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Consumer Willingness to Pay for Vehicle Attributes: What Do We Know?

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Abstract

As standards for vehicle greenhouse gas emissions and fuel economy have become more stringent, concerns have arisen that the incorporation of fuel-saving technologies may entail tradeoffs with other vehicle attributes important to consumers such as acceleration performance. Assessing the effects of these tradeoffs on consumer welfare requires estimates of both the degree of the tradeoffs, and consumer willingness to pay (WTP) for the foregone benefits. This paper has two objectives. The first is to review recent literature that presents, or can be used to calculate, marginal WTP (MWTP) for vehicle attributes to describe the attributes that have been studied and the estimated MWTP values. We found 52 U.S.-focused papers with sufficient data to calculate WTP values for 142 different vehicle attributes, which we organized into 15 general groups of comfort, fuel availability, fuel costs, fuel type, incentives, model availability, non-fuel operating costs, performance, pollution, prestige, range, reliability, safety, size, and vehicle type. Measures of dispersion around central MWTP values typically show large variation in MWTP values for attributes. We explore factors that may contribute to this large variation via analysis of variance (ANOVA) and find that, although most have statistically significant effects, they account for only about one third of the observed variation. Case studies of papers that provide estimates from a variety of model formulations and estimation methods suggest that decisions made by researchers can strongly influence MWTP estimates. The paper's second objective is to seek consensus estimates for WTP for fuel cost reduction and increased acceleration performance. Meta-analysis of MWTP for reduced fuel cost indicates that estimates based on revealed vs. stated preference data differ, as do estimates from models that account for endogeneity and those that do not. We find greater consistency in estimates of MWTP for acceleration despite substantial uncertainty about the overall mean. We conclude with recommendations for improving the understanding of consumers' MWTP for vehicle attributes.

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Keywords

Vehicle choice; fuel efficiency; vehicle attribute; willingness to pay

1. Introduction: Problem Formulation

Cars and light trucks are significant contributors to air pollution and to greenhouse gas (GHG) emissions in the U.S. and around the world. The incorporation of technologies to reduce emissions may not only increase vehicle costs but may also entail tradeoffs in other vehicle attributes important to consumers such as safety, comfort, or performance. Assessing the effects of these tradeoffs on consumer welfare requires estimates of both the degree of the tradeoffs, and consumer willingness to pay (WTP) for the foregone benefits.

Willingness to pay is defined as the maximum amount an individual is willing to give up to obtain a good or avoid a bad (Varian, 1992). Let $U(\mathbf{x},P)$ be the indirect utility function of a representative consumer, defined on a vector of vehicle attributes $(\mathbf{x} = x_1, x_2, \ldots x_k, \ldots x_n)$ and a measure of present value dollars, p, such as the price of the vehicle. The total derivative of U with respect to x_k and p (assuming all other attributes are held constant) is $dU = (\partial U/\partial x_k)dx_k + (\partial U/\partial p)dp$.[1] By setting the total derivative equal to zero we can solve for the change in income (present value dollars) that exactly compensates for a marginal change in attribute k (Equation 1).

$$\frac{dp}{dx_k} = -\frac{\partial U/\partial x_k}{\partial U/\partial p} \quad (1)$$

This measure, known as the compensating variation, gives the quantity of present value dollars that is required to keep the consumer's utility unchanged, given a marginal change in product quality, represented in this case by a change in attribute k. Although functional forms vary greatly from one research paper to another, in all cases we use the marginal compensating variation to estimate the marginal willingness to pay (MWTP).

In this paper, we calculate MWTP values from published studies of vehicle demand. Our research objectives are two-fold: 1) to identify the vehicle attributes for which MWTP estimates can be obtained from economic studies and to describe the resulting estimates and 2) to attempt to develop consensus central tendency measures of MWTP via meta-analysis for fuel costs and acceleration performance. Dozens of papers have examined how consumer demand for light-duty vehicles is affected by vehicle attributes, such as fuel economy, performance, or size. It is possible from these papers to derive estimates of consumer MWTP for those attributes. Most often, the published papers do not report WTP values, nor do they compare the estimated values with those from other papers.

Our method follows the procedure for meta-analysis recommended by Van Houtven (2008):

[1]The derivation is an adaptation of that presented in Gatta et al. (2015).

- Problem formulation: specifying research objectives and defining the scope of the analysis (Sections 1 and 2),
- Data collection: via a formal literature search (Section 3),
- Data evaluation and abstraction: insuring that the WTP are appropriate and acquiring them along with descriptors (e.g., units) and study attributes (Section 4),
- Data preparation: standardization of WTP and potential explanatory variables in constant dollars and units to the extent possible (Section 5),
- Data analysis: choice of statistical package, weighting and estimation method (Section 6).
- Presentation of results: tables, graphs, descriptive statistics, hypothesis tests (Section 6).

We limit the scope of our analysis to U.S. studies published between 1995 and 2015, with the sole exception of Lave and Train (1979), the first use of a random utility model to vehicle choice. We focus on peer-reviewed studies but also include a smaller number of studies from the grey literature. By means of a structured literature search (described in Section 2), we identified 52 U.S.-focused papers with sufficient data to calculate MWTP values for various vehicle attributes. Only a few provided MWTP estimates calculated by the authors. For most we calculated MWTP values using the coefficients of models estimated in the studies. When questions arose about issues such as units of measure or functional forms, we queried lead authors. We included data from all models presented in the papers that were not rejected as implausible by the authors. We calculated MWTP estimates for all attributes for which it was feasible to do so. A detailed description of data and methods is provided in Greene et al. (2017).

The first phase of data analysis is descriptive (see Section 5). The key finding is that calculated MWTP values for most attributes vary widely. In the second phase, we investigate factors that might be causing the large variability of MWTP estimates. We do this through an analysis of variance (ANOVA) featuring measurable characteristics of the studies (see Section 6.1). The ANOVA model, while statistically significant, explains only a small portion of the variation in the estimates. We then present case studies of four papers, each of which provides an array of estimates for different models and estimation methods using the same data set; they provide important indications of how decisions made by modelers about included variables, metrics, functional forms, and estimation methods can profoundly influence coefficient estimates (see Section 6.2). In the third phase of analysis we attempt to derive consensus estimates of MWTP for fuel cost reduction and reduced 0–60 mph acceleration time via traditional meta-analysis (see Section 6.3). We conclude with suggestions for future research (see Section 7).

