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Abstract: Engineering-based studies of energy efficiency often find that firms and consumers fail to adopt technologies that appear to provide net private benefits absent regulation. We examine the recent empirical literature on the extent to which expected future fuel costs are reflected in vehicle prices and therefore valued by consumers when making purchase decisions. These studies improve upon the prior literature due to their use of highly disaggregated panel data that allows for defensible identification strategies. These studies found that vehicle purchase prices reflect about 50 to 100 percent of future fuel expenses, assuming static consumer expectations about future gasoline prices and a discount rate of five to six percent. Recent regulatory analyses have estimated the benefits of more stringent vehicle standards implicitly assuming that no improvements in fuel economy will occur in the baseline, absent regulation. This assumption is consistent with consumers placing no value on future fuel costs when making vehicle purchase decision. The recent empirical evidence supports using a range of consumer valuation assumptions and applying this range consistently in the baseline and regulatory scenarios when modeling consumer purchase and firm investment decisions.

Key Words: Consumer valuation, fuel economy, vehicle purchase decisions, benefit-cost analysis

JEL Codes: D12, D22, R41, Q58

DISCLAIMER

1. Introduction[1]

It is not uncommon for engineering-based studies to claim that ample opportunities to reduce energy use are available at low or even negative costs relative to current technology. As Huntington (2011) observed, "this message is very popular among policymakers, because it suggests that they can undertake bold action towards improving energy efficiency without imposing costs on society." This view does not account for behavioral response or interactions with other markets, which often suggest more modest opportunities. In addition, this view often assumes that no new technologies will be adopted absent government regulation. However, U.S. energy intensity trends in recent decades do not support the contention that consumers and firms do not invest in energy efficiency. Even after accounting for the contribution of structural change to falling energy intensity, such as a shift from manufacturing to services, many sectors have seen substantial improvements in energy efficiency over time (Metcalf 2008; Huntington 2010; Levinson 2017).

While these broad economy-wide trends are suggestive, they do not identify to what extent consumers value or choose to adopt energy efficiency improvements absent regulation. Recent studies bring new evidence to bear on this question for the light-duty vehicle sector by estimating how much consumers account for fuel costs in vehicle purchase decisions. That is, does a vehicle's purchase price fully reflect the value of future fuel savings? Because fuel savings are often expected to far outweigh the upfront cost of purchasing a more fuel-efficient vehicle, the answer to this question has direct implications for vehicle technology adoption both with and without energy efficiency regulation.

Until recently, researchers mainly relied on cross-sectional data to estimate consumers' willingness-to-pay for future fuel savings, captured by measures of improved fuel economy. A typical approach was to use discrete choice modeling to estimate vehicle market shares. Empirical estimates from this literature

span a wide range, with some estimates implying substantial undervaluation and others substantial overvaluation of fuel savings, making it difficult to draw solid conclusions regarding the role of fuel economy in vehicle purchase decisions (Helfand and Wolverton 2011; Greene et al. 2018). Because vehicle price is often correlated with unobserved vehicle attributes, instrumental variables and other approaches have been used to address endogeneity issues, with varying degrees of success (e.g., Berry, et al. 1995).

Several papers have criticized the methodological approaches used to derive consumer willingness-to-pay estimates for fuel economy. Some have questioned the quality of the instruments (Allcott and Greenstone 2012; Langer and Miller 2013). Langer and Miller (2013) suggested that estimates of consumer willingness-to-pay based on a discrete choice framework are likely inconsistent because they failed to account for manufacturer pricing decisions, rendering any instrument invalid absent highly disaggregated transaction price data. Others observed that coefficients estimated via non-linear estimation techniques may be quite sensitive to the optimization algorithm and starting values utilized (Knittel and Metaxoglou 2014). Multicollinearity among vehicle attributes (e.g., fuel economy and performance/power/size) and unobservable aspects of vehicle quality also has raised questions of how to interpret coefficients that potentially conflate the value of fuel economy with other attributes (Sallee, et al. 2016; Busse, et al. 2013; Allcott and Wozny 2014; Allcott and Greenstone 2012).[2]

In this paper, we review a handful of recent studies have relied on highly disaggregated longitudinal (i.e., panel) data that allows for a much-improved identification strategy. Using the fact that a vehicle's fuel costs are a function of both fuel economy and future gasoline prices, they have examined how changes in gasoline prices over time have differentially affected the relative value of vehicles that vary in fuel economy. These papers leverage panel econometric techniques to control for unobserved attributes

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[2] See Helfand and Wolverton (2011) and U.S. EPA (2018) for detailed reviews of the literature.

through vehicle type and time fixed effects. While still few in number, the peer-reviewed studies to date

have found a narrower range of estimates, ranging from moderate to full valuation of fuel costs (Sallee,

et al. 2016; Allcott and Wozny 2014; Busse, et al. 2013).[3] The degree of observed undervaluation is

sensitive to identification strategy and assumptions about underlying parameters such as discount rate

and gasoline price expectations. Anderson and Sallee (2016) have described these three panel studies as

the most credible empirical look at consumer valuation of fuel economy. Finally, it is worth noting that

this literature does not shed light on whether there are market imperfections in the auto industry that

may reduce consumers' ability to optimize their vehicle purchases with respect to fuel economy.

However, a recent study suggests that automakers set the prices of new vehicles in a way that is

consistent with consumers valuing a substantial portion of fuel savings (Langer and Miller 2013).

The paper is organized as follows. Section 2 describes the asset valuation approach first applied to

vehicle purchase decisions by Kahn (1986), as it directly informs the identification strategies of three

recent panel data studies: Sallee, et al. (2016), Allcott and Wozny (2014), and Busse, et al. (2013).

