The Welfare Effects of Misperceived Product Costs: Data and Calibrations from the Automobile Market

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Abstract

This analysis exploits new data from the Vehicle Ownership and Alternatives Survey, which elicits beliefs over the financial benefits of owning higher-fuel economy vehicles. The data are used to test for underestimation and to document evidence of "MPG Illusion": consumers think as if fuel costs scale linearly in miles per gallon instead of gallons per mile. Counterfactuals suggest that the MPG Illusion reduces welfare by less than four dollars per new vehicle. Furthermore, even the most severe plausible underestimation of the financial benefits of fuel economy cannot account for the consumer welfare gains attributed to fuel economy standards.

JEL Codes: D03, D12, D83, D84, L91, Q41.

Keywords: Belief elicitation, bounded computational capacity, MPG Illusion, automobile demand, fuel economy standards, energy efficiency, behavioral welfare analysis.

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Consumers' choices depend both on preferences over outcomes and on beliefs about how choices map into these outcomes. Typical demand models assume that consumers have unbiased beliefs about how a product attribute maps into utility, implying that aggregate choice patterns map directly into underlying preferences. However, there is empirical evidence from different contexts that beliefs are sometimes systematically biased. For example, Starbucks customers tend to overestimate the calories in drinks and underestimate the calories in food (Bollinger, Leslie, and Sorensen 2011). People signing up for gyms are overconfident about their future attendance and about their likelihood of cancelling automatically-renewed memberships (DellaVigna and Malmendier 2006). More than 70 percent of seniors choosing between Medicare plans underestimate potential cost savings from switching (Kling *et al.* 2012).

This paper focuses on the choice of automobiles, one of the most expensive and complicated decisions that consumers make. In particular, I focus on consumers' beliefs about the differences in fuel costs between vehicles with different fuel economy ratings. This is motivated by recent work documenting that consumers are confused about the financial value of energy efficiency and that their beliefs may be systematically biased. Structured interviews by Turrentine and Kurani (2007) show that only a small fraction of vehicle owners are able to calculate the present discounted value of gasoline costs in the way that standard consumer choice models, taken literally, assume that they can. Furthermore, a set of lab experiments by Larrick and Soll (2008) document a cognitive bias called the "MPG Illusion," under which people intuitively think as if fuel costs scale linearly in miles per gallon (MPG). For example, people might perceive that the difference in gas costs between a 15-MPG vs. a 16-MPG vehicle is comparable to the difference between a 30-MPG and a 31-MPG vehicle, because both pairs differ by one MPG. In fact, the difference between the latter pair is about four times smaller, because fuel costs scale linearly in gallons per mile, not miles per gallon.

The distinction between whether choices are driven by misperceived product attributes versus true preferences has important economic meaning and policy consequence. In the former case, consumers are making mistakes which reduce their experienced welfare, and these mistakes can potentially be corrected through information disclosure or mitigated through other policies. However, if consumers do not systematically misperceive a product attribute, their choices reflect underlying preferences, and policies that distort those choices will reduce welfare.

Two potential forms of systematic misperceptions of the financial value of fuel economy have gained significant policy interest: systematic underestimation and the MPG Illusion. Systematic underestimation was one of the primary potential economic justifications for recent increases in the Corporate Average Fuel Economy standard, which requires automakers to increase the average fuel economy of new vehicle sales. The official Regulatory Impact Analysis for the increase in the standard for 2012 to 2016 argues that even without counting any benefits from externality reduction, about $15 billion per year in net benefits will flow to consumers as a result of owning higher-fuel economy vehicles that they do not currently demand. The proposed reason why consumers will benefit from being constrained to own different products is that we are currently making mistakes, including that our perceptions of the financial value of fuel economy might be systematically biased downward.[1] Without the assumption of misperceived product costs or some other investment inefficiency, the official cost-benefit analysis would have concluded that the 2012-2016 standards have a large net social *cost* – and the standards being promulgated for 2017 through 2025 are significantly more stringent (NHTSA 2011). Despite the significant policy implications, Parry, Walls, and Harrington (2007) argue in the Journal of Economic Literature that "there is little in the way of solid empirical (as opposed to anecdotal) evidence on this hotly contested issue"

Aside from systematic underestimation of the financial value of fuel economy, the MPG Illusion is a second systematic misperception that has garnered substantial policy attention. In 2010 and 2011, the U.S. Environmental Protection Agency engaged in a substantial effort to re-design the fuel economy information labels that dealerships must post on the windows of new vehicles (U.S. EPA 2011). The MPG Illusion was one of the several key motivations for redesigning the labels. The new labels continue to display fuel economy in miles per gallon, but they also report gallons per mile and emphasize the annual fuel cost under typical usage.

This paper asks three economic questions. First, to what extent are American automobile consumers subject to these two systematic biases, underestimation and the MPG Illusion? Second, to what extent do misperceptions affect allocations? Of particular interest is whether systematic underestimation of the financial value of fuel economy could significantly decrease the average fuel economy of vehicles purchased, which would increase the total private and social costs of gasoline usage and could perhaps justify policy interventions such as fuel economy standards. Third, what are the welfare costs of misperceptions? I answer these questions by parameterizing and empirically estimating beliefs and then using a simple discrete choice model to re-simulate demand in a counterfactual scenario with unbiased beliefs.

Beliefs are estimated using new data from the Vehicle Ownership and Alternatives Survey (VOAS). The VOAS is a nationally-representative 2100-person dataset that records demographic information, vehicles owned, and current expenditures on fuel. Using a carefully-designed set of questions, the VOAS elicits respondents' beliefs about their counterfactual fuel costs if they had instead bought the "second choice vehicle" that they had most closely compared against their current vehicle. The VOAS also elicits beliefs about counterfactual fuel costs for a hypothetical "replacement vehicle" that would be identical to their current vehicle, except with a randomly-

[1] In its Regulatory Impact Analysis of the 2012-2016 CAFE standards, the National Highway Traffic Safety Administration (2010, page 2) writes, "Although the economy-wide or "social" benefits from requiring higher fuel economy represent an important share of the total economic benefits from raising CAFE standards, NHTSA estimates that benefits *to vehicle buyers themselves* [original emphasis] will significantly exceed the costs of complying with the stricter fuel economy standards this rule establishes . . . However, this raises the question of why current purchasing patterns do not result in higher average fuel economy, and why stricter fuel efficiency standards should be necessary to achieve that goal. To address this issue, the analysis examines possible explanations for this apparent paradox, including discrepancies between the consumers' perceptions of the value of fuel savings and those calculated by the agency . . . "

The $15 billion dollar figure cited above is the annual average increase in consumer welfare (not including externality reductions) from NHTSA (2010), Table 13.

assigned difference in fuel economy. Respondents are told to assume that they drove these two alternative vehicles the same amount as their current vehicle. Because current fuel costs and the fuel economy ratings of the current vehicle and the two alternative vehicles are observed, the analyst knows the true value of counterfactual fuel costs. Comparisons of these true values against respondents' beliefs can be used to construct simple tests of the two potential systematic perceptual biases, systematic underestimation or overestimation and the MPG Illusion.

The data suggest that on average, consumers correctly estimate or slightly underestimate the difference in fuel costs between their first and second choice vehicles. However, the underlying mechanisms that generate this result are distinct when consumers compare pairs of vehicles with similar vs. more different fuel economy ratings. When comparing pairs of *similar* vehicles, some consumers miscategorize them as having "exactly the same" MPG and therefore incorrectly perceive zero difference in fuel costs, in a simple version of coarse thinking (Mullainathan, Schleifer, and Schwartzstein 2008). However, consumers that do perceive a difference in MPG between similar vehicles tend to overestimate the fuel cost differences, a result which may be related to contrast effects like those documented in Bhargava and Fisman (2012). Across consumers evaluating similar vehicles, coarse thinking and the contrast effect nearly offset each other. Consumers comparing vehicle pairs with very *different* fuel economy ratings do perceive a difference in MPG, and on average they correctly estimate or slightly underestimate the fuel cost differences.

The VOAS data also show clear evidence of the MPG Illusion. Consumers comparing low-fuel economy vehicles tend to underestimate the true fuel cost differences, while consumers comparing high-fuel economy vehicles tend to overestimate. This corroboration of Larrick and Soll's (2008) results is clearly visible graphically, appears not to be an artifact of the survey design, and is robust to a number of different ways of constructing the data.

To build on these empirical results, I formalize a discrete choice model of vehicle demand with misperceived product costs. Given the estimated belief parameters from the VOAS and a set of utility function parameters drawn from the literature, average preferences for different vehicles can be backed out from observed market shares. Along with van der Klaauw and Wolpin (2008), Delavande (2008a), Mahajan, Tarozzi, Yoong, and Blackburn (2009), and a few others, this analysis is innovative in that it analyzes both beliefs and preferences by combining data on elicited beliefs and observed choices.

The demand system allows me to calibrate a simple simulation of the short-run allocative effects and welfare losses from misperceived product costs, holding constant the choice set of vehicles. In a first set of simulations, I examine the effects of systematic underestimation or overestimation of fuel cost differences. One interesting policy implication comes from the lower bound case: the most severe underestimation that could possibly be justified by the VOAS data. In this case, the average fuel economy of vehicles sold is 0.77 MPG lower than in the optimum, and the net present value of short-run welfare losses is about \$95 per new vehicle, which equals about \$1.5 billion over the new vehicles sold in a typical year. This bound on short-run welfare losses from underestimation is an upper bound on the short-run welfare gains from a policy that attempts to correct this inefficiency. Interestingly, this is an order of magnitude less than the $15 billion in annual consumer welfare gains that are estimated to accrue from the current increment to the CAFE standard. Although this $15 billion estimate is "long-run" in that it depends on changes to the choice set of vehicles offered, I calculate that even within the long-run model, the lower bound empirical estimates from the VOAS cannot fully explain the apparent existing inefficiency. This study is therefore powerful in that it rules out misperceived product costs as a sole justification for fuel economy standards: some other inefficiency that reduces consumer welfare is required.

In a second set of simulations, I examine the effects of the MPG Illusion. Under the most likely parameter estimates, the MPG Illusion appears to increase the market shares of especially low-MPG vehicles and especially high-MPG vehicles by five percent or more per year by causing consumers to underestimate the fuel costs for these vehicles relative to medium-MPG vehicles. While these quantity effects are noticeable, the net present value of welfare losses averages only $4.45 per vehicle sold. Across all new vehicles sold in a typical year, this is about $71 million, or 0.018 percent of total market revenues. I document how these numbers vary with reasonable alternative assumptions around substitution patterns and the strength of the bias from the MPG Illusion.

These calibrations of the MPG Illusion, as well as those for systematic underestimation or overestimation, are also useful from a policy perspective in that they provide bounds on the welfare gains from a perfect information provision program that fully eliminates misperceived product costs. Because the fixed cost of updating the fuel economy information labels is small relative to the annual potential gains, it seems plausible that these benefits alone might justify the development costs unless the new labels are almost completely ineffective at debiasing consumers. Furthermore, there were other important reasons to develop the new fuel economy labels, primarily that they more clearly display energy cost information for electric vehicles. It would be interesting and important to extend this line of research by actually testing an information provision program using a randomized control trial.

The paper proceeds as follows. Section I discusses the economics literature on belief elicitation as well as several related papers on consumer choice in the automobile market. Section II details the Vehicle Ownership and Alternatives Survey. Section III formalizes the empirical tests of systematic misperceptions, and Section IV presents the empirical results. Sections V and VI present the methodology and results of the counterfactual simulations. Section VII concludes.

I Related Literature

A Belief Elicitation in Economics

The idea that it could be useful to combine belief data with observed choices in estimating preferences has developed substantial support (Manski 2004, McFadden 2000, 2006).[2] Most economic choices depend in some way on beliefs or expectations, and belief elicitation has been used to help understand choices in a variety of domains. An early area of interest was how individuals' expectations affect consumption, savings, and retirement decisions. This has included studies of beliefs of social security benefits (Bernheim and Levin 1989), portfolio returns (Dominitz and Manski 2007), life expectancy (van der Klaauw and Wolpin 2008), and future income (Dominitz 1998), among others.

