I. Introduction

In some situations, it appears that consumers choosing among products are less attentive to ancillary costs than to purchase prices. Consumers on eBay, for example, are less elastic to shipping and handling charges than to the listed purchase price (Hossain & Morgan, 2006). Mutual fund investors appear to be less responsive to ongoing management fees than to upfront payments (Barber, Odean, & Zheng, 2005). Senior citizens are two to five times more sensitive to a Medicare Part D plan’s premium than to its out-of-pocket costs (Abaluck & Gruber, 2011). Shoppers are less elastic to sales taxes than to purchase prices (Chetty, Looney, & Kroft, 2009).

Similarly, it is often asserted that gasoline costs are not fully salient to automobile consumers when they choose among automobiles with different fuel economy ratings (Greene et al., 2005). If this is true, consumers buy vehicles with lower fuel economy and higher resulting fuel costs than they would in their private optima. In 2007, the median-income American household spent $2,400 on gasoline, and consumers spent $286 billion in total (U.S. BLS, 2007). Misoptimization over such a large expenditure class could cause substantial welfare losses. The purported undervaluation of future gasoline costs would also help explain what Jaffe and Stavins (1994) call the “energy paradox”: consumers and firms are puzzlingly slow to make seemingly high-return investments in energy efficiency.

Externalities from energy use related to national security and climate change would add to these potential private losses. Policymakers have long debated whether it is preferable to address these externalities through gasoline taxes or corporate average fuel economy (CAFE) standards, which mandate an increase in the average fuel economy of new vehicles. In the absence of other market failures or misoptimization by consumers, economic analyses typically conclude that CAFE standards are highly inefficient relative to gas taxes.1 If consumers undervalue fuel costs when they choose among vehicles, however, CAFE standards can increase welfare, as they effectively force consumers to buy the energy-efficient vehicles that they would want if they were optimizing. This “paternalistic” argument for energy-efficiency policies has long been employed by both academic economists (Hausman, 1979)2 and the U.S. government.3 Put simply, while

1 Jacobsen (2010), for example, shows that the CAFE standard has a welfare cost of $222 per metric ton of carbon dioxide abated, compared to $92 per metric ton for an increase in the gasoline tax that reduces gasoline consumption by the same amount.

2 Hausman (1979) finds that consumers implicitly use a discount rate of 15% to 25% per year when they trade off purchase prices and future energy costs of new air conditioners. He then argues that “this finding of a high individual discount rate does not surprise most economists. At least since Pigou, many economists have commented on a ‘defective telescopic faculty.’ A simple fact emerges that in making decisions which involve discounting over time, individuals behave in a manner which implies a much higher discount rate than can be explained in terms of the opportunity cost of funds available in credit markets. Since this individual discount rate substantially exceeds the social discount rate used in benefit-cost calculations, the divergence might be narrowed by policies which lead to purchases of more energy-efficient equipment.”

3 For example, the Regulatory Impact Analysis that justifies the 2011–2015 increase in the CAFE standard argues that about $15 billion per year in net benefits will flow to consumers who undervalue the benefits of fuel economy (National Highway Traffic Safety Administration, 2010).
political feasibility plays an important practical role, paternalism is a leading economic justification for one of the most important and costly public policies affecting the U.S. automotive and energy industries. However, one problem with the paternalistic justification for fuel economy standards is that there is not much solid evidence on whether automobile buyers are actually misoptimizing (Parry, Walls, and Harrington, 2007).

The relevant null hypothesis is that consumers are willing to pay $1.00 more to purchase a vehicle with $1.00 less in total forecasted future fuel costs, discounted to present value at their intertemporal opportunity cost of funds. For expositional purposes, we say that rejecting this hypothesis is evidence that consumers “undervalue or overvalue gasoline costs.” This hypothesis is related to a long literature, dating at least to the energy crises of the 1970s, that estimates consumers’ implied discount rates for energy-efficiency investments and compares them to benchmark consumer discount rates.4 The typical empirical approach in this literature has been to exploit variation in the prices and energy efficiency ratings of a cross-section of energy-using durables. For example, our null hypothesis in a cross-sectional discrete choice framework would be that after conditioning on other observed product characteristics, a $1.00 increase in a product’s purchase price is associated with the same decrease in market share as a $1.00 increase in total discounted energy costs. Analogous cross-sectional approaches are used in a seminal paper by Hausman (1979) on air conditioners, as well as analyses of other energy-using durables such as houses (Dubin, 1992), water and space heating (Dubin & McFadden, 1984), and autos (e.g., Dreyfus & Viscusi, 1995; Espey & Nair, 2005; Goldberg, 1998).

For the cross-sectional estimator to be unbiased, the functional form for how other observed product characteristics enter utility must be correctly specified, and any unobserved characteristics must be uncorrelated with energy efficiency. Especially for automobiles, these assumptions appear problematic. Fuel economy is mechanically correlated with weight and horsepower, and it has often proven difficult to separately identify preferences for these different characteristics.5 Furthermore, fuel economy is highly negatively correlated with price in the cross-section, suggesting that larger vehicles have more observed and unobserved amenities.

This paper formalizes one potentially promising alternative approach, which exploits the significant fluctuations in gasoline price forecasts over the past fifteen years. The approach exploits the fact that a vehicle’s future fuel costs vary as a function of both fuel economy and forecast gasoline prices, so changes in gas price forecasts should affect the relative value of high-versus low-fuel-economy vehicles. Indeed, media reports and academic analyses have documented that as gasoline prices rise, the relative prices of low-fuel-economy vehicles drop (Busse, Knittel, & Zettelmeyer, 2013; Langer & Miller, 2013). The above null hypothesis, however, does more than predict that gasoline price forecasts should affect vehicle demand: it predicts exactly how much demand should be affected. Intuitively, if relative vehicle prices are not sufficiently responsive to changes in forecast gasoline costs, this suggests that consumers undervalue gasoline costs when they purchase vehicles. Conversely, if vehicle prices respond to gas price forecasts more than theory predicts, this suggests that consumers overvalue gasoline costs.

We begin from the primitives of a discrete choice utility function and show the empirical assumptions required to test the null hypothesis. We then implement this test using data from 86 million transactions at both auto dealerships and wholesale auctions between 1999 and 2008. For each month of this study period, these data are collapsed to the average price for each new and used vehicle in consumers’ choice sets.6 Each vehicle has a different present discounted value (PDV) of fuel costs, depending on its fuel economy rating, future survival probabilities, gasoline price forecasts, discount rates, and annual vehicle-miles traveled. We condition on vehicle fixed effects, which sweep out all observed and unobserved characteristics, and test whether relative prices move one-for-one with changes in the PDV of fuel costs.

Under the assumptions that consumers’ gas price forecasts match those of oil futures markets and that consumers’ real intertemporal cost of funds is 6%, auto consumers appear to be willing to pay only $0.76 in purchase price to reduce discounted future gasoline costs by $1.00. The corresponding implied discount rate, the discount rate for future gas costs that rationalizes market behavior, is just under 15%.

We show that the results are robust to a number of potential confounding factors, such as endogenous changes in utilization patterns and market shares in response to gas prices, changes in underlying preferences for “green vehicles,” and changes in characteristics over model years.

However, some empirical issues are extremely important. We use the grouping estimator (Wald, 1940; Angrist, 1991) to address potential measurement error, and we show that failing to do so would cause significant attenuation bias. We show that the result that consumers undervalue gas costs is

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4 The implied discount rate is simply a shorthand way of capturing how people appear to trade off upfront costs against an analyst’s estimate of future cash flows. Many underlying factors other than consumers’ actual discount rates might affect the implied discount rate, including time horizons, beliefs, and inattention. In our setting, as in many others, these factors are empirically indistinguishable. We therefore prefer the “undervaluation or overvaluation” language, as it is more explicitly agnostic. Regardless of the choice of language, the analyst must eventually take a stand on consumers’ actual discount rates in order to determine whether people’s decisions conform to the theoretical prediction.

5 At least since Atkinson and Halvorsen (1984), it has been pointed out that the high correlation between weight and fuel economy makes it difficult to separately identify demand for fuel economy. In fact, cross-sectional estimation of automobile demand in characteristic space sometimes gives a negative sign on fuel economy, which would imply that consumers dislike fuel economy.

6 By vehicle, we mean a model-by-age combination, where model is a highly disaggregated definition capturing essentially all variations in make, nameplate, trim, body type, fuel economy, engine displacement, number of cylinders, and design generation.
largely driven by older vehicles; prices for vehicles aged 11 to 15 years appear to be highly insensitive to gasoline prices, while prices for relatively new used vehicles move much more closely to the theoretical prediction. In addition, undervaluation appears to be more severe when current gas prices instead of oil futures are used as a proxy for consumers’ forecasts of future gas prices.

The data also show clear evidence of sticky information. In models such as Mankiw and Reis (2002), Sims (2003, 2010), and Woodford (2003), information about prices, inflation, and other economic variables takes time to diffuse through the population of consumers and firms, causing delays in responses to news. In this context, sticky information would cause vehicle prices to adjust with a delay to changes in gas price forecasts. Indeed, when the model is estimated using monthly differences instead of the de-meaning estimator, vehicle markets appear to be highly insensitive to the current month’s change in gas price forecasts. Four- to six-month lags of gas price changes are conditionally associated with the current month’s change in vehicle prices, suggesting that sticky information keeps vehicle markets from updating immediately. These results add a unique microdata-based analysis to the limited set of empirical tests of the sticky information model, which includes Coibion (2010), Khan and Zhu (2006), Klenow and Willis (2007), and Mankiw and Reis (2003). Aside from being of interest in macroeconomics and finance, sticky information also has important implications for how the undervaluation hypothesis can be tested: identifying off of high-frequency gas price variation can cause the econometrician to falsely conclude that consumers undervalue fuel economy as a product attribute when they are instead inattentive to changes in gas prices.

