More data will not only inform the policymaking process and enhance the efficacy of whatever policy gets implemented but will also aid consumers in adjusting consumption patterns. Fortunately, the market is already moving to provide more data on energy usage to consumers. As an example, Google announced this year a new product called PowerMeter that will allow users to track home energy consumption almost in real time on their computers (Groom, 2009). Indeed, feedback on energy usage has been shown to play a major role in reducing energy consumption, with studies showing that better information can lead to 5 to 15 percent savings in monthly bills (Darby, 2006). If consumers care not only about their own power bills but also care increasingly about individual contributions to climate change, then better data and information on energy consumption may lead even greater changes in consumption patterns than previous studies have indicated.

More data also informs empirical research. We should note how the data available to us has limited the extent of our findings. We have used high-frequency price and quantity data so that we can closely track behavioral changes in response to information revealed by the media while using data on hurricanes and lagged oil prices as instrumental variables. Unfortunately, such high-frequency data is only available in a form that is highly aggregated across the microeconomic decision makers and space. We do our best to circumvent this inconvenience; however, if microdata became available for future research, then the subsequent findings would be much richer. An additional limitation of the high-frequency data has been a lack of observations on the composition of the vehicle fleet. If such data became available, then future research could separate out the effects of increased environmental awareness on reduced driving and purchasing more fuel efficient vehicles. Despite such limitations, we have shown that an increase in environmental awareness is associated with statistically and economically significant decreases in expenditure on gasoline. In the process, we provided new estimates of the national short-run price and income elasticities of demand for gasoline, utilizing more recent gasoline consumption data and spatially-delineated supply side disruptions due to hurricanes.

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7. Tables

Table 1: States in each PADD.

PADD 1a	PADD 1b[19]	PADD 1c	PADD 2
Connecticut Maine Massachusetts New Hampshire Rhode Island Vermont	Delaware Maryland New Jersey New York Pennsylvania	Florida Georgia North Carolina South Carolina Virginia West Virginia	Illinois Indiana Iowa Kentucky Michigan Minnesota Missouri Nebraska North Dakota Ohio Oklahoma South Dakota Tennessee Wisconsin
PADD 3	**PADD 4**	**PADD 5**	
Alabama Arkansas Louisiana Mississippi New Mexico Texas	Colorado Idaho Montana Utah Wyoming	Alaska Arizona California Hawaii Nevada Oregon Washington	

Table 2: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
per capita expenditure (cents/week)	4235	4942.76	3130.33	1281.04	23405.76
real price (cents/gallon)	4235	169.71	52.32	91.49	366.23
predicted price from first stage	4235	169.71	50.70	100.01	383.26
quantity (1000s of gallons/week)	4235	1237714.00	846164.70	111426.00	3051006.00
per capita income (yr. 2000 dollars/week)	4235	585.43	70.43	449.22	774.23
population (millions of people in PADD)	4235	40.9	21.9	8.5	80.7
Environmental awareness	4235	0.96	0.06	0.5	1

[19] District of Columbia is also considered part of PADD 1b, but we do not include DC because of a lack of data for DC in many variables of interest.

Table 3: Top 30 costliest hurricanes (in 2006 dollars) through August 2008

Rank	Hurricane	Region of most impact	Year	Category	Damage
1	Katrina	SE FL, SE LA, MS	2005	3	$84.6 billion
2	Andrew	SE FL, SE LA	1992	5	48.1 billion
3	Wilma	S FL	2005	3	21.5 billion
4	Charley	SW FL	2004	4	16.3 billion
5	Ivan	AL, NW FL	2004	3	15.5 billion
6	Hugo	SC	1989	4	13.5 billion
7	Agnes	FL, NE US	1972	1	12.4 billion
8	Betsy	SE FL, SE LA	1965	3	11.9 billion
9	Rita	LA, TX, FL	2005	3	11.8 billion
10	Camille	MS, SE LA, VA	1969	5	9.8 billion
11	Frances	SE FL	2004	2	9.7 billion
12	Diane	NE US	1955	1	7.7 billion
13	Jeanne	FL	2004	3	7.5 billion
14	Frederic	AL, MS	1979	3	6.9 billion
15	New England		1938	3	6.6 billion
16	Allison	N TX	2001	Tropical Storm	6.4 billion
17	Floyd	Mid-Atlantic & NE US	1999	2	6.3 billion
18	NE US		1944	3	5.9 billion
19	Fran	NC	1996	3	5.0 billion
20	Alicia	N TX	1983	3	4.8 billion
21	Opal	NW FL, AL	1995	3	4.8 billion
22	Carol	NE US	1954	3	4.3 billion
23	Isabel	NC, VA	2003	2	4.0 billion
24	Juan	LA	1985	1	3.4 billion
25	Donna	FL, Eastern US	1960	4	3.3 billion
26	Celia	S TX	1970	3	3.0 billion
27	Bob	NC, NE US	1991	2	2.9 billion
28	Elena	MS, AL, NW FL	1985	3	2.8 billion
29	Carla	TX	1961	4	2.6 billion
30	Dennis	NW FL	2005	3	2.3 billion

Sources: Blake et al., 2007, & NOAA Hurricane Research Division of AOML.
Notes: 2008 hurricanes Gustav and Ike were almost certainly in the top 30 costliest hurricanes, but they occurred after August 2008. Hurricanes "New England" and "NE US" occurred prior to the modern naming system.