2. Literature Review

A rich literature on consumers' vehicle choices has developed over the last 50 years from innovations in the theory and empirical estimation of consumer demand, going back to

Lancaster's (1966) conception of consumer goods deriving their value from their attributes, rather than the good itself. Early applications of Lancaster's theory included efforts to predict transportation choice: Quandt and Baumol (1966) defined the value of a transportation mode by its speed, frequency of service, comfort, and cost. Hedonic price models arose from efforts to empirically test Lancaster's choice theory; they predict consumers' willingness to pay for goods as a function of their attributes (Rosen, 1974). McFadden (1974) applied the theory of demand for attributes to modeling consumers' choices among discrete modes of transportation. Consumers were assumed to base their choices on indirect utility functions comprised of an observable function of the attributes of the choices and of the consumers and an unobservable random utility component. By specifying the distribution of random utility as a type I extreme value distribution, McFadden derived the multinomial logit model, variations of which still dominate the literature today. The first application of the multinomial logit discrete choice model to automobile choice appeared in 1979 (Lave & Train, 1979). Lave and Train's model predicted consumers' choices among 10 vehicle classes using data from a survey of new car buyers in seven U.S. cities.

Over the past 35 years, formulations of discrete choice models applied to vehicle choices have increased in number and complexity. Methods have been developed for estimating discrete choice models using market sales data (Berry et al., 1995) and for estimating models from survey data with random coefficients to reflect variations in consumers' valuation of different attributes (McFadden & Train, 2000). Others have included extensive interactions with socioeconomic variables such as income, household size, and urban or rural environment to learn how consumer taste varies across population subsets.[2]

Despite the proliferation and refinement of econometric analyses of vehicle choice and WTP for vehicle attributes, there is little work synthesizing their results, and the reviews that do exist suggest lack of consensus. Greene and Liu (1988) provide one of few systematic reviews of the willingness to pay literature. They assess 10 papers that use data from 1978 to 1985 for MWTP for reduction in fuel costs, weight, interior size, and engine size-to-weight (power). They find large variation in estimates for all these attributes. Greene (2010) reassesses the economic evidence on MWTP specifically for fuel economy, using 25 studies published between 1994 and 2010. Again, wide variation in MWTP estimates was found. About half of the studies found that consumers undervalue fuel economy as opposed to the full or over-valuation estimated from the other half.

We find few literature reviews on attributes beyond fuel economy, despite the recognition that factors such as safety, reliability, and performance are important to consumers (Greene, 2010; Klier & Linn, 2012). Whitefoot and Skerlos (2012) review several estimates of MWTP for acceleration, footprint, and fuel economy in their simulation of optimal vehicle sizes based on technical constraints and the national fuel economy standards. They find that average MWTP ranges from $340 to $2,000 for an additional square foot of interior space, $160 to $5,500 for what an increase of 0.01 hp/lb will do to increase acceleration, and $800 to $9,000 for a reduction of one gallon of fuel used per 100 miles. They simulate several

[2]See Greene et al. (2017) for more detailed discussion of the development of WTP literature.

scenarios using combinations of the low, mid, and high values for each of the attributes with the hope that true willingness to pay lies within the large bounds.

Dimitopoulos et al. (2013) provide the only systematic meta-analysis of a vehicle attribute in the MWTP literature, in their meta-analysis of electric vehicle range. They reviewed 80 stated preference studies, of which 33 provided enough information to calculate MWTP. Estimates for MWTP vary widely, but the authors conclude that consumers were willing to pay, on average, between $66 and $75 (2005$) for a 1-mile increase in driving range. The distribution of estimates was positively skewed, with a median value of $55 and a range of $8 to $317. The authors present 95% confidence intervals of $49 to $84 (unweighted), $48 to $101 (weighted by observations per data set), and $29 to $104 (weighted by observations per data set and study sample size).

The meta-analysis of Dimitopoulos et al. (2013) produces several inferences concerning the effects of methods and study design. Studies employing random coefficient models assuming log-normal distributions for both purchase price and driving range produced much higher MWTP values than other methods. Studies that focused exclusively on battery electric vehicles (BEVs), not including other types of alternative fuel vehicles, produced higher estimates of MWTP for range. In general, MWTP for range was lower for studies that included longer driving ranges. Studies that included the option of fast-charging for EVs produced lower MWTP estimates. Finally, U.S.-based studies produced higher MWTP values than EU-based studies.

Recent work by Liao et al. (2016) and Greene et al. (2017) provides descriptive summaries of the MWTP literature for a breadth of vehicle attributes. Liao et al. summarize the statistical significance and direction of effect for technical, policy, and infrastructure-related attributes for electric vehicles. Greene et al. (2017) provide descriptive statistics of MWTP for vehicle characteristics, restricted to US samples from the years 1995–2015. The meta-analysis presented in this paper is based on the results of Greene et al. (2017).

In summary, there is a wide body of understudied literature on MWTP for vehicle attributes. There have been some attempts to review and synthesize this literature, but they have been limited in the scope of attributes considered. No recent study has yet reviewed the entire set of attributes available in the literature and sought to systemically explain the observed disparities.

3. Data Collection

For this study, data collection began with a systematic literature search for peer-reviewed publications and grey literature from academic or research institutions that suggested relevance to the following set of search terms.

Search parameters include the following:

- **Types of literature:** peer reviewed publications, grey literature from academic/ research institutions
- **Search engines:** Google Scholar, Econlit, Science Direct

- **Sample journals:** *Energy Economics, Econometrica, American Economic Review, Transportation Research (Parts A-E), Resource and Energy Economics, Review of Economics & Statistics, Transportation Research Board*
- **Publication Years**: 1980-present
- **Region:** primarily U.S.
- **Search terms**: willingness to pay, WTP, demand, stated preference, revealed preference, vehicle characteristics, vehicle attributes, automobile, design, fuel, choice.