In macroeconomics, elicited consumer confidence is a barometer of economic prospects, as discussed by Dominitz and Manski (2004), Ludvigson (2004), and others. Carroll (2003) and Mankiw, Reis, and Wolfers (2003) study inflation expectations, showing that consumers disagree and that individuals' beliefs tend to lag those of professional forecasters. This gave empirical foundations for new macroeconomic models of sticky information (Mankiw and Reis 2002). Studies such as Engelberg, Manski, and Williams (2009), Ehrbeck and Waldmann (1996), and Keane and Runkle (1990) test the rationality of expectations of professional macroeconomic forecasters and examine explanations for their biases.

Belief elicitation has also been used in labor, education, development, and other applied micro fields. In health care, takeup of preventive measures depends on expectations of the efficacy of the measures. Delavande (2008a) studies this in the context of birth control in the United States, while Mahajan, Tarozzi, Yoong, and Blackburn (2009) examine the adoption of antimalarial insecticide-treated bednets in India. Lochner (2007) shows how perceived arrest probabilities correlate with

[2] Manski (2004) writes, "The prevailing practice has been to assume that decision makers have specific expectations that are objectively correct (i.e., rational). This practice reduces the task of empirical inference to revelation of preferences alone, but has contributed to a crisis of credibility." He then argues for a combination of choice data with self-reports of expectations, which can be used to relax or validate assumptions about expectations.

Similarly, in his Nobel lecture (2000), McFadden argues that discrete choice models would benefit from incorporating realistic cognitive processes. He writes that "ultimately, behavioral economists need to move beyond stylized descriptions of choice behavior and become involved in market research experiments that explore directly the nature of economic choice processes . . . Discovery and exploitation of cognitive illusions in purchase behavior seems to coexist comfortably with the use of RUM-consistent discrete response models, adapted to use data on perceptions, as a major tool for predicting buyer behavior."

McFadden (2006) continues this line of argument: "The ideal rational consumer has the computational power to value complex commodities and consistently handle risk, discounting, and option calculations, and the logical clarity to work through the consequences of decisions and optimize choices. In practice, both computational and logical skills are limited. This may be inconsequential for repeated short-lived choices, such as picking out your breakfast cereal or deciding when to change lanes, but these limitations become critical for unfamiliar, not easily reversed choices, such as occupation, job change, house, automobile, children."

He then observes that "such processing deficiencies as disjunction and innumeracy do confuse choice," and argues that "even if individuals do not consciously "run the numbers" to determine choices, they still have to form perceptions and make judgments based on numerical information. The behavioral evidence is that innumeracy rates are high and significantly distort decisions."

individual characteristics and with future criminal behavior. Dominitz and Manski (1996), Jensen (2010), and Delavande and Kohler (2009) study perceived returns to schooling and educational choices. Gine, Townsend, and Vickery (2008) test how the expected timing of monsoons affects the timing of crop planting in India. Nyarko and Schotter (2002) show how beliefs affect play in laboratory games and document that players' actual beliefs differ from the assumptions around rational expectations or adaptive learning that would typically be made in the absence of belief data.

The literature in these diverse areas has built increasing credibility around beliefs elicited through surveys. The credibility of belief elicitation has been bolstered by findings that elicited beliefs predict observed behaviors, as shown in different contexts by Bernheim and Levin (1989), Lochner (2007), van der Klaauw and Wolpin (2008), Delavande (2008a), Gine, Townsend, and Vickery (2008), Mahajan, Tarozzi, Yoong, and Blackburn (2009). An additional approach to demonstrating the credibility of elicited beliefs has been to show that information provision causes people to update beliefs, as in Delavande (2008b) and Jensen (2010). These papers combined with earlier evidence cause Manski (2004) to argue that "we have learned enough for me to recommend, with some confidence, that economists should abandon their antipathy to measurement of expectations. The unattractive alternative to measurement is to make unsubstantiated assumptions."

The MPG Illusion is not the only documented example of systematically biased beliefs. For example, Bollinger, Leslie, and Sorensen (2011) show that consumers overestimate the calories in beverages and underestimate the calories in food products. McKenzie, Gibson, and Stillman (2007) document that residents of Tongo considering emigration to New Zealand underestimate their potential labor earnings. Jensen (2010) finds that the perceived returns to education among youth in the Dominican Republic are biased downward relative to his estimate of the actual returns. Other recent papers have documented that consumers choose contracts for mobile phones (Grubb 2009), health clubs (DellaVigna and Malmendier 2006), and credit cards (Shui and Aububel 2005) that do not minimize ex-ante expected costs, suggesting that they misestimate future product usage.

B Perceptions of the Financial Value of Fuel Economy

Turrentine and Kurani (2007) interview 57 northern California households about their most recent vehicle purchase. The sample included 14 households where at least one member worked in the financial services sector, had at least one college-level course that would have covered payback periods and net present value calculations, or otherwise had "high quantitative skills." Among other questions, the researchers asked people how much they would be willing to pay for a vehicle with higher fuel economy. Only two households arrived at plausible wilingness-to-pay answers through net present value calculations, and these two households had apparently not engaged in such a calculation when they had actually bought their vehicles. While this paper documents bounded computational capacity, it does not test whether perceptions of the financial value of fuel economy are systematically biased.

Allcott and Wozny (2011), Busse, Knittel, and Zettelmeyer (2012), Kahn (1986), and Sallee, West, and Fan (2009) test how much time series changes in gasoline prices affect the relative prices of low- vs. high-fuel economy vehicles. These papers are related to the present analysis in the sense that systematic overestimation or underestimation of the financial value of fuel economy could cause vehicle markets to be more or less responsive to gasoline prices than theory predicts. However, there are also factors other than biased beliefs that could cause vehicle markets to be less responsive to gas prices than a rational model would predict. For example, consumers might be inattentive to gas cost differences between vehicles, in the sense of Chetty, Looney, and Kroft (2009) or Gabaix and Laibson (2006). Under inattention, beliefs about cost differences may be systematically unbiased, but these cost differences are not salient when consumers are choosing between vehicles.

Attari *et al.* (2010) show that consumers overestimate the relative savings from household energy conservation activities that in fact save little energy, compared with activities that in fact save a lot of energy. This result may be consistent with the VOAS result that consumers overestimate cost differences when comparing vehicles that in fact have small cost differences. These results may also be distantly related to one element of prospect theory, that people overweight the probability of low-probability events (Kahneman and Tversky 1979). The effect observed in the VOAS is different in that it involves certain choices, not risky prospects, but it is conceptually related in that small factors are overweighted.

Larrick and Soll (2008) document the "MPG Illusion," a cognitive bias under which people perceive that fuel costs scale linearly in miles per gallon instead of gallons per mile. Figure 1 shows the annual fuel cost as a function of fuel economy in miles per gallon for a vehicle driven 12,000 miles per year and a gas price of $3 per gallon. The true difference in annual gas costs between an 11 MPG and a 13 MPG vehicle is almost exactly the same as the difference in annual gas costs between a 29 and a 49 MPG vehicle. This is counterintuitive for many consumers, because the differences in MPG ratings are so different. Figure 1 also includes an example of perceived annual fuel costs under what I will call the "full MPG Illusion," under which an individual perceives that fuel costs scale exactly linearly in miles per gallon.

Larrick and Soll (2008) document the MPG Illusion with three experiments. In their first experiment, participants were asked to rank order five pairs of vehicles in order of the reduction in gasoline use from switching from one to the other. The five pairs had MPG of 34 vs. 50, 18 vs. 28, 42 vs. 48, 16 vs. 20, and 22 vs. 24. Most people perceived that changing from 34 to 50 MPG saved the most gasoline, as this entailed the largest increase in MPG. In fact, that pair represents only the third largest savings. The 16 and 20 MPG pair of vehicles was ranked fourth out of five, as an improvement of four MPG appears small. In fact, that pair represents the second largest savings. Overall, sixty percent of participants ordered the pairs according to linear improvement in miles per gallon, whereas only one percent ordered the pairs correctly according to improvement in gallons per mile.

In Larrick and Soll's second experiment, participants were given a hypothetical vehicle purchase situation with a baseline model that gets 15 miles per gallon and a series of alternatives that were identical except for having higher fuel economy ratings. Most participants' willingness-to-pay for these vehicles showed a clear linear relationship with the MPG improvement, and people tended to underestimate the benefits of improving from 19 to 25 MPG and overestimate the benefits of improving to 55 MPG. Sixty-two percent appeared to base willingness-to-pay on linear improvement in miles per gallon, whereas only 15 percent based willingness-to-pay correctly on improvement in miles per gallon.

In their third experiment, participants were given a hypothetical choice situation which essentially asked whether replacing a 15 MPG vehicle with a 19 MPG vehicle saved more gasoline than replacing a 34 MPG vehicle with a 44 MPG vehicle. Three-quarters of participants preferred the latter replacement. In fact, the latter replacement saves less than half the gasoline as the former. A second group of participants had the choice framed in gallons per mile. This increased the share making the correct choice from 25 percent to 64 percent.

Larrick and Soll (2008) clearly document the phenomenon, but the Vehicle Ownership and Alternatives Survey allows three important improvements. First, the VOAS elicits beliefs over fuel costs for vehicles that the respondent actually owns or was considering buying, giving a more realistic choice situation. Second, the VOAS survey participants are in principle nationally representative, unlike the study participants in Larrick and Soll's experiments, giving fewer concerns about generalizability. Third, the nationally-representative VOAS data can be used not just to corroborate the existence of the MPG Illusion, but also to simulate its potential effects on market outcomes and welfare.

II Data

This section provides background on the Vehicle Ownership and Alternatives Survey. It describes the survey platform, outlines the questions asked, and presents descriptive statistics.

A The KnowledgePanel Survey Platform

The VOAS was administered through a platform called KnowledgePanel, which is operated by a private survey research company called Knowledge Networks. KnowledgePanel administers computer-aided self-interview surveys to a large panel of individuals across the 50 states. Each panel member takes approximately one survey per week. This survey platform has been used by other economists, including Heiss, McFadden, and Winter (2007) and Fong and Luttmer (2009).

All results presented later in this paper will be weighted to match the US population aged 18 and older on observable characteristics, as measured by the most recent Current Population

Survey. These sample weights are based on gender, age, ethnicity, education, census region, whether the household is in a Metropolitan Statistical Area, and whether it had internet access before recruitment.

While it is straightforward to re-weight any sample on the usual observable characteristics, the KnowledgePanel was chosen for this study because it is regarded as being relatively representative on other unobserved characteristics. Many surveys recruit either only through the internet or only via phone, thereby failing to sample people who do not use the internet or do not have phones. Knowledge Networks recruits both by phone, using Random Digit Dialing, and via mail, using Address-Based Sampling. As a result, KnowledgePanel includes households with both listed and unlisted phone numbers, cellular phones only, or no phone at all. Households without computers are given computers in order to complete the surveys.

All potential panelists are randomly selected to be invited to join the KnowledgePanel, while unselected volunteers are not able to join. Knowledge Networks engages in what they call "extensive refusal conversion," taking all reasonable steps to minimize non-response. For example, during phone recruitment, phone numbers are dialed at least 14 times if the phone is not answered, and incentives are given for completing the household demographic profiles. Of the invited households, just over 10 percent consented and completed the demographic profile to become a part of KnowledgePanel. Then, of the KnowledgePanel households invited to participate in the VOAS, 56 percent agreed to take the survey. In sum, although participants are likely to be unrepresentative on unobservables related to value of time and willingness to participate in surveys, the study population is as close as reasonably possible to being representative on unobservables.

B The VOAS Survey

The VOAS included four main sets of questions. Each respondent was asked comparable questions, although as will be described, respondents were randomized into one of 96 different versions of the survey questionnaire using a four-dimensional factorial design.

Part 1 asked about each person's "current vehicle," including the make, model, model year, engine size, whether manual or automatic transmission, and whether two-wheel or four-wheel drive. This level of precision allows an exact match to the U.S. Environmental Protection Agency's fuel economy rating for the respondent's current vehicle. This first set of questions also asked when the person bought the vehicle and how much he or she paid for it.

In Part 2, people were asked about fuel costs for their current vehicle. People were randomized into one of two frames, "Flow" and "Total." In the "Flow" frame, people were asked to report the flow of gasoline costs for their vehicle per week, per month, or per year. In the "Total" frame, people were asked how long they expected to own their vehicle and the total anticipated fuel costs over that future ownership period. The "Total" group was told in simple language to ignore consumer price inflation, so gasoline price expectations can be interpreted in real dollars.

