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What Do Consumers Believe About Future Gasoline Prices?*

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Abstract

A full understanding of how gasoline prices affect consumer behavior frequently requires information on how consumers forecast future gasoline prices. We provide the first evidence on the nature of these forecasts by analyzing two decades of data on gasoline price expectations from the Michigan Survey of Consumers. We find that average consumer beliefs are typically indistinguishable from a no-change forecast, justifying an assumption commonly made in the literature on consumer valuation of energy efficiency. We also provide evidence on circumstances in which consumer forecasts are likely to deviate from no-change and on significant cross-consumer forecast heterogeneity.

JEL classification numbers: D84, Q41, Q47, L62
Key words: gasoline prices; consumer beliefs; automobile demand; energy efficiency

1 Introduction

Gasoline prices are of central importance to the economy. They are particularly salient to consumers, as motor fuels alone account for 5% of all consumer expenditures. They also have macroeconomic implications because oil price shocks are strongly correlated with recessions, even more than gasoline's expenditure share would explain (Hamilton 2008). Moreover, consumer reactions to gasoline prices have been used to study a broad array of economic phenomena, ranging from the demand for automobiles (Busse, Knittel and Zettelmeyer Forthcoming; Li, Timmins and von Haefen 2009; Allcott 2012; Gillingham 2011; Linn and Klier 2010) and driving choices (Small and Van Dender 2007; Knittel and Sandler Forthcoming; Davis and Kilian 2011; Li, Linn and Muehlegger 2012), to consumption of leisure (West and Williams 2007), search behavior (Lewis and Marvel 2011), and mental accounting (Hastings and Shapiro 2011). Understanding how consumers respond to gasoline prices requires information about what consumers believe about *future* gasoline prices. For example, if an increase in today's price causes consumers to expect an even higher price tomorrow, the effect of current price shocks on the macroeconomy could be amplified, perhaps by enough to explain the stronger-than-expected correlation between current prices and economic growth.

Despite the importance of gasoline prices to economic research, little to no evidence exists regarding consumers' beliefs about future gasoline prices. How do consumers form their beliefs about future gasoline prices? Are their beliefs reasonable? How varied are these beliefs across individuals? Do beliefs respond differently to different types of gasoline price shocks? How should researchers model consumer beliefs? In the absence of direct evidence, prior research has been left to make assumptions that are often guided by convenience. In this paper, we seek answers to these questions using data from a high-quality survey that directly elicits consumer beliefs.

When consumers buy energy-using durable goods, they must forecast the future price of energy to determine their willingness to pay for energy efficiency. In turn, research that attempts to estimate or control statistically for consumers' valuation of energy efficiency must explicitly model consumers' beliefs about future energy prices and may draw biased inferences if these beliefs are mis-specified. This issue is most relevant for studies using identification strategies that rely on time-series variation in energy prices to identify demand—a strategy that is particularly common in automobile research (Kahn 1986; Goldberg 1998; Kilian and Sims 2006; Li et al. 2009; Allcott and Wozny 2011; Bento, Li and Roth 2012; Klier and Linn 2010; Sallee, West and Fan 2009; Whitefoot, Fowlie and Skerlos 2011; Langer and Miller 2011; Linn and Klier 2010; Busse et al. Forthcoming). These studies frequently assume that consumers adopt no-change forecasts for future gasoline prices in real terms; that is, they assume that the expected future price is the current price.[1] If consumer beliefs deviate significantly from this assumption, then researchers may under-estimate or over-estimate consumers' valuation of fuel economy (and other important attributes) depending on the

[1]Equivalently, consumers are assumed to believe that gasoline prices follow a martingale process. Throughout the paper, we use the "no-change" terminology as it accords with the literature on oil price forecasting (see, for example Alquist, Kilian and Vigfusson (2010)). We do not use the term "random walk", since a random walk process further implies that the price innovations are iid.

direction of the deviation.[2] In addition, if consumer beliefs are "unreasonable," in the sense that they are systematically biased or have low predictive accuracy in comparison to a benchmark, then these beliefs themselves may constitute a market failure that motivates government intervention.

In lieu of direct evidence, there is perhaps little reason to believe that consumer expectations will align conveniently with the no-change hypothesis favored by applied researchers. Future crude oil and gasoline prices are notoriously difficult to predict, and there is substantial controversy among academic and industry experts about what the future price of oil will be and how best to predict future prices (Hamilton 2009; Alquist and Kilian 2010; Alquist et al. 2010). The main goal of our paper is therefore to test directly whether consumers forecast the future price of gasoline to equal the current price.

We conduct our analysis using high-frequency data on consumer beliefs about future gasoline prices from the Michigan Survey of Consumers (MSC). Every month, the MSC asks a nationally representative sample of about 500 respondents to report their beliefs about the current state of the economy and to forecast several economic variables. Since 1993, the MSC has regularly asked respondents to report whether they think gasoline prices will be higher or lower (or the same) in five year's time and then to forecast the exact price change. To the best of our knowledge, we are the first researchers to use this unique cache of information on gasoline price expectations, and virtually no other existing work directly measures consumer beliefs about future energy prices in any context.[3]

Our analysis indicates that in normal economic climates the average consumer expects the future real price of gasoline to equal the current price. That is, in our preferred specifications, average consumer beliefs cannot be distinguished statistically from a no-change forecast. In particular, we generally cannot reject the hypothesis, commonly assumed in the automobile demand literature, that the average consumer's forecast of future gasoline prices moves one-for-one with changes in the current price. This result also suggests that consumer beliefs themselves are unlikely to constitute a market failure. While a no-change gasoline price forecast is obviously not perfect, we believe it is a good benchmark for determining whether consumer forecasts are reasonable.[4]

[2]This issue is a specific instance of the broader empirical problem, discussed by Manski (2004), that preferences and expectations are generally not both identified from choice data alone.

[3]One recent exception is Allcott (2012), which estimates automobile demand using a specially designed survey instrument that asks consumers to report (among other things) their beliefs about future gasoline prices in real terms. Allcott finds that consumers expect a real price increase on average, whereas we find that consumers expect no price change in real terms. Allcott draws on a single cross section of data from October 2010, however, at which time the MSC series also predicts a small increase in real prices and an even larger increase in nominal prices that is roughly equivalent to the increase in Allcott's survey. Thus, the discrepant results are largely reconciled if respondents in the Allcott survey answer in nominal terms, contrary to instructions (our favored interpretation), or if respondents in the MSC series answer in real rather than nominal terms (Allcott's favored interpretation).

[4]A no-change forecast for crude oil is theoretically sensible because rapidly rising or falling prices would induce storage and extraction arbitrage (Hamilton 2009). In addition, no-change forecasts predict future crude oil prices as well as or better than forecasts based on futures markets and surveys of experts (Alquist and Kilian 2010; Alquist et al. 2010). We therefore interpret the statistical similarity between the MSC forecast and the no-change benchmark as evidence that consumers hold reasonable beliefs, implying that consumer beliefs themselves are unlikely to constitute a market failure. This argument is based on the crude oil literature. Retail gasoline prices may behave differently on short time horizons, but they will be tethered to crude prices over a five-year horizon. Likewise, retail prices may spike in specific locations due to refinery outages or supply disruptions, at which time it is reasonable to expect

We do identify some specific settings in which the average consumer's price forecast is not consistent with a true no-change forecast. The first such case is the 2008 financial crisis, during which consumers predicted that gasoline prices would rebound following their sharp decline. In a companion paper, Anderson, Kellogg, Sallee and Curtin (2011), we show that this prediction turned out to be prescient. The second case deals with state-specific price shocks, such as those that might arise from local refinery outages. While we find that consumers forecast state-level price changes as being highly persistent, our tests reject the hypothesis that consumers' forecasts move one-for-one with state-level shocks. Interestingly, consumers perceive such shocks to be much more persistent than they actually are, on average. We also study consumers' responses to changes in state-level gasoline taxes. We are motivated to do so by two recent papers, Davis and Kilian (2011) and Li et al. (2012), which find that gasoline consumption is much more responsive to gasoline taxes than to pre-tax gasoline prices. These papers emphasize that this result may arise because consumers perceive changes in gasoline tax policy to be more persistent than price fluctuations caused by shifts in supply and demand. Using our data, however, we find no evidence that consumer forecasts respond more strongly to tax changes than to pre-tax price changes.

We also find substantial heterogeneity in forecasts across consumers. In our sample, the standard deviation in the price forecast across respondents each month averages 62 cents (in 2010 dollars). Using a simple simulation, we find that this heterogeneity may generate as much variation in consumers' willingness to pay for fuel economy as is generated by heterogeneity across consumers in vehicle miles traveled or discount rates. We also find that the degree of heterogeneity in consumers' forecasts co-varies with gasoline prices and that, when we study consumers who are surveyed twice (six months apart), this heterogeneity is mostly accounted for by individual fixed effects. We believe these results will be valuable for a nascent strand of research—such as Allcott, Mullainathan and Taubinsky (2012) and Bento et al. (2012)—that seeks to understand the policy and econometric implications of heterogeneity in consumers' valuation of fuel economy.

Anderson et al. (2011) presents results that are auxiliary to our main findings here. In that paper, we ask the relatively narrow question of *how well* consumer forecasts predict future gasoline prices and price volatility. We calculate the mean squared prediction error of the MSC forecast, showing that it is generally similar to that of the no-change benchmark but that it actually outperformed this benchmark during the financial crisis (as did futures prices). We also document a correlation between forecast heterogeneity and measures of future gasoline price volatility, but note that this correlation is driven entirely by the period of the financial crisis. In contrast, in the present paper we ask *what* consumers believe about future gasoline prices, how these beliefs respond to changes in the current price of gasoline, and what these beliefs imply for research on consumer demand for automobiles. We test directly whether or not the average MSC forecast is consistent with consumers adopting a no-change forecast based on the current price of gasoline and find that it is. We also provide additional results on state panel variation, the impact of taxes on forecasts,

mean reversion in prices in those specific locations, but we believe such occurrences will be too rare to influence our aggregate statistics.

and forecast heterogeneity. Thus, while the two papers both involve statistical tests comparing MSC forecasts to the current price of gasoline, they ask and attempt to answer a distinct set of questions.

The paper proceeds as follows. In section 2 we discuss a model of consumer demand for fuel economy that highlights the importance of gasoline price expectations. In section 3 we describe the MSC data and detail our transformation of the raw data into aggregate measures. Section 4 provides graphical evidence regarding the relationship between current gasoline prices and average consumer forecasts; we verify this evidence with regression-based tests in section 5. Section 6 discusses the response of consumer forecasts to state-level price variation, and section 7 examines the hypothesis that forecasts respond differently to tax and pre-tax price changes. Section 8 then examines cross-consumer forecast heterogeneity. Section 9 concludes.

2 Estimating the demand for automobile fuel economy

Consumer beliefs about future gasoline prices are important for understanding behavior in a variety of contexts. Here, we emphasize one key example—estimation of the demand for automobiles and automobile fuel economy—to make clear the importance of future beliefs in economic modeling. Consider the following standard expression for household utility that serves as the basis for many models of automobile demand:

$$u_{ijt} = -\alpha p_{jt} - \gamma E_{it} \left[\sum_{s=0}^{T} (1+r_i)^{-s} g_{t+s} m_{ij,t+s} GPM_j \right] + \beta X_j + \xi_j + \varepsilon_{ijt}. \tag{1}$$

Here, u_{ijt} is the utility that household i derives from purchasing vehicle j at time t; p_{jt} is the purchase price of this vehicle; $E_{it}[\cdot]$ and its contents, detailed below, are consumer i's expected fuel costs over the lifetime of the vehicle, in present-value terms; X_j is a vector of observable vehicle characteristics, such as interior volume and horsepower; ξ_j is unobservable (to the econometrician) vehicle quality; and ε_{ijt} is the idiosyncratic utility that an individual consumer derives from the vehicle.[5] Households are assumed to choose the vehicle model (if any) that gives them the highest utility, facilitating estimation of utility parameters using data on vehicle attributes and household choices. Similar utility models have been used in other energy-intensive durable goods settings, such as purchases of household appliances (Dubin and McFadden 1984).