Before continuing, it is worth doing a simple calibration to demonstrate why it is difficult to overstate the importance of this question. Substantial volumes of academic research and policy discussions have centered on the welfare losses from transport sector carbon emissions and the costs and benefits of different policy responses. Using the U.S. government’s estimated marginal damage of carbon emissions (Greenstone, Kopits, & Wolverton, 2011), gasoline consumption imposes an externality of $0.18 per gallon, or about 5% of the current gasoline price. Thus, if the carbon externality is not internalized, consumers account for about 95% of the total social cost of gasoline when they choose among vehicles with different fuel economy ratings. By comparison, an implied discount rate of 15%, well within the range of Hausman (1979) and other estimates in the literature, would suggest that consumers value only 75% of the cost of gasoline when they choose vehicles. Thus, while undervaluation and uninternalized carbon externalities distort vehicle purchases in the same direction, inducing consumers to buy vehicles that use more gas than in the first best, undervaluation could generate distortions several times larger than the distortions from climate change externalities.

The paper progresses as follows. In section IA, we discuss related literature. Section II models consumers’ utility functions. Section III presents our data, devoting particular attention to the construction of each vehicle’s total discounted gasoline costs. Section IV details our estimation strategy. Section V presents empirical results and a long series of robustness checks. Section VI details the evidence of sticky information, and section VII concludes.

A. Related Literature

Within the broader literature on consumer choice of energy-using durables and the effects of gasoline prices on market vehicles, our analysis is most closely related to four other papers. Kahn (1986) tests whether relative prices of used vehicles fully adjust to changes in the relative discounted present value of relative gas prices caused by the gasoline price shocks of the 1970s and 1980s. A working paper by Kilian and Sims (2006) builds on Kahn’s approach with updated data. The key difference between our analysis and these two papers is that we use transaction prices from auctions and dealerships instead of data from used-car price guides such as the Kelley Blue Book or the National Auto Dealers’ Association Used Car Guide. It is crucial to use transaction data because used-car price guides reflect the opinion of a small team of analysts who may or may not fully adjust their price assessments for each vehicle to reflect current market conditions. Data from used-car price guides could cause us to falsely conclude that vehicle market prices do not fully adjust to changes in gasoline prices.

Sallee, West, and Fan (2009) exploit transaction data from used-vehicle auctions to test whether vehicle prices move one-for-one with the present discounted value of future gasoline costs. Their identification strategy is different from and complementary to ours: they exploit the fact that autos with different odometer readings have different remaining lifetimes, and an increase in gas prices has a larger effect on the remaining present discounted value (PDV) of gas costs for autos with lower current odometer readings. One benefit of their approach is that it allows a more extensive set of fixed effects than we use. By construction, however, they are testing a different empirical hypothesis: they ask whether consumers correctly value differences in odometer readings within vehicle models when gas prices change, while we ask whether consumers correctly value differences in fuel economy across models when gas prices change. Conceptually, our hypothesis is closer to the policy-relevant question of whether consumers undervalue energy efficiency.

7 This literature includes Hausman (1979), Dubin and McFadden (1984), Davis and Kilian (2011a), Beresteanu and Li (2011), and others.
Busse et al. (2013) estimate how changes in gasoline prices affect equilibrium prices and quantities of new and used vehicles in different quartiles of the fuel economy distribution. They then plug these estimates into an Excel spreadsheet, which outputs the implied discount rates for the three different quartile pairs for used vehicles when using vehicle-miles traveled and survival probabilities from NHTSA, which uses the same underlying data as we do.

Unlike the regressions, this table is not weighted by number of transactions within an observation.

We also uncover additional empirical findings, such as the evidence of sticky information in section VI.

### II. Model

In this section, we specify a static discrete choice model. In the online supplement, Appendix A, we show that under the assumption of stationarity, this simple model can be derived from a dynamic model in which consumers buy and resell their vehicles. Consumers derive utility from owning a vehicle and consuming a numeraire good. We define a vehicle as a model-by-age combination, where $j$ indexes models and $a$ indexes age in years. Consumers also can choose an outside option, denoted $j = 0$, which is to own no vehicle. The utility of this outside option is normalized to 0. Consumer $i$ has budget constraint $w_i$.

The purchase price of vehicle $ja$ at time $t$ as $p_{jat}$. $G_{jat}$ is the PDV of future gasoline costs over the vehicle’s remaining life. The average consumer’s utility from owning and using vehicle $ja$ over its remaining life is $\psi_{jat}$; we call this the average usage utility. Individual $i$’s usage utility also has an unobserved deviation from average usage utility, denoted $\xi_{jat}$. The variable $\psi_{ja}$ captures the mean value of average usage utility for vehicle $ja$ across all time periods, and $\psi_{jat} = \psi_{jat} - \psi_{ja}$ is the period-specific deviation.

Consumer $i$’s indirect utility from vehicle $ja$ at time $t$ is

$$u_{jat} = \eta(w_i - p_{jat} - \gamma G_{jat}) + \psi_{jat} + \xi_{jat} + \epsilon_{jat}. \quad (1)$$

The marginal utility of money is $\eta$. The valuation weight on fuel costs is $\gamma$: if consumers value purchase prices and discounted fuel costs equally, then $\gamma = 1$. If consumers undervalue or overvalue fuel costs, then $\gamma < 1$ or $\gamma > 1$, respectively. This framework is analogous to the attention weight models in Chetty et al. (2009), DellaVigna (2009), and other analyses. We assume that both $\eta$ and $\gamma$ are constant.

In specifying the basic model, we assume that $\epsilon$ takes the extreme value distribution, giving the traditional representative-consumer logit model. Integrating over the distribution of $\epsilon$ gives a market-level relationship between prices and shares, denoted by $s$. Typically this identity is arranged to give the term $\ln s_{jat} - \ln s_{0t}$ on the left:

$$\ln s_{jat} - \ln s_{0t} = -\eta p_{jat} - \eta \gamma G_{jat} + \psi_{jat} + \xi_{jat}. \quad (2)$$

Of course, this identity can also be rearranged with prices on the left:

$$p_{jat} = -\gamma G_{jat} - \frac{1}{\eta}(\ln s_{jat} - \ln s_{0t}) + \psi_{jat} + \xi_{jat}. \quad (3)$$

This equation includes new variables $\psi_{jat} \equiv \psi_{jat}/\eta$ and $\xi_{jat} \equiv \xi_{jat}/\eta$, which represent the dollar value of the utility represented by $\psi_{jat}$ and $\xi_{jat}$. Section IV begins with this equation in presenting our empirical strategy.

### III. Data

Our data set includes average prices, quantities, and characteristics of all used passenger vehicle models registered in the United States, in monthly cross-sections from January 1999 to December 2008. Table 1 presents descriptive statistics.

Fuel economy data were obtained from the U.S. Environmental Protection Agency (EPA), which measures fuel use over a standardized laboratory drive cycle and then adjusts by

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**Table 1: Summary Statistics**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Number</th>
</tr>
</thead>
<tbody>
<tr>
<td>Year</td>
<td>2003.5</td>
<td>2.9</td>
<td>1999</td>
<td>2008</td>
<td>1,068,459</td>
</tr>
<tr>
<td>Model year</td>
<td>1996</td>
<td>5.2</td>
<td>1984</td>
<td>2007</td>
<td>1,068,459</td>
</tr>
<tr>
<td>Age</td>
<td>7.5</td>
<td>4.2</td>
<td>1</td>
<td>15</td>
<td>1,068,459</td>
</tr>
<tr>
<td>Price ($)</td>
<td>7,227</td>
<td>9,845</td>
<td>0</td>
<td>358,289</td>
<td>1,068,459</td>
</tr>
<tr>
<td>Quantity</td>
<td>18,537</td>
<td>27,612</td>
<td>0</td>
<td>370,512</td>
<td>1,068,459</td>
</tr>
<tr>
<td>PDV of gas cost ($)</td>
<td>7,163</td>
<td>4,147</td>
<td>686</td>
<td>41,576</td>
<td>1,068,459</td>
</tr>
<tr>
<td>Fuel economy (MPG)</td>
<td>18.8</td>
<td>4</td>
<td>6.9</td>
<td>52.9</td>
<td>1,068,459</td>
</tr>
<tr>
<td>Horsepower</td>
<td>174</td>
<td>61</td>
<td>46</td>
<td>700</td>
<td>1,024,709</td>
</tr>
<tr>
<td>Weight (pounds)</td>
<td>3,440</td>
<td>838</td>
<td>2.2</td>
<td>34,903</td>
<td>1,022,499</td>
</tr>
<tr>
<td>Wheelbase (inches)</td>
<td>110</td>
<td>13.9</td>
<td>79.9</td>
<td>972</td>
<td>1,025,023</td>
</tr>
<tr>
<td>Number of transactions</td>
<td>37.8</td>
<td>122</td>
<td>1</td>
<td>9,679</td>
<td>1,068,459</td>
</tr>
</tbody>
</table>

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*This 13% figure is from table 7 of Busse et al. (2013). It is the mean of the implicit discount rates for the three different quartile pairs for used vehicles when using vehicle-miles traveled and survival probabilities from NHTSA, which uses the same underlying data as we do.*
the results to account for the typical consumer’s actual in-
use fuel economy. For all model years, we use the EPA’s
most recent adjustment, which was calculated in 2008. Like
Greene et al. (2007), we also assume that fuel economy
degrades over each vehicle’s life at 0.07 MPG per year.
Vehicle class designations—pickups, sport utility vehicles,
minivans, vans, two-seaters, and five classes of cars based
on interior volume—are also taken from the EPA’s fuel
economy data set. All other vehicle characteristics, includ-
ing horsepower, curb weight, wheelbase, and manufacturer’s
suggested retail price (MSRP), are from Ward’s Automotive
Yearbook. All dollar figures in this paper are real July 2005
dollars, deflated using the Bureau of Labor Statistics Con-
sumer Price Index series for All Urban Consumers, All Items
Less Energy.