Section 3 discusses the results from these three longitudinal studies. Section 4 summarizes panel data

evidence from Langer and Miller (2013) on producer behavior that complements the consumer

valuation studies in Section 3. Section 5 describes how consumer valuation was incorporated into

benefit-cost analysis for the most recent final federal regulation governing light-duty vehicle greenhouse

gas emissions and fuel economy standards. Finally, Section 6 discusses possible paths forward for

incorporating insights from this literature into future benefit-cost analyses.

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[3] Killian and Sims (2006) and Sawhill (2008) rely on similar longitudinal approaches to examine consumer valuation of fuel economy. Since they remain unpublished, their empirical results are subject to change, and we do not include them in the discussion.

2. Asset Valuation Approach

The asset valuation approach examines whether relative prices for a durable good, in this case light-duty vehicles, fully adjust to equate ex ante rates of return across vehicle types in response to changes in expectations about future gasoline prices. Based on a hedonic approach in which the price of a vehicle is a function of various vehicle attributes and expected gasoline prices, Kahn (1986) derived an econometric equation that relates year-to-year changes in the market value of a vehicle to observables, changes in gasoline price expectations, and a stochastic error term. Key to this approach are several assumptions: the market is always in equilibrium (rates of return across vehicle types are equalized instantaneously); vehicles with a certain set of characteristics are perfect substitutes; and vehicle life expectancy expressed in terms of miles does not vary systematically with fuel economy.[4]

To understand how new information (i.e., expectations about future gas prices) affects the equilibrium prices of vehicles, the ex-ante total rate of return for vehicle type i at time t, R_{it}, is defined as:

$$R_{it} = F(x^i, m_{it}) - g_t m_{it}/MPG_i ,$$ (1)

where $F(.)$ is a function of the gross level of hedonic benefits, net all expenses apart from fuel cost and depreciation. The gross level of hedonic benefits depends on physical vehicle characteristics, x, and the level of usage, m. Fuel expenditures depend on the real price of gasoline, g, usage, m, and the fuel economy of the vehicle, MPG. At the beginning of period t, the consumer chooses m to maximize R_{it} such that the price of vehicle type i in period t, P_{it}, in present value terms is defined as:

$$P_{it} = \sum_{s=0}^{T-t} \frac{E_t R^*_{i,t+s}}{(1+r)^s}$$ (2)

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[4] For small changes in expectations, the envelope theorem allows one to ignore the endogenous change in usage when estimating the impact of a change in exogenous gasoline price expectations on market value.

where $R*$ is the maximized value, and r is the rate of return on comparable assets. For expositional simplicity, Kahn (1986) assumed that a vehicle of type i yields a constant stream of gross hedonic rents until time T when the vehicle is scrapped (but with no residual value).

Substituting the expression for R_{it} into the price equation yields an expression for the price of the vehicle in terms of the present discounted value of the rental stream over the lifetime of the vehicle, net of gasoline expenses. Because we do not directly observe R or its determinants, Kahn (1986) derived an equation for the change in vehicle price in terms of observables and gasoline price expectations, which leads to the regression:

$$\frac{P_{i,t+1}-P_{it}}{P_{it}} = -\delta_{it} + \gamma DG_{it} + y_t + \varepsilon_{i,t+1} \tag{3}$$

where δ_{it} is the rate of depreciation, DG is the sum of the expected and unexpected changes in gasoline costs divided by price for vehicle type i in time t, y_t is a time fixed effect, and ε is the error term. The null hypothesis is that γ, the coefficient on DG, is equal to -1, reflecting that changes in gasoline prices are fully incorporated into the relative prices of vehicles.[5]

To operationalize the asset valuation approach empirically, researchers must make several key assumptions: for instance, what discount rate is used in private purchase decisions, consumers' expectations around future gasoline prices, the on-road fuel economy of the vehicle, and how much the vehicle will be driven over its lifetime. Below, we discuss how these assumptions compare across three

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[5] Data available to Kahn (1986) were quite limited; he only had 25 to 30 model types annually, for cars age one through five, and average price data. Fuel economy ratings were not yet available from the EPA. Kahn assumed that cars were driven 10,000 miles annually over a ten-year lifetime, used a 5 percent discount rate, and explored two types of gasoline price expectations: the best predictor of future (real) gasoline prices are current (real) prices at the time of sale; and a mean-reverting time series approximation. Using ordinary least squares, Kahn rejected complete adjustment of vehicle prices to changes in gasoline prices. However, attenuation bias due to measurement error of fuel price expectations would bias the coefficient estimates towards zero. After controlling for measurement error using an instrumental variable approach, he found that vehicle prices moderately under- or fully adjusted to changes in gasoline prices, depending on the mix of age, firm, and vehicle fixed effects.

longitudinal consumer valuation studies, the extent to which alternate assumptions are explored within a study, and, when possible, the sensitivity of the results to these assumptions.

3. Evidence from Longitudinal Studies

Three recent longitudinal studies have drawn on the asset valuation approach to evaluate whether vehicle prices fully reflect gasoline price changes as predicted by an asset pricing model: Sallee, et al. (2016), Allcott and Wozny (2014), and Busse, et al. (2013). Although they all used slightly different empirical strategies, the goal in each case was to compare a vehicle that is identical in every way except in future fuel costs. Future fuel costs differ for vehicles of the same type due to differences in the price of fuel over time and how much the vehicle will be driven over its remaining lifetime. We briefly describe each study's basic empirical approach before turning to a discussion of the data sources (3.1), key assumptions that underlie the fuel cost calculation (3.2), and the results (3.3). The results section also contains more detail about each study's empirical specifications.