We identified literature using three different search strategies. We reviewed search engines such as Google Scholar, Science Direct, and Econlit directly using the listed search terms. In addition to these databases, we reviewed bibliographies of relevant literature for further sources. Finally, we ran searches on relevant economics, energy, or environment-focused academic journals. A fourth unanticipated strategy was receiving published or working paper suggestions through correspondence with other authors during our data processing and analysis stages. Our final sample included 52 relevant papers with sufficient data to calculate MWTP values. Each of these studies focused on the U.S., and all but one were published from 1995 to 2015.[3]

The studies in our sample have in common that they all provide information that can be used to estimate MWTP, even though they were conducted with a variety of stated goals. Some were estimated to predict vehicle sales, others to develop insights into consumers' vehicle choices, and others to evaluate specific policy or economic hypotheses. We chose not to attempt to determine which studies and which attribute estimates were "valid" and which were not. Dropping studies because the underlying research was not focused on MWTP raises the possibility of confirmation bias in choice of studies. It is likely that our approach increases the variance of the resulting MWTP estimates.

From our final sample of 52 studies, we were able to calculate 777 estimates of MWTP for vehicle attributes, within which there were 142 unique attributes. As Table 1 details, the majority of the estimates came from peer-reviewed literature (86.4%), and 13.6% came from seven papers from grey literature. Most of the estimates come from variants of logit models (73.0%). Models with random coefficients (MXL and BLP) provided 36.1% of the estimates. We found a mix of data types utilized: 58.2% of the estimates came from survey data (19.6% revealed-preference surveys such as the National Household Travel Survey that reflect respondents' actual vehicle purchases; 38.6% were from stated-preference surveys reflecting hypothetical choices), 29.3% came from market data (i.e., market transactions data, either individual or aggregated), and another 12.5% from other sources, including joint revealed-preference and stated-preference (RP-SP) data and literature summaries. New vehicle choices were the focus of almost 80% of the studies, with a reasonable balance between analyses based on market transactions (individual and aggregated) and surveys (Table 2).

[3]We retain Lave and Train (1979), the first application of a multinomial discrete choice model to automobile choice, as a useful comparison point despite its publication year falling outside our primary restriction criteria.

Newer studies tended to rely more heavily on survey data, particularly on stated preference-surveys, as a means of ascertaining preferences for alternative fuel technologies. Alternative fuel vehicles present special challenges due to limited availability of makes and models and lower consumer familiarity with their specific features (Potoglou & Kanaroglou, 2008). MWTP estimates based on stated-preference surveys, however, are susceptible to hypothetical bias, the difference between what people say they will do and what they actually do (Loomis, 2014). Efforts to combine revealed and stated preference data hold promise, but are nonetheless limited by the availability of compatible revealed preference data (Brownstone et al., 1996).

Motor vehicles have numerous attributes of interest to consumers. The many dimensions of vehicle attributes and the different ways of measuring them not only complicate the problem of estimating models and calculating MWTP for attributes but also contribute to the variability of MWTP estimates across studies. Frequently, attributes that are notionally the same are measured differently in different studies. Purchase price, for example, is represented in some studies by the manufacturer's suggested retail price and in other studies by transaction prices. The impact on the estimated price coefficient is also likely to vary depending on whether the data is comprised of individual vehicle purchases or market sales. In addition, attributes that seem readily measurable frequently have many dimensions. Acceleration performance may include launch from a stop, time to go from 0 to 30 mph, time to go from 0 to 60 mph, and acceleration for merging into traffic or passing at highway speeds. Safety, reliability, comfort, styling, and many other attributes also have many dimensions and are not as easily measured as acceleration. Data availability and statistical limitations make it impossible to include all relevant vehicle attributes, accurately and appropriately measured in the estimation of a model. In addition, many attributes are correlated. The certainty of omitted variables creates a strong potential for correlation between the error term and included variables, i.e., endogeneity (Greene, 2012). In some cases, instrumental variables (IVs) have been used to address endogeneity (Allcott & Muehlegger, 2008; Berry et al., 1995; Goldberg, 1995; Klier & Linn, 2012) but even the choice of IVs can strongly affect coefficient estimates.

Given the diversity of attribute measures, a significant challenge was standardizing units and measures across studies to enable cross comparison. We categorized attributes broadly into 15 groups, listed in Figure 1. These groups are intended to represent general categories of attributes that may have several dimensions. For example, acceleration time and braking distance are both measures of performance. As shown in Figure 1, the frequencies with which attributes are included in models do not always reflect consumers' priorities. For example, safety, reliability, and comfort rarely appear in the literature despite their importance to consumer decision making. In many cases, this is a result of limited data on these characteristics and few available proxies. In other cases, attributes are included as proxies for multiple attributes that are difficult to measure. Vehicle weight, for example, correlates strongly with vehicle size class and fuel costs.

After vehicle price (not shown but included in almost every model) and vehicle class, fuel cost and performance are the most frequently included attributes. Vehicle class typically serves as a fixed effect to control for omitted factors, rather than as a variable of interest in and of itself. A more complete description of the data can be found in Greene et al. (2017).

4. Estimating MWTP: Data Evaluation and Abstraction

Our goal was to calculate MWTP estimates for vehicle attributes that represent the central tendency of the sample upon which they were estimated. To do this, we use mean parameter estimates except when models assume random parameters with lognormal distributions, in which case we use medians. When attributes or price are interacted with consumer attributes we use central tendency measures of the attributes provided in the paper in question or obtained from other sources when the necessary data was not available in the paper.[4] Few researchers present the MWTP values implied by their estimated models (Daziano, 2013; Espey & Nair, 2005; Fan & Rubin, 2010; Hidrue et al., 2011; McManus, 2007). This is unfortunate, because published articles almost never provide all the information necessary to precisely calculate unbiased MWTP estimates. The ease of ‘backing out’ MWTP varies by the model and specification used. We find three main categories of empirical models from which to derive MWTP estimates:

- Hedonic price models,
- Multinomial logit (MNL) and nested multinomial logit (NMNL) discrete choice models, and
- Mixed logit (MXL) and other discrete choice models with random distributions of preferences.