In any given future time period $t+s$, fuel costs equal the number of miles $m_{ij,t+s}$ the vehicle is driven, multiplied by the vehicle's fuel consumption rate in gallons per mile GPM_j, multiplied by the future real price of gasoline g_{t+s}. Discounting at rate r_i and summing over the full, T-period lifetime of the vehicle gives total lifetime fuel costs in brackets. The expectations operator is required because the vehicle's lifetime, future miles driven, and the future real price of gasoline (which embodies expectations about future gasoline prices and inflation) are not known with certainty at

[5] ε_{ijt} is typically modeled as iid logit or generalized extreme value. Random coefficients logit models that allow for heterogeneity in γ have generally not been used in the energy efficiency valuation literature, though a recent paper (Bento et al. 2012) has begun to explore the implications of such an approach.

the time of purchase.[6] Thus, when trading off the purchase price of a vehicle (and other vehicle attributes) against expected lifetime fuel costs, a consumer must consider the fuel efficiency of the vehicle, the number of miles she plans to drive, and the future price of gasoline in real terms.

In this model, testing whether consumers fully value the benefits of fuel economy is equivalent to testing the null hypothesis that $\alpha = \gamma$. Empirically implementing this test requires that a researcher populate the expected fuel costs term with each of its underlying components. Miles traveled, fuel consumption per mile, discount rates, and time horizons (or close approximations thereof) are all readily observable to researchers, if not for individual vehicles and consumers, then at least for broad classes of vehicles and consumers.[7] In contrast, expected future gasoline prices have not been directly observable to researchers in any form. In lieu of direct evidence, applied researchers frequently assume that consumers use a no-change forecast (Busse et al. Forthcoming; Sallee et al. 2009). That is, researchers assume that the expected future real price of gasoline equals the current price, simply replacing future gasoline prices g_{t+s} in the expression above with the current price g_t. Less frequently, researchers estimate their own econometric forecast models to predict future gasoline prices as a function of current and lagged macroeconomic variables, sometimes specifying a probability distribution for the evolution of future prices (Kilian and Sims 2006). More recently, Allcott and Wozny (2011) assume that expected future gasoline prices equal the price of crude oil in futures markets plus an add-on to account for refining costs, distribution, marketing, and taxes.

Because fuel consumption per mile is highly correlated with a vehicle's other attributes, such as engine size, weight, horsepower, and interior volume, the variation in expected fuel costs needed to identify these models comes largely (and often exclusively, to the extent that vehicle-specific fixed effects are used) through time-series variation in expected gasoline prices. Thus, correct specification of consumer beliefs about future gasoline prices is crucial to identification of the ratio γ/α. Suppose, for instance, that the researcher models consumers as having a no-change forecast. Under this assumption, whenever the current gasoline price increases by \$1, consumer beliefs about the future price will also increase by \$1. If, however, consumer beliefs about the future price actually increase by less than \$1, then the no-change assumption will lead to an estimate of γ that is biased toward zero: consumers will seem under-responsive to lifetime fuel costs. If, on the other hand, consumer beliefs increase by more than \$1, then conventional estimates of γ will be biased upward.

[6] Of course, variation in other parameters may also be important. Technically, the vehicle's future fuel consumption per mile (which varies with driving conditions and can degrade over time) and the real rate of discounting from one future period to the next are not known with certainty either. Moreover, miles driven in any future period may depend on the price of gasoline. Beliefs about future gasoline prices, however, are uniquely without empirical support in the existing literature.

[7] Fuel consumption per mile for virtually every vehicle sold in the last several decades is readily available to consumers and researchers alike from the Environmental Protection Agency (EPA) based on standardized testing procedures. Estimates for expected vehicle lifetimes (or rather, the probability that a vehicle survives a given number of years) and the number of miles that vehicles are driven are available directly from the National Highway Transportation Safety Administration, can be calculated from the National Household Travel Survey or other surveys, or can be obtained from state administrative datasets, as in Knittel and Sandler (Forthcoming). Lastly, discount rates for vehicle purchase decisions can be inferred from market interest rates, including rates on new and used car loans (after adjusting for expected inflation), which are available at the micro level in some vehicle transaction data sets and in aggregate from the Federal Reserve.

This strong dependence of inferences about consumers' valuation of fuel economy on assumptions about gasoline price expectations is the main motivation for our study. While we have emphasized here the subset of the automobile demand literature focused specifically on consumer valuation of fuel economy, misspecification of consumer beliefs about future gasoline prices has the potential to contaminate econometric estimates of consumer preferences for other key attributes, including vehicle price, size, and horsepower, in any study that uses time-series variation in gasoline prices to aid in identification (for example, Berry, Levinsohn and Pakes 1995).

3 Data

3.1 Data sources

Our expectations data come from the Michigan Survey of Consumers (MSC), which every month asks a nationally representative random sample of about 500 respondents to state their beliefs about the current state of the economy and to forecast several economic variables. A subset of these questions are aggregated into a single measure known as the University of Michigan Consumer Sentiment Index, which is widely followed as a leading indicator of economic performance. The survey has a short panel component: about one-third of respondents each month are repeat respondents from six months earlier, another third are new respondents that will be surveyed again in six months, and the final third are new respondents that will never be surveyed again. A core set of questions appears in every survey, but the survey has added and discontinued and even restarted various questions over time, so not all information is available in every time period.

We are primarily interested in two questions related to expected future gasoline prices that appear in nearly every survey dating back to 1993:[8]

> **Question:** "Do you think that the price of gasoline will go up during the next five years, will gasoline prices go down, or will they stay about the same as they are now?"

If respondents answer "stay about the same," their expected price change is recorded as zero. If respondents answer "go up" or "go down," they are asked a follow-up question:

> **Question:** "About how many cents per gallon do you think gasoline prices will (increase/decrease) during the next five years compared to now?"

If consumers report a range of price changes, they are asked to pick a single number. If they refuse or are unable to pick a single number, then the median of their reported range is recorded instead. If consumers respond that they "don't know" or refuse to respond at any stage of the questioning, then their non-response is noted as such, but only after being prompted several times to give a response. Less than 1% of respondents are coded as non-response. The survey has also asked an identical set of questions about expected twelve-month future gasoline prices since 2006 and

[8] There are several short gaps in the data availability: November 1993–February 1994, December 1999–February 2000, and January–April 2004.

occasionally during 1982-1992. We focus here on the five-year forecast because this time horizon is more relevant for automobile demand and because the data coverage is significantly better.[9]

The survey was designed to elicit expectations about gasoline price changes in nominal terms, and there are several compelling reasons to believe that respondents answer in nominal rather than real dollars. First, experienced survey practitioners generally believe that respondents answer in nominal terms unless they are specifically coaxed into a real-price calculation (Curtin 2004). Second, because the questions about gasoline prices follow a series of questions about expected inflation and prices in general, we suspect that consumers are primed to answer in nominal terms. Third, the question asks for gasoline price changes in cents per gallon, so that answering in real terms would require the respondent to make an inflation adjustment calculation. Finally, should respondents ask for clarification, interviewers are instructed to tell respondents to answer in nominal values. Thus, we assume from here on that consumers respond in nominal terms.

In addition to the MSC data, we collected data on gasoline prices from the U.S. Energy Information Administration (EIA). These data record the monthly, sales-weighted average retail price of gasoline (including taxes) by regional Petroleum for Administration of Defense District (PADD) for all grades (regular, midgrade, and premium) and formulations (conventional, oxygenated, and reformulated) of gasoline. We match MSC respondents by state to each of the seven PADD regions contained in the EIA data.

Because we believe that consumers are reporting expected future gasoline prices in nominal terms, we need to deflate these prices by a measure of expected inflation to facilitate comparison to current gasoline prices in real terms. Fortunately, the MSC asks a series of questions that allow us to deflate each respondent's gasoline price forecast using his or her stated beliefs about future inflation. The first question is: "What about the outlook for prices over the next 5 to 10 years? Do you think prices will be higher, about the same, or lower, 5 to 10 years from now?" If respondents answer "about the same," their expected inflation rate is recorded as zero. If respondents answer "higher" or "lower," then they are asked a follow-up question: "By about what percent per year do you expect prices to go (up/down) on the average, during the next 5 to 10 years?" (underlining in the original survey codebook). We use the responses to these questions to deflate nominal price forecasts by expected inflation, as described in section 3.2.[10]

Lastly, we collected data on the Consumer Price Index (CPI) from the Bureau of Labor Statistics to put all prices into a common unit.[11] We have complete data on all of these variables—actual gasoline prices, inflation expectations, and CPI—for our study period of January 1993 to December

[9] Note that even if consumers expect to own a vehicle for fewer than five years, future gasoline prices still determine valuation of fuel economy because they influence resale value.

[10] The average inflation expectation in the survey is quite stable over time, with the mean forecast ranging only between 2.5% and 5.9% and the median forecast ranging only between 3% and 4%. To some extent, this variation over time appears to be influenced by gasoline prices, a regularity noted by van der Klaauw, Bruine de Bruin, Topa, Potter and Bryan (2008). To verify the robustness of our results to this variation, we have used inflation forecasts from the Philadelphia Federal Reserve's survey of experts, rather than MSC inflation forecasts, to deflate respondents' nominal gasoline price forecasts. Our results are qualitatively unaffected by this change.

[11] We use series CUUR0000SA0LE, which is the non-seasonally adjusted index for all urban consumers, all items less energy.

2009 (except for several short gaps due to missing MSC data).

3.2 Data procedures

We construct our variables of interest from these raw data in several steps. Let $\tilde{C}_{it}^{60}$ be respondent i's expectation at time t for the change in nominal gasoline prices over the next 60 months (5 years), and let $\tilde{P}_{it}$ be the nominal price of gasoline in respondent i's PADD. (Henceforth, tildes denote nominal variables.) The expected price change is reported directly in the MSC data, while the current price is given by the EIA retail price data. We use these data to construct respondent i's expectation at time t for the nominal gasoline price 60 months into the future:

$$\tilde{F}_{it}^{60} \equiv E_{it}\left[\tilde{P}_{i,t+60}\right] = \tilde{P}_{it} + \tilde{C}_{it}^{60}, \tag{2}$$

which is the nominal price of gasoline plus the expected price change in nominal terms.

Now, let r_{it} be respondent i's expectation at time t for the average annual inflation rate over the next 60 months. We deflate the expected future nominal price by five years at this expected inflation rate and then deflate again by the realized CPI to construct the expectation at time t for the real price of gasoline 60 months into the future (in January 2010 dollars):

$$F_{it}^{60} \equiv E_{it}[P_{i,t+60}] = \tilde{F}_{it}^{60} \cdot (1 + r_{it})^{-5} \cdot CPI_{t,Jan2010}, \tag{3}$$

where $CPI_{t,Jan2010}$ is the CPI inflation factor from time t to January 2010 (the lack of a tilde on F_{it}^{60} denotes real dollars). Deflating the price forecast by five years of expected inflation puts the forecast in time-t dollars for an apples-to-apples comparison with the current price of gasoline at time t; deflating both variables by realized inflation puts everything in January 2010 dollars for an apples-to-apples comparison across the many months of the survey.