Part 3 began by asking what vehicle the respondent would have bought if the model he or she actually did buy did not exist: the "second choice vehicle." As with the current vehicle, each person was asked to report the make, model, model year, and other details of the second choice vehicle, meaning that it also can be exactly matched to a fuel economy rating. Respondents were then asked if they thought that the fuel economy of their second choice vehicle was better, worse, or "exactly the same" as their current vehicle. People were then asked about the counterfactual fuel costs if they had instead bought their second choice vehicle. The Flow and Total question framing was maintained for each respondent, and people within each frame were additionally randomized into either the "Absolute" or "Relative" frame. In the "Absolute" frame, respondents were asked how much they thought they would spend on fuel if they owned their second choice vehicle. In the "Relative" frame, respondents were asked what they thought would be the additional savings or cost reduction for fuel for their second choice vehicle relative to their current vehicle.

In Part 4, people were asked about the counterfactual fuel costs if they instead owned a "replacement vehicle" that was the same as their current vehicle except that it got different fuel economy. The MPG difference was randomly selected from a set of 12 different values: -10, -8, -7, -5, -3, -2, 2, 3, 5, 7, 8, and 10. To give an intuitive sense of how these vehicles would look at a dealership, respondents were shown a list of seven vehicles, their pictures, and their MPG ratings. This display is reproduced as Online Appendix Figure A1. To keep cognitive burden low, each person was kept in the same frame (Flow vs. Total and Absolute vs. Relative) as in Parts 2 and 3, and the questions were worded similarly.

In each of Parts 3 and 4, people were clearly instructed to assume that they drove second-choice and replacement vehicles the same amount as their current vehicle. This means that differences in fuel costs result only from differences in fuel economy. Notice that because the fuel economy ratings of each vehicle are known exactly, the true difference in fuel costs between the current vehicle and the two alternative vehicles is exactly known. This will be central to the analysis that follows.

Aside from the two different types of frames and the randomly-selected replacement vehicle MPG difference, the fourth randomly-assigned dimension of the VOAS was into "Incentive" and "Non-Incentive" groups. The randomly-selected half of respondents in the Incentive group were told at the outset of the VOAS that they would receive up to $10, depending on how close their answers were to the "correct" answers. When asked about current gasoline prices in Part 2, this group was told that they would receive more money if their answer fell within the range of current gasoline prices in their area. When asked to report fuel cost beliefs for alternative vehicles in Parts 3 and 4, respondents were told that they would receive more money if their answer "makes sense" given their answers to other questions on this survey. In total, the VOAS included an average of 12 questions, depending on the frame to which respondents were assigned. Online Appendix I presents more detail on each of the survey questions.

Online Appendix II gives precise detail on several procedures that were run after the data were collected to flag a small number of responses that were outlying and seem to reflect confusion, lack of effort, or recall error instead of a respondent's true beliefs. First, respondents whose answers in Part 2 implied that their current annual vehicle-miles traveled were less than 108 or more than 200,000, the 1st percentile and top-code value, respectively, of the distribution in the National Household Travel Survey, were flagged in analyses of Parts 2-4. Second, answers to Parts 3 or 4 that were higher or lower than the implied correct value by an unusually large amount were also flagged. These procedures were fixed before I carried out any data analysis. Flagged data are not used in any part of the analysis that follows.

Online Appendix III presents descriptive evidence to substantiate the credibility of the belief elicitation. While one should in general be concerned about confusion over survey questions, lack of respondent effort, or recall error, there is no evidence that these factors meaningfully affect the estimation or policy conclusions. Furthermore, while in some cases belief elicitation surveys resort to artificial scenarios, the VOAS frames questions in ways that approximate actual choice situations. For example, many consumers do compare fuel costs when choosing between their first choice and second choice vehicles. It is thus more likely that the VOAS data reflect beliefs that American consumers act on at the time of choice.

C Descriptive Statistics

Table 1 presents descriptive statistics. The first panel comprises demographic characteristics. The rightmost column of Table 1 includes comparisons to the data from the National Household Travel Survey (NHTS), a survey of approximately 25,000 households that records demographic information, vehicle ownership, odometer readings, and many other variables. Like the VOAS, the NHTS is also weighted to be nationally-representative, so the means are comparable.

The second and third panels detail responses to questions in Parts 1 and 2. The average model year is 2001.6, about 1 year later than the average model year observed in the NHTS. This is consistent, given that the NHTS model year data were recorded just over one year before the VOAS. The fourth and fifth panels detail information on the "Second Choice Vehicle" from Part 3 and the "Replacement Vehicle" from Part 4.

In total, 2122 people completed the survey and were included in the sample weights. Of these, 108 reported that they do not own a vehicle and were exempted from the remaining questions, leaving 2016 respondents who could have answered questions in Parts 2-4. Observation counts lower than this reflect a combination of non-response and individual data points that were flagged and dropped. Notice that because only the "Total" frame group was asked how long they expect to own the vehicle, the Future Holding Period has observations for only about half the sample. Similarly, Current Fuel Price and Future Fuel Price expectations were only elicited from the Flow and Total frames, respectively.

As detailed earlier, respondents were randomly assigned into cells in a four-dimensional factorial design. The dimensions were "Total" vs. "Flow" framing, "Relative" vs. "Absolute" framing, Incentive vs. non-Incentive groups, and the fuel economy difference between their current vehicle and the hypothetical "replacement vehicle" in Part 4. The randomization was successful: F-tests reported in Online Appendix Table A1 fail to reject that demographic characteristics are balanced across each of the randomizations.

III Empirical Strategy

This section presents an empirical strategy for testing for misperceived product costs using data from the Vehicle Ownership and Alternatives Survey. I first construct a "valuation ratio," which reflects each respondent's valuation of the fuel cost difference between his current vehicle and an alternative vehicle. Second, I present a straightforward test of systematic underestimation or overestimation of the financial value of fuel economy. Third, I present tests of the MPG Illusion.

A Valuation Ratios

A consumer's fuel costs in a given vehicle are the product of vehicle-miles traveled (VMT), the price of gasoline per gallon, and the vehicle's energy intensity rating in gallons per mile, which is the inverse of fuel economy in miles per gallon. Denote these three variables as m_i, g, and e_j^*, respectively, where i indexes consumers and j indexes vehicles. The fuel cost per unit time is:

$$G_{ij}^* = m_i g e_j^* \tag{1}$$

The current vehicle fuel costs reported in Part 2 of the VOAS can be used to determine the fuel costs for any alternative vehicle of a different MPG, if the alternative vehicle is driven the same amount. Denote the current vehicle as $j = o$ and the alternative vehicle as $j = a$. In the VOAS, each respondent has two alternative vehicles, the "second choice vehicle" from Part 3 and the "replacement vehicle" from Part 4. The true fuel costs for an alternative vehicle are simply the fuel costs for the current vehicle scaled by the ratio of the fuel intensities.

$$G_{ia}^* = G_{io}^* \frac{e_a^*}{e_o^*} \tag{2}$$

Given the reported fuel costs G_{io}^* from Part 2, this G_{ia}^* is the correct value for annual fuel costs for alternative vehicles in Parts 3 and 4. The variable $\widetilde{G}_{ia}$ denotes respondent i's belief about fuel costs for vehicle a, as reported in Parts 3 and 4. Throughout the paper, true values will be adorned with a star and consumers' perceptions with a tilde.

To capture how person i perceives the financial value of a difference in fuel economy, I construct a "valuation ratio" denoted ϕ_{ia}. This variable reflects the percent of the true difference in fuel costs between consumer i's current vehicle and an alternative vehicle that the consumer perceives:

$$\phi_{ia} \equiv \frac{\widetilde{G}_{ia} - \widetilde{G}_{io}}{G^*_{ia} - G^*_{io}} = \frac{\widetilde{e}_a - \widetilde{e}_o}{e^*_a - e^*_o} \tag{3}$$

The denominator is the true fuel cost difference between the current vehicle and the alternative vehicle being evaluated in Part 3 or 4, as implied by the consumer's reported current fuel costs. The numerator is respondent i's belief about that difference. Under perfect beliefs, ϕ_{ia} would equal one. If $\phi_{ia} > 1$, the consumer overestimates the financial value of the fuel economy difference between the two vehicles. If $\phi_{ia} < 1$, the consumer underestimates that value. The value of ϕ_{ia} is undefined and coded as missing if $e^*_a = e^*_o$. Conceptually, this is desirable because a consumer evaluating two vehicles with the same fuel economy cannot reveal how he or she values a difference in fuel economy.

As an example of how this variable is constructed, consider respondent number 360 in the VOAS. She owns a 15 MPG Jeep Grand Cherokee, and her second choice vehicle was a 24 MPG Subaru Legacy Wagon. She expects to hold the Jeep for another two years and spend \$2400 total on gas over that time. Compared to the Jeep, she believes that she would be spending \$1200 less on gas for the Subaru. In reality, if she had the Subaru and drove it the same amount, she would spend $\$2400 \cdot 15/24 = \$1500$ on gas, or \$900 less. The value of ϕ_{ia} for her second choice vehicle is thus $\frac{1200-2400}{1500-2400} = 1.33$.

The second equality in Equation (3) clarifies that the ϕ variable effectively reflects a difference in perceived energy intensity, and it is invariant to multiplicative effects on fuel costs for the current and alternative vehicles. This invariance covers four potentially-relevant cases. First, in 2008 the EPA retroactively adjusted fuel economy ratings for vehicles from previous model years. This adjustment was essentially a common multiplicative increase in the energy intensity rating of all vehicles of a given model year, and the adjustment factor increases slightly over the model years from 1985 to 2008. The TESS dataset is constructed with each vehicle's original fuel economy rating, not the retroactive rating from 2008. However, because ϕ is invariant to common multiplicative changes in energy intensity ratings, as long as the current vehicle and alternative vehicle do not have very different model years, using the adjusted ratings would not noticeably change the results. The median absolute difference in model years between people's first and second choice vehicles in the VOAS data is one year.

Second, depending on driving patterns and maintenance decisions, any consumer's realized fuel economy may be different than the EPA's estimate. Even if people are aware of this, it also does not affect ϕ as long as people believe that their idiosyncratic behaviors affect their realized fuel intensity equally in all vehicles. In general, this will be a reasonable assumption.

Third, consumers may mis-report the fuel costs G^*_{io} for their current vehicle. This is certainly possible: Table 1 shows that the national average vehicle-miles traveled implied by VOAS respondents' reported fuel costs is somewhat less than the national average VMT estimated using the NHTS. Equation (3) shows that as long as people's errors in assessing m_i and g are common to both the current vehicle and the alternative vehicle under evaluation, which would be a natural assumption, the value of ϕ is unaffected. In other words, ϕ should still be interpreted as a misperception of relative energy intensity of two vehicles, even if respondents don't know their exact fuel costs.

Fourth, as documented in Allcott (2011), consumers have differing expectations of future gasoline prices. For VOAS respondents in the Total group, beliefs are elicited for total future fuel costs for the current and alternative vehicles, which of course depend on expected gas prices. However, as long as we assume that respondents implicitly use the same expected fuel price g for all vehicles, the value of ϕ is unaffected. While this assumption is usually quite natural, one reason it might be violated is if a consumer has first and second choice vehicles with different manufacturer-recommended gasoline types, primarily premium vs. regular. This affects a small number of consumers, and adjusting for it does not affect the empirical results.

Of course, consumers' perceptions of vehicles-miles traveled m_i and future fuel costs g could also be systematically biased, and focusing on ϕ ignores these potential sources of error. I do not study misperception of VMT because it proved infeasible to gather observed odometer readings in the VOAS, meaning that there is no true value of m_i against which to compare beliefs. I do not study misperception of future fuel costs because there is no objectively correct value of future fuel costs other than their realized values. To test for rational expectations of g, one would want to repeat the VOAS many times over a sufficient number of years or decades in order to average over idiosyncratic oil price shocks. Allcott (2011) and Anderson, Kellogg, and Sallee (2011) test whether consumers' expectations of future gas prices are consistent with current prices and oil futures, but this is conceptually distinct from the misperception studied here.