Vehicle prices are based on microdata obtained from Man-
heim, a firm that intermediates approximately half of auto
auction transactions in the United States. The principal sellers
are dealerships, rental car companies, and auto manufacturers
that are reselling off-lease vehicles. Buyers are typically deal-
erships, which then retail the used vehicles. We observe each
of Manheim’s approximately 45 million transactions between
1999 and 2008. While only about one in four used vehicles
traded passes through an auction (Manheim, 2009), the auc-
tion market is the largest source of transaction price data.
Furthermore, the Kelley Blue Book and other price guides,
the starting point for price negotiations in many nonauction
transactions, are largely based on auction prices. To get \(P_{\text{man}}\),
we simply collapse the data to the level of mean price for
each vehicle in each month after excluding vehicles rated as
low quality or scrap quality.

Some alternative specifications employ prices from the JD
Power and Associates’ (JDPA) Power Information Network,
which collects detailed microdata on approximately 31% of
U.S. retail auto transactions through a network of more than
9,500 dealers. For each vehicle \(j\), we obtained monthly mean
prices adjusted for customer cash rebates and, if the transac-
tion included a trade-in, the difference between the trade-in
vehicle’s actual resale value and the negotiated trade-in price.
We use the Manheim used-vehicle price data in our base spec-
fications because these data include more than twice as many
observations at the \(j\) level, while there are fewer than 1,000
observations in JDPA that are not in Manheim.

We observe national-level registered quantities of each
vehicle from 1999 through 2008 in the National Vehicle
Population Profile, a data set obtained from market research
firm R. L. Polk. The quantities represent all vehicles reg-
istered to private individuals and to fleets such as taxi and
rental car companies and corporate and government motor
pools. These quantity data are matched to the price data using
vehicle-specific serial numbers called vehicle identification
numbers.

We define the choice set to include all “substitutable”
used gasoline-fueled light-duty vehicles that have EPA fuel
economy ratings and are less than 25 years old. By substi-
tutable, we mean cars, pickups, SUVs, minivans, and other
light trucks but not motorcycles, cutaway motor homes,
limosines, camper vans, chassis cab and tilt cab pickups,
hearses, and other unusual vehicles, where we expect the
substitution elasticity to be very small. In our base speci-
fication, we also exclude cargo and passenger vans as well as
ultraluxury and ultrahigh performance exotic vehicles due
to their low substitutability with the rest of the market. It turns
out that including these vehicles does not change the results.

We define a model \(j\) to capture all possible variation in
fuel economy ratings and much of the observable varia-
tion in prices. This is more disaggregated than a nameplate,
which refers to a colloquial name such as “Ford Taurus” or
“Honda Civic.” We define a model at the level of make, name-
plate, trim, body type, fuel economy, engine displacement,
and number of cylinders. As a result, the average make and
nameplate combination in our data set has seven different
models. For example, there are eleven different configura-
tions of model year 2004 cars called the “Honda Civic” that
appear in our data set as separate “models,” including coupé
and sedan versions of the DX, EX, and LX; the Si Hatchback;
the Civic Hybrid; and several others.

Vehicles with the same model name are typically offered
for several consecutive model years, although some are
offered for many more. As extreme examples, both the Ford
F-150 and Honda Civic have been offered in every model year
since 1973. Of course, the 1973 and 2008 versions of these
models are very different. Every several years, auto manufac-
turers redesign their models and define a new generation of a
vehicle. For example, Honda introduced new generations of
and 2012 model years. A generation is a well-defined con-
cept, and the generation definitions for each vehicle can even
be found on Wikipedia. Within each generation, models do
not change significantly. We redefine each new generation of
a car or truck as a separate model \(j\) in our data set.

A. Discounted Gasoline Costs

The variable \(G_{jat}\) is the present discounted value of lifetime
gasoline costs over future years \(y\), for the average driver of
vehicle \(j\) at time \(t\):

\[
G_{jat} = \sum_{y=0}^{L} \delta^y \cdot g_y \cdot m_{jay}^{-1} \cdot \phi_{jay}.
\]  

\(L\) denotes the maximum possible lifetime of a vehicle,
which we take to be 25 years. The variable \(g_y\) is the gaso-
line price forecast for year \(y\), \(m_{jay}\) is expected vehicle-miles
traveled, \(f_{jay}\) is fuel economy in miles per gallon, \(\phi_{jay}\) is the
probability that the vehicle survives to year \(y\) conditional on

10 These excluded exotic vehicles are the Acura NSX, Audi R8 and TT,
Chrysler Prowler and TC, Cadillac Allante and XLR Roadster, Chevo-
let Corvette, Dodge Viper and Stealth, Ford GT, Plymouth Prowler, and
all vehicles made by Alfa Romeo, Bentley, Ferrari, Jaguar, Lamborghini,
Maserati, Maybach, Porsche, Rolls-Royce, and TVR.
surviving to its current age \(a\), and \(\delta\) is the annual discount factor.

Our parameter of interest \(\gamma\) is the coefficient on this variable, and the decisions we make here mechanically affect the parameter estimates. For example, using a lower discount rate than consumers actually face would inflate \(G_{jat}\), thereby biasing \(\gamma\) toward 0. Alternatively, understating a vehicle’s expected lifetime or usage would deflate \(G_{jat}\), biasing \(\gamma\) away from 0.

Vehicle-miles traveled and survival probability. To estimate vehicle-miles traveled (VMT), we use publicly available data from the 2001 National Household Travel Survey (NHTS), a nationally representative survey of approximately 25,000 households that includes the age, fuel economy, and vehicle class for each vehicle owned. As part of the survey, about 25,000 vehicles in the national sample had their odometers read twice, with several months between readings. These two readings were then used to estimate annualized VMT. We regress annualized VMT on class dummies and vehicle age and use these estimates to fit \(m_{jay}\) for all vehicles in our sample. When we adjust for uncertainty in the first-step estimates of \(G_{jat}\) (Murphy & Topel, 1985), we use the Huber-White robust standard errors from this regression.

Our base specification assumes that this fitted \(m_{jay}\) does not depend on the gasoline price forecast in year \(y\). Either of two separate arguments can justify this. First, empirical estimates of VMT demand show that it is relatively inelastic (Hughes, Knittel, & Sperling, 2008; Small & Van Dender, 2007; Gillingham, 2010; Bento et al., 2009; Kilian & Murphy, 2011; Davis & Kilian, 2011b). Second, the envelope theorem can be used to show that since indirect utility \(u_{jat}\) is a function of an optimized value of VMT, changes in VMT caused by marginal changes in gasoline prices have only second-order effects on \(u_{jat}\) and vehicle prices. In appendix C, however, we derive an alternative approach that makes \(m_{jay}\) a function of \(g_5\) and allows for nonmarginal changes. The results are very similar to the base specification.

We use an analogous approach to fit vehicle survival probabilities based on the NVPP registered quantity data. We use a grouped data probit model, where the outcome variable is the number of vehicles of a model and model year registered next year divided by the number of vehicles registered today. We estimate coefficients on vehicle age dummies, model year, and fuel economy, with robust standard errors clustered by vehicle, and then we predict survival probabilities \(\phi_{jay}\) for all vehicles in our sample.

Discount Rate. The discount rate \(r = \delta^{-1} - 1\) is the intertemporal opportunity cost of money: the rate at which a vehicle’s purchase price is amortized over future years or future gasoline costs are discounted to the present. To implement this empirically, we calculate the weighted average \(\delta\) across used vehicle buyers. For vehicle buyers whose marginal dollar comes from a loan or lease, the opportunity cost of paying more to purchase a vehicle is the annual percentage rate (APR). For consumers whose marginal dollar comes from savings, the opportunity cost is the return that could be realized on savings.

Table 2 details the calculation. Using data from the 2001, 2004, and 2007 Surveys of Consumer Finances (SCF), we estimate that 37% of used vehicles are financed, while 63% are paid for in cash. We transform interest rates reported in the SCF from nominal to real by deflating by inflation expectations implied by Treasury inflation-protected securities. In the SCF, the average real interest rate for used vehicle loans is 6.9%. For vehicles purchased with cash, we assume that the opportunity cost of funds is equity market returns, and the average real return on the S&P 500 between 1945 and 2008 (inclusive) was 5.8%. As shown in table 2, averaging these two discount rates weighted by their share of transactions gives a 6.2% discount rate, which we round to 6% for our base specification.