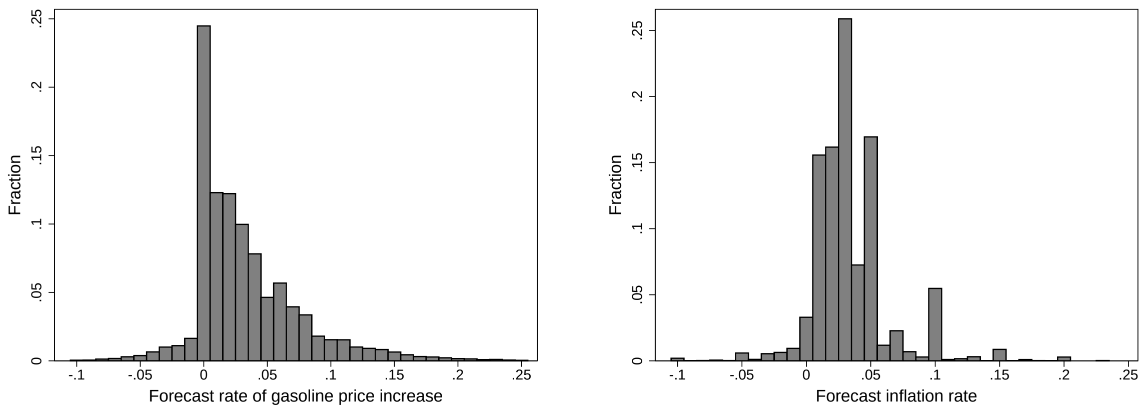
We also convert the current price of gasoline from nominal to real dollars: $P_{it} \equiv \tilde{P}_{it} \cdot CPI_{t,Jan2010}$. Having thus constructed both the real price forecast and the real current price of gasoline, we can then construct the expectation at time t for the real change in gasoline prices over the next 60 months:

$$C_{it}^{60} = F_{it}^{60} - P_{it}, \tag{4}$$

which is simply the real price forecast minus the current real price.

Figure 1 plots histograms for the forecasted annual rate of change in nominal gasoline prices and the forecasted inflation rate across all respondents with non-missing values for both forecasts during 1993–2009. Figure 2 then plots the distribution of nominal gasoline price forecasts conditional on the inflation forecasts for these same respondents. (Summary statistics for this sample of individual MSC respondents are provided in the Appendix.) Several salient facts emerge from these figures. First, the vast majority of respondents forecast nominal increases in both gasoline prices and overall price levels (inflation). Second, average expected increases are relatively small, at 3.2% per year for gasoline prices and 3.5% per year for inflation, with virtually no respondents forecasting

Figure 1: Marginal distributions of gasoline price and inflation expectations



Note: Figure plots histograms for the forecasted annual rate of change in nominal gasoline prices and the forecasted inflation rate across all 77,144 respondents with non-missing values for both forecasts during 1993–2009, weighted by their individual MSC sampling weights. The forecasted rate of gasoline price increase is given by $(1 + \tilde{C}_{it}^{60}/\tilde{P}_{it})^{1/5} - 1$, where $\tilde{C}_{it}^{60}$ is the respondent's forecasted change over five years and $\tilde{P}_{it}$ is the current price, both in nominal terms. The forecasted inflation rate is reported directly by survey respondents.

annual rates of change less than negative 5% or greater than 20% for either variable. Third, while there is noticeable clustering at zero for gasoline price forecasts, and on multiples of 5% for inflation, there is considerable density throughout the distribution.[12] Fourth, and finally, while respondents that forecast higher rates of inflation also tend to forecast higher annual rates of increase in gasoline prices, the correlation is far from perfect, with conditional distributions overlapping to a considerable degree. These descriptive statistics foreshadow our econometric results below: most consumers forecast moderate increases in nominal gasoline prices and moderate increases in nominal prices overall, with a slight positive correlation between the two, so that the average consumer has roughly a no-change forecast in real terms.[13]

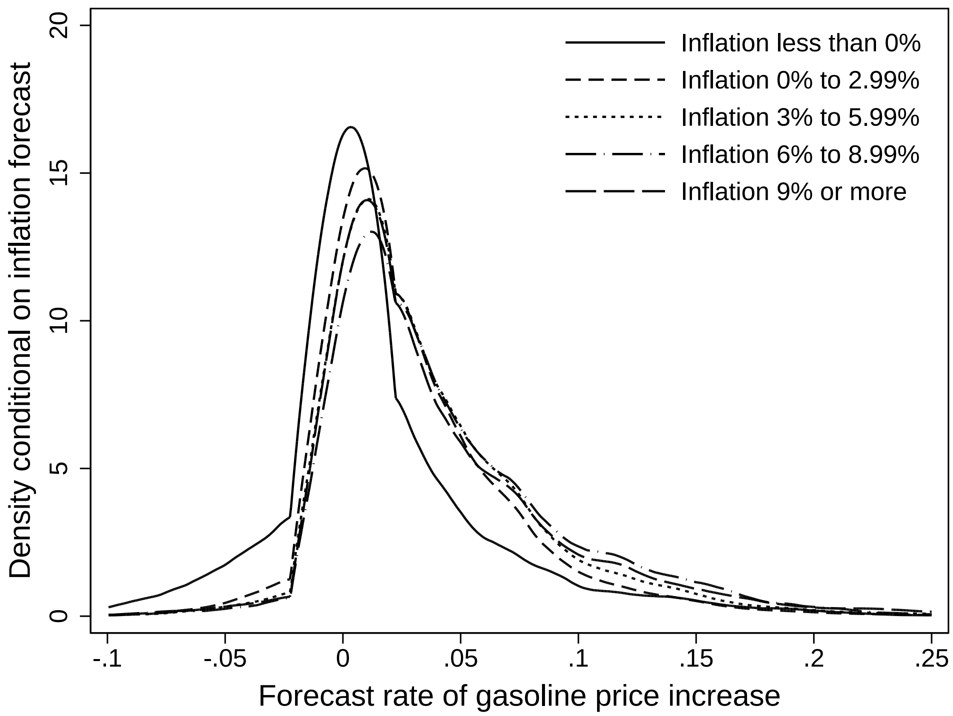
Our analyses in sections 4 through 7 examine the average (mean or median) forecast across MSC respondents, while section 8 studies cross-sectional heterogeneity.[14] To calculate mean MSC forecasts, our preferred approach is to calculate each individual's real gasoline price forecast first, as described above, and then take the mean or median in the final step. This approach is superior to deflating average nominal price forecasts by average inflation rates, since the expectation of a ratio

[12]While there is noticeable clustering on multiples of $0.05 per gallon in the raw, nominal forecast change data for gasoline prices, this clustering largely disappears in the conversion to annual rates of change due to considerable variation over time and across geography in the current price of gasoline.

[13]One possible concern with our data is that by categorizing all respondents who report "about the same" as having zero-change forecasts for gasoline prices and inflation, the survey might bias us towards finding a no-change forecast on average by treating those with small changes as zero. The figures demonstrate that this is unlikely to pose a problem because (1) only a modest fraction of respondents report no change, and even fewer report no change in both forecasts, and (2) most respondents who say "higher" or "lower" expect *small* changes. Thus, any bias created by equating "about the same" to zero would be small.

[14]Sections 4 through 7 below report mean results, which we believe are most relevant for the empirical literature on automobile demand, but we note throughout that our conclusions are robust to use of the median instead.

Figure 2: Distribution of gasoline price expectations conditional on inflation forecasts



Note: Figure plots the distributions (density functions) of the forecasted annual rate of change in nominal gasoline prices conditional on the forecasted inflation rate across all 77,144 respondents with non-missing values for both forecasts during 1993–2009, weighted by their individual MSC sampling weights. The forecasted rate of gasoline price increase is given by $(1+\tilde{C}^{60}_{it}/\tilde{P}_{it})^{1/5}-1$, where $\tilde{C}^{60}_{it}$ is the respondent's forecasted change over five years and $\tilde{P}_{it}$ is the current price, both in nominal terms. The forecasted inflation rate is reported directly by survey respondents. Each density function plots the distribution of gasoline price forecasts conditional on the range of inflation forecasts indicated in the legend. Densities were estimated using an Epanechnikov kernel with bandwidth of 0.01. See text for details.

does not equal the ratio of expectations. In constructing these mean and median values, we use weights provided by the MSC that correct for survey sampling issues, such as ownership of multiple phone lines and non-response probabilities, so that our means and medians are representative of all U.S. households.[15] Table 1 presents summary statistics for the monthly aggregate data during 1993–2009.

[15]Prior to aggregation, we omit a handful of observations for which the rates of increase exceed 50% and the rates of decrease exceed 33% annually, since such rates lead to implausibly high and low price forecasts for these respondents and an explosion in the variance of responses in a handful of months. Omitting these observations does not affect our main conclusions related to average price forecasts.

Table 1: Summary statistics for monthly aggregate data

Variable	Mean	Std. Dev.	Minimum	Maximum
Real, levels				
Forecast gas price	2.089	0.722	1.272	4.544
Current gas price	2.044	0.643	1.230	4.197
Forecast gas price change	0.046	0.154	-0.143	0.816
Real, logs				
Forecast gas price	0.653	0.311	0.208	1.469
Current gas price	0.671	0.282	0.204	1.434
Forecast gas price change	-0.018	0.064	-0.125	0.308
Nominal, levels				
Forecast gas price	2.135	0.964	1.173	5.367
Current gas price	1.765	0.736	0.971	4.112
Forecast gas price change	0.370	0.257	0.106	1.260
Nominal, logs				
Forecast gas price	0.645	0.403	0.132	1.643
Current gas price	0.492	0.376	-0.032	1.413
Forecast gas price change	0.153	0.055	0.061	0.427

Note: Table reports summary statistics for sample of monthly aggregate data. Sample size is 189 months. See text for details.

4 Graphical analysis of mean consumer forecasts

We depict our price series graphically in figures 3 and 4. Figure 3 presents, in nominal terms, the mean current price of gasoline ($\tilde{P}_t$), the mean forecast change over 5 years ($\tilde{C}_t^{60}$), and the mean forecast level ($\tilde{F}_t$) during our study period. The mean nominal expected change always exceeds zero and rises with the increase in nominal gasoline prices over this time period. There is generally little month-to-month volatility in the mean forecast change, except in 2008, when gasoline prices shot up and then plummeted during the financial crisis. This figure suggests that we would reject a null hypothesis of a *nominal* no-change forecast: consumers consistently expect nominal gasoline prices to rise, and the expected change increases with the current nominal price.

The picture changes considerably after deflating by forecasted inflation. Figure 4 presents, in real dollars, the mean price of gasoline (P_t), the mean forecast level (F_t^{60}), and the mean forecast change over 5 years (C_t^{60}). Note that the real forecast change hovers near zero for most of the study period, with large deviations only around September 11, 2001 and the large price swings during the financial crisis of 2008. This figure suggests that the mean MSC respondent forecasts the real price of gasoline in 5 years to equal the price at the time of the survey. That is, consumer forecasts are consistent with a *real* no-change forecast. Intuitively, the two characteristics of the nominal data that would lead to a rejection of a no-change forecast—the consistently positive forecast change and the correlation between the expected change and current prices in levels—are both eliminated when we account for expected inflation. Inflation alone will cause prices to rise over a five-year horizon, and a constant rate of inflation will have a larger impact on nominal prices in cents per gallon when the current price is higher.[16]

[16] Both figures 3 and 4 present prices in levels. The appendix includes figures in logged prices, where we first log

Figure 3: Nominal gasoline prices and forecasts.