B Testing for Systematic Underestimation or Overestimation

Each VOAS respondent has two values of ϕ_{ia}, one for the difference between the current vehicle and second choice vehicle in Part 3, and one for the difference between the current vehicle and the hypothetical "replacement vehicle" in Part 4. Does the average consumer systematically overestimate or underestimate the financial value of fuel economy? A simple way to calculate the mean ϕ and the standard error of the mean is to regress it on a constant:

$$\phi_{ia} = \gamma + \varepsilon_{ia} \tag{4}$$

The regression is weighted to be nationally-representative, and standard errors are robust. One also might be interested in the median value of ϕ, so I therefore also present quantile regressions that estimate the 50th percentile of ϕ.

I consider two mechanisms that could cause consumers to misperceive fuel cost differences between the first and second choice vehicles. First, consumers might mistakenly categorize two vehicles as being exactly the same, in a simple version of "coarse thinking" (Mullainathan, Schleifer, and Schwartzstein 2008). This might be more likely for vehicles that are more similar. Second, given a belief that two vehicles do have different MPG, consumers might underestimate or overestimate the resulting fuel cost differences.

The VOAS offers the unique opportunity to independently observe these two mechanisms. In Part 3, respondents report whether they believe that their current vehicle has better, worse, or "exactly the same" fuel economy as their second choice vehicle. This captures the first mechanism. In Part 4, consumers are given a hypothetical vehicle with a specified difference in fuel economy and asked to translate this difference in MPG rating into a difference in fuel costs. This captures the second mechanism. We also observe the combination of the two mechanisms through the difference in fuel costs for the first and second choice vehicles elicited in Parts 2 and 3.

C Testing for the MPG Illusion

Under Larrick and Soll's (2008) MPG Illusion, consumers perceive that gasoline costs scale linearly in miles per gallon instead of in gallons per mile. I now formalize that bias mathematically and detail both suggestive empirical tests and a formal approach to estimating the extent of the MPG Illusion.

Although they presumably would not use this language, consumers subject to the MPG Illusion effectively perceive that the first-order Taylor expansion of fuel costs as a function of fuel economy around some reference point holds over the entire support of the MPG distribution. Defining fuel economy in miles per gallon as $f = 1/e$ and denoting the "reference fuel economy" as f_r, the MPG Illusion can be formalized as:

$$\widetilde{G}_{ij} = G_i^*(f_r) + \frac{\partial G_i^*}{\partial f^*}|_{f^*=f_r} \cdot (f_j^* - f_r) \tag{5}$$

This equation matches the dashed red line in Figure 1. Perceived gasoline costs are approximately correct in the neighborhood of f around f_r. As fuel economy f_j^* increases, however, the consumer perceives that the cost reduction from an incremental increase in fuel economy, $\frac{dG_i}{df^*}|_{f^*=f_r}$, remains constant. In reality, it decreases.

With a few lines of algebra, one can derive perceived fuel intensity under the MPG Illusion $\widetilde{e}_j^I$ as a function of true fuel intensity e_j^*:

$$
\begin{aligned}
m_i g \widetilde{e}_j^I &= m_i g e_r + \frac{\partial(m_i g f^{*-1})}{\partial f^*}|_{f^*=f_r} \cdot (f_j^* - f_r) && (6)\\
\widetilde{e}_j^I &= e_r - f_r^{-2} \cdot \left(f_j^* - f_r\right) \\
&= 2e_r - \frac{e_r^2}{e_j^*} && (7)
\end{aligned}
$$

Of course, the average consumer may not be subject to the "full MPG Illusion": perceptions might be somewhere between the first-order Taylor expansion and the true value. I therefore allow consumers' perceived fuel intensity $\widetilde{e}_j$ to be the weighted average of the true fuel intensity e_j^* and the perceived fuel intensity under the full MPG Illusion $\widetilde{e}_j^I$. The weighting parameter $\lambda \in [0,1]$ captures the extent to which consumers are subject to the MPG Illusion. This weighting parameter will feed directly into the counterfactual simulations: it tells the simulation how biased consumers' perceptions are, and thus mechanically drives the estimated welfare gains from eliminating the MPG Illusion.

The equation for perceived fuel intensity $\widetilde{e}_j$ is thus:

$$
\widetilde{e}_j = \lambda \widetilde{e}_j^I + (1-\lambda)\, e_j^* \tag{8}
$$

The empirical observations of ϕ from the VOAS can be used to estimate λ. Substituting the definition of $\widetilde{e}_j$ under the MPG Illusion from Equation (8) into the definition of ϕ from Equation (3), we have the ϕ for a consumer whose only calculation error is from the MPG Illusion:

$$
\begin{aligned}
\phi_{ia} &= \lambda \cdot \frac{\widetilde{e}_{ia}^I - \widetilde{e}_{io}^I}{e_{ia}^* - e_{io}^*} + (1-\lambda) \cdot 1 && (9)\\
&= \lambda \cdot \frac{-e_r^2 \left(e_{ia}^{*-1} - e_{io}^{*-1}\right)}{e_{ia}^* - e_{io}^*} + (1-\lambda) \cdot 1
\end{aligned}
$$

Intuitively, ϕ will be the λ-weighted average of the ϕ under the full MPG Illusion and the $\phi = 1$ with no bias. As fuel intensities e_{io} and e_{ia} decrease by an equal amount, meaning that the consumer is considering higher-MPG vehicles, the fraction multiplying λ becomes larger in absolute value, making ϕ_{ia} larger. This is the mathematical restatement of how the MPG Illusion causes consumers to understate the cost difference between low fuel economy vehicles and overstate the cost differences between high fuel economy vehicles.

Figure 2 plots ϕ as a function of fuel economy for $\lambda = 0$, 1/4, 1/2, and 1. The curve crosses unity at the reference MPG f_r and has slope that depends on λ, which captures the extent of the

MPG Illusion. If consumers' perceptions are unaffected by the MPG Illusion, the slope is flat. The more that perceptions are affected by the MPG Illusion, the steeper the slope.

The upward slope of ϕ as a function of the fuel economy of vehicles under consideration suggests two basic illustrative tests for the MPG Illusion. Both tests will use a variable $\overline{f}_{ia}$, defined as the harmonic mean fuel economy rating of respondent i's current vehicle and alternative vehicle: $\overline{f}_{ia} = \frac{1}{(e_{io}+e_{ia})/2}$. The first is to graph locally-weighted regression estimates of ϕ as a function of $\overline{f}_{ia}$. The second is to use linear regressions to test whether ϕ slopes upward in $\overline{f}_{ia}$:

$$\phi_{ia} = \alpha_1 \overline{f}_{ia} + \alpha_0 + \mu_{ia} \tag{10}$$

If the basic illustrative tests show evidence of the MPG Illusion, the belief parameters λ and e_r can also be estimated using the values of ϕ. An empirical analogue to Equation (9) can be derived by adding a mean-zero error term υ and re-arranging:

$$(\phi_{ia} - 1) = \left(\lambda e_r^2\right) \cdot \frac{f_{io}^* - f_{ia}^*}{e_{ia}^* - e_{io}^*} + \lambda \cdot (-1) + \upsilon_{ia} \tag{11}$$

This equation can be estimated using least squares, again with nationally-representative sample weights and robust standard errors clustered by respondent i.

IV Results

A Systematic Underestimation or Overestimation

A.1 Graphical Results

Figures 3 and 4 illustrate the distribution of ϕ for beliefs elicited in Parts 3 and 4, respectively. The orange section at the top of the bars reflects observations flagged by the procedure described in Online Appendix II. These values are omitted from all analyses other than this graph. The dark blue bars reflect the distribution of valid valuation ratios. As with all figures, tables, and analyses in this paper, the observations are weighted by the VOAS sample weights to generate a distribution of ϕ that is representative of the U.S. population.

If all respondents had perfect information and unbounded computational capacity, the distributions would have a point mass at $\phi = 1$. In reality, the reported ϕ's are very dispersed. Approximately 57 percent of respondents report a ϕ for their second choice vehicle that is less than 0.5 or greater than 1.5. That is, 57 percent of consumers mis-report the difference between the gasoline costs for their current and second choice vehicles by more than 50 percent. The standard deviation of ϕ across Parts 3 and 4 is 2.17.

The ϕ variable represents the percent by which a respondent has mis-reported relative fuel costs. Is this large in an absolute sense? Sixty-nine percent of respondents estimated a fuel cost for their second choice vehicle that was within \$200 of the true annual fuel cost. As one comparison statistic, a typical vehicle depreciates by an average of \$2000 per year over its first ten years of life. This means that 31 percent of U.S. vehicle owners misestimate their second choice vehicle's annual fuel costs by more than 10 percent of the depreciation costs.[3]

Two features of Figure 3 stand out. First, there are a number of negative values: the data suggest that 23 million U.S. vehicle owners do not correctly know the *order* of fuel economy ratings of their current and second choice vehicles. Of these people, about 81 percent are comparing vehicles that in fact differ by two MPG or less. Second, there are a large number of consumers with $\phi = 0$, meaning that their first and second choice vehicles in fact have different fuel economy ratings, but they incorrectly perceive that the ratings are exactly the same. Of these people, about 74 percent are comparing vehicles that in fact differ by two MPG or less. By contrast, Figure 4 has a much smaller mass at $\phi = 0$ compared to Figure 3: very few respondents report the same fuel cost beliefs for the hypothetical replacement vehicle after being explicitly told that the vehicle had a different MPG rating. Largely because of this smaller mass at $\phi = 0$, we can foresee the empirical result that the average ϕ for Part 4 will be larger than for Part 3, especially for vehicle pairs with similar MPG ratings.

Figures 5 and 6 provide additional insight into the mechanisms causing belief errors. Figure 5 shows the probability of miscategorizing the first and second choice vehicles as having "exactly the same" fuel economy rating, as a function of the true difference in fuel intensity. As we see on the left side of the figure, about 25 percent of consumers miscategorize MPG as exactly the same when comparing vehicles that differ by less than 0.01 gallons per mile. When comparing vehicles with increasingly different fuel economy ratings, consumers are increasingly unlikely to miscategorize. This illustrates how the mass with $\phi = 0$ for second choice vehicles in the previous Figure 3 is largely consumers comparing very similar first and second choice vehicles.

Figure 6 shows the average valuation ratio ϕ as a function of the difference in fuel intensity between the current and alternative vehicle for both Part 3 and Part 4. Consider first the left side of the graph, which illustrates consumers comparing vehicles with similar fuel economy ratings. In Part 4, when considering a replacement vehicle with known MPG difference, it is clear that consumers overestimate the difference in fuel costs, giving an average ϕ above 1.5. This related to the contrast effect: when comparing vehicles that are similar but known to be different, consumers overstate the importance of the difference.

The average γ for similar-fuel economy second choice vehicles from Part 3 depends on two

[3] The 57 percent and 31 percent figures in this subsection exclude values of ϕ that differ from unity by an amount that can be explained by rounding error. To determine what apparent misperceptions can be explained by rounding error, I implement a procedure suggested by Manski and Molinari (2010). (This procedure is not used for other results in this paper because rounding error only affects the dispersion of ϕ, not any systematic patterns. All other results in this paper are robust to excluding values of ϕ whose deviations from unity can be explained by rounding error.)

effects. First, some consumers miscategorize the MPG ratings as exactly the same. Second, those that perceive different MPG ratings overestimate the fuel cost differences. The left side of Figure 6 illustrates how the net effect is an average valuation ratio ϕ in Part 3 that is equal to or slightly less than one.

Now consider the right side of Figure 6, which illustrates the average valuation ratios for consumers comparing vehicles with a larger difference in fuel economy ratings. In both Part 3 and Part 4, the valuation ratios are equal to or slightly less than one on the right side of the graph. The fact that the valuation ratios for the two parts are comparable reflects what we saw on the right side of Figure 5: consumers comparing very different vehicles are unlikely to miscategorize them as having the same MPG rating.

A.2 Statistical Results

Having presented the data graphically, I now present the basic statistical tests of overestimation or underestimation of the value of fuel economy. Because Parts 3 and 4 are informative about different sources of belief errors, Table 2 present the regressions separately for each part. As in all other regression tables, standard errors are in parenthesis, and the regressions are weighted to be nationally representative. In this table only, the stars correspond to tests of whether the coefficients differ from one, corresponding to a test of $\gamma = 1$.