In hedonic price models, vehicle price is the dependent variable, and the vehicle’s attributes are explanatory variables. Although the price function is intended to be a demand function, it is not always clear that the demand function has been identified as distinct from the vehicle cost function. In the simplest form, the price of vehicle j, p_j, is a linear function of its weighted attributes (x_{jk}), with γ_ks as weights, as shown in Equation 2.

$$p_j = \sum_{k=1}^{K} \gamma_k x_{jk} \quad (2)$$

If the hedonic price function can reasonably be considered to approximate a demand function, the marginal value or MWTP for the kth attribute is the derivative of price with respect to x_{jk} (Equation 3).

$$\frac{dp_j}{\partial x_{jk}} = \gamma_k \quad (3)$$

[4]Because the distribution of income is skewed, we use median rather than mean income whenever it is reported in a paper or we can obtain the data from a reliable government source.

If attributes are interacted with other variables or if more complex functional forms are used, the derivative of price with respect to the attribute will be more complex and may depend on the values of other variables. For example, if all variables are entered as logarithms, the derivative of price would be γ_k/x_{jk}, and a mean value of x_k would be used to calculate the central tendency MWTP.

In MNL and NMNL models, the indirect utility function of consumer i is a function of vehicle attributes and, in general, other variables describing the consumer, plus a random utility component. Because we always use the estimated utility functions for the typical consumer (random utility = 0) we omit the random utility term in the equations below. Purchase price is almost always one of the variables in the utility function. However, the coefficient of any variable that is measured in present value dollars can be used if price is not included. Because purchase price is measured in present value dollars, the negative derivative of the utility function with respect to price is the marginal utility of a dollar of income (since one dollar of price is equivalent to a negative dollar of income). The indirect utility function can be transformed into a monetary utility function by multiplying through by $1/(-\beta)$, where β is the coefficient of purchase price, the minus sign being added so that utility is measured in positive dollars. This is illustrated in Equation 4 for a simple linear utility function.

$$U_{ij} = \beta p_j + \sum_{k=1}^{K} \alpha_k x_{jk} \Rightarrow \frac{U_{ij}}{-\beta} = -p_j + \sum_{k=1}^{K} -\frac{\alpha_k}{\beta} x_{jk} \quad (4)$$

In Equation 3, the marginal WTP (in dollars) for a change in attribute k is the derivative of U_{ij} with respect to x_{jk}, or $-\alpha_k/\beta$. Although simple linear utility functions such as Equation 4 are sometimes encountered, in general, utility functions are more complex and include interactions among variables and transformations of variables. In general, MWTP is always obtained by dividing the derivative of utility with respect to an attribute (∂U/∂x, whose units are utility per unit of the attribute) by the negative of the derivative of utility with respect to a measure of present value dollars such as vehicle price (-∂U/∂P, whose units are utility per dollar, present value). Although we omit the consumer and vehicle subscripts in equation 5, the derivatives are often a function of consumer attributes and occasionally of vehicle attributes. In such cases, we use measures of central tendency for those variables (e.g., mean household income) for the population appropriate to the sample used in estimating the choice model.

$$MWTP_k = -\frac{\partial U / \partial x_k}{\partial U / \partial p} \quad (5)$$

Because all the attribute coefficients we found were statistically estimated, the estimated α's and β's are random variables due to estimation error. This creates two kinds of problems. First, the error in coefficient estimates is generally asymptotically normally distributed. In that case, there is always some probability density at zero, making expected value of the ratio undefined (Carson & Czajkowski, 2013). Mitigating the importance of this issue is the fact that there are strong, *a priori* theoretical and empirical reasons to believe that the true mean price response is neither zero nor positive. Second, in general, the mean of a ratio of random variables is not equal to the ratio of the means and can be strongly influenced by their covariance. Methods that overcome this problem exist (e.g., Bliemer and Rose, 2013) but, unfortunately, while published papers almost always provide standard errors (or t-statistics), they almost never provide covariances for coefficient estimates. The delta method, for example, requires covariances to obtain relatively precise measures of the expected value of the ratio.

Given the limitations of the information available in published studies, we adopted the convention, widely used in the literature, of estimating MWTP for an attribute conditional on the central tendency estimate of the price derivative. While this ratio is also the first order Taylor series approximation to the ratio of two random variables, we prefer to describe the MWTP estimate as conditional on the value of the price derivative because the interpretation is clearer. In addition, we use the range from the mean of the attribute derivative plus one standard error, divided by the central tendency price derivative to the mean minus one standard error divided by the central tendency price derivative as a measure of uncertainty or reliability. This is not equivalent to +/− one standard deviation of MWTP because it is conditional on the mean (or median) estimate of the price derivative. In the case of a simple linear utility function in which MWTP is the ratio $-\alpha_k/\beta$, the conditional range of uncertainty is shown in Equation 6, where s_k is the standard error of estimate of α_k.

$$-\frac{\alpha_k \pm s_k}{\beta} \quad (6)$$

We use half of the range of uncertainty to weight observations in our meta-analysis of MWTP for fuel cost and acceleration performance.

Likewise, in the case of mixed logit and other random coefficient models, unbiased MWTP estimates must be obtained by the Delta method or by simulation methods that require data generally only available to the model developer. Consequently, our central tendency estimates of MWTP, like nearly all those in the extant literature, should be interpreted as conditional on the central tendency estimate of the price derivative.

If neither price nor the vehicle attribute is interacted with personal characteristics, MWTP is the value for a “representative consumer.” Frequently, models include vehicle price divided by household income (p/Y), implying that the marginal value of a dollar of income decreases with increasing income. In the utility equation below (Equation 7), attributes of the vehicle, x_{jk}, are interacted with attributes of the consumer, z_i, such as income.

$$U_{ij} = \beta^* \left(\frac{p_j}{Y_i}\right) + \sum_{k=1}^{K} \alpha_k x_{jk} z_i \quad (7)$$

In this case the WTP for attribute j depends on the central tendency values of the coefficients and on both median income, $\bar{Y}_i$, and the mean value of another consumer attribute, $\bar{z}_i$ as shown in Equation 8.

$$MWTP_k = -\frac{\alpha_j \bar{z}_i}{\beta / \bar{Y}_i} \quad (8)$$

In these cases, MWTP varies across individuals. To derive a central tendency estimate of MWTP, the central value for income and the other consumer or vehicle attribute(s) must be known. Frequently, authors provide mean values for vehicle attributes, but they do not provide the joint distributions of income and other consumer attributes. When authors do not provide such data, it is often possible to find the appropriate data in other sources (e.g., Census Bureau reports). In such cases, care has been taken to match the relevant year and population whenever possible (e.g., new car buyers or all households? U.S. households or those in California?). The convention adopted in this paper is to use mean or median values (depending on the data available) for all variables for the relevant population, at the midpoint year of the sample data.