Busse, et al. (2013) estimated reduced-form regressions for equilibrium vehicle prices and sales (as well as market shares) for new and used cars and light-duty trucks. Estimates of the effect of gasoline prices on vehicle price and quantity were then combined with future vehicle miles traveled (VMT), gasoline prices, and vehicle survival rates (and for new vehicles, the elasticity of demand) to examine how consumers' willingness-to-pay for vehicles of different fuel economies changes in response to gasoline prices. Key to their identification strategy was the inclusion of detailed "vehicle type" fixed effects that hold constant the make, model, model year, trim, doors, and other vehicle features to control for unobservable vehicle characteristics that may be correlated with fuel economy. This strategy was also employed by the other two studies discussed below.

Unique to Busse et al.'s (2013) specification is that the impact of gasoline prices was allowed to vary with the fuel economy quartile of the vehicle. Vehicle price for transaction i in region r on date t for

vehicle type *j* is a function of gasoline prices interacted with the miles-per-gallon (mpg) quartile of the vehicle (among all models offered in *t*), controlling for block-group demographics, the timing of purchase (end of year, end of month, and/or weekend), time (i.e., region-specific annual and monthly), and vehicle type fixed effects. For used cars, they also controlled for the odometer reading at the time of purchase to account for depreciation over time. Equilibrium sales are a function of gasoline prices interacted with the mpg quartile of the vehicle, mpg quartile, and time (region-specific annual and monthly), dealer, and mpg quartile fixed effects. When translating effects on equilibrium prices into willingness-to-pay measures, Busse et al. (2013) assumed supply is fixed in relation to gasoline price changes for used vehicles but upward sloping for new vehicles.

Allcott and Wozny (2014) derived their empirical specification from a static discrete choice modeling framework in which the typical market share specification for a used vehicle is inverted such that the price of vehicle model *j* of age *a* at time *t* is a function of its discounted remaining lifetime fuel costs, its relative market share, the average utility from using the vehicle over its lifetime, and a period-specific change in utility from its use. To translate this into an empirical specification, the market share for vehicle type *j* and age *a* at time *t* was moved into the error term; time dummies absorbed any changes in either overall market price or the no purchase share; and monthly dummies were interacted with an indicator variable to instrument for fuel economy (set equal to one when a vehicle of a certain type and age had fuel economy above the median, though they also examined specifications with more disaggregated fuel economy categories). The empirical specification is quite similar to that of Kahn (1986), where the null hypothesis is that the coefficient on fuel costs is equal to one, indicating that changes in fuel costs are fully incorporated into relative vehicle prices over time. As with Busse et al., they included detailed vehicle type fixed effects. The fuel economy indicator variable also was interacted with monthly time trends. Also similar to Busse, et al. (2013), they assumed the supply of used vehicles to be uncorrelated with gasoline prices, allowing them to move the market share into the error term.

Sallee, et al. (2016) outlined a conceptual model similar to Kahn (1986), where the price of a used

vehicle of type *i* at time *t* is a function of the expected discounted value of operating the vehicle over its

remaining lifetime (which relates to age or odometer readings) minus expected discounted fuel and

maintenance costs. They assumed vehicle supply is unrelated to gasoline expenses and therefore fixed.

Unlike the other studies, Sallee, et al. (2016) used month by vehicle type fixed effects to introduce a high

level of heterogeneity; depreciation schedules are unique to each vehicle type (via odometer readings).

3.1 Vehicle Data

Busse, et al. (2013), Allcott and Wozny (2014), and Sallee, et al. (2016) all relied on individual vehicle

transaction data from dealer sales and wholesale auctions, which gave them actual prices and allowed

them to control for vehicle types at a highly disaggregated level (Table 1). For instance, in Allcott and

Wozny, a vehicle "model" captured variations in make, nameplate, trim, body type, fuel economy,

engine displacement, number of cylinders, and design generation (e.g., the sample contained 11

different 2004 Honda Civic 'models'). The other two papers defined vehicle types at a similar level of

specificity. In Busse et al., vehicle "type" was the interaction of make, model, model year, trim level,

doors, body type, displacement, cylinders, and transmission. Sallee et al. had almost 9,500 unique

vehicle models or types, as defined by Vehicle Identification Number (VIN) stub, i.e., model name,

vintage, cylinders, displacement, and sometimes transmission and trim levels.

The data sets were large enough that both Busse et al. (2013) and Sallee et al. (2016) used a ten percent

random sample to make regression analysis computationally feasible. Alcott and Wozny (2014) relied on

transaction data from both wholesale and dealership auctions; Sallee et al. mainly relied on transaction

data from dealer sales at wholesale auctions;[6] while Busse et al.'s data reflected the prices paid by

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[6] Sellers at these auctions are typically dealers, manufacturers, governments, rental car companies or other
businesses that are often re-selling off lease vehicles, and the buyers are typically dealerships. While the main

consumers at dealerships. All three studies only included transactions through mid-2008 to limit the

effect of the recession on vehicle prices. To be included in the data set, vehicles must also have had a

fuel economy rating (e.g., post-1978) and a complete VIN stub, which contains information on many

vehicle attributes to more accurately match it to fuel economy.

Table 1: Vehicle Data Used in Longitudinal Studies

Authors (Pub. Date)	Transaction Data	Vehicle Types	Number of Observations	Vehicle Age	Vehicle Price Data Source	Omitted Vehicle Types
Busse, et al. (2013)	1999-2008, individual transaction	New & used cars & light trucks	~1.86 million (new); ~1.1 million (used)	0 -24 years old	Dealership sales	
Allcott & Wozny (2014)	1999-2008, individual transaction	Used cars & light trucks	~932,000	1-15 years old	Used vehicle dealer and wholesale auction sales	Vans, ultra-luxury, high performance, etc.
Sallee, et al. (2016)	1993-2008, individual transaction	Used cars & light trucks	~1.43 million	10,000 – 100,000 miles	Used vehicle wholesale auction sales	Diesel and hybrids

To ensure that the vehicle choice set from which buyers purchased consisted of true substitutes, all of

the studies limited their data sets to certain classes of vehicles. Allcott and Wozny (2014) defined this

choice set as all gasoline-fueled light-duty cars, trucks, SUVs and minivans less than 25 years old. They

excluded vehicles where the substitution elasticity is expected to be small (e.g., motorcycles,

motorhomes, limousines, cargo vans, and ultrahigh performance or ultra-luxury vehicles). Sallee, et al.