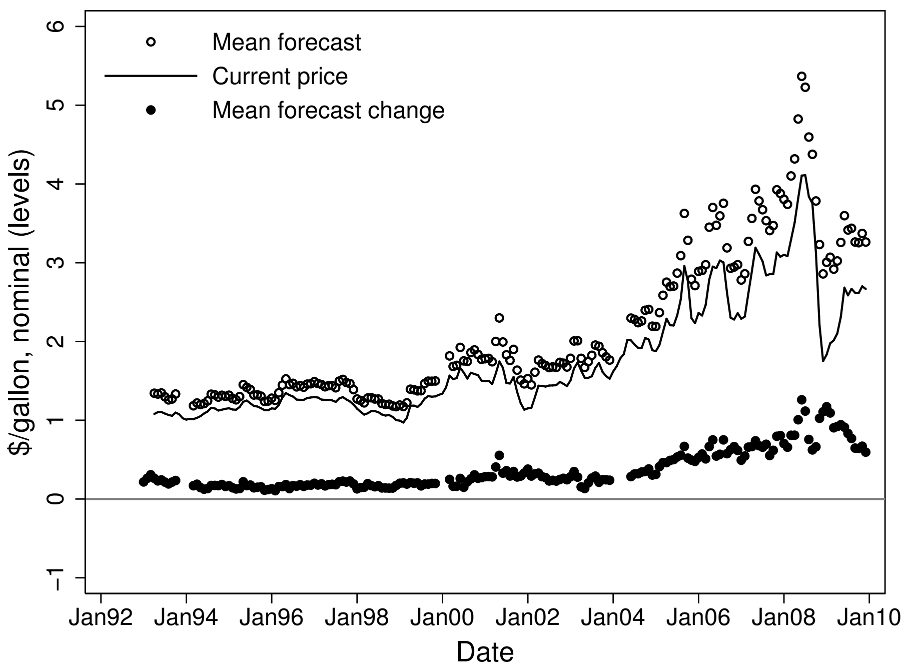
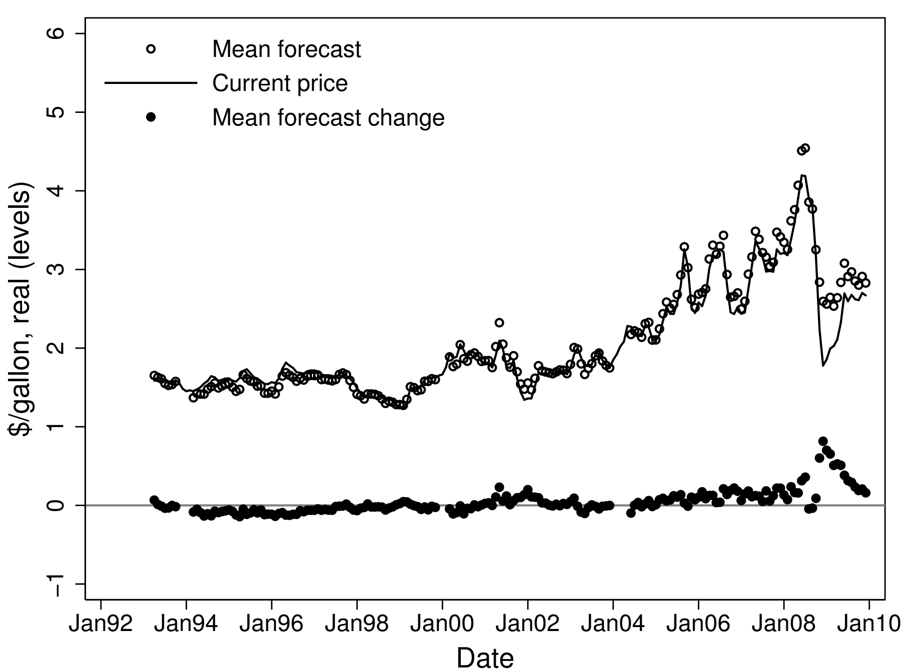


Figure 4: Real gasoline prices and forecasts.



The only large, sustained deviation from a real no-change forecast is during the financial crisis of 2008, during which the price of gasoline fell by half. Consumers expected prices to rebound quickly. As discussed in Anderson et al. (2011), futures markets predicted a similar rebound, and this prediction turned out to be correct: prices rose by about one-third of the original decline within six months. Thus, in our sample, when consumers deviate substantially from a real no-change forecast, their deviation is accurate. We cannot say definitively why consumers forecasted a price rebound during the crisis, but it is consistent with an ability to distinguish between the short-run depression of demand brought on by a recession and the long-run growth of global demand for oil.

5 Regression analysis of mean consumer forecasts

We now test formally the null hypothesis that the average MSC respondent expects future gasoline prices to equal the current price.[17] A simple way to implement a regression-based test would be to regress the expected future price on the current price:

$$F_t^{60} = \beta_0 + \beta_1 P_t + \varepsilon_t \tag{5}$$

and then test the joint null hypothesis that $\beta_0 = 0$ and $\beta_1 = 1$. This test is equivalent to testing the joint null hypothesis that: (1) the forecast price equals the current price on average (a test on the intercept); and (2) the forecast price correlates one-for-one with the current price (a test on the slope). This model could be estimated either in levels, as written, or in logs. We do not estimate this particular model, however, since the data demonstrate a high degree of persistence that limits the usefulness of such a test. Indeed, F_t^{60} has a first-order autoregressive coefficient of 0.980 in levels and 0.984 in logs, while the current price of gasoline P_t has a first-order autoregressive coefficient of 0.973 in levels and 0.978 in logs. Augmented Dickey-Fuller (ADF) tests fail to reject unit roots in the real price and forecast series in all cases.[18]

Thus, we run two separate regressions to implement statistically valid tests of our joint null hypotheses related to the intercept and slope. We test the first part of our hypothesis—that the forecast price equals the current price on average—by imposing that $\beta_1 = 1$ in the model above and then regressing the forecast price change on a constant:

$$C_t \equiv F_t^{60} - P_t = \beta_0 + \varepsilon_t, \tag{6}$$

individual responses and then take averages, which yields similar results.

[17]We emphasize that our goal is to test whether consumers have a no-change forecast, as is commonly assumed in applied work, and not to test whether consumers' forecasts are rational. A test of rational expectations would involve a regression of realized future prices on consumers' forecasts. The related issue of consumers' forecast accuracy is discussed in Anderson et al. (2011).

[18]This statement is true regardless of whether we focus on the full sample or pre-2008 sample, model prices in logs or in levels, analyze means or medians, or allow for a trend or not. We use a version of the ADF test that de-means and de-trends using GLS to increase power according to Elliott, Rothenberg and Stock (1996), and we determine the optimal number of lagged differences using the modified AIC of Ng and Perron (2001).

Table 2: Does the mean forecast change in gasoline prices equal zero on average?

Panel A: Real gasoline prices and price forecasts

	Full sample: 1993–2009		Excluding crisis: 1993–2007	
	Levels	Logs	Levels	Logs
Constant	0.0457	-0.0180	0.0065	-0.0320
	(0.0332)	(0.0136)	(0.0204)	(0.0103)

Panel B: Nominal gasoline prices and price forecasts

	Full sample: 1993–2009		Excluding crisis: 1993–2007	
	Levels	Logs	Levels	Logs
Constant	0.3686	0.1535	0.2984	0.1411
	(0.0619)	(0.0113)	(0.0435)	(0.0076)

Note: Standard errors (in parentheses) were estimated using Newey-West with 12 lags. Full sample for 1993–2009 includes 189 monthly observations; sample excluding crisis for 1993–2007 includes 165 monthly observations. See text for details.

where the no-change null hypothesis implies that $\beta_0 = 0$. The forecast change series is less persistent than either of the individual price series, and spurious regression is not a concern for regression on a constant in any case.[19]

We report results from simple regressions of C_t on a constant in columns 1 and 3 of table 2. Column 1 uses the full sample and finds a mean expected price change of 4.6 cents; however, this result is not statistically significant (its p-value is 0.169).[20] Column 3 uses a subsample that excludes the financial crisis and, consistent with our graphical analysis, finds a smaller point estimate of 0.7 cents that is also statistically insignificant. When specified in logs (in columns 2 and 4), this regression indicates that respondents forecast a small percentage decrease in real prices, which appears to be driven by the early part of the sample.

There are two important caveats to this interpretation. First, while the mean forecast price is approximately equal to the current price on average, there do exist months for which we can statistically reject equality between the current price and mean forecasted price when we test the individual micro data one month at a time. This is not surprising given 500 individual observations per month. As figure 3 demonstrates, however, these deviations from equality are economically quite small in most periods (only a few cents). Second, while the forecasted price change is roughly

[19] The series C_t^{60} has a first-order autoregressive coefficient of 0.880 in levels and 0.891 in logs, and we were able to reject a unit root in the mean forecast change in two cases: levels in the full sample and logs in the pre-2008 sample. If the price and forecast series were cointegrated, then we could estimate the dynamic response of expected prices to current prices using an error correction model. By imposing that expectations eventually equal current prices, however, this model *assumes* a long-run no-change forecast. Moreover, we are not always able to reject a unit root in the difference between the two price series.

[20] The serial correlation in the residuals is strong when we do not include a trend, and even 12 lags is not sufficient to capture fully the serial correlation. Thus, the Newey-West standard errors are likely biased toward zero (and toward rejecting the no-change hypothesis).

zero on average over the sample, there does appear to be a slight upward trend, with the earlier periods (forecast price decline) balancing the later periods (forecast price increase). While this trend might be consistent with growing concern about dwindling supplies of low-cost crude oil, the trend is weak and the deviations from equality are small.

We test the second part of our hypothesis—that the forecast price varies one-for-one with the current price—using the first-differenced equation 7, since both the forecasted and current price series are stationary in differences:

$$\Delta F_t^{60} = \beta_0 + \beta_1 \Delta P_t + \varepsilon_t. \tag{7}$$

This first-differenced model is especially relevant for studies of automobile demand that rely on time-series variation in gasoline prices to identify consumers' valuation of fuel economy. Identification in such studies comes from observing how vehicle prices and quantities change in response to changes in gasoline prices (typically interacted with vehicle efficiency). Thus, it is the response of consumers' gasoline price forecasts to *changes* in the current price of gasoline that is most relevant in this and other literatures that rely on such identification.

Table 3 presents our regression results. Panel A presents results with real variables. Results in levels based on the full 1993–2009 sample imply that when the mean current price of gasoline increases by \$1.00, the mean real-price forecast increases by about \$0.87. Results in logs based on the full sample imply that when the current price of gasoline increases by 1%, the mean real-price forecast increases by about 0.83%. We cannot statistically reject the null hypothesis of a real no-change forecast at a conventional 5% level, but this is partly because estimates using the full sample have sizable standard errors. The point estimates are economically significant. They suggest less-than-full adjustment, so that consumers anticipate mean-reverting gasoline prices.

This result (and much of the imprecision) is driven by the data from the financial crisis of 2008, which led to a large deviation between the current and expected future price. When we limit the sample to the 1993–2007 period, as reported in the right-hand side of the table, the regression coefficients are all tightly estimated and close to 1, consistent with a no-change forecast. Results in levels based on the limited 1993–2007 sample imply that when the current price of gasoline increases by \$1.00, the mean forecast price increases by \$0.99. The estimates reject even modest deviations from the no-change null hypothesis with a narrow 95% confidence interval of \$0.91 to \$1.07. Results in logs based on the limited sample imply that when the current price increases by 1%, the mean forecast price increases by 0.96%. Again, the estimates reject even modest deviations from the no-change null with a 95% confidence interval of 0.89% to 1.07%.

Figure 5 presents these results graphically: forecasted gasoline prices increase one-for-one with current prices on average. To highlight the importance of the financial crisis, data from 2008 and 2009 are denoted with x's. These observations clearly have the largest residuals. This figure also illustrates that while the slope is one, the correlation is not perfect, even during normal times. Thus, the current price is a somewhat noisy measure of average stated beliefs.

In table 3 panel B, we do not adjust for inflation, but rather regress changes in the mean

Table 3: Does the mean forecast gasoline price change one-for-one with the current price?