In random coefficient models such as MXL, some or all coefficients of the indirect utility function are specified as random variables. Commonly, the papers use normal distributions for coefficients of attributes whose marginal values may be either positive or negative, and lognormal distributions are used when marginal values are believed to be either always positive or always negative (e.g., fuel costs). The convention used in this paper is to use mean values for normally distributed random coefficients and median values for lognormally distributed coefficients for the central tendency estimates of those coefficients. MXL models can become exceedingly complex when there are multiple, correlated random coefficients, and vehicle attributes are interacted with several other variables. Most authors provide sufficient information to derive central tendency MWTP measures using the convention described above.

5. Data Preparation and Descriptive Statistics for MWTP

For each paper, MWTP calculations were made in a separate spreadsheet. The spreadsheets contain the coefficient values, units in which attributes were measured, values of potential explanatory variables, assumptions used in the calculations, and all formulas used to calculate MWTP. All dollar measures were converted to 2015 dollars using the Consumer Price Index. Sources are provided for any external data we introduced to calculate MWTP. In addition to checking our own work, we e-mailed all spreadsheets to the lead author of the applicable paper. Many authors graciously responded with comments and corrections. We made all corrections indicated by the authors.

For each attribute we graphed MWTP estimates to visually identify extreme values. After removing outlier candidates, we calculated the standard deviation of the remaining estimates. If the outlier candidates were more than three standard deviations from the mean of the trimmed sample, we considered the data points to be outliers and excluded them from our trimmed sample. Many of the trimmed samples exhibited substantial skewness, suggesting that median values might be better measures of central tendency than mean values. For this reason we include medians as well as means in summary tables.

Even after trimming, the most striking feature of the central tendency MWTP estimates is their variability. Descriptive statistics for the 10 groups of attributes with the greatest number of observations are shown in Table 3. Due to the skewness of the data and presence of outliers in the untrimmed sample, we present not only means and standard deviations but also medians and inter-quartile ranges for both the trimmed and untrimmed (raw) samples. In general, one standard deviation exceeds the mean of the MWTP estimates for most of the attributes, even for the trimmed samples. For 29 of the 37 MWTP metrics in Table 3, the interquartile range also exceeds the median in the trimmed sample. We do not include MWTP estimates for vehicle classes (indicators typically included to control for unobserved attributes) in Table 3 because class definitions and reference classes generally differed across studies making the MWTP estimates not comparable. In general, the signs of the mean and median MWTP values in the trimmed samples seem intuitively plausible except for the value of increased miles per dollar. For the hybrid fuel type, the sign changes from the mean to the median value, reflecting the high variability of the estimates and their skewed distribution. The heterogeneity of our sample of papers may explain some of the variability. Some of the models were estimated using U.S. samples, others used a single state or a group of states. Some are based on market sales, others on surveys, and still others on stated-preference choice experiments. The ability of these and other factors to account for the variability of MWTP estimates is explored in the following section.

When reasonable to do so, we converted different metrics for the same attribute to a common metric. For example, fuel cost is measured more than five different ways in our sample (Table 3). To increase the number of estimates that could be directly compared, we converted dollars per gallon per mile ($/0.01 gpm), tens of miles per dollar (10 mi/$), miles per gallon (mpg), and dollars per year ($/year) to their equivalent in the common measure of cents per mile (cpm). Gallons per mile was converted by multiplying by the price of fuel from the study in question. Dollars per year was converted by dividing by 100 and multiplying by the average annual miles driven per year. Miles per gallon was converted by dividing by the change in gallons per mile and then by the fuel price in cents per gallon. Miles per dollar was converted by dividing by the fuel price and then using the miles per gallon conversion.[5] In this way we were able to convert 117 of the original 122 fuel cost estimates into common units.

Performance is also measured in five different ways in the literature (Table 4), three of which are useful measures of acceleration performance that can be transformed into a

[5]In some cases, we made additional assumptions to estimate fuel costs. Vehicle lifetimes were derived from a report from the National Highway Traffic Safety Administration (NHTSA) (2006) by taking the midpoint of the median lifetime, the age by which 50% of the vehicles have been retired and 50% are still on the road, of cars (13 years) and light trucks (14 years) to give an expected lifetime of 13.5 years. The NHTSA report (NHSTA, 2006, Tables 7 and 8) gives different annual miles for cars and light trucks, but the average for new vehicles is approximately 15,000, and we use that value in our calculations. A discount rate of 10% was chosen as a reference point for discounting fuel savings over vehicle lifetimes. This is intended to reflect both the cost of capital and the decrease in vehicle use with age (about 3% to 4% per year). We estimate the present value of a one cent per mile change in fuel cost is about $1,150.

common metric (horsepower and top speed cannot). Willingness to pay for reductions in the number of seconds required to accelerate from 0–30 mph (11 observations) and 0–60 mph (8 observations) and MWTP for horsepower/pound (hp/lb, 29 observations) can be converted to seconds 0–60 mph. Seconds 0–30 can be approximately converted to seconds 0–60 by multiplying by 2.5. In general, it takes longer to accelerate from 30–60 mph than from 0–30 mph, so the conversion factor should be greater than 2.0. The ratios of 0–60 to 0–30 mph acceleration times for 15 recent model year GM, Ford, and Chrysler vehicles measured by the State of Michigan (2014) averaged 2.54, with a standard deviation of 0.1. The ratio of rated engine horsepower to vehicle weight has been shown to be an accurate predictor of 0–60 mph acceleration times (U.S. Environmental Protection Agency, 2015, December). U.S. Environmental Protection Agency (2015, December) provides 0–60 acceleration times and horsepower/weight (hp/wt) ratios for light-duty vehicles by model year from 1978 to 2014. A power function fit of hp/wt to seconds 0–60 mph produced the Equation 9:

$$\mathrm{hp/wt} = 0.3542(\mathrm{seconds}\ 0-60)^{-0.88},\ \mathrm{R}^2 = 0.97 \quad (9)$$

Solving the equation for the change in seconds 0–60 corresponding to an 0.01 increase in hp/wt based on the 1995 to 2014 average hp/lb. for light-duty vehicles (U.S. Environmental Protection Agency, 2015, December, Table 3.5) gives an approximate value for the reduction in 0–60 mph acceleration time of 1.68 seconds. Because we did not convert estimates for horsepower or top speed, we ended up being able to use 48 of the original 68 measures of performance in this direct comparison.[6]

6. Meta-Analysis of MWTP Estimates

The meta-analysis of MWTP estimates has two objectives: (1) to discover factors that may help explain the large variances of MWTP estimates and (2) to attempt to generate consensus central tendency estimates for MWTP for two of the vehicle attributes, reduced fuel costs and acceleration times. These attributes were selected based on policy relevance.