(2016) excluded diesels and hybrids and dropped used vehicles with fewer than 10,000 or more than

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results are based on vehicles sold by dealers, the authors explore a sensitivity using vehicles sold directly by the manufacturers or by fleet operators at auction.

100,000 miles, though they examined the inclusion of older vehicles as a sensitivity. Busse et al. (2013) excluded vehicles with more than 150,000 miles.[7]

3.2 Key Assumptions Underlying the Calculation of Expected Fuel Costs

Two of the studies presented results as the percent of expected fuel costs internalized into vehicle purchase prices by the market. This calculation relies on estimates of the expected future fuel costs over the remaining lifetime of the vehicle from the time of purchase, which is a function of the buyer's expectations about future gasoline prices, the vehicle's fuel economy and remaining mileage, and the discount rate. Busse, et al. (2013) estimated the implicit discount rate at which fuel costs would be fully internalized into vehicle purchase prices; as described below we translate these into a metric more readily comparable to the other studies' results. Table 2 summarizes how each component of this calculation was specified in the three recent longitudinal studies.

All of the studies relied on the EPA combined (city and highway) average fuel economy ratings. Allcott and Wozny (2014) used fuel economy ratings that incorporated a 2008 refinement to better reflect on-road use, while Busse, et al. (2013) and Sallee, et al. (2016) excluded this adjustment by relying on a vehicle's fuel economy rating at the time of sale. Allcott and Wozny (2014) also accounted for degradation in fuel economy over time at a rate of 0.07 miles-per-gallon annually.

Each study also emphasized the importance of the discount rate in determining the present value of future fuel costs. Sallee, et al. (2016) used a 5 percent private discount rate in their base specification, while Allcott and Wozny (2014) relied on a 6 percent private discount rate. As several of the authors noted, a 5 to 6 percent private discount rate is consistent with evidence on the average interest rate on car loans. However, borrowing rates could be higher in some cases, which may justify higher private

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[7] High-mileage vehicles brought to auction are expected to be in remarkably good condition or quite valuable, which makes them less substitutable with other used vehicles. Low mileage vehicles are also outliers.

discount rates. Allcott and Wozny and Sallee et al. explicitly examined the sensitivity of their results to different discount rate assumptions.

Busse, et al. (2013) did not assume a discount rate to estimate the percent of fuel costs internalized into the vehicle purchase price. As previously mentioned, they instead estimated the implicit discount rate at which consumers would fully internalize fuel costs into vehicle prices. They supplemented their paper with a spreadsheet tool that allows users to conduct their own sensitivity analyses and determine *either* the discount rate *or* the percent of fuel costs internalized, holding all other assumptions constant. We used this tool to determine the percent of fuel costs internalized in their model for a range of discount rates and other assumptions to facilitate comparisons with the results of the other studies.

Table 2: Key Assumptions that Underlie Fuel Cost Estimates

Authors (Pub. Date)	Fuel Economy	Discount Rates	Future Fuel Price Assumption	VMT/Vehicle Lifetime
Busse, et al. (2013)	Combined average EPA MPG rating at time of sale	Estimation outcome	Gasoline price at the time of sale; 6-, 12-, and 24-month futures	Vintage-based annual miles driven using their own data and NHTSA data, separately for cars and trucks, adjusted by average survival rates from NHTSA
Allcott & Wozny (2014)	EPA MPG rating, with 2008 in-use adjustment; degrades at 0.07 MPG/yr with age	6% (0% - 15% sensitivity)	Gasoline price at the time of sale; Oil futures-based forecast	Fitted values from regressing annualized NHSTA VMT data on class dummies and age, conditional on predicted survival probabilities with grouped probit model
Sallee, et al. (2016)	Combined average EPA MPG rating at time of sale	5% (10% sensitivity)	Gasoline price at the time of sale	Regressed predicted odometer readings for cars and trucks by age on actual odometer readings for make-specific measure of VMT relative to average using NHTSA data; used to adjust predicted mileage and survival probabilities

Another key input for estimating expected fuel costs is future gasoline prices. All three studies included scenarios in which gasoline price expectations were set equal to the monthly seasonally and/or

inflation-adjusted retail gasoline price at the time of vehicle sale. They supported this assumption by citing work by Anderson, et al. (2013) that found evidence that consumers expect future prices to resemble current gasoline prices. In addition, Busse, et al. (2013) and Allcott and Wozny (2014) examined scenarios in which consumers' gasoline price forecasts mirror oil futures markets. Busse, et al. (2013) examined gasoline price futures delivered in 6-, 12-, and 24-months, while Allcott and Wozny (2014) also assumed consumers form their gasoline price expectations based on information from oil futures markets up to six or seven years into the future.

The three studies estimated annual VMT based on assumptions about the probability that a vehicle survives through that year. Busse, et al. (2013) relied on vintage-based VMT for cars and trucks separately (generated from their own data as well as from NHTSA) and average survival rates from NHTSA. For used vehicles, they also included a spline in odometer reading at 10,000-mile intervals to account for the effect of depreciation on vehicle prices. Allcott and Wozny (2014) estimated annualized VMT from a subset of vehicles in NHTSA's 2001 National Household Travel Survey (NHTS). Annualized VMT was then regressed on class dummies and vehicle age to generate fitted vehicle type-age-year VMT values. A similar approach was used to generate vehicle predicted survival probabilities using a grouped probit model.