Panel A: Real gasoline prices and price forecasts

	Full sample: 1993–2009		Excluding crisis: 1993–2007	
Variable	Levels	Logs	Levels	Logs
Current price	0.8742	0.8250	0.9938	0.9624
	(0.0895)	(0.0933)	(0.0430)	(0.0340)
Constant	0.0017	0.0011	0.0021	0.0012
	(0.0029)	(0.0011)	(0.0020)	(0.0010)

Panel B: Nominal gasoline prices and price forecasts

	Full sample: 1993–2009		Excluding crisis: 1993–2007	
Variable	Levels	Logs	Levels	Logs
Current price	1.0899	0.8804	1.2571	1.0147
	(0.1137)	(0.0902)	(0.0299)	(0.0268)
Constant	0.0012	0.0007	0.0010	0.0005
	(0.0034)	(0.0012)	(0.0021)	(0.0010)

Note: Standard errors (in parentheses) were estimated using Newey-West with 12 lags. Full sample for 1993–2009 includes 185 monthly observations; sample excluding crisis for 1993–2007 includes 161 monthly observations. See text for details.

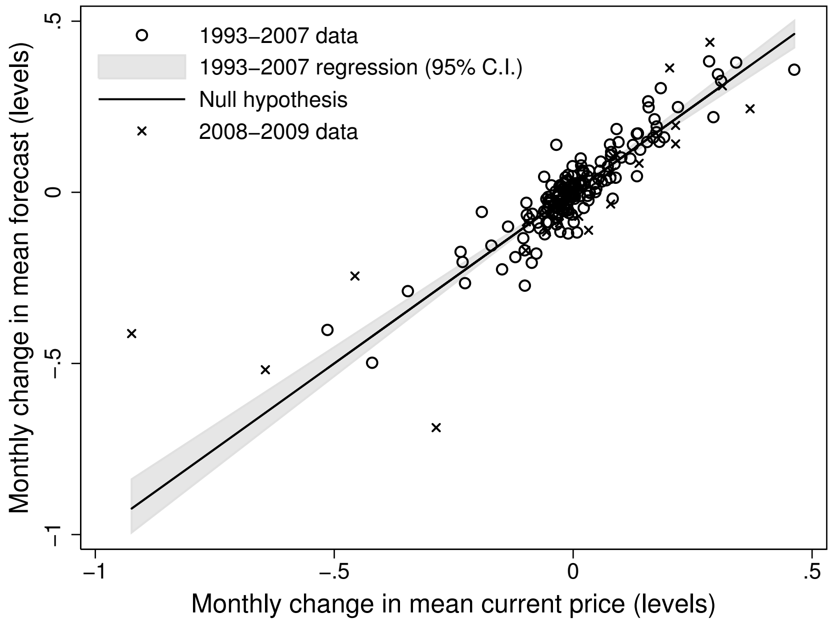
nominal forecast on changes in the mean nominal price. In both the full sample and the sample excluding the financial crisis, consumers' nominal price forecasts increase more than one-for-one with current prices. The coefficient of 1.26 when the financial crisis is excluded (column 3) is particularly large and strongly statistically significant, consistent with the qualitative analysis of figure 4. The estimates using logged nominal prices and forecasts, however, are quite similar to those in panel A, consistent with the facts that average expected inflation is fairly constant over time and that multiplication by a constant has no effect on the coefficient estimate in a log-log model.

The results in table 3 estimate the immediate response of expectations to changes in the current price of gasoline. It is possible that the long-run response to price changes differs from the short-run response, perhaps because consumers only update their expectations about future gasoline prices and inflation periodically. Thus, we estimate autoregressive distributed lag (ARDL) models that allow expectations to respond to both current and lagged changes in the gasoline price. That is, we estimate dynamic models of the form:

$$\Delta F_t^{60} = \beta_0 + \sum_{k=0}^{q} \beta_k \Delta P_{t-k} + \sum_{k=1}^{q} \gamma_k \Delta F_{t-k}^{60} + \varepsilon_t. \tag{8}$$

Table 4 presents the results of these regressions. Depending on the particular price series we used, we found that it was necessary to include up to 12 periods of lagged prices and forecasts to eliminate the serial correlation in the error term. Thus, all of our results are based on an

Figure 5: Does the mean forecast gasoline price change one-for-one with the current price?



Note: Figure shows graphically the regression results corresponding to column 3 of panel A of table 3 above. See table and text for details.

ARDL model with 12 lags (i.e., $q = 12$ in the equation above). The table presents the long-run response of expectations to a permanent increase in the price of gasoline. As the table demonstrates, accounting for a delayed response narrows the gap between estimates based on the full and pre-crisis samples. Long-run responses estimated using the 1993–2007 pre-crisis sample are very similar to the immediate responses in the previous table, while responses estimated using the full 1993–2009 sample are now much closer to a no-change forecast.[21] These results lend further support to our inference that the average consumer uses a no-change forecast.

6 State gasoline prices and consumer forecasts

Thus far, our analysis has focused on gasoline prices and forecasts that are aggregated to the national level. In this section, we study how consumer forecasts respond to panel variation in state gasoline prices—that is, price variation that represents deviations from long-run state averages and from the national time series. As we explain below, this response is of interest both for determining whether or not consumers distinguish between price shocks that have different levels of persistence

[21] We also examined the impulse response functions associated with a permanent increase in the current price of gasoline. We found, however, that the long-run responses occurred quite quickly: in most cases, the short-run effect was statistically indistinguishable from the long-run effect upon impact. This finding is consistent with the fact that the long-run coefficients in table 4 are fairly similar to the coefficients in table 3, which measure the immediate impacts of changes in the current price on expected future prices.

Table 4: Does the mean forecast gasoline price change one-for-one with the current price over the long run?

Panel A: Real gasoline prices and price forecasts

	Full sample: 1993–2009		Excluding crisis: 1993–2007	
Variable	Levels	Logs	Levels	Logs
Current price	0.9838	0.8992	1.0263	0.9660
	(0.0611)	(0.0533)	(0.0789)	(0.0820)

Panel B: Nominal gasoline prices and price forecasts

	Full sample: 1993–2009		Excluding crisis: 1993–2007	
Variable	Levels	Logs	Levels	Logs
Current price	1.2900	0.9519	1.2608	0.9628
	(0.1037)	(0.0616)	(0.0925)	(0.0762)

Note: Table reports long-run response of mean forecast to a permanent increase in the current price of gasoline; standard errors are in parentheses. All regressions assume a lag structure of 12 months. Full sample for 1993–2009 includes 143 monthly observations; sample excluding crisis for 1993–2007 includes 119 monthly observations. See text for details.

(panel shocks are mean-reverting) and for interpreting research on automobile demand that uses, to varying degrees, panel variation in gasoline prices for identification.

To study variation at the state level, we collect a balanced panel of tax-inclusive state-specific retail gasoline prices from the EIA.[22] We adjust prices for inflation using the CPI-U less energy, as we do with our national data. We then collapse our MSC forecast data to state-by-month averages, deflating with individual inflation forecasts and weighting by the survey's probability sampling weights, as we do with our national data.

To understand how our state panel will compare to the national data, we first assess the extent to which gasoline price variation over time is national versus state-specific. To do so, we regress the current price of gasoline, from 1993 to 2007, on a set of state dummies and then regress the residuals of this regression on month-of-sample dummies. We find an R^2 of 0.982, implying that only 1.8% of the temporal price variation in the data is state-specific. Thus, the vast majority of price variation consumers observe over time is driven by national-level shocks rather than state-specific shocks.

We next analyze the persistence of state-specific shocks by regressing the current price on the one-year and five-year lagged prices in our state panel. Panel A of table 5 reports coefficient estimates from regressions that include state fixed effects but not time fixed effects. Panel B adds time period (year-by-month) fixed effects. Thus, panel A estimates the persistence of gasoline price shocks that come from temporal variation in national prices (because 98.2% of variation is national), whereas panel B identifies the persistence of the state-specific price shocks that remain

[22]We first collect pre-tax retail prices from EIA, to which we then add state and federal per-gallon gasoline taxes, state ad-valorem gasoline taxes, and state sales taxes. We draw on, extend, and in a few instances correct the computer code developed by Davis and Kilian (2011) that incorporates these taxes based on information from a variety of private and government data sources.

Table 5: How persistent are state-specific gasoline price shocks?

Panel A: Real gasoline price autoregressions with state fixed effects

	Twelve-month lags		Sixty-month lags	
Variable	Levels	Logs	Levels	Logs
Lagged price	0.9992	1.0256	0.4877	1.7327
	(0.0636)	(0.0398)	(0.2213)	(0.1482)

Panel B: Real gasoline price autoregressions with time and state fixed effects

	Twelve-month lags		Sixty-month lags	
Variable	Levels	Logs	Levels	Logs
Lagged price	0.2565	0.3199	0.1280	0.1132
	(0.0570)	(0.0607)	(0.0489)	(0.0440)

Dependent variable is the current real price of gasoline in a month and state. The lagged price is a 12-month lag in columns 1 and 2 and a 60-month lag in columns 3 and 4. Variables are not first differenced. Standard errors (in parentheses) are two-way clustered on state and month-of-sample. Panel A includes state fixed effects. Panel B includes state and month fixed effects. Sample is pre-crisis, from 1993–2007, with 9,000 observations for columns 1 and 2 and 7,200 observations for columns 3 and 4.

after removing the national time series.

Table 5 shows that national shocks are far more persistent than state-specific shocks. The one-year lagged coefficients in panel A are very close to 1. In contrast, the corresponding estimates in panel B show that, on average, only one-quarter to one-third of an idiosyncratic price shock in a state today will persist one year later. The five-year lagged coefficients tell a qualitatively similar story, though these estimates are sensitive to the exact specification used and are imprecisely estimated in the absence of month-of-sample fixed effects.[23] These estimates accord with intuition: idiosyncratic state-level shocks, such as local refinery outages, are typically short-lived and can be eliminated by market forces. National-level price variation, however, is primarily driven by crude oil prices that are set globally and well-approximated by a random walk.

We next turn to our consumer forecast data and ask whether or not consumers react differently to national and state price shocks when forming their forecasts. A fully informed and rational consumer would predict significant mean reversion for state-specific gasoline price shocks, but it may be difficult for consumers to distinguish between price movements that are national and those that are specific to their states. Table 6 reports estimates from regressions of the forecasted price on the current price (in first differences), mimicking our main specification from table 3, using the state panel. We vary the inclusion of time fixed effects to show how consumer forecasts change

[23]Further, the five-year coefficients vary when logs are used instead of levels, when we change the exact time period used, and when we weight by the number of MSC respondents so as to better mimic the identification in our forecast regressions. Nevertheless, across all specifications we have analyzed we find that state-specific deviations exhibit far less persistence than national time series changes.

Table 6: Does the mean forecast gasoline price change one-for-one with the current state-level price?

Panel A: Real gasoline prices and price forecasts, state panel with state but not time fixed effects

	Full sample: 1993–2009		Excluding crisis: 1993–2007	
Variable	Levels	Logs	Levels	Logs
Current price	0.8795	0.8119	0.9855	0.9473
	(0.0222)	(0.0175)	(0.0344)	(0.0284)

Panel B: Real gasoline prices and price forecasts, state panel with time and state fixed effects

	Full sample: 1993–2009		Excluding crisis: 1993–2007	
Variable	Levels	Logs	Levels	Logs
Current price	0.8666	0.8038	0.8741	0.8522
	(0.0456)	(0.0476)	(0.0565)	(0.0630)

Standard errors (in parentheses) are clustered on state. Regressions are weighted by the number of survey observations. Panel B includes state and month fixed effects. Full sample for 1993–2009 includes 8,156 observations; sample excluding crisis for 1993–2007 includes 7,120 observations.

when we isolate state-specific gasoline price variation. Panel A includes only state fixed effects, whereas panel B includes both state and time fixed effects. All regressions are weighted by the MSC sample size to improve precision, and standard errors are clustered at the state level.[24]

The results in panel A, which are identified primarily from temporal variation in the national average gasoline price, closely match the coefficients from our national time series in table 3. Thus, switching to a state panel dataset does not change the relationship between gasoline price changes and changes in consumer forecasts that we established with our national data. In particular, consumers' gasoline price forecasts change one-for-one with the current price of gasoline during the pre-crisis period.