We begin by using Stata's™ ANOVA procedure to identify factors that might explain differences in MWTP estimates across studies. ANOVA and regression analysis are based on the same general linear model. However, the objective of the ANOVA is to investigate possible explanations for the variability of MWTP estimates rather than to develop estimates of conditional means and confidence intervals. In this analysis we are more interested in discovering whether factors such as the type of model or sample region or type of data affect the resulting MWTP estimates than we are in estimating the marginal effects of particular models or regions or data types.[7] All our factors but one, the midpoint year of the data used in a study, are categorical variables, which makes ANOVA a logical method to use. In addition, Stata's™ ANOVA procedure allows nesting of factors, a useful feature for combining MWTP estimates for different attributes. Results of the ANOVA of all MWTP

[6]Several other performance measures are not included here or in Table 54, such as engine size and relative descriptions such as "high" or "low."

[7]We did recover the regression coefficients from the ANOVA.

estimates are presented first. Although many measurable factors are found to significantly affect the MWTP estimates, the majority of the variation remains unexplained. In all the analyses described in this section, the small number of observations identified as outliers in Greene et al. (2017) were excluded (see also Table 3), giving us a total of 734 MWTP estimates.

We then explore possible explanations for the remaining variation via "case studies" of four papers that present several alternative sets of estimates from the same data set by changing the variables included in a model, the way attributes are measured, interactions between attributes and demographic variables, and methods of estimation. Comparison of results from these studies indicates that factors under the control of the analyst can profoundly affect the resulting MWTP estimates.

Finally, we focus specifically on MWTP estimates for reduced fuel costs and acceleration times, the most commonly included attributes besides vehicle price. This analysis attempts to find consensus MWTP estimates and confidence intervals. Because these attributes are the most directly related to fuel economy and GHG emissions and are of interest to most vehicle buyers, achieving consensus values for them would prove useful for future analyses. We also use subgroup analysis (Borenstein & Higgins, 2013) to explore differences along a single dimension (e.g., data type) that may suggest explanations for the relatively large confidence intervals resulting from the meta-analysis.

6.1 ANOVA of All MWTP Estimates

Previous studies of MWTP for fuel economy and performance and the estimates presented below indicate that heterogeneity of estimates across studies rather than estimation error is the predominant source of variation in MWTP estimates. To estimate how much of that variance could be accounted for by observable and readily measurable factors, we combined the MWTP estimates for all attributes and conducted an analysis of variance. Stata's™ ANOVA allows continuous variables (e.g., date in our case) to be included in a model. The observations were not weighted by their conditional standard errors because the goal of the analysis is not to find consensus estimates but rather to identify factors that may be responsible for the variability of the MWTP estimates.

The key to the ANOVA is accounting for the fact that the MWTP database includes estimates for many different attributes measured with different metrics. This is accomplished by nesting the units in which attributes are measured within the Group type of attribute being measured and dropping empty cells. Ten factors are included in the full ANOVA model:

- Data Type: market data, stated-preference (SP) survey, revealed-preference (RP) survey, SP/RP, literature review
- Statistical Model: the method of Berry et al. (1995) (BLP), mixed logit (MXL), multinomial logit (MNL), nested MNL, hedonic price, other
- Assumed Endogeneity (typically estimation via instrumental variables): yes, no
- Authors' Preferred Form: yes, no

- Interaction Variable: none, vehicle type, income, demographic
- Choice Level: fuel type, make-model, powertrain, vehicle class
- Sample Region: U.S., CA, ME, MD+VA+TN, CO, WA, Canada, Austin TX
- Journal Rank: Top 25, 26–100, 100–300, >300, unranked or grey literature
- Date: midpoint year of data set used in estimation minus 1970
- Group: Attribute type (see Figure 1)
- Metric: Units of measurement of attribute.

The sample size decreased to 717 because not all observations had data for all factors. As shown in Table 5, the full model had an R^2 of 0.41 and an adjusted R^2 of 0.33 with an F-statistic of 5.01 and a p-value of 0.0000. The units with which attributes were measured (Metrics) were nested within the attribute Group to account for the differences in MWTP that will naturally arise when attributes are measured in different units. The Stata™ ANOVA procedure automatically groups observations and computes pooled variances.

The ANOVA model in Table 5 assumes that the factors affect all attributes in the same way. This is unlikely. For example, the difference between stated and revealed preferences will likely differ depending on what attribute is being considered, and Assumed Endogeneity is likely to be a more important consideration for some variables than for others. The passage of time, represented by the Date variable will also likely affect preferences for attributes differently. We included two interactions between factors: Date with Group and DataType with Assumed Endogeneity. The interactions are significant at the 0.05 level although Date and Data Type effects alone are not. We do not show the many regression coefficients associated with the ANOVA; in general, only one or two levels of each factor or interaction are individually statistically significant. For example, only the regression coefficient of Date interacted with Pollution was individually significant among the interactions of date with Group and that MWTP for reduced emissions decreased over time. Consumers' preferences undoubtedly have changed over time. However, the data appear to be too noisy to detect such trends. With so many degrees of freedom in the ANOVA model, overfitting is also likely.

Several factors are directly under the control of the researcher: which variables to interact with attribute variables, the units in which the attributes were measured, the type of model estimated, whether the estimation method assumes endogenous vehicle prices, and the preferred model form. Researchers also influence the rank of the journal in which their research is published through their selection of journals to which the work is submitted. Other factors describe the data: Data Type, Choice Level, and Sample Region. However, all these factors together (plus attribute type and units) account for only a minor portion of the variance in the MWTP estimates. The great majority of variation is due to "other factors."