While Sallee, et al. (2016) relied on the same raw NHTSA data as Busse, et al. (2013) and Alcott and Wozny (2014) for average annual VMT and survival probabilities for cars and trucks as a function of vehicle age, they inverted the underlying formulas to define remaining vehicle mileage and the probability of survival as a function of the odometer reading. They then regressed predicted odometer readings for cars and trucks, separately, by age on actual odometer readings for each vehicle in the dataset by make to generate a measure of how much a specific vehicle type is driven relative to the average. This was used to adjust the predicted mileage and survival probabilities up or down, which

then allowed them to introduce more heterogeneous depreciation schedules than other studies (i.e., at the VIN stub level interacted with monthly time dummies).

3.3 Results

Table 3 presents a selection of results from the three recent longitudinal studies when using different assumptions about future gasoline price projections and the discount rate. In constructing Table 3, we focus on the used vehicle specifications across the three studies. (We return later to alternate specifications and the other key assumptions affecting future fuel costs.) We do not present standard errors in the table for ease of presentation. However, it is worth noting that the standard errors for the studies are quite small; the large volume of individual vehicle transactions data allows for estimation with a high degree of precision.

Table 3: Percent of Future Fuels Costs Internalized in Used Vehicle Purchase Price at Different Gasoline Price Expectations and Discount Rates (Reflecting Base Case Assumptions)

Authors (Pub. Date)	Future fuel price assumption	Discount rate assumption			
		3%	5%	6%	10%
Busse, et al. (2013)*	Gasoline price at time of sale	54-87%	60-96%	62-100%	73-117%
	24-month gasoline price futures	71-103%	78-114%	81-119%	96-139%
Allcott & Wozny (2014)	Gasoline price at time of sale	48%		55%	65%
	Oil futures based forecast	67%		76%	87%
Sallee, et al. (2016)	Gasoline price at time of sale		101%		142%

*Range represents results from comparing different quartiles of the fuel economy distribution.

Busse, et al. (2013) estimated the effects of future fuel costs on vehicle prices separately by fuel economy quartile. Thus, their results depend on which quartiles of the distribution are used for comparison. As previously mentioned, their results were presented in terms of the implicit discount rate that would fully internalize future fuel costs into vehicle purchase prices. Using retail gasoline prices at the time of sale and NHTSA VMT data to project future fuel costs, they estimated implicit discount rates

ranging from 6 percent to 21 percent in the used car market, depending on the fuel economy quartile comparison. Alternately, we can assume a given discount rate and use the authors' spreadsheet tool to calculate the percent of fuel prices internalized into the purchase price. Using this approach, we find that used car buyers internalize 62 percent to 100 percent of fuel prices using a 6 percent discount rate. We present similar calculations in Table 3 for alternative discount rates and future gas price projections using the spreadsheet tool and results from the study's online appendix. For several combinations of assumptions, the market appears to fully value or even overvalue future fuel prices.

Allcott and Wozny (2014)'s base specification used an instrumental variables estimator that grouped mpg into two quantiles to mitigate potential attenuation bias due to measurement error in fuel economy. Using gasoline prices at the time of purchase and a 6 percent discount rate to project fuel costs, they found that the used car market internalizes 55 percent of future fuel prices into purchase prices. Allcott and Wozny rejected the null hypothesis of full valuation of fuel costs except under discount rates exceeding 11 percent. The base specification used by Sallee, et al. (2016) (i.e., vehicles with odometer readings between 10,000 and 100,000 miles, static gas price expectations, and a 5 percent discount rate) cannot reject the null hypothesis that the used car market fully internalizes future fuel costs into purchase prices.

Table 3 demonstrates the importance of alternative discount rate assumptions. At discount rates of 5 to 6 percent, vehicle prices reflect 55 percent to 119 percent of expected future fuel costs, depending on the study and specification. At higher discount rates, results from the three studies show that the market appears to incorporate a greater percentage of future fuel costs into used vehicle prices; in fact, consumers appear to *over*-value future gasoline prices at higher discount rates in several specifications. At lower discount rates, the opposite is true with a range of 48 percent to 103 percent.

Table 3 also demonstrates the influence of assumptions regarding gasoline price expectations. Overall, for the 5 to 6 percent discount rate, vehicle prices reflect 55 percent to 101 percent of expected future fuel costs when fuel price expectations are based on gasoline price at the time of vehicle purchase, but between 76 percent and 119 percent when price expectations are based on oil futures. Because gasoline price futures were lower than prices at the time of sale during the study periods in Busse, et al. (2013) and Allcott and Wozny (2014), the market appears to internalize a higher proportion of fuel costs in vehicle prices when they are used as the fuel price expectation.

Table 4 shows the sensitivity of study results to vehicle age, as well as assumptions about key parameters such as vehicle mileage or survival probabilities. Each paper also presented additional sensitivity analyses.

Table 4: Percent of Future Fuel Costs Internalized in Purchase Price, Varying Other Key Assumptions

Authors (pub. date)	Basis of comparison	Lower VMT or survival probability	New/newer vehicles only	Oldest vehicles	More MPG groupings	More aggregate gas prices	Manufacturer or fleet operator sales
Busse, et al. (2013)*	62-100%	71-134%	75-129%			76-118%	
Allcott & Wozny (2014)	55%				49%		
	76%	84%	93%	26%	64%		
Sallee, et al. (2016)	101%			30%			70-86%

*Range represents results from comparing different quartiles of the fuel economy distribution.

While each study assumed a vehicle's lifetime mileage is independent of gasoline price changes, the results may still be sensitive to the underlying data used to forecast the probability that a vehicle survives another year and the annual number of vehicle miles traveled while in use. As shown in Table 4, two studies explicitly examined alternative specifications of VMT or vehicle scrappage rates. Busse et al.