Column (1) uses all (non-flagged) values of ϕ, which are the same values in dark blue in Figures 3 and 4. Column (2) presents results for the subset of respondents comparing vehicles that differ by more than 0.01 gallons per mile, which is exactly the difference between a 20 MPG vehicle and a 25 MPG vehicle and approximately the difference between a 15 MPG vehicle and an 18 MPG vehicle. We have already seen these results visually on the right side of Figure 6. The mean and median values of ϕ are equal to or slightly less than one, and the estimates are statistically less than one in three of the four regressions. This shows that consumers tend to either correctly estimate or slightly underestimate the value of fuel economy when comparing vehicles that are sufficiently different.

Column (3) presents results for the complementary set of respondents: those comparing vehicles that differ by less than 0.01 gallons per mile. Recalling Figure 6, we know that the values will be slightly less than one for Part 3 and significantly more than one for Part 4.

Column (4) repeats Column (3) but omits respondents that have $\phi = 0$. The results for Part 4 do not change much, as few people report the same fuel costs for vehicles that they are explicitly informed have different MPG. In Part 3, however, the point estimates of the mean and median ϕ are now larger than one, and the median ϕ is statistically significantly larger than one. Furthermore, although the mean ϕ's in Column (4) differ between Part 3 and Part 4, the point estimates of the medians are very similar and are not statistically distinguishable. This suggests that the Part 3 result that $\gamma < 1$ for consumers comparing similar vehicles is largely driven by consumers who miscategorize vehicles as having exactly the same MPG.

Because the average respondent purchased his vehicle five years before the VOAS survey, one might be concerned that recall error could be a potential confounding factor. To test this, I replicated Table 2, except with a linear control for time since purchase, which is a reasonable measure of the probability of recall error. Since higher-income people tend to have purchased vehicles more recently, the regression also controls for the deviation from average of log(Income). The estimated mean and median ϕ in this regression are thus the predicted values for a respondent who has mean log(Income) and has just bought the vehicle. Time since purchase is not strongly associated with ϕ, and the qualitative results are unchanged. The regression results are included as Online Appendix Table A2.

B The MPG Illusion

B.1 Graphical Results

Recall that consumers subject to the MPG Illusion perceive as if fuel costs scale linearly in miles per gallon instead of gallons per mile. This causes them to systematically underestimate the fuel cost differences between pairs of low-MPG vehicles and systematically overestimate the differences between pairs of high-MPG vehicles. Thus, a graph of ϕ against the harmonic mean MPG of the current and alternative vehicles should be upward-sloping.

Figure 7 graphs ϕ as a function of $\overline{f}_i$, using an Epanechnikov kernel-weighted local mean smoothing procedure. The line has a clear upward slope. Figure 7 also includes the point estimates of the the same functions estimated separately for the values of ϕ from Parts 3 and 4. While the means for Part 3 are lower at all values of $\overline{f}$ because of the larger number of $\phi = 0$ observations, both lines have a comparable upward slope.

The MPG Illusion parameter λ is identified from the slope of Figure 7. As shown in Figure 2, the more steeply sloped the relationship between ϕ and $\overline{f}$, the higher λ will be. On Figure 2, the line for $\lambda = 1/4$ goes from ϕ just larger than 0.8 at 10 MPG to $\phi \approx$1.5 at 35 MPG. On Figure 7, the mean of ϕ goes from just less than 0.9 at 10 MPG to slightly above 1.4 at 35 MPG. Thus, we should expect that the estimated value of λ would be approximately 1/4.

The reference fuel intensity e_r is the fuel intensity at which consumers correctly perceive the financial value of a marginal increase in fuel economy. In Figure 1, this is the point where the MPG Illusion line is tangent to the true cost line. In Figure 2, this is where the average valuation ratio curve crosses one. While λ is effectively identified off of the slope of the valuation ratio curve, $\widehat{e_r}$ is identified off of the average level of the observed valuation ratios. Put differently, e_r is determined by whether consumers tend to underestimate or overestimate the value of fuel economy, which is what we examined earlier.

B.2 Statistical Results

Table 3 presents the "reduced form" test of the MPG Illusion: the regression of ϕ on $\overline{f}$. From Figure 7, we can already see that the slope is positive. Column 1 is the basic regression from Equation (10). A one mile per gallon increase in the harmonic mean fuel economy of the current and alternative vehicles is associated with a 0.028 increase in ϕ. Column 2 tests whether the slope is different for ϕ's reported on Part 3 versus Part 4. The point estimate differs only slightly, and this difference is not statistically significant. Column (3) tests whether the slope is different for the Total group vs. the Flow group and the Relative group vs. the Absolute group. The fact that these slopes are not statistically different suggests that the framing of the survey questions is not what generates the MPG Illusion result. Column (3) also shows that the slope is not statistically different in the Incentive vs. Non-Incentive groups.

Table 4 presents estimates of Equation (11). The first row is the coefficient λe_r^2, while the second row is the estimate of λ. The estimated $\widehat{\lambda}$ is 0.262, which is quite close to the 1/4 suggested by superimposing Figure 7 on Figure 2. Dividing the two coefficients and taking the square root, we have that the estimated reference fuel intensity $\widehat{e}_r$ is 0.0505 gallons per mile. The reference fuel economy $\widehat{f}_r$ is thus $1/0.0505 = 19.8$ miles per gallon.

In summary, responses on the VOAS survey have been translated into ratios that reflect the percentage of fuel cost differences between vehicles that American consumers perceive. These ratios are smaller for pairs of low-MPG vehicles and larger for pairs of high-MPG vehicles, which is consistent with the MPG Illusion. The belief structure of the MPG Illusion has been parameterized, and we now have a nationally-representative estimate of the extent of the bias. This estimate can now be fed into a discrete choice model of U.S. vehicle markets that predicts the allocative and welfare effects of the MPG Illusion and of systematic underestimation or overestimation of the financial value of fuel economy.

V Counterfactual Simulations

In this section, I set up a simple discrete choice model of automobile demand under biased beliefs. I then detail a methodology for calculating welfare effects. Finally, I will present information on how the utility function parameters are calibrated using a combination of observed market shares and existing elasticities from the literature.

A Model

A set of consumers, indexed $i \in \{1, ..., M\}$, choose from a set of new vehicles, indexed $j \in \{1, ..., J\}$. There is no outside option, as it is not clear how to model how imperfect beliefs would cause substitution into and out of the new vehicle market. Each consumer is risk neutral, with constant marginal utility of money η and wealth w_i. As introduced earlier, consumer i in vehicle j will incur true annual fuel cost G^*_{ij}. This depends on fuel price g, vehicle energy intensity e_j, and utilization m_i, which for simplicity is modeled as exogenous, inelastic, and known with certainty. Each vehicle has price p_j and average utility ξ_j.

Capturing the way that consumers substitute across vehicles with different fuel economy ratings is crucial for the counterfactual simulations. If consumers do not want to substitute from large sedans to midsize sedans as they become aware of the true fuel costs G^*, the counterfactual market shares will not change substantially. On the other hand, if many consumers that were buying large sedans were close to indifferent between large sedans and midsize or small cars, counterfactual market shares would change substantially.

The nested logit structure allows me to parsimoniously capture substitution patterns across classes while retaining simplicity and transparency. In this model, consumer i has a taste shock ζ_{ik} common to all vehicles in class k. The distribution of ζ depends on a nested logit substitution parameter $\sigma \in [0, 1)$, which determines the within-class correlation in utility levels: a larger σ means that each consumer has stronger preference to purchase a vehicle from some particular class. The nested logit model is equivalent to a random coefficients model with random coefficients on nest indicator variables. Each consumer also has an idiosyncratic taste shock ϵ_{ij} for vehicle j.

If consumer i purchases vehicle j, he receives utility $\xi_j + \zeta_{ig} + (1-\sigma)\epsilon_{ij}$ from owning the vehicle and has $w_i - p_j - G^*_{ij}$ left over to purchase the numeraire good. The indirect utility that the consumer experiences is therefore:

$$V^*_{ij} = \eta \left(w_i - p_j - G^*_{ij} \right) + \xi_j + \zeta_{ig} + (1-\sigma)\epsilon_{ij} \tag{12}$$

Following the terminology of Kahneman (1994), I define this as "experienced utility." This is distinguished from "decision utility," which is the function that consumers act as if they are maximizing when they choose which vehicle to buy. By definition, rational consumers maximize experienced utility. Consumers that misperceive product costs, however, do not. Decision utility is the same as experienced utility, except that it depends on perceived fuel cost $\widetilde{G}_{ij}$:

$$\widetilde{V}_{ij} = \eta \left(w_i - p_j - \widetilde{G}_{ij} \right) + \xi_j + \zeta_{ig} + (1-\sigma)\epsilon_{ij} \tag{13}$$

In these simulations, perceived fuel costs $\widetilde{G}$ could differ from actual fuel costs G^* because of either systematic underestimation or overestimation ($\gamma \neq 1$) or because of the MPG Illusion ($\lambda \neq 0$):

$$\widetilde{G}_{ij} = \gamma G^*_{ij} \cdot \frac{\widetilde{e}_j}{e^*_j} \tag{14}$$

B Welfare Effects

In the context of a discrete choice model, how can one calculate the change in experienced consumer surplus due to misperceived product costs? I adapt an approach introduced by Allcott and Wozny (2011), which is to break experienced utility into two parts, decision utility and a belief error, and then aggregate each part over consumers.

Experienced utility can be written as the sum of decision utility and an error term V_{ij}^b:

$$V_{ij}^* = \widetilde{V}_{ij} - V_{ij}^b \tag{15}$$

The two parts of experienced utility, V_{ij}^b and $\widetilde{V}_{ij}$, can each be easily aggregated over consumers. Substituting in from Equations (12) and (13), the belief error is:

$$V_{ij}^b = \eta \left(G_{ij}^* - \widetilde{G}_{ij} \right) \tag{16}$$

The belief error derives only from misperceived product costs, and hence is the difference between actual and perceived G_{ij}. V_{ij}^b can be thought of as the difference between anticipated and actual consumption of the numeraire good. Belief errors are summed over each individual's choice probabilities P_{ij} and then over all individuals in the market. Dividing by η to transform to dollar terms, this sum is:

$$CS^b = \sum_{i=1}^{M} \sum_{j=1}^{J} P_{ij} \left(G_{ij}^* - \widetilde{G}_{ij} \right) \tag{17}$$

"Decision consumer surplus" can be thought of as the surplus that would accrue to consumers if decision utility were actually realized. This can be aggregated using the standard formula originally from Small and Rosen (1981), modified for the nested logit. Omitting the constant for simplicity and summing over all the consumers in the market, this is:

$$CS^d(\widetilde{V}) = \frac{1}{\eta} \sum_{i=1}^{M} \ln \left[\sum_{k} \left[\sum_{j \in \mathcal{K}} \exp \left(\frac{\widetilde{V}_{ij}}{1-\sigma} \right) \right]^{1-\sigma} \right] \tag{18}$$

In this equation, k indexes nests, and $\mathcal{K}$ represents the set of vehicles in the nest of which vehicle j is a member. Analogously to Equation (15), experienced consumer surplus is total decision consumer surplus minus the sum of the belief errors:

$$CS^* = CS^d(\widetilde{V}) - CS^b \tag{19}$$

The counterfactuals consider the case without misperceived product costs. With $\gamma = 1$ and $\lambda = 0$, we then have $CS^b = 0$ and $\widetilde{V} = V^*$. The change in experienced consumer surplus from the base case to the counterfactual is:

$$\Delta CS = \left[CS^d(V^*) - 0\right] - \left[CS^d\left(\widetilde{V}\right) - CS^b\right] \tag{20}$$

The appeal of this approach is the resulting simplicity: it allows the use of the Small and Rosen (1981) analytical consumer surplus formula instead of requiring the analyst to simulate out the unobserved taste shocks ϵ_{ijat}. It can be used to analyze any form of misoptimization, as long as consumers' mistakes are additively separable from decision utility. It is general to any discrete choice setting, not just automobiles, and could be easily extended to random coefficients models.