Factors unaccounted for in this analysis include at least the following:

- Decisions we made in estimating MWTP. These include estimates we may have had to supply for mean values of attributes, vehicle price or interaction variables when they were not available in the paper. Estimating WTP conditional on the mean value of the price derivatives is another source of potential variability.

- Researchers' decisions about which variables to include in the model and which to exclude.
- Correlations among variables included in the estimated model and excluded or unobserved variables.
- Choices of functional forms for variables, and interactions and distributions of random coefficients.
- Specific decisions about estimation methods, such as choices of instrumental variables in models assuming endogeneity.

In addition, the categories we chose for the factors included in the ANOVA are typically simplifications of actual differences from model to model.

6.2 Case Studies of Papers with Multiple Coefficient Estimates

Several papers provide alternative results with different sets of included variables, different metrics for the same attribute, or different estimation methods, all estimated from the same data set by the same authors. These studies provide valuable insights into how strongly factors that have not been included in the meta-analysis may influence MWTP estimates. Haaf et al. (2014) tested alternative types of models, choices of included variables, and choices of metrics for attributes. Klier and Linn (2012) present results for instrumental variables (IV) using a variety of different instruments. Petrin (2002) shows how augmenting market sales data with survey data can change coefficient estimates. Brownstone et al. (1996) illustrates how the choice of demographic variables interacted with vehicle attributes can produce counterintuitive results.

Haaf et al. (2014) estimated a variety of discrete choice models, including MNL, NMNL, and random coefficient models, using the same data set of sales of makes and models in the U.S. from 2004–2006. The estimated coefficients of vehicle price (in 10,000s of $) ranged from −0.19 to −0.61, except for one model estimated using the method of BLP, which produced a coefficient estimate of −1.56. Because the coefficient of price enters in the denominator of the MWTP estimate, such differences can be a major source of variability in MWTP estimates.

Coefficients of vehicle attributes were even more varied. In the six models that represented fuel cost as gallons per mile, three coefficients had a negative sign (as expected), while three had a positive sign. In addition to model form and estimation method, the models differed with respect to the metrics of vehicle size included. Those with positive signs on fuel cost coefficients used width and length*width/height to measure vehicle size, while those with negative signs included only length*width. Haaf et al. (2014) chose the variables for the different models (all of which had appeared in other studies) based on objective measures of model fit and adequacy, rather than the modelers' judgment. Omitted-variables bias is a likely explanation for estimates with counterintuitive signs.

Klier and Linn (2012) provide results for 14 different estimations of vehicle choice models at the make and model level using U.S. sales data for 2000–2008. The authors compared estimates made by means of ordinary least squares (OLS) with estimates using two different sets of instrumental variables (IVs). The OLS estimates were very different from the IV estimates: the price coefficient was about one fifth as large, the coefficient of cost per mile was positive, and that of hp/wt was more than two orders of magnitude smaller than that obtained by the IV methods. The authors clearly state that they believe that the OLS estimates were biased by failing to account for endogeneity bias. Nonetheless, the exercise demonstrated how strongly the method of estimation can influence results.

Klier and Linn (2012) also demonstrate that the instruments selected for the IV method can have a large impact on coefficient estimates. Instruments similar to those used by Berry et al. (1995) (BLP) produced a coefficient estimate for hp/wt of 9.53, while those created by the authors based on engine characteristics produced an estimate of 38.75. Other coefficients do not vary as much between the two sets of IVs (e.g. the coefficient of log of price is −1.86 for the BLP instruments and −1.28 for the engine instruments). Nonetheless, the experiment clearly illustrates how strongly even the choice of instruments in IV estimation can affect MWTP estimates.

Some estimates may be robust to changes in a model's formulation while other are highly sensitive. Klier and Linn (2012) compared seven sets of coefficient estimates from models differing with respect to variables included, except for one that employed a different error structure. The four that measured performance as hp/wt had similar coefficient estimates for both hp/wt (47.20, 38.75, 40.74, and 42.18) and the log of price (−1.79, −1.28, −1.34, and −1.49, in the same order). On the other hand, the same four models showed much greater differences in the estimated coefficients of fuel cost per mile (−13.24, −11.05, −22.94 and −3.29). The model that produced the fuel cost coefficient of −22.94 differed by the inclusion of the lagged value of the dependent variable. The one that produced the estimate of −3.29 used a different set of instruments. Models including hp and weight as separate variables rather than as their ratio produced yet a different set of estimates for the coefficients of the log of price (−0.99, −0.60, and −1.06) and fuel cost (−3.95, −0.98, and +0.43). A consequence of the sensitivity of estimates to choice of variables and instruments is that the estimates of the MWTP for 0.01 hp/lb based on Klier and Linn fall into two clusters that differ in magnitude by a factor of 5 to almost 40: ($303, $264, $303, and $283) and ($52, $51, and $8).

Augmenting market sales revealed-preference data with data on consumer attributes can also lead to dramatic changes in MWTP estimates. Random coefficient models were compared with fixed coefficient logit models by Petrin (2002), who also augmented vehicle sales data with data from the Consumer Expenditures Survey (CES) describing the average attributes of consumers purchasing new vehicles by income group. Four estimation methods were compared: OLS and IV for logit models and a Generalized Method of Moments algorithm for the random coefficient (RC) models, with and without the fitting to CES microdata. While many of the coefficient estimates are similar among the four models, the estimated coefficient of Miles/Dollar (miles per gallon/fuel price) for the OLS, IV, RC, and RC augmented with microdata models are, respectively: 0.18, 0.05, −0.54, and −15.79, with only the augmented RC (ARC) model estimate being statistically significant but having a counterintuitive sign. For the RC and ARC models, the estimated standard deviations are only 0.04 (RC) and 2.58 (ARC), implying that nearly all consumers would prefer fewer miles per dollar. There are also major differences between the two estimation methods for other attributes, such as hp/lb (Greene et al., 2017).