Table 4: First stage regression results

Dependent Variable: real price of gasoline (cents/gallon)	OLS
Lagged (by one week) oil price (year 2000 dollars)	2.552***
	(0.0102)
padd1b	-0.240
	(0.744)
padd1c	-8.208***
	(0.745)
padd2	-7.183***
	(0.744)
padd3	-10.98***
	(0.745)
padd4	-1.693**
	(0.745)
padd5	12.75***
	(0.745)
Wind speed when hurricane was at minimum distance	0.0934***
	(0.00960)
Inverse of the minimum distance between hurricane and PADD population center	130.1
	(95.41)
Inverse of the number of days prior to the hurricane achieving minimum distance	9.773***
	(3.506)
Inverse of the number of after the hurricane achieved minimum distance	9.485***
	(2.868)
Constant	86.93***
	(0.625)
Observations	4235
R-squared	0.939

*** p<0.01, ** p<0.05, * p<0.1
Standard errors in parentheses

Table 5: Second stage regression results

Dependent Variable: per capita expenditure (cents/week)	OLS (1)	OLS (2)	2SLS (3)	2SLS (4)
Real price (cents/gallon)	25.16***	24.72***		
	(0.518)	(0.551)		
Predicted price (cents/gallon)			25.04***	24.50***
			(0.554)	(0.592)
Per capita personal income ($/week)	0.652	2.149**	1.684*	3.375***
	(0.833)	(1.044)	(0.862)	(1.086)
Environmental awareness		-807.2**		-893.8**
		(339.5)		(349.6)
padd1b	2371***	2423***	2407***	2465***
	(65.35)	(68.84)	(67.11)	(70.85)
padd1c	1171***	1390***	1324***	1570***
	(133.9)	(162.4)	(138.2)	(168.5)
padd2	2517***	2733***	2667***	2911***
	(132.9)	(161.0)	(137.2)	(167.1)
padd3	9209***	9480***	9398***	9703***
	(160.1)	(196.4)	(165.3)	(203.9)
padd4	2504***	2718***	2652***	2894***
	(132.6)	(160.3)	(137.0)	(166.4)
padd5	1673***	1821***	1773***	1940***
	(102.9)	(120.2)	(106.4)	(124.9)
Constant	-2488***	-2677***	-3181***	-3407***
	(509.1)	(515.1)	(524.5)	(531.5)
Observations	4235	4235	4235	4235
R-squared	0.894	0.894	0.888	0.889

*** p<0.01, ** p<0.05, * p<0.1
Standard errors in parentheses

Table 6: Elasticity estimates

Regression	Mean price[20]	Mean per capita income	Mean per capita quantity	Price coefficient estimate	Price elasticity estimate	Income coefficient estimate	Income elasticity estimate
1	169.71	585.43	29.81	25.16	**-0.16**	0.65	**0.08**
2	169.71	585.43	29.81	24.72	**-0.17**	2.15	**0.25**
3	169.71	585.43	29.81	25.04	**-0.16**	1.68	**0.19**
4	169.71	585.43	29.81	24.50	**-0.18**	3.38	**0.39**

[20] The means of both the observed real price and the predicted price from the first stage regression are identical at 169.71 cents.

8. Figures

Figure 1: Historical Prices and Quantity Supplied of Gasoline in the United States

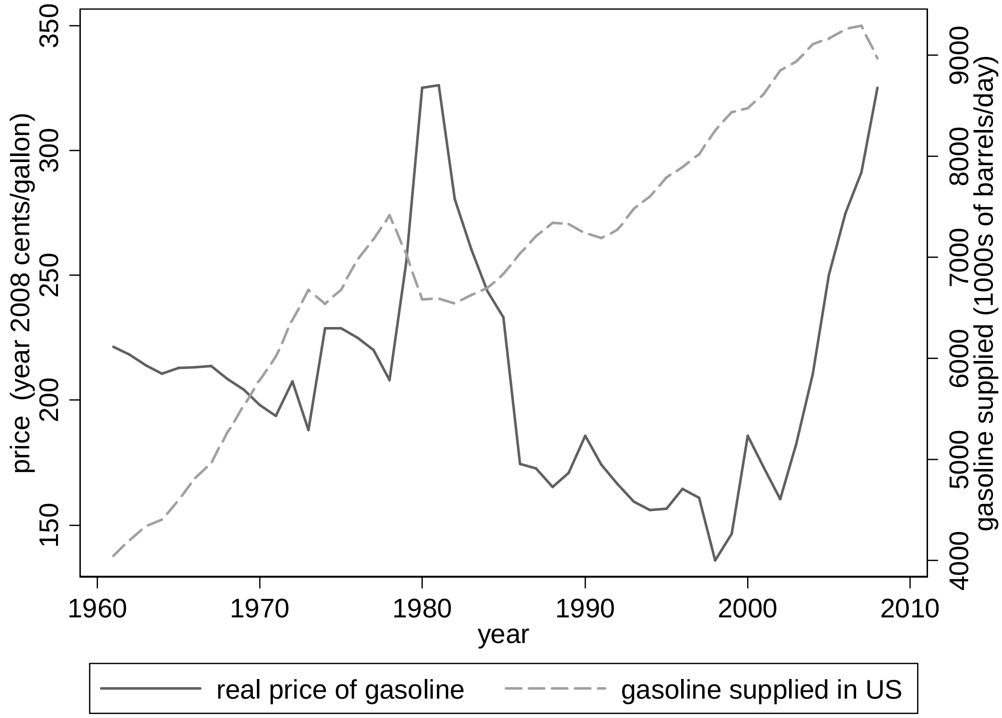

Figure 2: Observed and predicted prices by PADD over time