While we think that this is the most reasonable and straightforward approach, it surely is debatable. For example, the real average used-vehicle loan APR reported by dealerships through the JD Power Information Network is 8.9%, 2 percentage points higher than the average value reported in the SCF. On the other hand, including years before 1945 or after 2008 would give lower stock market returns. Furthermore, if we modeled consumers with declining marginal utility of consumption, they would want to risk-adjust returns for covariance with the market. Because annual changes in gasoline prices have very low correlation with market returns, risk adjustment using the capital asset pricing model would give an interest rate close to the real risk-free rate: about 1.6%. In the results section, we show the sensitivity of \(\gamma\) to alternative discount rates.

Gasoline price forecast. We use three measures of vehicle consumers’ gasoline price forecasts: seasonally adjusted retail prices, oil futures prices, and beliefs elicited via surveys. The seasonally adjusted retail price measure is equivalent to assuming that consumers forecast that gasoline prices are a martingale with seasonal trends. To construct this measure, we take the U.S. city average motor gasoline retail prices for all types of gasoline from the U.S. Energy Information Administration’s (2011) Monthly Energy Review and convert to real July 2005 dollars.\(^{11}\) We then eliminate seasonal trends by regressing the level of monthly gasoline prices

<table>
<thead>
<tr>
<th>Payment Method</th>
<th>Share of Vehicles</th>
<th>Discount Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Financed</td>
<td>37%</td>
<td>6.9%</td>
</tr>
<tr>
<td>Leased</td>
<td>0%</td>
<td>NA</td>
</tr>
<tr>
<td>Cash</td>
<td>63%</td>
<td>5.8%</td>
</tr>
<tr>
<td>Weighted average</td>
<td></td>
<td>6.2%</td>
</tr>
</tbody>
</table>

\(^{11}\) Edelstein and Kilian (2009) and Kilian (2010) also use data on the real price of gasoline.
on eleven-month dummies, subtracting the fitted values, and readjusting so that the mean monthly gasoline price is unchanged.

Our second measure assumes that oil futures markets reflect vehicle consumers’ gasoline price forecasts. To construct this measure, we use light sweet crude oil spot prices from the U.S. Energy Information Administration’s (2011) Monthly Energy Review and futures prices from the New York Mercantile Exchange and the Intercontinental Exchange. The oil futures prices are transformed into current dollars using inflation expectations implied by Treasury inflation protected securities, then deflated into real July 2005 dollars, then transformed to dollars per gallon of gasoline using the average historical relationship between oil and gasoline prices.\(^\text{12}\) (Appendix table A1 reports annual average retail gas prices and futures-based gas price forecasts.) In every year of our sample, there are futures trades for settlement dates up to six to seven years in the future, and in later years, trades are observed for dates as far as ten years out.\(^\text{13}\)

Our third measure is derived from the Michigan Survey of Consumers, which elicits beliefs about future gasoline prices, inflation, and other economic variables from a nationally representative sample. Respondents are asked whether they think the price of gasoline will go up, go down, or stay the same during the next five years. Those who think it will change are asked how much the price will increase or decrease. Anderson, Kellogg, and Sallee (2011) analyze these data, and interested readers should refer to their paper for more details. For our analysis, the authors provided us with the mean real gasoline price forecast across all respondents for each month between 1999 and March 2008. Each respondent’s forecast is deflated to current dollars as of the date of the survey using his or her own inflation expectation.

Figure 1 plots seasonally adjusted retail gasoline prices along with the gasoline prices implied by oil futures at three different horizons. The figure illustrates that futures prices differ from retail prices in two important ways. First, the futures market does not believe that gasoline prices are a martingale. Especially when spot prices spiked in mid-2008, the futures market expected prices to eventually decrease at least slightly. As a result, \(G\) averages 7\% larger under the martingale forecast than the futures forecast. This suggests that the \(\hat{\gamma}\) estimated under the martingale forecast will be smaller than the \(\hat{\gamma}\) with the futures-based forecast. Second, while the two series follow the same trends, retail prices are substantially more volatile from month to month. This is not a spurious result of adjusting for seasonality: retail prices are also more volatile when we do not condition on month-of-year effects. As we shall see, this will cause \(\hat{\gamma}\) to differ substantially between the two forecasts when using a monthly difference estimator.

It is important to acknowledge several limitations of oil futures price data in light of recent work in this area. First, Kilian (2010) has shown that in the short run, there can be important deviations between crude oil and gasoline prices. Over our sample period, monthly oil spot prices predict 94\% of the variance in monthly gasoline prices, not 100\%. However, what matters for our analysis is the expected future relationship between oil and gasoline: oil futures could be a good measure of long-run gasoline price forecasts even if the short-run relationship does not have an \(R^2\) of 1. Second, Alquist and Kilian (2010), Alquist, Kilian, and Vigfusson (2013), and Baumeister and Kilian (2011) have shown that oil futures prices are typically not as good as current oil prices at predicting actual future oil prices at both short-term horizons of twelve months and longer-term horizons of up to seven years. This suggests that factors other than oil price expectations can affect futures markets, which would introduce noise in our estimates. Third, oil futures are traded with high liquidity only for settlement dates less than two to three years in the future. While this is a concern, it is not clear if this would bias the estimates in any particular direction.

B. Vehicle Price Trends

Three related facts about vehicle prices have important implications for our empirical strategy. First, as figure 2 illustrates, low-MPG vehicles are more expensive than high-MPG vehicles. The figure shows the results of a regression of manufacturer’s suggested retail price on a set of MPG indicator variables for all models of model years 1984 through 2008 in the Ward’s Automotive Yearbook data. Between 15 and 30 MPG, which includes nearly all of our data set, MSRP decline from $30,000 to $11,000. This figure corroborates
concerns about the traditional cross-sectional approaches to estimating $\gamma$: low-MPG and high-MPG vehicles are systematically different, and some of these differences may be unobservable. The figure also means that we must control for factors such as depreciation that differentially affect vehicles with higher price levels and might be correlated with gas prices.

Second, figure 3 shows that vehicle prices have systematic seasonal patterns, and they tend to decrease within each year. Because this systematic depreciation is approximately a percentage of price and lower-MPG vehicles have higher prices, these patterns affect the price levels of low-MPG vehicles more than high-MPG vehicles. Since gas price forecasts rise on average during the study period, failing to account for within-year trends that affect low- versus high-MPG vehicles differently could cause us to falsely attribute seasonality to adjustments caused by gas price forecasts.

Third, there are other underlying shifts in seasonally adjusted average prices that could affect low-MPG versus high-MPG vehicles differently. If correlated with changes in gasoline prices, such shifts could bias our estimator. The double line at the bottom of figure 3 shows that after de-meaning prices within vehicles and removing seasonal trends using month dummies, prices declined somewhat from 1999 to 2003. The decline from 1999 to 2002 appears to be driven by a decrease in the absolute price level for low-MPG vehicles. This may have been precipitated by an increase in the number of new low-MPG vehicles sold during the mid- and late 1990s, which appears to have caused their prices to drop as they became available for resale as used vehicles. Manheim’s analysts attribute the nadir in 2003 to the 2001 economic slowdown, during which both low- and high-MPG vehicles were offered at attractive lease terms and an unusually large share were leased instead of sold. When this larger volume of vehicles came off lease two years later, this depressed resale prices. We therefore document whether the estimates are sensitive to excluding the period before 2004.

De-meaned and seasonally detrended prices remained relatively steady from 2004 to 2007 before dropping sharply as the 2008 recession took hold. It is possible that this recession differentially affected low- versus high-MPG vehicles, for example, by differentially affecting people of different income levels, who tend to buy different types of vehicles. We therefore eliminate from our base specification all data beginning with April 2008, when the recession began to affect vehicle market prices. Similarly, we would certainly not want to include data from 2009, when the Cash for Clunkers program significantly changed used-vehicle markets, differentially affecting prices of low-MPG versus high-MPG vehicles.

IV. Estimation

A. Empirical Strategy

We use vehicle fixed effects and look within the same vehicle over time as gasoline price forecasts change. The benefit of a panel is that the fixed effects soak up unobserved vehicle characteristics that may be correlated with MPG: formally, our estimator is still unbiased even if $E[G|\psi] \neq 0$.