C Simulation Data

Table 5 presents descriptive statistics on the choice set and basic assumptions. The choice set is defined as all new vehicles available in 2007. A model j is defined at the "nameplate" level of aggregation, for example "Honda Civic" or "Ford F-Series." There are 213 models in the choice set.[4]

This simulation is "short-run" in the sense that the choice set of models offered and their characteristics and prices are held constant across the counterfactuals. Relative to a model with endogenous prices but exogenous product characteristics, this could understate or overstate the effects of systematic underestimation of the value of fuel economy on new vehicle average MPG. If automakers respond to an increase in demand for high-MPG vehicles by increasing their prices, this would decrease equilibrium quantity of high-MPG vehicles relative to the short-run counterfactual simulation. On the other hand, if there are decreasing marginal costs of production, an increase in quantity demanded for high-MPG vehicles could cause a decrease in equilibrium prices and thus an increase in equilibrium quantities of high-MPG vehicles relative to the simulation.

[4] I define the choice set to be all substitutable gasoline-fueled light duty vehicles with EPA fuel economy ratings. This includes cars, pickups, SUVs, minivans, and other light trucks, but not motorcycles, cutaway motor homes, limousines, chassis cab and tilt cab pickups, hearses, and cargo, passenger, and camper vans. I also exclude the following ultra-luxury and ultra-high performance exotic vehicles: the Acura NSX, Audi R8 and TT, Chrysler Prowler and TC, Cadilliac Allante and XLR Roadster, Chevrolet 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. I also combine all models within each of Audi, BMW, Land Rover, Lexus, and Mercedes-Benz, because each has low market share and many different nameplates.

Relative to a model with endogenous prices and endogenous characteristics, the short-run model likely understates the effects of systematic underestimation of the value of fuel economy. A counterfactual increase in demand for fuel economy would cause automakers to introduce additional fuel saving technologies, which is the primary channel of long-run welfare gains estimated in the CAFE standard Regulatory Impact Analysis. Furthermore, an increase in demand for fuel economy might also cause automakers to offer a wider variety of high-MPG models, which could further increase the average MPG of vehicles sold. Despite these differences, this short-run model is important *per se* because it provides an estimate of the gains possible through changes in consumer choices alone, and because it does not require the extensive set of assumptions that a long-run model would require.

Vehicle prices are from the Power Information Network, which collects data on approximately one-third of total US retail transactions from a network of more than 9,500 dealers. The price p_j for each model is the mean price observed across all transactions over calendar year 2007, accounting for customer cash rebates and the market value of any trade-in. All dollar amounts are in real 2010 dollars. Market shares are the sum of vehicles registered across all 50 states as of July 1, 2008.

Fuel economy ratings f_j are from the U.S. Environmental Protection Agency's database of MPG ratings. The EPA tests each vehicle in standardized laboratory conditions and then adjusts the results to account for the typical consumer's in-use fuel economy. To remain consistent with the VOAS, I use the EPA's original adjusted fuel economy rating for model years before 2008, not the retroactive adjustment calculated in that year. Vehicle classes, which define the nests k for the nested logit substitution patterns, are also officially defined in the EPA data. There are nine classes: two-seater, mini-compact, sub-compact, compact, midsize, large car, SUV, pickup, and minivan.

In the simulations, G_{ij} represents the expected discounted value of lifetime gasoline costs. This is the discounted sum over each year of the vehicle's life of vehicle-miles traveled times real gasoline price times fuel intensity times the vehicle's cumulative survival probability for that year. I use an annual discount rate of 6 percent, based on Allcott and Wozny's (2011) calculation of the mean intertemporal opportunity cost of capital for vehicle buyers. I use the mean value of vehicle-miles traveled for all vehicles of each age observed in the National Household Travel Survey. I assume a real gasoline price of \$3 per gallon. Cumulative survival probabilities are fitted by estimating how the registered quantities at the vehicle level decrease as vehicles age.

To be concrete, a vehicle that survives to my assumed maximum age of 25 years can expect to be driven 236,000 miles over that period. However, only 10 percent of vehicles survive to age 25. Multiplying by cumulative survival probabilities, the average vehicle can expect to be driven 153,000 miles over its lifetime. At a gasoline cost $g = \$3$ per gallon and a 6 percent discount rate, a 20-MPG vehicle will have $G_j^* \approx \$15,500$. For simplicity, vehicle-miles traveled is assumed to be fully price inelastic and homogeneous across vehicles and consumers.

The nested logit substitution parameter σ is calibrated to match substitution patterns observed in the VOAS second choice data. Specifically, 34 percent of Americans have first and second choice vehicles both from the same class, while 66 percent of Americans have first and second choice vehicles from different classes. The σ parameter that matches this in the simulations is $\sigma = 0.18$.

The average marginal utility of money parameter $\overline{\eta}$ is calibrated such that the mean own-price elasticity of demand across the available models is -5. This value was chosen to be consistent with the mean own price elasticity estimated by Berry, Levinsohn, and Pakes (1995, Table V) for new vehicles. I assume that η is lognormally distributed with coefficient of variation equal to one. The Berry, Levinsohn, and Pakes (1995) contraction mapping is used to back out the average utility parameters ξ_j that match observed and predicted market shares, conditional on prices, lifetime gasoline costs, and parameters $\overline{\eta}$ and σ.

The values of γ are drawn from the results of Column (1) in Table 2, which estimate mean and median ϕ from Parts 3 and 4. For the Base Case, I use $\gamma = 0.88$, the mean γ for consumers comparing first and second choice vehicles. I focus on this instead of the γ from Part 4 because it reflects the beliefs from the consumer's actual choice situation, instead of the hypothetical "replacement vehicle" in Part 4. However, I consider both Part 3 and Part 4 in constructing lower and upper bounds for γ. The lower bound is the bottom of the 90% confidence interval for the median ϕ in Part 3, which is $\gamma = 0.6$. The upper bound is the top of the 90% confidence interval for the mean ϕ in Part 4, which is $\gamma = 1.4$.

The MPG Illusion parameter λ is set to 0.262 to match the empirical estimates. In the base case considering MPG Illusion in isolation, the reference fuel economy parameter is calibrated to $f_r = 23.6$ MPG, the point at which the MPG Illusion does not affect the harmonic mean fuel economy of vehicles sold.

VI Simulation Results

The basic idea of the counterfactual simulations is to compare market shares and welfare in a world with systematically misperceived product costs to a "counterfactual" world with no systematic misperceptions. I focus first on the effects of systematic underestimation or overestimation of the financial value of fuel economy, assuming zero MPG Illusion. Next, I consider the effects of the MPG Illusion in isolation. Finally, I simulate the effects of both in combination.

A Systematic Underestimation or Overestimation

Column (1) of Table 6 presents the effects of systematic underestimation with $\gamma = 0.88$ under the Base Case utility function parameter assumptions. The parameter λ is zero throughout Table 6, meaning that I temporarily assume zero MPG Illusion and consider underestimation or overestimation in isolation. By distorting vehicle choices away from the optimum with "perfect beliefs," systematic underestimation of the financial value of fuel economy reduces consumer welfare by a present discounted value of \$8.10 over the life of each vehicle sold. Over the 16 million new vehicles sold in the U.S. in a typical year, this sums to \$130 million.

The empirical estimates of γ in Table 2 could justify a range of γ parameters other than the point estimate of $\gamma = 0.88$. Column (2) considers the most extreme empirically-justifiable overestimation of the value of fuel economy, which is $\gamma = 1.4$. If this is the initial inefficiency, moving to $\gamma = 1$ would decrease harmonic mean fuel economy by 0.67 and would increase experienced consumer surplus by \$87 per new vehicle sold, or \$1.4 billion over the vehicles sold in a typical year.

Column (3) considers the most extreme empirically-justifiable underestimation of the financial value of fuel economy, which is $\gamma = 0.6$. In this case, the harmonic mean fuel economy of vehicles sold is 0.77 MPG lower than in the optimum. The consumer welfare losses in this bounding case are \$94.90 per new vehicle sold, or \$1.519 billion per year. This means that in the short run, perfect information disclosure or some other policy that optimally corrects underestimation would increase harmonic mean fuel economy by no more than 0.77 MPG and would increase consumer surplus by no more than \$1.519 billion. By comparison, the current 2012-2016 CAFE standard increases fleet average fuel economy to 35 MPG from the current 20 MPG, and the official cost-benefit analysis estimates a \$15 billion consumer surplus gain.

This estimated gain is the difference between the fuel cost savings to consumers and the costs of producing higher-fuel economy vehicles. This gain is "long-run" in the sense that the model simulates producers that modify the choice set by increasing the fuel economy of existing vehicle models. However, even within this long-run model, even the most extreme underestimation cannot explain why the market would leave these potential gains on the table. At the new auto loan discount rate, which is comparable to the discount rate I use, the official cost-benefit analysis estimates about \$2600 in fuel cost savings from introducing a set of fuel economy technologies, compared against about \$940 in costs.[5] For the perceived benefits to not exceed the costs, consumers would have to value the true benefits by $\gamma = 940/2600 \approx 0.36$. This is substantially below the empirical lower bound of $\gamma = 0.6$, which itself is substantially below the point estimate of $\gamma = 0.88$.

The allocative and welfare effects of biased beliefs depend on substitution parameters. If consumers have low marginal utility of money η, meaning that they are not very price elastic, even a large change in perceived costs will have only a small effect on purchasing patterns and consumer welfare. On the other hand, if η is large, even slight underestimation of gasoline costs could significantly affect average MPG and welfare. In Column (4), I double the average η parameter in the population, which nearly doubles mean own-price elasticity compared to the values estimated by Berry, Levinsohn, and Pakes (1995). Compared to Column (1), this nearly doubles the distortion in average MPG and the consumer welfare costs. Column (5) shows that even doubling η at the lower bound case of $\gamma = 0.6$ would suggest only \$2.5 billion in annual consumer welfare losses.

When η is heterogenous, relatively low-η consumers buy relatively more expensive vehicles, which tend to have low fuel economy. As a result, buyers of low-MPG vehicles are less price elastic

[5] The values \$940 and \$2600 are simple averages of the vehicle price increases and fuel cost savings of the CAFE regulation for cars and trucks, as reported in Table VIII-16 of NHTSA (2010).

than buyers of high-MPG vehicles. Column (6) assumes that η is uniform in the population, which effectively increases the own-price elasticity of demand for low-MPG vehicles relative to Column (1). Because buyers of low-MPG vehicles have the largest welfare losses from underestimating the value of fuel economy, increasing the price elasticity of demand for low-MPG vehicle buyers increases the allocative distortions and welfare losses from underestimation.

Column (7) presents results when the nested logit substitution parameter σ is increased to 0.6, meaning that 2/3 of second choices are in the same vehicle class as first choices. By inducing people to stay within their preferred vehicle classes in the counterfactuals, this reduces the allocative effects and welfare gains from moving from misperceived product costs. Alternative simulations not included in the table showed that these results are also not highly sensitive to defining nests at a more disaggregated level. This suggests that the basic results would not be very sensitive to alternative assumptions about substitution patterns, such as the use of more flexible random coefficients.

B The MPG Illusion

Now consider the MPG Illusion in isolation. Figure 8 illustrates the allocative effects of the MPG Illusion under the Base Case parameter assumptions with $\lambda = 0.26$. The blue bars indicate the current market share for vehicles at each fuel economy level. The black line illustrates the change in market share when moving to a counterfactual with no MPG Illusion. Because the MPG Illusion causes consumers to underestimate gas costs for especially low-MPG and especially high-MPG vehicles, the market shares of these vehicles decrease by several percent in a counterfactual simulation with $\lambda = 0$. In this counterfactual, consumers substitute to medium-MPG vehicles, and the market share of these vehicles increases by several percent.

Column (1) of Table 7 presents the Base Case simulation results for the MPG Illusion. As the Base Case simulations are calibrated to leave the harmonic mean fuel economy unchanged, there is no change in gasoline costs. By distorting vehicle choices away from the optimum with "perfect beliefs," the MPG Illusion reduces consumer welfare by a present discounted value of \$3.66 over the life of each vehicle sold. Over the 16 million new vehicles sold in the U.S. in a typical year, this sums to \$59 million. This amount is large relative to the fixed costs of redesigning fuel economy labels, so unless these labels are highly ineffective at debiasing consumers, it seems likely that they could increase welfare. However, this annual distortion is small relative to the total size of the automobile market: it is only 0.013 percent of the \$400 billion in annual gross revenues.