The results in panel B of table 6, which add time period fixed effects, show that consumer forecasts change less than one-for-one with state-specific gasoline price changes, but they still change by a substantial amount. Across the four columns in table 6 the coefficient on the first difference in the state gasoline price ranges from 0.80 to 0.87, indicating that consumers expect 80% to 87% of a local gasoline price change today to persist five years later.[25] A coefficient of 1 can be ruled out in all four of the regressions in panel B, implying that we can reject no-change beliefs regarding state-level price shocks. Furthermore, the difference between the coefficients in panel A

[24]Two-way clustering on state and month of sample produces slightly smaller standard errors on average, which is as expected given that there is negative serial correlation in the differenced data and that there is no obvious reason why there should be substantial cross-state correlation in price forecasts, conditional on the current price. We therefore report the more conservative state-clustered estimates.

[25]Results are very similar if we modify the regression to use contemporaneous variables (rather than first differences) and include time and state fixed effects. Then, the coefficients range from 0.79 to 0.86.

and panel B is statistically significant for the pre-crisis sample but not for the full sample.[26]

Thus, when we identify our coefficient using only state-specific gasoline price changes, consumer forecasts do display some mean reversion. Nevertheless, this level of mean reversion is far below the actual mean reversion we estimate in table 5. We interpret this result as evidence that consumers cannot readily distinguish between price fluctuations that occur locally and those that reflect aggregate factors. Local gasoline prices are salient to consumers, but under normal circumstances most consumers will have little information on gasoline prices in other states. It is therefore not obvious how consumers would distinguish idiosyncratic state-specific variation from national variation, particularly given that national-level factors are by far the dominant driver of price changes. As a result, consumers treat all gasoline price changes as being highly persistent.

Our findings carry implications for research that uses a panel research design to study consumer decisions that require forecasting. For example, Busse et al. (Forthcoming) runs regressions of vehicle prices and market shares on local gasoline prices to gain insight into how consumers' demand for fuel economy responds to gasoline prices. To the extent that controls for national-level prices are included in the regressions (the paper varies its use of these controls across robustness checks), the results will be driven more by state-level variation and less by national variation.[27] Ex-ante, our "rational consumer" priors suggest that papers such as Busse et al. (Forthcoming) should be leery of relying solely or even partially on state-level idiosyncratic variation to identify parameters related to durable investment decisions—particularly when these parameters are subsequently used to simulate impacts of permanent gasoline price or tax changes—as this variation is transitory and mean-reverting.

Fully-informed, rational consumers should largely ignore state-specific price shocks when purchasing new vehicles. However, our results in table 6 suggest that consumers actually perceive state-level price variation to be quite persistent, suggesting that approaches relying on state-level variation may nonetheless yield valid estimates. Overall, our panel analysis should serve as a reminder to researchers that the relationship between consumer forecasts and current prices may depend on what price variation is used for identification. Researchers should be cautious when using local gasoline price variation and not take for granted that expected future prices equal current

[26] To test the difference between the panel A and B results, we cluster bootstrap our data on state and estimate the coefficient including and excluding time fixed effects for each drawn sample. We then compare the distribution of estimated coefficients across trials. The coefficient distributions with and without the fixed effects are very similar for the full sample, but our bootstrap test of the difference in coefficients for the pre-crisis sample produces p-values of 0.052 and 0.057 for the level and log specifications respectively.

[27] The main specifications of Busse et al. (Forthcoming) use year fixed effects, though the fact that the data are monthly implies that most of the gasoline price variation used (82% of it, per our calculations) is still at the national level. In a robustness test of the paper's new vehicle quantity results, month-of-sample fixed effects are used. This test yields similar estimates to what was found in the main specification, though with much larger standard errors. This outcome reflects our findings that: (1) consumers forecast state-level shocks as being highly persistent; and (2) state-level variation is quite small relative to national-level variation. The paper's vehicle price regressions also use month-of-sample fixed effects in a robustness test. However, in this case, the critical coefficient is for the interaction of the gasoline price with fuel economy, so that identification is still largely coming from national-level gasoline price variation. Other papers in this literature that include time-period fixed effects, such as Allcott and Wozny (2011) and Li et al. (2009), also focus on interactions between fuel economy and gasoline prices, thereby avoiding a strong reliance on state-level variation.

prices in all specifications.

7 Do forecasts respond differently to tax and pre-tax price changes?

Our analysis of the state panel also allows us to comment on a literature that examines whether or not consumers respond differently to the tax and non-tax components of gasoline prices. Much of the research examining the effects of gasoline prices is motivated by policy questions about the efficacy of corrective taxation to reduce gasoline-related externalities. This research typically uses gasoline price variation driven primarily by global oil price fluctuations that pass through into retail prices, and then uses derived elasticities to predict how a tax change would influence consumption.

Davis and Kilian (2011) and Li et al. (2012), however, argue that gasoline consumption responds much more strongly to changes in gasoline taxes than it does to pre-tax gasoline price changes. This argument implies that prior research has underestimated the effectiveness of gasoline taxes at reducing externalities. For example, Davis and Kilian (2011) uses taxes as instruments for the tax-inclusive price in a state panel dataset and estimates that a 10-cent gasoline tax could lower carbon emissions from vehicles in the U.S. by 1.5%. This estimate is two-and-a-half times larger than the effect implied by the paper's OLS estimates.

Both Davis and Kilian (2011) and Li et al. (2012) use a state panel to run regressions of current gasoline consumption on current gasoline prices and rely fully on state-level variation to identify the consumption elasticity. Their challenge is then to explain *why* consumers would respond differently to the two components of price, given that posted prices in this market are always tax-inclusive. Both papers emphasize that taxes and non-tax price changes may have different impacts on consumer expectations of future prices. Consumers may expect gasoline price changes that are due to tax policy to be more persistent than those due to fluctuations in supply and demand. As a result, tax changes may be more likely to lead consumers to make long-run investments that lower gasoline consumption.

The model implicit in this reasoning is that current consumption is a function both of the current price of gasoline and consumer expectations about the future price. We specify this model here in an additive linear form:

$$\ln(C_{st}) = \beta \ln(\tilde{P}_{st} + \tau_{st}) + \gamma \ln(F^k_{st}(\tilde{P}_{st}, \tau_{st})) + \alpha_s + \delta_t, \tag{9}$$

where the subscript t denotes the current period, s denotes state, and the superscript k denotes some future period. C is current gasoline consumption; F is a forecast of future gasoline prices, which is a function of both current taxes τ and current pre-tax prices $\tilde{P}$; α are state fixed effects; and δ are time period fixed effects.

Taking derivatives of equation 9 and rearranging, we can write the difference between the marginal effect of a tax change (in cents per gallon) on logged gasoline consumption and the

Table 7: Does the mean forecast respond equally to taxes and pre-tax prices?

	Level regressions			First differences		
Pre-tax price	1.1037	1.2279	0.8769	1.0042	0.9075	0.9081
	(0.0086)	(0.1227)	(0.0451)	(0.0330)	(0.0617)	(0.0618)
Tax	0.5449	0.7666	0.4950	0.5408	0.0775	0.0859
	(0.1449)	(0.1397)	(0.1771)	(0.4793)	(1.0781)	(1.10828)
Fixed Effects	None	Time	Time, State	None	Time	Time, State

Standard errors (in parentheses) are clustered on state. All variables are in first differences in columns 4-6. Sample is restricted to 1993 to 2007, and regressions are weighted by MSC sample size. Columns 1-3 have 7,593 observations and columns 4-6 have 7,120 observations.

marginal effect of a pre-tax price change (in cents per gallon) on logged gasoline consumption as:

$$\frac{\partial \ln(C_{st})}{\partial \tau_{st}} - \frac{\partial \ln(C_{st})}{\partial \tilde{P}_{st}} = \frac{\gamma}{F_{st}^k} \cdot \left(\frac{\partial F_{st}^k}{\partial \tau_{st}} - \frac{\partial F_{st}^k}{\partial \tilde{P}_{st}} \right). \tag{10}$$

Davis and Kilian (2011) and Li et al. (2012) find that the object described in equation 10 is large, which requires that $\frac{\partial F_{st}^k}{\partial \tau_{st}} - \frac{\partial F_{st}^k}{\partial \tilde{P}_{st}}$ be positive, assuming that γ is positive, as theory would predict.[28] Our data allow us to test this condition directly by evaluating whether or not consumers' forecasts show more or less response to tax changes than to pre-tax price changes. To do so, we run regressions of our mean MSC forecast on both the tax and pre-tax price (adjusted for inflation) and compare coefficients. We do this in both levels and first-differences, and we vary the fixed effects included. We focus on the pre-crisis period of 1993 to 2007 and weight regressions by the number of MSC observations in each state and month. Consistent with Davis and Kilian (2011), we only include per-gallon specific taxes in our tax measure, excluding ad-valorem taxes, which are mechanically related to the pre-tax price.

Table 7 reports our results. In all specifications, tax changes have a smaller estimated impact on forecasts than does the pre-tax price. The difference in the estimated coefficients is statistically significant in the levels regressions but not in the first differenced regressions. Still, there is no support in any of the estimates for the hypothesis that forecasts are especially responsive to gasoline tax changes. This is not to say that tax changes are not in fact more persistent.[29] Rather, our

[28] It seems unlikely that γ, which represents the change in *current* consumption resulting from a change in beliefs, could be particularly large, especially in Davis and Kilian (2011), in which the time period is one month. We have directly tested this hypothesis by running a first-differenced regression of the log of gasoline consumption in a state and month on both the current price and the average MSC forecast. Estimates indicate that forecasts have no effect on current consumption, and the inclusion of the forecast changes the coefficient on current price very little. We do not include these regressions in the paper, however, because we believe they are potentially biased by measurement error. Conditional on the current price, our state-specific measure of the consumer forecast has little variation remaining, particularly after differencing, so we are concerned that measurement error in the forecast is a problem in this specification.

[29] Taxes will not be perfectly persistent, both because they change relatively frequently (as shown by Davis and Kilian (2011) and Li et al. (2012)) and because taxes are in nominal cents per gallon, the real value of which erodes over time.

regressions suggest that consumers do not readily distinguish between tax and non-tax changes in making forecasts. This result might not be surprising given that most tax changes are small (and therefore may go unnoticed) and that taxes are never separately listed at the pump. It is also consistent with our finding in section 6 that consumers do not distinguish between national and state-specific price shocks. In sum, our forecast data do not provide support for the hypothesis, suggested by other researchers, that excess sensitivity of forecasts to tax changes is likely to explain the finding that current gasoline consumption is more sensitive to tax policy than to pre-tax price changes.

8 Heterogeneity in consumer forecasts

Thus far, we have focused on mean consumer beliefs by studying the average of the MSC responses each month. Here, we investigate the heterogeneity in consumers' forecasts that is present in the individual-level MSC data. These data demonstrate what we consider to be substantial forecast dispersion across respondents in each MSC survey month. In our sample, the average standard deviation of the real five-year price forecast across respondents within a month is 62 cents (the corresponding standard deviation of logged forecasts is 0.25).[30] In what follows, we ask how this heterogeneity relates to individual-level factors such as demographics, how it varies over time, and how it compares to other sources of heterogeneity that affect consumers' valuation of fuel economy.