We move from equation (3) to our base specification estimating equation in three steps. First, we define an econometric error term that contains $\xi$ and the market share term: $\varepsilon \equiv (-1/\eta) \ln s_{jat} + \xi_{jat}$. Second, we add time dummies $\tau_t$, which absorb the outside option share $s_{0t}$ and any shift in the overall market price level. Third, we define $f_{50}$ as the median of the MPG distribution, and we include $\psi_{jat}$, eleven indicator variables for month-of-year interacted with $1(f_{jat} > f_{50})$. As we discuss momentarily, these control for the differential seasonal trends in the prices of low- versus high-MPG vehicles. Our base specification is

$$p_{jat} = -\gamma G_{jat} + \tau_t + s_{jat} + \psi_{jat} + \varepsilon_{jat}. \quad (5)$$

Equation (5) is quite intuitive: it tests whether the relative vehicle prices move one-for-one with changes in the relative PDV of gasoline costs. If vehicle prices do not respond sufficiently to gasoline costs, we conclude that the market undervalues gasoline costs. If vehicle prices respond more...
than predicted to gasoline costs, we conclude that the market overvalues gasoline costs.\footnote{Although we derive it differently, this is fundamentally the same estimating equation used by Kahn (1986) and Busse et al. (2013). The latter paper uses a slightly different configuration of fixed effects and controls. Sallee et al. (2009) allow $G$ to vary at the transaction level instead of at the $jat$ level, based on the odometer reading of the specific auto being transacted. They can then insert $jat$-level fixed effects. This allows them to relax our two identifying assumptions and substitute an alternative assumption, which is that the within-$jat$ relationship between odometer readings and transaction prices is not affected by unobserved factors that are correlated with gas prices.}

Figure 4 illustrates our identifying variation by graphing the average $G$ for an example month within age and fuel economy groups. Younger vehicles and lower-MPG vehicles have higher $G$. Equation (5) is identified by interacting this cross-sectional variation by the time series variation in gasoline price forecasts illustrated in figure 1. As gasoline price forecasts fluctuate over time, the bars in figure 4 extend and contract proportionally. A given change in gas price forecasts has a larger effect on the level of $G$ for younger and lower-MPG vehicles, and we test for whether relative prices move correspondingly.

Equation (5) is a consistent estimator of $\gamma$ if $E[G\epsilon|(\tau, v, \psi)] = 0$. Because $\epsilon$ contains both $s$ and $\xi$, this actually contains two different economically meaningful identifying assumptions:

**Assumption 1:** $E[Gs|(\tau, v, \psi)] = 0$.

**Assumption 2:** $E[G\xi|(\tau, v, \psi)] = 0$.

In words, assumption 1 is that gasoline costs are uncorrelated with market shares, conditional on time dummies and vehicle fixed effects. For new vehicles, this assumption would not hold: sales of low-fuel economy vehicles decrease relative to high-fuel economy vehicles when gas prices increase, as documented by Busse et al. (2013), Klier and Linn (2010), and Li et al. (2009). This assumption might also not hold for older used vehicles, whose scrappage rates respond most to changes in gasoline prices (Li et al. 2009). Therefore, we limit our sample to used vehicles less than or equal to 15 years old. In appendix B, we show that weakening this assumption by allowing for endogenous market shares does not significantly affect the estimates, largely because we have limited our sample to the ages for which the conditional correlation between gasoline prices and market shares is insignificant.

Assumption 2 states that changes in discounted gasoline costs are not correlated with changes in preferences and unobserved characteristics that vary over the different model years within a generation of a vehicle. In section V, we discuss and test several potential violations of this assumption and document that they do not appear to substantially affect the results.

**B. Measurement Error and the Grouping Estimator**

Jerry Hausman’s (2001) “iron law of econometrics” is that the magnitude of a parameter estimate is usually smaller in absolute value than expected. This is due to attenuation bias, which can occur even in seemingly high-quality data. In most applications in which the null hypothesis is that a parameter equals 0, this makes a test more conservative. By contrast, in our test of whether $\hat{\gamma} = 1$, this iron law would make us more likely to falsely reject, meaning that we could falsely conclude that consumers undervalue gasoline costs. One potential source of measurement error is the EPA fuel economy ratings, as discussed by Sallee (2010). As in any other application, the use of fixed effects exacerbates attenuation bias, as even small amounts of measurement error in $G$ worsen the signal-to-noise ratio in $G|\psi$.

We address measurement error using the grouping estimator, which is just Wald’s (1940) binary instrumental variables (IV) estimator generalized to the case with many group indicator variables. Wald’s (1940) original objective in developing the estimator was to address measurement error, and Ashenfelter (1984), Angrist (1991), and others have used the grouping estimator for this same purpose in various applications. In our base specification, we place each $jat$-level observation into one of 222 mutually exclusive and exhaustive groups: above- and below-median MPG vehicles for each of the 111 months in the sample. This grouping retains the fundamental identifying variation, which comes from how time series changes in gas price forecasts affect $G$ for high- versus low-MPG vehicles. However, identifying $\gamma$ off of group-level aggregates means that we average over any observation-level measurement error.

Formally, we define $Z^u_{jat} = 1(f_{jat} > f^{50}) \times 1(t = u)$ as an indicator variable for whether observation $jat$ occurs at time $u$ and has above-median MPG. We denote $Z_{jat}$ as the vector of 100 $Z^u_{jat}$ variables for every month of the sample beginning with January 2000, and we instrument for $G_{jat}$ with $Z_{jat}$. Between instruments $Z_{jat}$, time controls $\tau$, and month-by-MPG group controls $\nu_{jat}$, we have a full set of indicator variables in the first stage for each of the 222 groups; the second-stage fitted values of $G$ are essentially group-level averages.
We also present results for groups at different levels of aggregation. Aggregating observations into fewer larger groups allows us to average over measurement error that is more severe or correlated across observations. However, using fewer groups effectively reduces the amount of identifying variation, which increases the IV standard errors.

We need not control for any variables that vary at a more disaggregated level than $Z_{jat}$. For example, consider our controls $\nu_{jat}$ that soak up differential monthly price trends for above- versus below-median MPG vehicles. The highest-MPG quartile also has different monthly price trends from the second-highest MPG quartile. However, we do not need to control for this because the fitted values of $G$ do not vary between these two quartiles, and thus $\gamma$ is not identified off these differential price trends. In alternative specifications where we define $Z_{jat}$ by more disaggregated MPG groups, we also control for differential price trends for each separate MPG group.

V. Results

A. Graphical

Figure 5 illustrates our identification. On the vertical axis is the difference between the mean price across transactions for vehicles with below-median MPG versus above-median MPG. On the horizontal axis is the difference in mean $G$. These are raw data, unadulterated by fixed effects, time controls, or other manipulations. Even in the raw data, it is starkly visible that relative prices and relative gas costs are negatively correlated. The slope of a best-fit line would be $-1$ if $\gamma = 1$ and if fixed effects are uncorrelated with $G$.

Figure 6 is a plot of the price and gas cost residuals that identify $\gamma$. The single solid line is the difference between average $G_{jat}(v, \psi)$, the seasonally detrended and de-meaned transaction price, for above- minus below-median MPG vehicles. If $\gamma = 1$, the single and double lines should move in parallel. From this figure, it is again clear that relative prices are at least somewhat responsive to relative gasoline costs. However, vehicle prices do not appear to respond very much to the high-frequency volatility in retail gasoline prices.

To test whether prices are as responsive as theory predicts under the martingale and futures-based forecasts, we now turn to the formal estimates.

B. Base Specification

For our base specification, we estimate equation (5) using the fixed effects (de-meaning) estimator while grouping $Z_{jat}$ at the level of above- and below-median MPG by time, assuming a 6% discount rate and using data from January 1999 through March 2008. To reflect the fact that $p_{jat}$ is an average across varying numbers of transactions, we weight the $jat$-level observations by the number of transactions. We are careful to call this our base specification, indicating that the alternative specifications modify individual assumptions from this base, but we do not call it our “preferred specification.” This is because different readers may prefer different sets of alternative assumptions.

Table 3 reports the estimated coefficients on $G$ from equation (5), which correspond to $-\hat{\gamma}$. We denote the futures- and martingale gas price forecasts as $G^f$ and $G^m$, respectively. Columns 1 and 2 show that the estimated $\hat{\gamma}$ coefficients are 0.76 and 0.55. The smaller $\hat{\gamma}$ for the martingale forecast is consistent with our earlier discussion of the fact that the martingale forecast implies higher levels of $G$ and more monthly volatility compared to the futures forecast.

Using consumers’ gas price forecasts elicited from the Michigan Survey of Consumers, Anderson et al. (2011) show that the average consumer believes that real gasoline prices
in five years will be the same as they are at the time of the survey. This suggests that the martingale-based \( \hat{\gamma} \) will be very close to the MSC-based estimate. This is indeed the case: when we use the MSC-based gas price forecast provided by Anderson et al., \( \hat{\gamma} = 0.51 \) (SE = 0.029), not statistically distinguishable from the martingale-based \( \hat{\gamma} \).

One way to test whether it is more realistic to assume the futures-based or martingale gas price forecast is to test which fits the data better in a horse race. Because \( G^m \) and \( G^f \) are highly correlated, we do not include both in a regression. Instead, we estimate equation (5) using \( G^f \) and add \([G^m - \hat{G}^f]\) as an explanatory variable. Column 3 presents the results of this regression. Neither the futures nor the martingale assumption appears to fully capture consumers’ forecasts: conditional on \( G^f \), \([G^m - \hat{G}^f]\) is still associated with vehicle prices. (Mechanically, this also means that conditional on \( G^m \), \([G^m - \hat{G}^m]\) is still associated with vehicle prices.) Of course, these results are conditional on the model being correctly specified. Because there appears to be some evidence for both forecasts under this model, we present both sets of results in most of the robustness checks that follow.