(2013) found that the consumer valuation estimate increased when VMT was based on used vehicle transactions or trade-ins, which show lower annual VMT than NHTSA data. Allcott and Wozny (2014) found that when estimating vehicle survival probabilities using the cross-sectional age distribution observed in the NHTS, the estimated degree of valuation increased somewhat from 76 percent to 84 percent when future fuel prices were based on oil futures forecasts.[8]

Only Busse, et al. (2013) evaluated new vehicle purchases. Because the supply of new cars is elastic, determining the equilibrium vehicle price change in this market required estimates from both price and market share regressions, as well as assumptions about the elasticity of demand for new vehicles. When new vehicle demand was assumed to be relatively less elastic, then new vehicle prices appeared to reflect a greater degree of fuel costs than used vehicles, though there was still evidence of moderate undervaluation in some cases. If new vehicle demand was based on upper bound elasticity estimates, then the market appeared to incorporate less of the value of fuel costs in vehicle purchase prices. Allcott and Wozny (2014) presented results for used vehicles by age, including those that were one to three years old. While not new vehicles, their results demonstrated a pattern similar to Busse, et al.'s (2013) less elastic case; they found fuel costs more fully reflected in vehicle prices for newer vehicles (1-3 years old), and a much lower degree of valuation when limiting their sample to the oldest vehicles only (11-15 years old). Sallee et al. (2016) also found a significant decrease in the degree of valuation in purchases of older vehicles.

Allcott and Wozny (2014) only explored sensitivity of the results to a limited number of alternate specifications based on the fuel price at the time of vehicle purchase. One sensitivity they explored under both fuel price expectation scenarios was the effect of a change in the number of mpg groupings utilized. They found that the degree of fuel cost valuation decreased with more disaggregated mpg

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[8] The NHTS contains fewer observations of older vehicles than the vehicle registration data used in their base specification, which therefore should make lifetime fuel costs smaller for newer vehicles.

groupings (i.e., five to 10 mpg quantiles instead of just two) under both fuel price specifications. This difference reflected the tradeoff between using fewer larger groups to address measurement error that is correlated across observations and retaining variation when identifying from group-level aggregates. In addition, Busse, et al. (2013) used monthly, station-level gasoline price information to construct alternate gas price measures using different levels of aggregation. Their base specification, which allowed gasoline prices to vary across local markets, showed less internalization of fuel costs compared to nationally aggregated gasoline prices, an approach more comparable to the other studies. Finally, Sallee et al. explored the sensitivity of future fuel price shocks on transaction prices when varying the type of seller. As shown in the last column of Table 4, the estimates suggested modest undervaluation when focusing on sales by fleet operators or manufacturers instead of dealer sales.

4. Producer Side Considerations

To our knowledge, only Langer and Miller (2013) have examined what automakers' responses to changes in fuel prices imply about consumer valuation of vehicle fuel economy. They investigated to what extent automakers changed the cash incentives available to consumers in response to short-run fluctuations in gasoline prices to incentivize the purchase of relatively fuel-inefficient vehicles. If manufacturers exhibit this behavior, it implies that they believe consumers respond to expected fuel costs when purchasing a vehicle. Such behavior creates a disconnect – at least in the short run – between changes in fuel costs and the degree to which they are reflected in average vehicle prices. Thus, discrete choice model findings of less than full pass through that are based on market share and average prices instead of individual transaction price data may not be indicative of undervaluation by consumers; instead they may reflect the industry's attempts to mitigate the effects of fuel prices on vehicle sales and market share by subsidizing fuel costs.

Using disaggregated data on cash incentive programs offered by four automakers between 2003 and 2006, Langer and Miller (2013) regressed vehicle-specific cash incentives that varied by region and week on estimated vehicle fuel costs (proxied by the ratio of retail gasoline prices to miles per gallon), the weighted average fuel costs of its close competitors, and the weighted average fuel costs of other vehicles produced by the same automaker, as well as age polynomials and region, time, and vehicle fixed effects. Weights were based on the Euclidean distance between vehicle attributes such that vehicles with similar characteristics were assumed to be closer substitutes. The measure of a vehicle's expected cumulative fuel costs was predicated on the assumption that consumers use current gasoline prices to forecast future prices. Vehicle lifetime was assumed to be 14 years and miles per year were spread evenly over vehicle lifespan, which implies that SUVs and trucks are driven more intensively than cars. The authors explored the sensitivity of the results to discount rate (5 and 10 percent), vehicle lifetime (10 and 18 years), national rather than regional fuel prices and cash incentives, fuel costs based on four weeks' worth of historical gasoline prices instead of current prices, and weights reflecting different substitutability patterns across vehicles.[9]

Langer and Miller (2013) found that the cash incentives offered to consumers for a specific vehicle increased with own fuel costs and decreased with competitor fuel costs. On average, manufacturers offset approximately 40 percent of the changes in short-run fuel prices using cash incentives, assuming a 7 percent discount rate. The authors interpreted this result as a lower bound on the proportion of fuel prices internalized by consumers. For comparison with the estimates from the asset valuation literature in Table 1, they estimated a manufacturer offset of 36 percent using a 5% discount rate and 47 percent using a 10% discount rate. When Langer and Miller (2013) arranged the data into directly comparable MPG quartiles, they found remarkably similar results to Busse, et al. (2013) regarding the degree to

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[9] The alternative weighting schemes included equal weights across vehicles in the same segment – e.g., luxury cars; equal weights across vehicles of the same type – cars, trucks, SUVs; and equal weights across all vehicles.

which fuel costs were reflected in vehicle prices. Using subsample regressions, Langer and Miller (2013) also found that auto manufacturers responded more to changes in fuel prices in the car market (61 percent) than in either the sport utility vehicle (30 percent) or truck (18 percent) markets. They did not have a definitive explanation for this result but hypothesized that it may reflect either differences in the intensity of competition or in consumer preferences across these different market segments. Heterogeneity in consumer valuation by type of vehicle purchased was not emphasized in the three longitudinal studies in Section 5 but is a potentially important area for future research.