Variation across individual survey responses could be interpreted in several ways. Dispersion could reflect true disagreement across individuals. Alternatively, it could constitute a measure of uncertainty, or it could simply reflect random noise in the survey instrument. In Anderson et al. (2011), we consider the possibility that dispersion reflects uncertainty, but we fail to find a strong correlation between the MSC dispersion and two measures of oil price volatility in the years prior to the financial crisis. And, while we cannot rule out that noise exists in our data, we show below that a large fraction of the dispersion persists across individuals who are surveyed twice. Thus, our preferred interpretation is the former, that dispersion reflects disagreement across individuals in their forecasts of the future price. This interpretation accords with prior literature (Mankiw, Reis and Wolfers 2004; Curtin 2010) and is consistent with the fact that the survey elicits a point estimate from each individual.

Throughout this section, we discuss how we believe our findings inform research on consumer demand for energy-consuming durable goods. This literature has for the most part assumed away factors that would lead to heterogeneity in valuation of energy efficiency. In the context of vehicle demand, these factors include not just heterogeneity in future price forecasts but also in vehicle miles traveled, local gasoline prices, and consumers' discount rates. Some recent papers, however, have begun to explore the econometric and policy implications of heterogeneity. Bento et al. (2012) studies the estimation of vehicle demand models like those in our equation (1), and finds that

[30] We obtain these figures by regressing the forecasts (for the entire sample period, not just the pre-crisis period) on month-of-sample dummies and then taking the standard deviation of the residuals. We continue to omit extreme outliers as discussed in footnote 15 above.

assuming homogeneity can lead to biased estimates of the average consumer's willingness to pay for fuel economy.[31] Allcott et al. (2012) presents a model of optimal taxation in the presence of consumers that are myopic about future energy expenses and exhibit heterogeneity in the intensity of their use of energy-consuming durables (i.e., heterogeneity in miles traveled in the case of vehicles). The paper does not discuss, however, heterogeneity in consumers' forecasts of future energy prices. It is our hope that the results below will provide useful guidance to this nascent literature as it continues to explore the implications of consumer heterogeneity.

8.1 What explains forecast heterogeneity?

We begin by examining how much of the variation in consumers' price forecasts is predictable, based on observable characteristics of the respondents. Within the MSC dataset we observe demographic information such as age, income, and education that might plausibly be correlated with gasoline price forecasts. To quantify these correlations in the data, we first strip out aggregate factors by regressing the individual real forecasts on month-of-sample fixed effects. We then regress the residuals from this regression on an income polynomial and on dummy variable categories for education, race, marital status, gender, and state of residence. This regression yields an R^2 of only 0.053 when run in levels and 0.078 when run in logs. Some demographic factors have a statistically significant impact on forecasts, but these effects tend to be small in magnitude. For instance, males' forecasts are on average 12 cents higher than females' forecasts, and college graduates have forecasts that are on average 5 cents higher than those of high school graduates with no college education. Overall, however, it appears that observable demographic factors explain very little of the forecast heterogeneity across respondents.

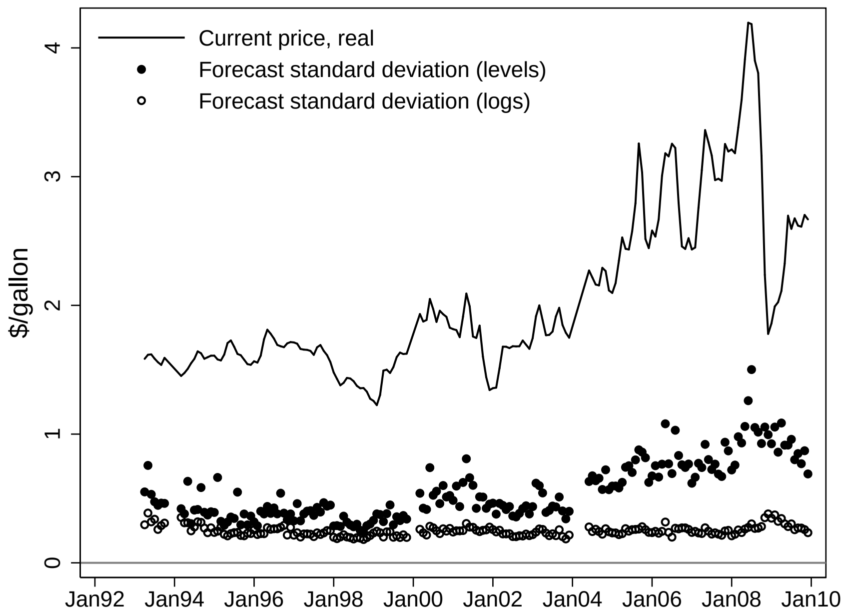
A related issue concerns the extent to which forecasts are stable for each individual. That is, is it the case that someone who has a relatively high forecast today will also have a relatively high forecast tomorrow? Because many of the MSC respondents appear in the sample twice, six months apart, we are able to address this question through regressions with individual fixed effects. We first limit the sample to the 26,384 respondents for whom we have 2 observations. We then regress these respondents' real price forecasts on month-of-sample dummies and the local gasoline price and then regress the residuals from this regression on a set of individual fixed effects. The R^2 of this second regression is 0.65 in levels and 0.66 in logs, implying that the majority of the heterogeneity in the data is stable within individuals.

This result implies that, while there may be considerable heterogeneity in consumers' future gasoline price forecasts, changes in consumers' forecasts over time (largely in response to current gas price changes) exhibit substantially smaller cross-sectional variation. This finding is relevant for investigations of consumers' valuation of fuel economy because research in this area typically relies on time series variation in gasoline prices for identification.[32] To the extent that different

[31] The bias cannot be definitively signed, although the example provided in the paper suggests that it is toward zero.

[32] Estimation strategies that instead use only cross-sectional variation in vehicle market shares, characteristics, and prices are generally now viewed as plagued by omitted variables bias arising from unobservable vehicle characteristics

Figure 6: Standard deviation of forecasts over time



Note: Figure shows gasoline price (in 2010 dollars per gallon) and the standard deviation (in logs and levels) of MSC five-year forecast across individuals within each month.

consumers react to gasoline price changes in the same way, even if their overall forecasts are very different, the concerns about bias raised by Bento et al. (2012) will be reduced, though they will not disappear entirely. Additionally, research that attempts to infer the degree of heterogeneity in the population (through random coefficient demand models, for instance) will under-estimate overall heterogeneity when time series identification strategies are used.

8.2 Variation in forecast heterogeneity over time

Researchers attempting to model heterogeneity will need to know whether or not forecast heterogeneity is stable over time, or whether the amount of dispersion in the data is a function of the gasoline price level. To find out, we take the standard deviation of consumers' real price forecasts, in both logs and levels, in each month of our sample. We then plot these standard deviations against real gasoline prices in figure 6. It is clear from this figure that the standard deviation of forecasts in levels is positively correlated with the gasoline price. However, the standard deviation in logs appears roughly constant over time, with the exception of a small rise during the financial crisis.

We verify the graphical evidence from figure 6 with time series regressions of the standard

that might be correlated with fuel economy. Thus, nearly all recent research in this literature uses model fixed effects of various stripes in estimation.

Table 8: Does the standard deviation of consumers' forecasts vary with the gasoline price?

	Full sample: 1993–2009		Excluding crisis: 1993–2007	
Variable	Levels	Logs	Levels	Logs
Gasoline Price	.216	-0.012	0.325	0.068
	(0.081)	(0.053)	(0.070)	(0.038)

Dependent variable is the standard deviation of the MSC forecasts within each month. Standard errors (in parentheses) were estimated using Newey-West with 12 lags. Full sample for 1993–2009 includes 185 monthly observations; sample excluding crisis for 1993–2007 includes 161 monthly observations.

deviation of the MSC forecast on the gasoline price. Results are reported in table 8, which confirms a strong, positive statistical association between the gasoline price and variance of the forecasts in levels but little relationship between these variables in logs.

We conclude from this analysis that researchers interested in modeling heterogeneity should be wary of assuming a constant variance of gasoline price forecasts if modeled in levels, but that doing so in logs appears to be consistent with the data. Bento et al. (2012) show that ignoring heterogeneity can lead to biased estimates of the average consumer's valuation of fuel economy; our results thus imply that temporal variation in heterogeneity can then lead to temporal variation in the magnitude of this bias that is correlated with gasoline prices.

8.3 Comparison of forecast heterogeneity to other sources

Heterogeneity in consumer forecasts may be important for studies of fuel economy demand, but equation 1 above emphasizes that there are several such sources of heterogeneity. Differences across individuals in miles traveled, discounting, and local gasoline prices will also contribute to heterogeneity in consumer valuation of fuel economy. Is forecast heterogeneity important when compared with these other factors?

We study this issue via a simulation in which we independently draw 100,000 values for annual miles driven, discount rates, local gasoline prices, and gasoline price forecasts from their respective empirical (or calibrated parametric) distributions.[33] For each draw, we calculate the present value

[33]To model heterogeneity in miles driven, we take independent draws from a lognormal distribution calibrated to match the mean and variance across households of annual vehicle miles per driver, as reported by Li et al. (2012), based on National Household Transportation Survey data from 1995 and 2001 for households that report two odometer readings for each vehicle they own. The distribution of annual vehicle miles per household is highly right-skewed, with a reported mean of 18,549 and standard deviation of 13,034; we divide each by the reported mean of 1.69 drivers per household. To model heterogeneity in discount rates, we take independent draws from the empirical distribution of new-car loan rates observed in 601,344 individual car transactions based on a nationally representative sample of dealers during 2000–2009 (see Anderson and Sallee (2011)); the mean loan rate is 5.8%, while the standard deviation is 4.3%. To model heterogeneity in local gasoline prices, we take independent draws from a normal distribution with mean \$3 and standard deviation of \$0.15, which is consistent with variation in average gasoline prices across zip codes as reported in the November 2008 preliminary draft of Busse et al. (Forthcoming). Finally, to model heterogeneity in gasoline price forecasts, we take independent draws from the empirical distribution of inflation-adjusted consumer

of expected lifetime fuel costs for a car that gets 24 miles per gallon (roughly the national average) and a car that gets 25 miles per gallon. To model expected lifetimes, we adopt a time horizon of 35 years and weight fuel costs in each year by the probability that a vehicle survives to that year; survival rates by year are determined endogenously by how intensively the household drives the vehicle, according to the random draw for annual miles and a survival function based on cumulative miles.[34] Finally, for each draw, we calculate the difference in expected lifetime fuel costs for the cars that get 24 and 25 miles per gallon and take logs. We repeat this same series of calculations four times for the same set of 100,000 draws, in each case replacing one of the heterogeneous components in the calculation (miles driven, discount rates, local gas prices, and gas price forecasts) with its sample-mean value.

Table 9 reports the results of these calculations. We report the percent reduction in the overall variance of the logged valuation of fuel economy that occurs when we replace each component of the calculation with its sample mean, and we interpret these reductions as the fraction of overall variance generated by the component.[35]

While these calculations require a 35-year time horizon, consumers in our data only report five-year gasoline price forecasts. Thus, as one benchmark, the first and second columns assume that expected gasoline prices grow (or decay) exponentially for 35 years according to each consumer's forecast for the annual rate of change in gasoline prices. As an alternative, more conservative benchmark, the third and fourth columns truncate this exponential growth at 5 years, so that expected gasoline prices plateau at the consumer's five-year price forecast and stay there permanently.