One way of putting \( \hat{\gamma} \) in context is to compare the observed vehicle price adjustments to the amounts predicted by theory. Consider a hypothetical set of used vehicles that have different fuel economy ratings but would all be driven 12,000 miles per year over a remaining lifetime of seven years. The double line in figure 7 reflects the change in vehicle prices that would be expected in response to a $1.00 increase in the gas price forecast, relative to the price of a 25 MPG vehicle. The single line shows the predicted relative price changes for the base specification \( \hat{\gamma} = 0.76 \). The equations for the double line and the single line are, respectively, (Price Change if \( y = 1 \)) = \((1 - 0.76) \times \frac{1}{25 - 1/7} \times 12,000 \times \sum \delta^j \) and (Predicted Price Change) = \((1 - \hat{\gamma}) \times \frac{1}{25 - 1/7} \times 12,000 \times \sum \hat{\delta}^j \).

The double line shows the price changes if \( \gamma = 1 \) in response to a $1 increase in the gas price forecast for vehicles that would be driven 12,000 miles per year over a remaining lifetime of seven years, relative to a 25 MPG vehicle. The single line shows the predicted relative price changes for the base specification \( \hat{\gamma} = 0.76 \). The equations for the double line and the single line are, respectively, (Price Change if \( y = 1 \)) = \((1 - 0.76) \times \frac{1}{25 - 1/7} \times 12,000 \times \sum \delta^j \) and (Predicted Price Change) = \((1 - \hat{\gamma}) \times \frac{1}{25 - 1/7} \times 12,000 \times \sum \hat{\delta}^j \).

### Table 3.—Base Specification Results

<table>
<thead>
<tr>
<th></th>
<th>(1) Futures Forecast</th>
<th>(2) Martingale Forecast</th>
<th>(3) Both</th>
</tr>
</thead>
<tbody>
<tr>
<td>( G^f )</td>
<td>-0.76 (0.046)</td>
<td>-0.73 (0.046)</td>
<td></td>
</tr>
<tr>
<td>( G^m )</td>
<td>-0.55 (0.032)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>([G^m - G^f])</td>
<td>-0.14 (0.037)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Time dummies</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Month-by-MPG group controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Vehicle fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>931,888</td>
<td>931,888</td>
<td>931,888</td>
</tr>
</tbody>
</table>

This table presents estimates of equation (5) assuming the futures-based and martingale gas price forecasts, denoted \( G^f \) and \( G^m \), respectively. All specifications use data from 1999 through March 2008 and use the grouping estimator with groups at the level of time by MPG group, with two MPG groups. Observations are weighted by number of transactions. Robust standard errors, clustered by vehicle, are in parentheses.

### Figure 7.—Predicted Mispricing

The double line shows the price changes if \( \gamma = 1 \) in response to a $1 increase in the gas price forecast for vehicles that would be driven 12,000 miles per year over a remaining lifetime of seven years, relative to a 25 MPG vehicle. The single line shows the predicted relative price changes for the base specification \( \hat{\gamma} = 0.76 \). The equations for the double line and the single line are, respectively, (Price Change if \( y = 1 \)) = \((1 - 0.76) \times \frac{1}{25 - 1/7} \times 12,000 \times \sum \delta^j \) and (Predicted Price Change) = \((1 - \hat{\gamma}) \times \frac{1}{25 - 1/7} \times 12,000 \times \sum \hat{\delta}^j \).

### C. Standard Errors

Throughout the paper, we report robust standard errors, clustered at the level of model \( j \) by age \( a \). These standard errors are unbiased in the presence of serial correlation over time in the price of, for example, a three-year-old Honda Civic DX sedan. Clustering at the level of nameplate by age gives a standard error of 0.054. This standard error is unbiased in the presence of serial correlation over time in the price of, for example, all three-year-old models of Honda Civic. Clustering at the level of model \( j \) gives a standard error of 0.086. Analogously, this is unbiased in the presence of serial correlation in the price of all Honda Civic DX sedans of any age.

In addition, all standard errors can be adjusted to account for the fact that \( G \) is a generated regressor estimated from first-step regressions that predict each observation’s vehicle-miles traveled and survival probability. Murphy and Topel (1985) show that the true covariance matrix is additively separable in the usual covariance matrix and an additional matrix that accounts for the uncertainty in the first-step parameter estimates. We estimate this additional variance by bootstrapping draws from the estimated distribution of first-step parameters and estimating \( \hat{\gamma} \) for each draw. Using the base specification with \( G^f \) as an example, the clustered, robust IV standard error is 0.046. The standard deviation of the bootstrapped set of \( \hat{\gamma} \) estimates is 0.023. Adding together these two variances and taking the square root gives an adjusted standard error of 0.052.

### D. Alternative Specifications

#### Level of grouping. Correcting for measurement error appears to be extremely important. Rows 1 through 3 of
the fact that excluding the early period does not significantly change the result mitigates our earlier concern that market-level trends over 1999–2003 could bias the estimator. In row 12, including the gas price spike of 2008 increases \( \hat{\gamma} \) more under \( G' \) than under \( G'' \). This is consistent with the fact that futures markets did not expect the high spot prices in 2008 to be sustained, which mechanically decreases \( G \) and thus increases \( \hat{\gamma} \).

There are two explanations for the fact that including the latter part of 2008 moves \( \hat{\gamma} \) statistically closer to 1 under the futures-based gas price forecast. First, changes in vehicle markets unrelated to changes in gasoline price forecasts could bias the estimated \( \gamma \). Second, the true \( \gamma \) may have increased over this period as gas prices fluctuated substantially. This would be consistent with models of endogenous or “rational” inattention in which consumers pay more attention to more important attributes (Gabaix, 2012; Sallee, 2011). It would also be consistent with models in which large changes cause consumers to update beliefs between coarse categories, for example, from gas costs being “inconsequential” to gas costs being “high” (Mullainathan, 2002).

**Alternative discount rates.** Rows 21 to 25 of table 4 show the sensitivity of \( \hat{\gamma} \) to the assumed discount rate. At a discount rate just higher than 11%, we fail to reject \( \gamma = 1 \) with 90% confidence using the Murphy-Topel standard errors and the futures forecast. The implied discount rate, the discount rate that rationalizes the data by giving \( \gamma = 1 \), is just under 15% for the futures forecast and just over 24% for the martingale.

**Changes in characteristics.** The identifying assumption that \( E[G|\xi(\tau, \psi)] = 0 \) would be violated if a model’s characteristics change in ways that are correlated with \( G \). For example, since gasoline price forecasts rise on average during the study period, if characteristics improve more over model years for high-MPG models, we would misattribute these vehicles’ increased desirability to changes in gasoline price forecasts. Our policy of redefining a new generation of a model as a different \( \gamma \) addresses the bulk of these concerns. Even within a generation, however, there can be some variation in observable characteristics (Knittel, 2011, figure 1).

An additional suggestive test is to add controls for observable characteristics to the estimation. Rows 31 to 35 reestimate the base specification with progressively more control variables: horsepower, curb weight, wheelbase, antilock brakes, stability control, and traction control. The estimated \( \hat{\gamma} \) remains very similar. Although whether controlling for observables affects a parameter estimate does not directly tell us whether controlling for unobservables would affect the estimate, it is plausible that changes in observable and unobservable characteristics are correlated, by logic similar to that of Altonji, Elder, and Taber (2005). Therefore, this suggests that changes in unobservable characteristics might not bias our estimates.

### Table 4.—Alternative Assumptions

<table>
<thead>
<tr>
<th>Row</th>
<th>Gas Price Forecast: Specification</th>
<th>Futures</th>
<th>Martingale</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( \hat{\gamma} )</td>
<td>( SE(\hat{\gamma}) )</td>
<td>( \hat{\gamma} )</td>
</tr>
<tr>
<td>Base</td>
<td>2004–March 2008</td>
<td>0.80</td>
<td>0.037</td>
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<tr>
<td></td>
<td>2009–end 2008</td>
<td>0.85</td>
<td>0.035</td>
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<tr>
<td>Discount rate</td>
<td>0%</td>
<td>0.59</td>
<td>0.046</td>
</tr>
<tr>
<td></td>
<td>3%</td>
<td>0.67</td>
<td>0.035</td>
</tr>
<tr>
<td></td>
<td>10%</td>
<td>0.87</td>
<td>0.040</td>
</tr>
<tr>
<td></td>
<td>11%</td>
<td>0.90</td>
<td>0.053</td>
</tr>
<tr>
<td></td>
<td>15%</td>
<td>1.01</td>
<td>0.060</td>
</tr>
<tr>
<td>Characteristics</td>
<td>Sample with characteristics</td>
<td>0.76</td>
<td>0.049</td>
</tr>
<tr>
<td></td>
<td>Control for HP</td>
<td>0.76</td>
<td>0.049</td>
</tr>
<tr>
<td></td>
<td>Control for HP, weight</td>
<td>0.76</td>
<td>0.049</td>
</tr>
<tr>
<td></td>
<td>Control for HP, weight, wheelbase</td>
<td>0.76</td>
<td>0.049</td>
</tr>
<tr>
<td></td>
<td>Control for all characteristics</td>
<td>0.75</td>
<td>0.048</td>
</tr>
<tr>
<td></td>
<td>Control for HP</td>
<td>0.76</td>
<td>0.049</td>
</tr>
<tr>
<td></td>
<td>Control for weight</td>
<td>0.76</td>
<td>0.049</td>
</tr>
<tr>
<td></td>
<td>Control for all characteristics</td>
<td>0.75</td>
<td>0.048</td>
</tr>
<tr>
<td>Preferences</td>
<td>Exclude hybrid vehicles</td>
<td>0.76</td>
<td>0.046</td>
</tr>
<tr>
<td></td>
<td>Exclude “green” vehicles</td>
<td>0.73</td>
<td>0.048</td>
</tr>
<tr>
<td></td>
<td>Exclude SUVs</td>
<td>0.71</td>
<td>0.065</td>
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<td></td>
<td>Exclude all cars</td>
<td>0.87</td>
<td>0.087</td>
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<td></td>
<td>Exclude minivans</td>
<td>0.70</td>
<td>0.046</td>
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<td>Age-by-time controls</td>
<td>One year per group</td>
<td>0.79</td>
<td>0.041</td>
</tr>
<tr>
<td></td>
<td>Two years per group</td>
<td>0.79</td>
<td>0.043</td>
</tr>
<tr>
<td></td>
<td>Four years per group</td>
<td>0.78</td>
<td>0.044</td>
</tr>
</tbody>
</table>