The sensitivity analyses by Langer and Miller (2013) revealed that the main estimate declined with discount rate (36 percent for a 5 percent discount rate) and vehicle lifetime (35 percent with an 18-year vehicle lifetime). They also found that the degree to which manufacturers offset short-run fuel price changes with cash incentives was sensitive to the weighting scheme utilized. When weights were equal within a vehicle segment, the average offset was similar to the main result: 43 percent. Weights that ignored vehicle heterogeneity introduced measurement error and biased the estimates toward zero (e.g. equal weights by vehicle type reduce the average offset of fuel price changes to 24 percent). Use of national gas prices and cash incentives raised the estimate of the average offset to 45 percent; use of historical instead of current gasoline prices increased it to 54 percent.

5. Consumer Valuation of Fuel Costs in Recent Regulatory Analysis

To estimate the value of fuel savings resulting from a tightening of light-duty vehicle emission or fuel economy standards, the analyst must compare projected fuel costs under the baseline scenario—the world without the new regulation—to fuel costs under the policy scenario. Estimating future fuel costs under both scenarios requires a series of assumptions about discount rates, vehicle lifetime, miles traveled, mpg achieved, and future fuel prices. In this section we summarize the assumptions used in

each step of this estimation process in recent regulatory analysis of federal light-duty vehicle greenhouse gas emissions and fuel economy standards.

The most recent final regulatory action governing light-duty vehicles was the joint EPA-NHTSA rulemaking that set greenhouse gas emission standards for model year 2017-2025 vehicles and fuel economy standards for model year 2017-2021 vehicles (U.S. EPA 2012). The analysis discounted future fuel costs at two different rates, per OMB guidance: 3 percent as a proxy for the social discount rate and 7 percent as a proxy for the opportunity cost of capital. For convenience, we mainly rely on the EPA's estimates for the remainder of this section.

Consistent with the studies discussed in Sections 3 and 4, the EPA used NHTSA data on vehicle survival rates and miles driven by vehicle age.[10] The EPA used projected future fuel prices from the Energy Information Administration's (EIA) Energy Outlook 2012 Early Release reference case forecast, as well as the high and low oil price forecasts as sensitivities, to calculate fuel savings. Specifically, future fuel savings that result from purchasing a more fuel-efficient vehicle were valued using the projected fuel price in each year in which reduce fuel consumption was expected to occur, which was then discounted back to the present and summed. This approach measures the actual expected consumer fuel savings, rather than the value consumers consider when purchasing a vehicle. The latter is used in the studies described in Sections 3 and 4, which rely on the empirical finding that consumers have static expectations about gasoline prices – i.e., that future prices will mirror the prices observed at the time of vehicle purchase (Anderson et al. 2013). Averaging the annual projected change in gasoline prices for

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[10] Unlike the studies in Section 3, the EPA did not assume that miles driven were constant across baseline and policy scenarios. Because improved fuel economy from tightened vehicle emission standards lowers the marginal cost of driving, vehicles may be driven more intensively under the policy scenario, an outcome known as the "rebound effect" (e.g., Greene et al. 1999; Small and Van Dender 2007). The EPA assumed that a 10 percent decrease in travel cost per mile would lead to a 1 percent increase in miles traveled and explored sensitivities from 0 to 20 percent. Incorporating a rebound effect lowers the estimate of fuel savings from the policy, all else equal, because the decrease in costs from improved fuel economy is partially offset by the increase in miles driven.

2017 to 2035 yields a small projected price increase of 0.8 percent. Thus, use of the EIA data

corresponding to the projected year in which reduced fuel consumption would occur would contribute

to a slight divergence between fuel costs considered by consumers at the time of vehicle purchase and

actual projected fuel costs, with the latter being slightly larger.

The EPA also assumed that in the baseline there would be no improvement in fuel economy beyond

existing regulatory requirements set by the model year 2012-2016 vehicle emission standards. The

EPA's technology model used the first five years of fuel expenses when deciding the order in which

technologies would be adopted to comply with the tightened standard,[11] but this approach was not

used in deciding whether or how technologies would be applied in the absence of the standards. Rather,

only the standard itself was assumed to drive additional investments in fuel economy.[12] This method of

calculating the benefits and costs of the regulation is consistent with the assumption that consumers do

not account for any fuel expenses in their vehicle purchase decisions.

Using a discount rate of 3 percent, the present value of the estimated fuel savings ($475 billion) from

the 2017-2025 model year car and light-duty truck greenhouse gas emission standards far outweighed

the present value of estimated compliance costs ($150 billion). The present value of fuel savings ($364

billion) also outweighed the present value of compliance costs ($144 billion) using a 7 percent discount

rate. These estimates suggest that there are substantial private benefits from improvements in fuel

economy beyond the model year 2012-2016 standards, with approximately 70 percent of the

discounted fuel savings occurring in the first 10 years of a vehicle's lifetime. The EPA's assumption that

none of these improvements would occur in response to market forces in the baseline scenario is

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[11] Five years of discounted fuel expenses is equivalent to 30 to 50 percent of future fuel costs, depending on the discount rate.