Columns (2) through (6) present counterfactual simulations of eliminating the MPG Illusion under different parameter assumptions. Columns (2) and (3) use alternative values of λ that reflect the upper and lower bounds of the empirical 90 percent confidence interval of $\widehat{\lambda}$ from Table 4. Column (4) assumes that consumers are twice as price elastic as in the Base Case, and Column (5) assumes a homogeneous η with the same average. Column (6) increases the value of σ to 0.6. As in the previous set of simulations, increasing price sensitivity and decreasing substitutability increase and decrease, respectively, the allocative effects and welfare losses from the MPG Illusion.

The VOAS data suggest the existence of both the MPG Illusion and perhaps some systematic underestimation of the financial value of fuel economy. Column (7) of Table 7 simulates the joint effects of these two forms of misperceptions, setting $\gamma = 0.88$ and $\lambda = 0.26$. These results are conceptually the combination of the distortions from Column (1) from each of Table 6 and Table 7. The effects are slightly less than additive: the sum of consumer welfare losses from Column (1) of Tables 6 and 7 is \$189 million per year, while the consumer welfare loss simulated in Column (7) is \$172 million per year.

VII Conclusion

It has been argued that consumers systematically misperceive the value of fuel economy, either by underestimating the financial benefits or by being subject to the MPG Illusion. This paper tests these hypotheses using new nationally-representative data from the Vehicle Ownership and Alternatives Survey. The data show that on average, consumers correctly estimate or slightly underestimate the value of fuel economy. For vehicles with similar MPG, there are two offsetting mechanisms: some consumers incorrectly categorize similar vehicles as having exactly the same MPG, while those who do perceive an MPG difference overestimate the resulting fuel cost differences. There is robust evidence of the MPG Illusion, which corroborates the results of Larrick and Soll (2008). Counterfactual simulations show that while the MPG Illusion may have a noticeable effect on market shares, the welfare costs are less than four dollars per new vehicle sold. The analysis also shows that the most severe possible systematic underestimation of the value of fuel economy does not by itself justify the current fuel economy standard.

This re-introduces a puzzle: if engineering analyses such as the CAFE Regulatory Impact Analysis are correct that the gasoline cost savings from higher fuel economy vehicles would outweigh their incremental production costs, why are automakers not already producing these vehicles? The VOAS data are powerful in that they bound the effects of systematic underestimation, which was one proposed explanation. However, there may be other sources of inefficiency, such as naive present bias, as in the automobile market model of Heutel (2011), or inattention to fuel economy as a product attribute. Clearly defining and empirically testing these different models seems to be an important area of ongoing research.

One basic advantage of this approach of combining belief elicitation with counterfactual simulations is that it provides straightforward and transparent estimates of the potential welfare effects of misperceived product costs. However, other approaches would be useful complements. For example, it would be especially interesting and important to measure the effects of information provision using a randomized control trial. This would provide both an independent test for misperceived product costs and an estimate of the effects of a real-world policy.

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Tables

Table 1: Descriptive Statistics

	N	*Mean*	*SD*	*Min*	*Max*	*NHTS Mean*
Demographics						
Income	2122	56,088	43,472	2,500	200,000	58,745
Education (Years)	2121	13.8	2.5	5.5	20.0	14.0
Age	2122	46.1	16.7	18	93	46.5
Male	2122	0.48	0.50	0	1	0.49
Household Size	2122	2.79	1.63	1	10	3.03
Rural	2122	0.16	0.37	0	1	0.18
Liberal	2115	0.00	1.00	-2	2	
Own Vehicle						
Model Year	2016	2001.6	5.65	1984	2011	2000.7
Years Since Purchase	1963	5.08	4.30	-0.17	40.58333	
Future Ownership Period	997	4.37	4.17	0.08	40	
Purchase Price	1462	18,269	9,944	500	100,000	
MPG	2015	22.1	5.4	10	55	22.6
Fuel Costs						
Current Fuel Price ($/gallon)	992	2.81	0.23	2.00	3.98	
Future Fuel Price ($/gallon)	987	3.45	1.11	1.20	10.99	
Annualized Fuel Cost ($)	1998	1,522	1,762	40	50,000	
Implied VMT	1998	10,752	10,438	324	176,471	12,001
Second Choice Vehicle						
Model Year	1754	2003.4	5.4	1984	2011	
MPG	1742	22.3	5.5	9	56	
Annualized Fuel Cost ($)	1660	1,586	1,849	20	47,500	
Replacement Vehicle						
MPG Difference	2014	0.25	6.04	-10	10	
Annualized Fuel Cost ($)	1875	1,665	2,032	31	49,000	

Notes: Statistics weighted by nationally-representative sample weights. Excludes flagged responses. NHTS average VMT and MPG are from 2001 survey; all other NHTS variables from 2009 survey. The NHTS average VMT excludes values less than 108 miles per year to be consistent with the VOAS outlier check described in Online Appendix II. The Liberal score is self-reported political ideology normalized to mean zero, standard deviation one, with lower being more conservative and higher being more liberal.

Table 2: Estimating Systematic Underestimation or Overestimation

Part 3: Second Choice Vehicle ϕ

	All	$\|\Delta$ GPM$\|>0.01$	$\|\Delta$ GPM$\|\leq 0.01$	$\phi \neq 0$
	(1)	(2)	(3)	(4)
Mean	0.88	0.93	0.86	1.17
	(0.08)	(0.05)	(0.12)	(0.16)
Median	0.70	0.83	0.35	1.26
	(0.07)***	(0.04)***	(0.21)*	(0.1)**
Obs.	1415	461	954	671

Part 4: Replacement Vehicle ϕ

	All	$\|\Delta$ GPM$\|>0.01$	$\|\Delta$ GPM$\|\leq 0.01$	$\phi \neq 0$
	(1)	(2)	(3)	(4)
Mean	1.33	0.95	1.77	1.91
	(0.04)***	(0.02)**	(0.09)***	(0.09)***
Median	1.00	0.90	1.24	1.31
	(0.009)	(0.03)***	(0.04)***	(0.05)***
Obs.	1875	1002	873	826

Notes: Excludes flagged observations. Weighted for national representativeness. Standard errors in parenthesis. *, **, ***: Statistically different *from one* with 90, 95, and 99 percent confidence, respectively.

Table 3: Association Between Valuation Ratio and Average MPG

	All	Separate	Frames
	(1)	(2)	(3)
Average MPG	0.028	0.029	0.037
	(0.008)***	(0.007)***	(0.017)**
Average MPG x Second Choice ϕ		-.004	-.002
		(0.024)	(0.024)
Average MPG x Total Cost Group			-.010
			(0.016)
Average MPG x Relative Cost Group			0.01
			(0.016)
Average MPG x Incentive Group			-.015
			(0.016)
Second Choice ϕ		-.374	-.400
		(0.595)	(0.599)
Total Cost Group			0.208
			(0.392)
Relative Cost Group			-.115
			(0.389)
Incentive Group			0.209
			(0.385)
Const.	0.533	0.686	0.533
	(0.192)***	(0.164)***	(0.387)
Obs.	3290	3290	3290
F statistic	12.074	10.939	4.391
R^2	0.004	0.013	0.014

Dependent Variable: ϕ_{ia}.

Notes: Excludes flagged observations. Weighted for national representativeness. Robust standard errors in parenthesis, clustered by respondent i. *, **, ***: Statistically significant with 90, 95, and 99 percent confidence, respectively.

Table 4: Estimating the MPG Illusion

	$\phi - 1$
	(1)
λe_r^2	0.0007
	(0.0002)***
λ	0.262
	(0.085)***
Obs.	3290
F statistic	11.836
R^2	0.011

Dependent Variable: $\phi_{ia} - 1$.

Notes: Excludes flagged observations. Weighted for national representativeness. Robust standard errors in parenthesis, clustered by respondent i. *, **, ***: Statistically significant with 90, 95, and 99 percent confidence, respectively.

Table 5: Simulation Parameters

	Mean	*SD*	*Min*	*Max*
Choice Set				
Number of Models	213			
Price p_j (\$)	26,019	9,195	12,038	61,990
Gallons per Mile e_j	0.047	0.009	0.018	0.070
PDV of Lifetime Gas Cost G_ij	14,543	2,872	5,617	21,676
2007 Sales Quantity	65,653	87,471	202	627,809
Parameters				
Real Annual Discount Rate	6%			
Gasoline Price g (\$ per gallon)	3			
Calibrations				
Vehicle Own-Price Elasticity	-5			
% Second Choices in Same Class	34			

Note: All dollars are real 2010 dollars.

Table 6: Simulation Results for Underestimation and Overestimation

Case	(1) Base Case	(2) High γ	(3) Low γ	(4) High $\overline{\eta}$	(5) Low γ, High $\overline{\eta}$	(6) Uniform η	(7) High σ
Parameters							
λ	0	0	0	0	0	0	0
γ	0.88	1.40	0.60	0.88	0.60	0.88	0.88
$\overline{\eta}$	0.19	0.19	0.19	0.39	0.39	0.19	0.10
σ	0.18	0.18	0.18	0.18	0.18	0.18	0.6
Fuel Economy and Gas Use							
Δ Harmonic Mean MPG	0.21	-0.63	0.77	0.34	1.33	0.39	0.17
Δ Gas Costs (/new vehicle sold)	-135	411	-473	-216	-800	-243	-110
Δ Gas Costs (\$millions per year)	-2,165	6,576	-7,572	-3,457	-12,793	-3,885	-1,752
Δ Gas Costs (% of total)	-0.0097	0.0293	-0.0337	-0.0154	-0.0570	-0.0173	-0.0078
Welfare							
ΔConsumer Welfare (\$/vehicle)	8.1	81.9	94.9	12.9	157.2	14.6	6.6
ΔConsumer Welfare (\$million/year)	130	1310	1519	207	2515	233	105
ΔConsumer Welfare/Market Rev	0.00029	0.00294	0.00341	0.00046	0.00564	0.00052	0.00024

Note: All dollars are real 2010 dollars.

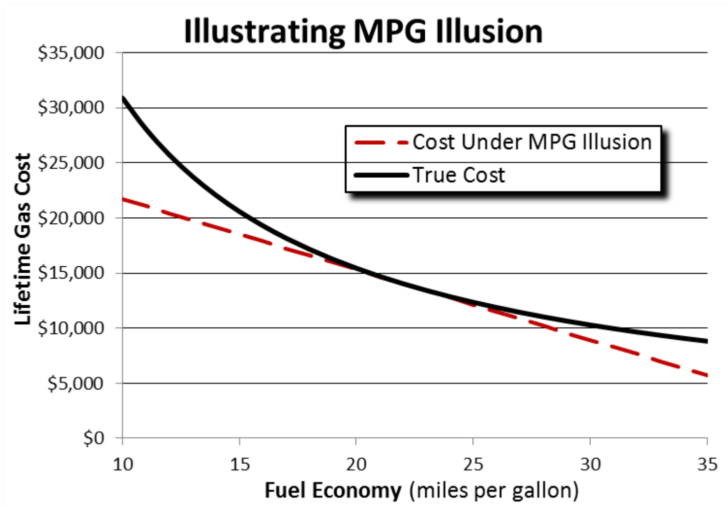
Table 7: Simulation Results for the MPG Illusion

Case	(1) Base	(2) High λ	(3) Low λ	(4) High $\overline{\eta}$	(5) Uniform η	(6) High σ	(7) Both
Parameters							
λ	0.26	0.40	0.12	0.26	0.26	0.26	0.26
γ	1.00	1.00	1.00	1.00	1.00	1.00	0.88
$\overline{\eta}$	0.19	0.19	0.19	0.39	0.19	0.08	0.19
σ	0.18	0.18	0.18	0.18	0.18	0.6	0.18
Fuel Economy and Gas Use							
Δ Harmonic Mean MPG	-	-	-	-	-	-	0.21
Δ Gas Costs (/new vehicle sold)	-	-	-	-	-	-	-130
Δ Gas Costs ($millions per year)	-	-	-	-	-	-	-2,086
Δ Gas Costs (% of total)	-	-	-	-	-	-	-0.0093
Welfare							
ΔConsumer Welfare ($/vehicle)	3.66	8.52	0.80	6.48	4.07	2.66	10.72
ΔConsumer Welfare ($million/year)	59	136	13	104	65	43	172
ΔConsumer Welfare/Market Rev	0.00013	0.00031	0.00003	0.00023	0.00015	0.00010	0.00039

Note: All dollars are real 2010 dollars.