This table presents estimates of equation (5) under alternative assumptions. Unless otherwise stated, all specifications include 1999 through March 2008. For these specifications, \( N = 931,618 \) for row 41, \( N = 874,497 \) for row 45. All specifications include a full set of month-by-year time dummies and \( \xi \) is correlated across observations. Inattention in which consumers pay more attention to more important attributes (Gabaix, 2012; Sallee, 2011). It would also be consistent with models in which large changes cause consumers to update beliefs between coarse categories, for example, from gas costs being “inconsequential” to gas costs being “high” (Mullainathan, 2002).
Changes in preferences. Aside from representing changes in vehicle characteristics, changes in $\xi_{ijt}$ can also represent changes in preferences for a vehicle with the same characteristics. Since gasoline price forecasts rise on average during the study period, differential trends in preferences for low- versus high-MPG vehicles would violate the assumption that $E[G\xi|t, v, \psi] = 0$, which would bias $\hat{\gamma}$.

One potential concern is that consumers became increasingly “green,” or environmentally oriented, over the study period, resulting in increased preference for high-fuel-economy vehicles independent of the financial savings. This would bias $\hat{\gamma}$ upward, as it would increase the prices of high-MPG vehicles over the study period as gasoline price forecasts rose. To test this, we exclude hybrids and the top 60 most green vehicles ranked by Yahoo (2009). Rows 41 and 42 of table 4 show that this does not affect the results.

An opposite concern is that preferences for particular classes of large vehicles, for example SUVs or pickups, strengthened over the study period. This would bias $\hat{\gamma}$ downward, as it would increase the prices of low-MPG vehicles over time, attenuating the decrease in relative prices that the model would expect as gasoline price forecasts rose. To test this, rows 43 through 45 exclude SUVs, minivans, and all cars, respectively, from the estimation. While the point estimates change somewhat, the differences are not statistically significant, except when excluding cars and using the martingale gas price forecast.

Age-by-time controls. Rows 51 to 53 of table 4 include age-by-time controls to account for potential changes in depreciation patterns over time. These controls address bias that would occur if depreciation patterns changed as gas prices rose over the study period and the age composition of above- versus below-median MPG groups changed. For example, older vehicles could have become systematically more valuable in later years, and there could be increasingly more old below-median or above-median MPG vehicles on the road. The table shows that identifying $\hat{\gamma}$ only off of within-age variation in $G$ does not significantly change the estimates.

E. Observation Weights and Heterogeneity by Vehicle Age

A natural question to ask is whether $\gamma$ might be heterogeneous across consumer groups. For example, the types of consumers who buy newer or older vehicles might be more or less informed about or attentive to fuel economy. In fact, there is significant heterogeneity in $\gamma$ by vehicle age. Column 1 of table 5 displays estimates of equation (5) for specific vehicle age groups. The $\hat{\gamma}$ is 0.93 for vehicles aged 1 to 3, but it drops to 0.26 for vehicles aged 11 to 15. All estimates in table 5 use the futures-based gas price forecast, but the martingale forecast similarly shows that $\hat{\gamma}$ declines with vehicle age.

The differences in $\hat{\gamma}$ depend mechanically on the differences in $G$. Returning to figure 4, we can see how $G$ varies with age. In June 2004, the transaction-weighted average values of $G$ for above-median and below-median MPG vehicles aged 11 to 15 were $2,620 and $4,150, respectively. These are about 37% of the values for vehicles aged 1 to 5 years. These figures depend on underlying data for survival probabilities and VMT. According to the registration data, the average vehicle between 11 and 15 years old will survive for 6.1 more years. According to the NHTS odometer readings, the average vehicle between 11 and 20 years old will be driven 8,980 miles per year, conditional on survival.

Several factors could explain the differences across ages. First, we could systematically overstate $G$ for the nationwide population of older vehicles by overestimating either VMT or survival probabilities. This appears to be unlikely. Because vehicle registrations must be renewed every year at some cost, it is unlikely that many vehicles would have their registrations renewed if they were not in use. Thus, it seems most accurate to estimate survival probabilities from vehicle registration data, and it is unlikely that this would overstate survival probabilities. However, we can also estimate survival probabilities using the cross-sectional age distribution observed in the NHTS. There are fewer older vehicles observed in the NHTS than in the registration data, suggesting that the NHTS might undersample households that own the oldest vehicles, even after weighting for national representativeness on other observables. As a result, using the NHTS to calculate survival
probabilities should make $G$ smaller for new vehicles, thereby increasing $\gamma$. Depending on the shape of the survival functions, this could change the estimated $\gamma$ for older vehicles in either direction. Column 2 of table 5 presents estimates of $\gamma$ using the NHTS survival probabilities. All of the point estimates increase, but none of them changes significantly, and the pattern of decreasing $\gamma$ with vehicle age is unchanged.

Second, even if our $G$ is appropriate for the U.S. population of older vehicles, the population of vehicles going through auctions might have smaller $G$. This would happen if auctioned vehicles had lower future VMT or survival probabilities, perhaps because they are low quality or being sold for scrap. The data also do not support this. The average odometer readings for 11- to 15-year-old vehicles differ by only a few percent between Manheim-auctioned vehicles and vehicles in the NHTS, so auctioned vehicles have not been more heavily used. Furthermore, in constructing vehicle prices using the NHTS, so auctioned vehicles have not been more heavily used. Column 3 presents these same specifications using JDPA retail prices, which are for autos that are in good enough condition for retail sale. The significant decrease in $\tilde{\gamma}$ for older vehicles remains.

Third, the identifying assumption that $E[G_t | (\tau, v, \psi)] = 0$ might be increasingly violated for older vehicles. As gas prices rise, increased scrappage of older gas guzzlers would raise the prices of these vehicles both because demand is downward sloping and because selective scrappage of the lowest-quality gas guzzlers would raise the average quality of remaining ones. However, while there is a strong negative correlation between $G$ and market share for vehicles older than 15 years (which are excluded from our regressions), the correlation between $G$ and age conditional on $(\tau, v, \psi)$ for 11- to 15-year-old vehicles is not statistically significant, and the point estimate is actually positive.

Fourth, buyers of older vehicles may have higher intertemporal opportunity costs of capital, that is, higher discount rates $r$, compared to buyers of younger vehicles. If this were the case, we use of the average discount rate still gives an unbiased estimate of the market average $\gamma$. However, it would cause us to overstate $\gamma$ for younger vehicles and overstate $\gamma$ for older vehicles, and it would give the pattern of decreasing $\gamma$ with age observed in table 5. The SCF data do not support this hypothesis: auto loan interest rates are not statistically significantly different by vehicle age, and the standard errors are tight enough to rule out that the average interest rate for 11- to 15-year-old vehicles is greater than 0.5 percentage points above the average rate for 1- to 5-year-old vehicles. However, Adams, Einav, and Levin (2009) analyze subprime auto loans with interest rates of 25% to 30%, and consumers buying older vehicles may have very high intertemporal opportunity costs of capital because they cannot get any loan.

One implication of the differences in $\tilde{\gamma}$ across ages is that regression weighting matters. In our base specifications, we weight $jat$-level observations by the number of observed transactions. Column 5 of table 5 shows that most vehicles that pass through auctions are less than five years old, meaning that the $jat$-level observations for newer vehicles have more underlying transactions and thus are weighted more heavily. The difference in $\gamma$ coefficients across ages means that the estimated $\gamma$ for all ages should be smaller when weighting observations equally instead of by number of transactions. The first row of column 4 confirms this, showing that $\tilde{\gamma} = 0.62$ for equal weights. Comparing columns 1 and 4 shows that when the regressions are restricted to particular age groups, the $\gamma$ coefficient does not depend much on how observations are weighted.

VI. Sticky Information

Mankiw and Reis (2002), Sims (2003), Woodford (2003), and others propose models of “sticky information,” in which macroeconomic news diffuses slowly through the population of consumers and firms. This causes prices, savings, investment, and other decisions to respond to information with a delay. Sticky information could explain the visual evidence in figure 6 that vehicle market prices do not respond to high-frequency fluctuations in retail gasoline prices.

Interestingly, neither the two surveys that have elicited consumers’ beliefs about gasoline prices was structured to provide evidence on sticky information. The Vehicle Ownership and Alternatives Survey analyzed by Allcott (2011, 2013) asks consumers what current gasoline prices are in their area and shows that responses are very close to state-level averages. However, the survey was carried out in October 2010, when gas prices had not fluctuated by more than $0.10 per gallon for eight months. If the survey were repeated at a time of more volatility, the sticky information model predicts that beliefs would lag current prices.