[12] Note also that vehicle sales were held constant for purposes of the analysis. The EPA did not examine the impact of the regulation on the decision of whether to delay vehicle purchases or to purchase a used instead of new vehicle.

consistent with the assumption that consumers internalize no future fuel savings associated with more fuel-efficient vehicles. Holding all else equal, the compliance costs, social benefits, and fuel savings from the regulation would all be smaller if EPA had incorporated some market adoption of fuel-saving technologies in the baseline.[13]

6. Potential Implications of New Empirical Evidence for Regulatory Analyses

Assumptions about consumer valuation of fuel costs are important in determining baseline adoption of fuel economy, and the estimation of the benefits and costs of a proposed change in the regulatory standard. If consumers fully value future fuel expenses at the time of purchase but do not adopt more fuel-efficient vehicles in the baseline, one possible explanation for this apparent paradox is that producer-side market imperfections limit the range of fuel economy offered to consumers. While it is possible that automakers, absent regulation, fail to offer the full range of fuel-saving options of interest to consumers—a hypothesis that is posited in the 2017-2025 rulemaking—few studies examine whether producer-side behavior leads to under-provision of fuel economy. Another (not mutually exclusive) hypothesis for why consumers might not purchase a more fuel efficient vehicle in the baseline is that the expected value of private fuel savings is offset by the full opportunity cost of purchasing the more fuel efficient vehicle. The full opportunity cost consists of both the cost of the fuel-saving technology that was added to the vehicle and any associated losses in other vehicle attributes that are valued by the consumer.[14]

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[13] The agencies conducted a sensitivity analysis in which they assumed market-driven improvements in fuel economy for technologies with a one-year payback period, beyond those required by the 2012-2016 standards. The agencies did not report the results of this sensitivity analysis, except to note that the costs, benefits, and fuel savings resulting from the new regulation were all smaller under this assumption.

[14] The potential for changes in other vehicle attributes due to the standards is not estimated by the EPA, nor is it addressed by the literature discussed in Sections 3 and 4. It is beyond the scope of this paper to assess how their treatment in regulatory analysis could be improved.

If instead consumers undervalue the cost savings generated by improvements in fuel economy when making vehicle purchase decisions, more stringent fuel economy standards can result in private net benefits due to mandating more fuel-efficient vehicles in the marketplace. Note that whether the regulation results in net private benefits does not determine whether it would be net beneficial overall; the quantified net benefits would also depend on the magnitude of the societal benefits resulting from a reduction in negative externalities.

Empirical evidence from the consumer valuation studies described in Section 3 suggests that vehicle purchase prices reflect about 50 to 100 percent of future fuel expenses, assuming static consumer expectations about future gasoline prices and a discount rate of five to six percent. Of these, only Busse, et al. (2013) examined new vehicles; they found that 75 to 100 percent of fuel expenses are reflected in new vehicle prices. Fuel savings calculations in recent regulatory analyses are consistent with consumers not valuing any future fuel expenses in the baseline, which is well outside of this range. Given the magnitude of the estimated fuel savings resulting from this methodology, consideration of alternate assumptions that incorporate the recent literature on consumer valuation of fuel savings is warranted.

The range of consumer valuation estimates from the empirical literature provides a starting point for use in regulatory analysis. Based on the handful of disaggregated panel data studies to date, regulatory agencies could assume that 50 to 100 percent of future fuel expenses are reflected in consumer vehicle purchase prices. The selected range should be applied consistently such that technologies that are projected to be adopted in the baseline should not contribute to the costs or benefits of new regulation. If consumers are assumed to fully consider future fuel expenses in their vehicle purchase decisions, then an increase in fuel economy in response to regulation should not yield net private benefits because in a properly functioning market any technologies that are net beneficial to consumers would have already been adopted in the baseline. As noted above, this does not speak to the net social benefits of a

regulatory change as those also depend on the magnitude of the social benefits from adopting fuel-saving technologies beyond what would occur in the baseline.

If consumers internalize less than 100 percent of future fuel expenses in their vehicle purchase decisions, then tighter regulations could yield net private benefits because fuel cost savings could outweigh the higher cost of vehicles. For instance, assume for expositional purposes that consumers use a 7 percent discount rate and consider eight years' worth of discounted fuel costs in their purchase decisions, which corresponds to internalizing about 60 percent of lifetime fuel costs. In the baseline, these assumptions imply that all fuel-saving technologies that cost less than the first eight years of discounted fuel savings will be adopted because consumers recognize that they will yield net private benefits absent regulation. Net private benefits in the policy scenario would only derive from the adoption of additional technologies that were not already adopted under the baseline: those that cost more than the first eight years of fuel savings but less than fuel savings over the entire vehicle lifetime.

The literature also provides insight into consumers' assumptions about future fuel prices when making vehicle purchase decisions. Anderson et al. (2013) found that consumers value future fuel costs based on fuel prices at the time of purchase. While regulatory agencies typically rely on EIA forecasts as the best available projection of future fuel prices, it is possible to utilize these data in a different way than has been done in the past. When projecting which technologies would be adopted by the market under the baseline and policy scenarios, analysts could assume that fuel prices remain constant at the level forecast for the time of purchase instead of allowing fuel prices to fluctuate over the lifetime of the vehicle (e.g., 2020 vehicle purchase decisions would be based on EIA-forecasted 2020 fuel prices). The fluctuating EIA price forecast would still be used to calculate the fuel savings realized after the vehicle is purchased, although it may be of interest to perform sensitivity analysis of the fuel price forecast when calculating the realized fuel savings from the regulation.

Finally, the literature notes that 5 to 6 percent are typical interest rates faced by consumers purchasing

vehicles in recent years (though firms may face higher interest rates when making capital investment

decisions). Private discount rates are the most appropriate to use when forecasting how firms and

consumers will make investment and purchasing decisions; they can be expected to make these

decisions based on their own opportunity costs rather than those of society as a whole. Therefore, a

private discount rate is most appropriate to use when examining consumer purchase responses and

running the technology adoption model to determine the level of fuel economy in both the baseline and

the policy scenarios. Those discount rates nevertheless do not reflect social intertemporal opportunity

costs for purposes of the benefit-cost analysis.

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