One might be concerned that the survey responses we observe are noisy measures of true gasoline price forecasts, which would tend to inflate the importance of gas price forecasts relative to other sources of heterogeneity. Thus, while columns one and three take the raw forecasts from the full MSC sample to be our empirical distribution, columns two and four are based on an empirical distribution that isolates the persistent, cross-sectional variation in forecasts across households using the sub-sample of MSC respondents that are surveyed twice.[36] These various assumptions

forecasts observed in the MSC data, which we express as annual percent rates of change and apply exponentially over time to the current local gas price. We do not weight by MSC sampling weights, but the sample mean and variance of the forecasts are virtually identical with or without MSC weights.

[34] Lu (2006) reports average survival probabilities by age for cars and light trucks (based on detailed R.L. Polk data for vehicle registrations) and average miles driven by age for cars and light trucks (based on the National Household Transportation Survey). We estimate survival rates as a function of cumulative miles separately for cars and trucks using logistic models, which fit quite well. Since roughly half of all vehicles sold are trucks, we take the simple, unweighted average survival rate of cars and trucks as a function of cumulative miles to be our survival function. For reference, survival rates at 100, 200, and 300 thousand miles are 86%, 31%, and 5%. For each random draw in our simulation, we predict the survival probability in each year based on this function, assuming the vehicle is driven the same number of miles each year.

[35] We base our calculations on the logged value of fuel economy because it is invariant to the starting level of fuel economy at which consumers value the marginal improvement. In addition, the formula for lifetime fuel costs is linearly separable in some components after taking logs, and approximately so for other components, which allows us to parse the underlying sources of heterogeneity more precisely. Finally, the variance in logs is more robust to the inclusion of outliers that would potentially have a large impact on the variance when measured in levels.

[36] We focus on the two-thirds of MSC respondents that are surveyed twice and regress their monthly forecasts on a vector of time dummies and individual fixed effects, taking the estimated fixed effects to be our empirical distribution of forecasts. The raw forecasts have a sample standard deviation of 5.0% per year, while the persistent forecasts have

Table 9: Percent decrease in variance of household valuation of fuel economy when imposing homogeneity in components of lifetime fuel costs

Component	Gas price grows to $t = 35$ Raw forecasts	Gas price grows to $t = 35$ Persistent forecasts	Gas price plateaus at $t = 5$ Raw forecasts	Gas price plateaus at $t = 5$ Persistent forecasts
Annual miles driven	33.7	37.3	39.7	42.4
Local gasoline price	0.5	0.7	1.1	1.2
Discount factor	28.3	36.4	48.1	51.4
Gas price forecast	60.4	47.6	19.2	13.9

Note: Table shows the percent *reduction* in the logged variance of the marginal value of fuel economy (i.e., the difference in lifetime fuel costs for cars that get 24 and 25 miles per gallon) when we replace each of the various components with its sample-mean value. Columns 1 and 2 assume that gas price forecasts grow exponentially for 35 years, while columns 3 and 4 assume that gas price forecasts grow exponentially to year 5 and then plateau. Columns 1 and 3 take the raw forecasts from the full MSC sample to be our empirical distribution of forecasts, while columns 2 and 4 use only the persistent forecasts (as estimated by individual fixed effects) from the sub-sample of MSC respondents that are surveyed twice. Percentages in each column do not sum to 100 because, although the individual components are statistically independent, lifetime fuel costs are not linearly separable in these components after taking logs. That is, the individual components interact with one another. See text for details.

yield a range of increasingly conservative estimates for the importance of gasoline price forecasts as one moves from left to right across table 9.

Our results indicate that gasoline price forecasts account for anywhere between 14% and 60% of the overall variance in the marginal value of fuel economy across households. We suspect that the "right" answer lies somewhere between these two extremes. Annual miles and discount rates both generate a large, roughly similar amount of variance, while heterogeneity in local gasoline prices explains very little. While these calculations should only be viewed as suggestive given the simplicity of our analysis, they imply that gasoline price forecasts are a potentially important source of heterogeneity in consumer valuation of fuel economy—potentially as important as discount rates and annual miles driven. Forecast heterogeneity is thus deserving of attention in the literature on consumers' demand for fuel economy, which has heretofore focused primarily on heterogeneity in vehicle miles traveled (when heterogeneity is considered at all).

Our findings also speak to an issue that has, to the best of our knowledge, not yet been raised in the literature: heterogeneity in forecasts carries different welfare implications than heterogeneity in miles traveled. Heterogeneity in miles should lead to positive assortative matching, so that the most fuel efficient vehicles will tend to be purchased by households that travel many miles. Relative to a random allocation, this matching increases welfare in two ways. First, it increases private welfare by reducing the overall cost of driving, since the most efficient vehicles are allocated to those who drive the most. Second, it reduces overall vehicle emissions and thereby reduces pollution externalities from driving. Heterogeneity in price forecasts will also lead to sorting, so that fuel efficient vehicles

a sample standard deviation of 4.2% per year.

will be purchased by households with relatively high future price forecasts. This sorting, however, does not lead to welfare benefits because it reduces neither the total cost of driving nor total emissions. In fact, sorting based on forecast heterogeneity can act as noise that leads to less than perfect sorting on miles traveled, thereby reducing welfare rather than improving it. The extent to which this occurs depends on the relative variances of miles traveled and price forecasts in the population. We believe our findings here provide useful initial evidence on this issue.

9 Conclusion

Do consumers exhibit a reasonable forecast of future energy prices? Our analysis suggests that they do, at least in the important case of gasoline. Using two decades of high-quality survey data from the Michigan Survey of Consumers, we find that consumers, on average, report forecasts that are consistent with a real no-change model of future gasoline prices, which recent research suggests is a sensible benchmark. Thus, if average consumers do undervalue fuel economy, the undervaluation likely does not stem from consumers having systematic bias in their beliefs about energy prices.

How should future research model consumer forecasts of energy prices? Our analysis provides substantial guidance. Researchers are likely to be justified in assuming that average consumers employ a no-change forecast in most circumstances. The deviation from the no-change forecast during the financial crisis of 2008, however, implies that researchers should use caution when estimating demand for automobiles as a function of current gasoline prices during this time period. Estimates will likely be improved by assuming consumers forecast mean reversion in this window. More generally, if the deviation from the no-change forecast during the crisis was driven by consumers perceiving the deep recession and consequent drop in gasoline prices to be temporary, it may be more accurate to model consumer forecasts as mean-reverting during other steep economic downturns that trigger precipitous gasoline price declines.

Researchers should also be attentive to heterogeneity in forecasts, which we show is substantial and potentially as important as other sources of heterogeneity in generating variation in consumers' valuation of fuel economy. Little of this heterogeneity can be explained with common demographic factors, which implies that residual variation will be large even when a rich set of controls are available. Importantly, the amount of forecast heterogeneity is increasing with the current gasoline price when measured in levels, but it is roughly constant in logs.

Our results also provide guidance on how different sources of identifying variation will affect forecasts. Our state panel analysis suggests that consumers cannot easily distinguish between state-specific gasoline price shocks and the national time series. That is, while consumers respond somewhat less to state-specific shocks, consumers predict far more persistence than is consistent with historical price data. Our analysis of the relative impact of tax changes versus pre-tax price changes on consumer forecasts fails to support the notion that consumers respond more strongly to gasoline tax changes, perhaps because taxes are not salient in this market, where all posted prices are tax-inclusive.

Throughout the paper we used the case of demand for fuel economy in autombiles to illustrate the implications of our findings, but our results should prove useful well beyond the specific literature on consumer valuation of energy efficiency. Virtually all research involving consumer responses to energy prices requires assumptions about how consumers forecast future prices, including models of search, models of demand for energy-using durables, and studies of the macroeconomic effects of energy price shocks. We believe that the stylized facts established here regarding the nature of consumer beliefs about gasoline prices will improve these various literatures, as well as serve as an important data point for the more general question of how consumers forecast future economic outcomes like inflation and growth.

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Appendix

Table A1 presents summary statistics for the sample of 77,144 individual MSC respondents with non-missing values for both gasoline price and inflation forecasts during 1993–2009.

Table A1: Summary statistics for individual response data

Variable	Mean	Std. Dev.	Minimum	Maximum
Real, levels				
Forecast gas price	2.123	0.958	0.182	13.923
Current gas price	2.073	0.660	1.164	4.519
Forecast gas price change	0.050	0.629	-3.040	11.596
Real, logs				
Forecast gas price	0.668	0.403	-1.704	2.634
Current gas price	0.684	0.290	0.151	1.508
Forecast gas price change	-0.016	0.255	-2.062	2.081
Nominal, levels				
Forecast gas price	2.175	1.146	0.188	12.046
Current gas price	1.799	0.752	0.919	4.423
Forecast gas price change	0.376	0.651	-3.000	9.950
Nominal, logs				
Forecast gas price	0.664	0.457	-1.671	2.489
Current gas price	0.510	0.383	-0.084	1.487
Forecast gas price change	0.154	0.211	-1.962	1.913
Nominal, percent per year				
Forecast rate of gas price change	0.032	0.045	-0.325	0.466
Forecast inflation rate	0.035	0.037	-0.330	0.500

Note: Table reports summary statistics for sample of 77,144 individual MSC respondents with non-missing values for both gasoline price and inflation forecasts during 1993–2009, weighted by their individual MSC sampling weights. See text for details on construction of these variables. At bottom, the forecasted rate of gasoline price increase is given by $(1+\tilde{C}_{it}^{60}/\tilde{P}_{it})^{1/5}-1$, where $\tilde{C}_{it}^{60}$ is the respondent's forecasted change over five years and $\tilde{P}_{it}$ is the current price, both in nominal terms. The forecasted inflation rate is reported directly by survey respondents.

Figures A1 and A2 provide corollaries to figures 3 and 4 using logged values. Specifically, we log the individual values of the nominal and real gasoline price forecasts and then average across observations. These averages are used to generate the "Logs" results in tables 2, 3, and 4.

Figure A1: Nominal gasoline prices and forecasts in logs.

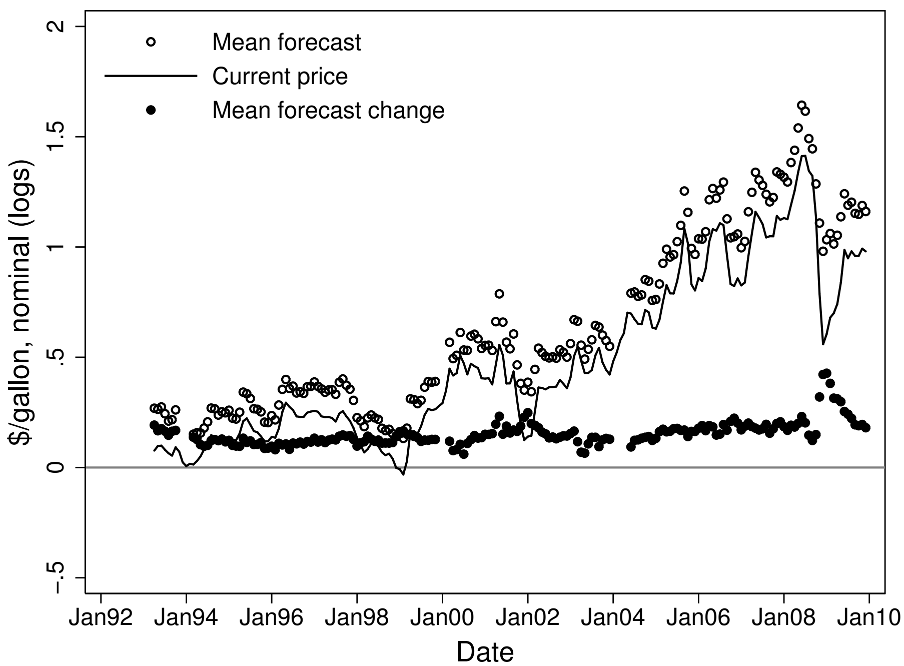

Figure A2: Real gasoline prices and forecasts in logs.