The Michigan Survey of Consumers (Anderson et al., 2011) is a repeated cross-section that covers multiple periods of gas price volatility. However, it does not ask consumers their beliefs about current gas prices. Instead, it asks only whether consumers believe that prices will increase or decrease relative to “current prices.” We do not know what consumers believe are “current prices” in months when retail gasoline prices have changed significantly.

One prediction of a sticky information model is that $\gamma$ should be attenuated when using the difference estimator instead of the de-meaning estimator. This is because the former is identified only off the variation at monthly frequency, while the latter is identified off of de-meaned levels over the entire period that the vehicle is observed. Table 6 tests this by estimating equation (5) using the difference estimator instead of the fixed-effects (demeaning) estimator. In this table, unlike tables 4 and 5, we report the coefficient on the $G$ variable, which is $-\gamma$, instead of $\gamma$ itself. Columns 1 to 3 use the futures-based forecast $\hat{G}^f$, while columns 4 to 6 use the martingale forecast $\hat{G}^m$. Columns 1 and 4 show that the contemporaneous differences in $G$ are negatively associated with contemporaneous differences in vehicle prices, as
would be expected. However, the estimates are significantly attenuated relative to the fixed-effects estimates, especially for the martingale forecast. Columns 2, 3, 4, and 6 add lags of the change in $G$. These results show that changes in vehicle prices are strongly associated with changes in gasoline prices as far as three to four months in the past. The association becomes smaller and statistically insignificant by the fifth or sixth monthly lag.

Table 7 builds on these results by estimating equation (5) using more aggregated units of time $t$ instead of monthly time units used in the rest of the paper. For example, the “2-month units” row presents estimates with prices and gasoline costs aggregated to the bimonthly level. The fixed-effects estimates of $\gamma$ in the top panel do not change with this increased aggregation, as the demeaning estimator identifies $\gamma$ off lower-frequency variation. However, the estimates from the difference estimator move toward the fixed-effects estimates as we aggregate over more months. This provides additional evidence that markets do not immediately adjust to high-frequency gasoline price variation.

Klenow and Willis (2007) use the data underlying the Consumer Price Index to document that U.S. retailers set prices based on information that is up to one year old. Our results complement theirs by providing additional empirical support for the sticky information model in this particular market. Table 6 suggests that changes in gasoline price forecasts take four to six months to be fully incorporated into vehicle market prices. This could be either because consumers are not aware that gasoline prices have changed or because they somehow do not incorporate this knowledge into their willingness to pay when shopping for vehicles.

These results also highlight the distinction between models of rational inattention in macroeconomics and finance, in which agents do not immediately update beliefs about time-varying decision variables, and consumer choice models of static inattention, such as Gabaix and Laibson (2006) or Chetty et al. (2009). Energy-efficiency policies such as CAFE standards are motivated by the latter form of inattention or some similarly static misoptimization, not by inattention to high-frequency fluctuations in energy prices. While our strategy of exploiting time series variation in energy costs allows us to sweep our unobserved product attributes using fixed effects, it is important to account for the fact that consumers appear to update gasoline price forecasts with some delay. Using quarterly or higher-frequency variation and a difference estimator could cause an analyst

### Table 6.—Difference Estimator

<table>
<thead>
<tr>
<th></th>
<th>(1) Futures Forecast</th>
<th>(2) Martingale Forecast</th>
<th>(4) Martingale Forecast</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta G_t$</td>
<td>$-0.33$ (0.036)</td>
<td>$-0.30$ (0.041)</td>
<td>$-0.27$ (0.044)</td>
<td>$-0.16$ (0.009)</td>
<td>$-0.16$ (0.011)</td>
</tr>
<tr>
<td>$\Delta G_{t-1}$</td>
<td>$-0.43$ (0.029)</td>
<td>$-0.49$ (0.033)</td>
<td>$-0.14$ (0.009)</td>
<td>$-0.13$ (0.012)</td>
<td></td>
</tr>
<tr>
<td>$\Delta G_{t-2}$</td>
<td>$-0.40$ (0.030)</td>
<td>$-0.34$ (0.032)</td>
<td>$-0.13$ (0.012)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta G_{t-3}$</td>
<td>$-0.26$ (0.028)</td>
<td>$-0.13$ (0.013)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta G_{t-4}$</td>
<td>$-0.08$ (0.037)</td>
<td>$-0.07$ (0.016)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta G_{t-5}$</td>
<td>$0.03$ (0.035)</td>
<td>$-0.09$ (0.013)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta G_{t-6}$</td>
<td>$-0.02$ (0.040)</td>
<td>$-0.03$ (0.014)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Number of observations: 835,837

This table presents estimates of equation (5) with the difference estimator instead of the fixed-effects (de-meaning) estimator. The dependent variable is $\rho_{t,0} = \rho_{t-1}$. The table reports the coefficient on $\Delta G_t = G_{t} - G_{t-1}$, which corresponds to $-\gamma$. All specifications use data from 1999 through March 2008, include a full set of month-by-year time dummies and MPG group by month-of-year controls, and use the grouping estimator with groups at the level of time by MPG group, with two MPG groups. Observations are weighted by the number of observed transactions in each pair of differenced months. Robust standard errors, clustered by vehicle, are in parentheses.

### Table 7.—Time Aggregation

<table>
<thead>
<tr>
<th></th>
<th>(1) Futures Forecast</th>
<th>(2) Martingale Forecast</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed effects</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1-month units (base)</td>
<td>0.76 (0.046)</td>
<td>0.55 (0.032)</td>
<td>931,888</td>
</tr>
<tr>
<td>2-month units</td>
<td>0.76 (0.045)</td>
<td>0.57 (0.032)</td>
<td>503,146</td>
</tr>
<tr>
<td>3-month units</td>
<td>0.75 (0.045)</td>
<td>0.57 (0.034)</td>
<td>342,551</td>
</tr>
<tr>
<td>4-month units</td>
<td>0.74 (0.046)</td>
<td>0.59 (0.034)</td>
<td>263,573</td>
</tr>
<tr>
<td>6-month units</td>
<td>0.72 (0.046)</td>
<td>0.58 (0.038)</td>
<td>182,300</td>
</tr>
<tr>
<td>Differences</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1-month units (base)</td>
<td>0.33 (0.036)</td>
<td>0.16 (0.009)</td>
<td>835,837</td>
</tr>
<tr>
<td>2-month units</td>
<td>0.49 (0.035)</td>
<td>0.21 (0.010)</td>
<td>446,100</td>
</tr>
<tr>
<td>3-month units</td>
<td>0.65 (0.038)</td>
<td>0.24 (0.015)</td>
<td>294,862</td>
</tr>
<tr>
<td>4-month units</td>
<td>0.82 (0.038)</td>
<td>0.39 (0.017)</td>
<td>219,650</td>
</tr>
<tr>
<td>6-month units</td>
<td>0.86 (0.036)</td>
<td>0.57 (0.026)</td>
<td>141,295</td>
</tr>
</tbody>
</table>

This table presents estimates of equation (5) with time units at different levels of aggregation. All specifications use data from 1999 through March 2008, include a full set of time dummies and MPG group by season controls, and use the grouping estimator with groups at the level of time by MPG group, with two MPG groups. Observations weighted by the number of observed transactions in each pair of differenced months. Robust standard errors, clustered by vehicle, are in parentheses.
to misattribute inattention to high-frequency fluctuations in gasoline costs to static undervaluation of fuel economy as a product attribute.

VII. Conclusion

At least since the energy crises of the 1970s, economists and policymakers have been interested in how consumers trade off future costs of energy using durable goods with their purchase prices. We propose a different and relatively plausible approach to estimating demand for energy efficiency, which exploits the interaction of time series variation in gasoline price forecasts with cross-sectional variation in fuel economy ratings of different vehicles. In our base specification assuming the futures-based gas price forecast, consumers appear to value discounted future gasoline costs only 76% as much as they value purchase prices. The parameter estimates are insensitive to many factors, including the potential endogeneity of market shares and vehicle-miles traveled and potential changes over time in consumer preferences or vehicle characteristics. However, assuming a lower discount rate or using the martingale gas price forecast strengthens the qualitative conclusion that $\gamma < 1$. On the other hand, other specifications move $\gamma$ closer to 1, including plausibly higher discount rates and adding the 2008 recession to the sample. Although $\gamma$ is less than 1 in most of our alternative specifications, it is not hard to imagine plausible combinations of alternative assumptions that could generate this result. Importantly, the parameter estimates are very different for subsamples of younger versus older vehicles.

Given the uncertainty in these estimates, it is worth returning to our calculation from the introduction. Even if $\gamma$ is closer to 1 than our base specifications suggest, misoptimization distorts vehicle markets more than the failure to internalize climate change externalities. Given the amount of policy attention and academic interest surrounding climate change, this remarkable result suggests that economists should be devoting significant additional effort to understanding how consumers value energy costs and understanding the policy consequences of potential undervaluation.

REFERENCES


Langer, Ashley, and Nathan Miller, “Automakers’ Short-Run Responses to Changing Gasoline Prices,” this REVIEW 95 (2013), 1198–1211.