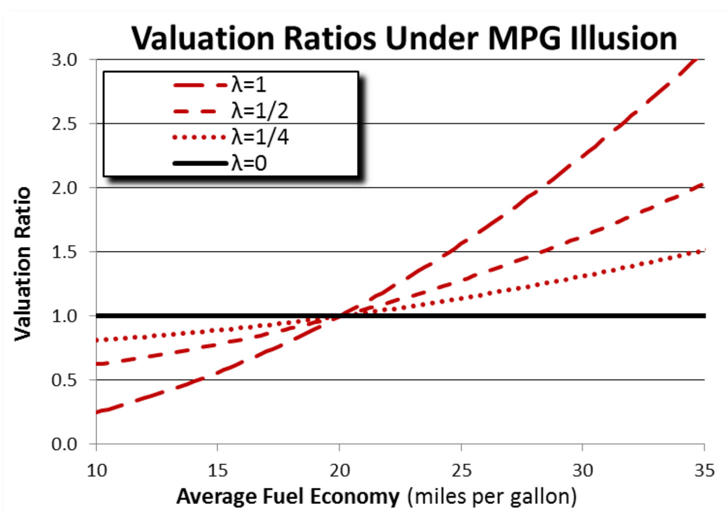
Figures

Figure 1: Illustrating MPG Illusion



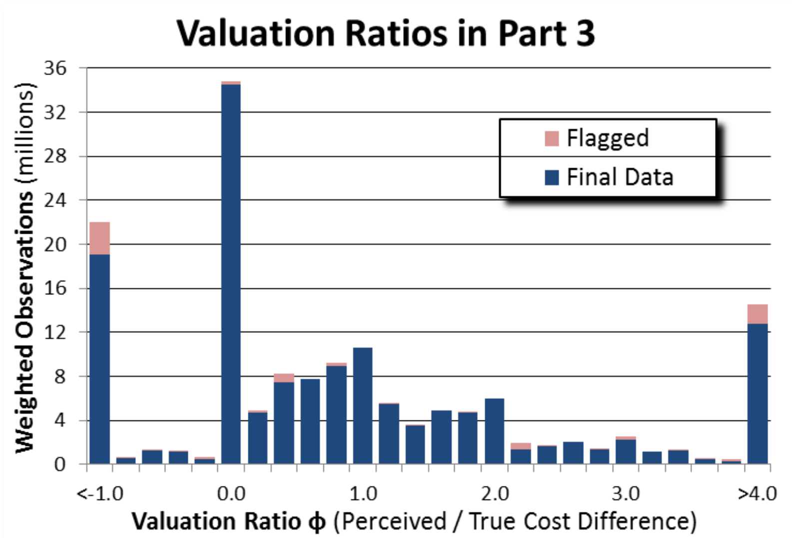
Notes: The black line shows the true annual gas cost as a function of fuel economy for a vehicle driven 12,000 miles per year with a gasoline price of \$3 per gallon. The dashed red line shows the perceived fuel costs if consumers are subject to one particular parameterization of the MPG Illusion, which is that they believe the first order Taylor expansion of fuel costs around a reference fuel economy of 22 MPG.

Figure 2: Valuation Ratios Under MPG Illusion



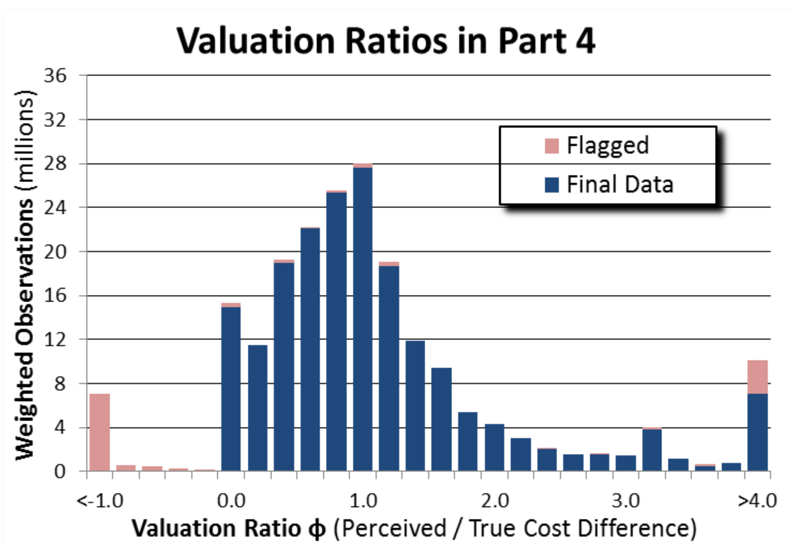
Notes: This figure shows the predicted valuation ratio ϕ as a function of the average fuel economy of a pair of vehicles under different levels of the MPG Illusion parameter λ.

Figure 3: Histogram of Valuation Ratios for Second Choice Vehicles



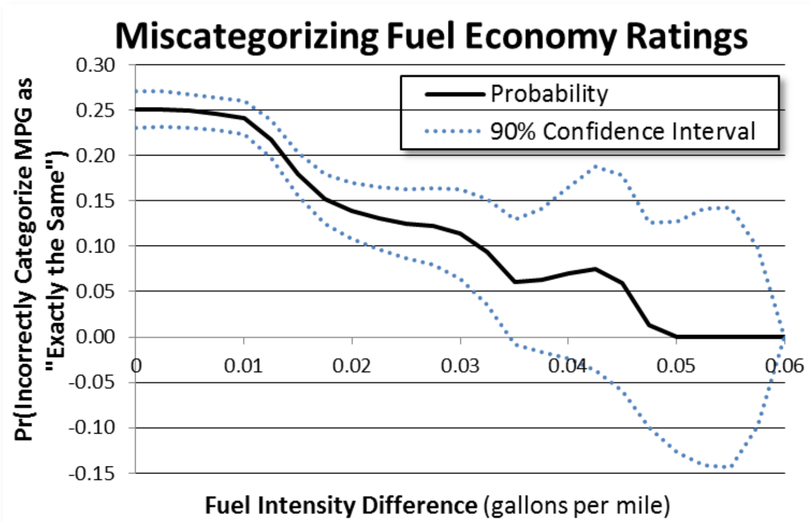
Notes: This figure shows the distribution of valuation ratios for second choice vehicles using data elicited in Part 3 of the VOAS. Flagged data are those eliminated through the procedure detailed in Online Appendix II.

Figure 4: Histogram of Valuation Ratios for "Replacement Vehicles"



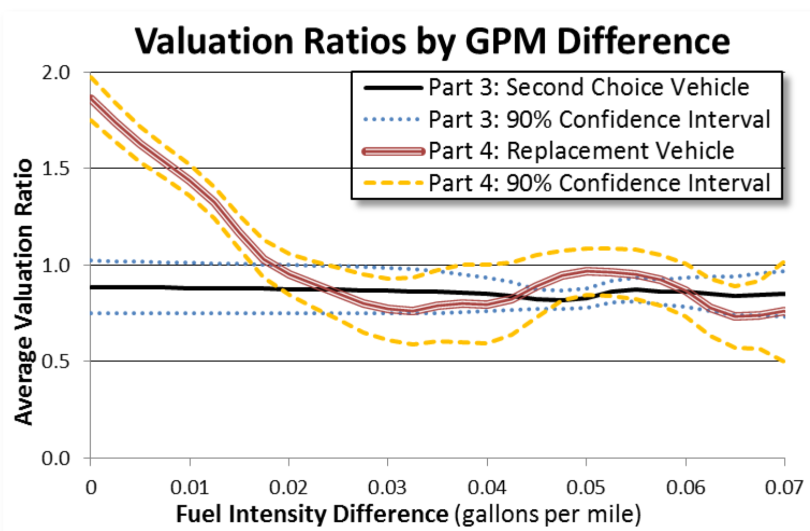
Notes: This figure shows the distribution of valuation ratios for second choice vehicles using data elicited in Part 4 of the VOAS. Flagged data are those eliminated through the procedure detailed in Online Appendix II.

Figure 5: Probability of Miscategorizing First and Second Choice Vehicles as "Exactly the Same" Fuel Economy



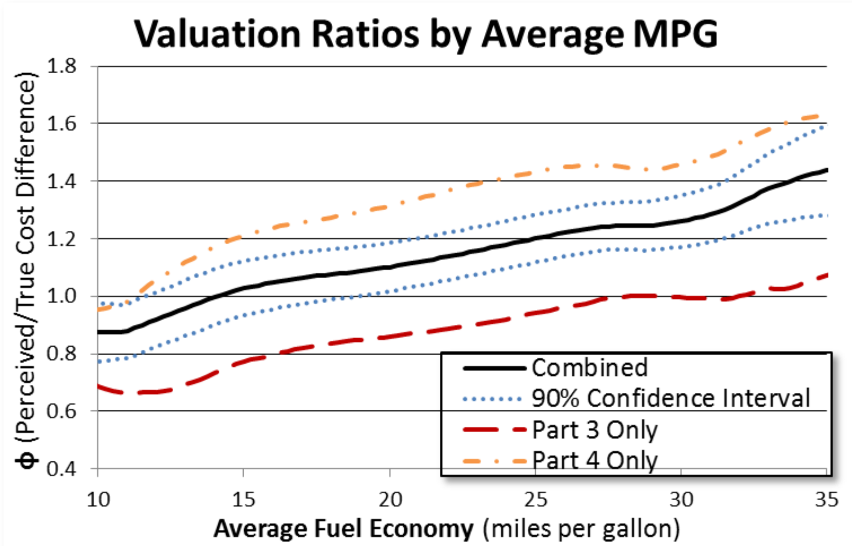
Notes: This figure graphs the probability that consumers incorrectly report that their second choice vehicle had the same fuel economy as their first choice vehicle, as a function of the true difference in fuel intensity. Epanechnikov kernel-weighted local mean estimation.

Figure 6: Valuation Ratios by Fuel Intensity Difference



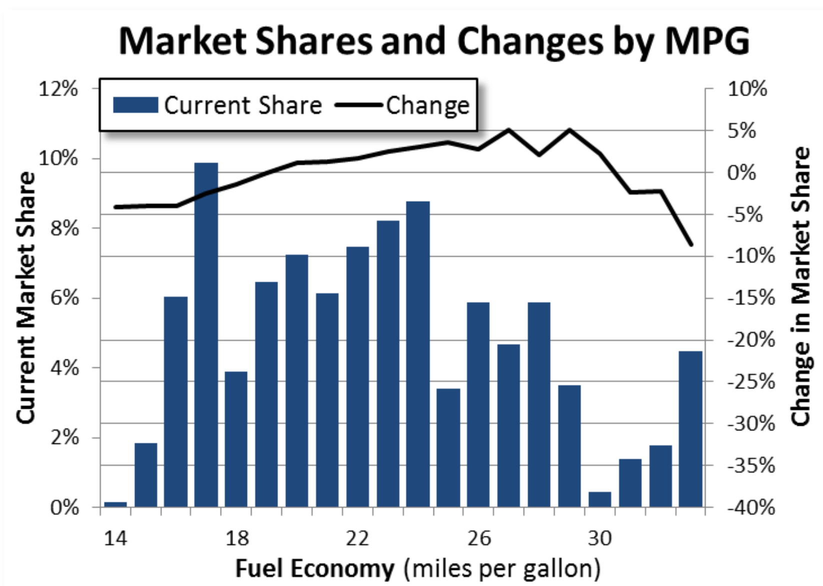
Notes: Epanechnikov kernel-weighted local mean estimation.

Figure 7: Valuation Ratios as a Function of Average Fuel Economy



Note: Epanechnikov kernel-weighted local mean estimation.

Figure 8: Allocative Effects of the MPG Illusion



Notes: This figure plots the current market share of each vehicle and the change in market shares in a counterfactual that moves from the estimated MPG Illusion to zero MPG Illusion. This corresponds to the Base Case parameter assumptions in Column (1) of Table 7.