The choice of demographic variable to interact with a vehicle attribute can also strongly influence coefficient and MWTP estimates. Brownstone et al. (1996) estimated MNL models to predict vehicle transactions for 1,153 California households owning one vehicle and 1,156 households owning two vehicles. Vehicle price was interacted with household income category and the presence and age of children, creating a multiplicity of MWTP estimates for different income groups and household compositions. Estimates of the willingness to pay for a \$1 present value decrease in operating cost are shown in Figure 2. High and low MWTP estimates reflect +/− one standard error of the operating cost coefficient. The number of vehicles owned by the household (1 or 2) is shown in the horizontal axis labels, and "luxury" indicates the household owns at least one luxury vehicle. (Income categories are in 1993 dollars but MWTP estimates have been converted to 2015 dollars.) Three of the ten mean estimates are negative, suggesting that at least three categories of consumers would prefer higher operating costs. This result is due to positive coefficient estimates for vehicle purchase price for three of the household categories. The positive price coefficients create similarly anomalous MWTP estimates for other attributes for these household categories. Other researchers using the same database but different model formulations produced widely varying MWTP estimates for operating cost, acceleration, availability of fuel for alternative fuel vehicles, and pollutant emissions (Greene et al., 2017).

6.3 Meta-analysis of MWTP Estimates for Fuel Cost and Acceleration Performance

This section presents a meta-analysis of MWTP for these two attributes. The goals is to identify a consensus estimate for each attribute, if possible, and to estimate confidence intervals. Fuel cost and performance are the variables most commonly included in econometric models (after vehicle price). They are also directly relevant to vehicles' GHG emissions and fuel economy. Unlike attributes such as vehicle size or weight, acceleration and fuel cost are rarely described by authors as proxies for omitted attributes.

For the analysis of overall central tendency for these two attributes, Stata's™ metaan DerSimonian-Laird (D-L) random effects method was used (Kontopantelis & Reeves, 2010). For studies with different sample sizes, the D-L method is known to be less efficient than other methods for computing between-study variance but "remarkably efficient for computing the treatment effect" (here the MWTP) (Jackson et al., 2010). Our focus is on the treatment effect, the magnitude of the MWTP estimate. Although sample sizes in the underlying studies vary, samples sizes are relatively large, ranging from surveys of hundreds of respondents to purchases by millions of car buyers. In addition, the nature of the data and therefore the meaning of the sample size varies also. For this reason, weighting MWTP estimates by sample sizes is not as useful as it might be in other fields where samples are designed to test hypotheses and sizes range from tens to hundreds. Instead, as a measure of reliability, observations were weighted by half of their uncertainty intervals (their standard errors of estimation, conditional on the central value of the price derivative). The D-L method assumes a random effects model, which in meta-analysis means that the true effect being measured (MWTP) may differ across studies.[8] Fixed effects (FE) models that assume all studies are measuring the same effect but with measurement error are an alternative to the D-L method available in the metaan routine. We tested FE models but rejected them for three reasons:

1. The studies in our database come from different time periods and are sampled from different populations (e.g., California versus U.S., stated-preference survey of potential car buyers versus actual market sales), implying that heterogeneity in MWTP across studies should be expected. In addition, as the ANOVA analysis and case studies demonstrate, choices made by modelers about included and excluded variables, estimation methods, and more can bias or reduce bias in coefficient estimates. As a consequence, what is being measured should be expected to differ from one study to another.[9]

2. Weighting by our uncertainty measure caused most studies, and especially those with high MWTP values and correspondingly large standard errors, to be severely discounted by the FE method. The result was that FE mean MWTP estimates were as much as two orders of magnitude smaller than those produced by the D-L method estimates.

3. The Cochrane's Q heterogeneity tests of both the FE and D-L methods rejected the null hypothesis of homogeneity at p-levels smaller than 0.001, and the I^2 statistic typically attributed 98%−99% of the differences across studies to heterogeneity as opposed to measurement error.[10]

MWTP estimates from both random parameter and fixed parameter models are weighted by the uncertainty metric based on the standard errors of estimation of the attribute coefficient. Most random coefficient models do not provide simulated standard errors of mean MWTP estimates. We calculated approximate values using the standard errors of the estimated means of the distributions of the attribute coefficients. While this is clearly inferior to a simulated estimate, we considered it preferable to either omitting estimates from random coefficient models or using the standard deviation of the random coefficient (which represents heterogeneity of preferences in the population rather than estimation uncertainty).

We divide the studies into subgroups based on data type (here, RP-SP is grouped with SP), model type (fixed or random coefficient) and whether potential endogeneity was taken into account in estimating the model. Our subgroup analysis is exploratory and descriptive rather than definitive. We do not test hypotheses of differences between mean effects because of the many effects not controlled for.

[8]For purposes of the meta-analysis of central tendency, every WTP estimate is considered to be a "study" in that it represents a different model formulation or estimation method, even if not a different data set.

[9]As we have noted above, assumptions and approximations we have used in calculating WTP values also add to the differences across studies.

[10]Interpretation of this result should consider that our standard error measure undoubtedly underestimates the true within study error.

6.3.1 Fuel Economy: $0.01 Reduction in Fuel Cost per Mile—Results of the metaan analysis for fuel cost, based on estimates that could be reasonably converted to MWTP for a $0.01/mile reduction, are shown for fixed coefficient models in Table 6, models with random coefficients in Table 7, and for both types of models combined in Table 8. The original 117 observations that can be used for this analysis is reduced to a total of 95 (68 from models with fixed coefficients and 27 from models with random coefficients) after deleting 7 outliers and excluding 15 other observations for which standard errors were not available. In all three tables, the D-L random effects meta-analysis method has been used. For models with fixed coefficients (weighted by the uncertainty metric), the mean MWTP for a $0.01/mile (2015 $) reduction in fuel cost is $853 with a 95% confidence interval (C.I.) of $636 to $1,071 (see Table 6).[11] Based on data from National Highway Traffic Safety Administration (NHTSA) (2006), a light-duty vehicle in the U.S. can be expected to travel approximately 115,000 discounted miles over its lifetime (future miles discounted at 6% per year). This would suggest a MWTP of $1,150 for a $0.01/mile reduction in fuel cost. This is not necessarily a “correct” or “rational” MWTP, but it provides a meaningful reference point for comparison with the meta-analysis mean estimates. The mean for all fixed coefficient studies is about three-quarters of the reference value, with the high end of the metaan 95% C.I. falling just below the reference value. The p-values strongly reject the null hypothesis of homogeneity across estimates, confirming the inappropriateness of the fixed effect model.

MWTP estimates for fuel cost in Table 6 appear to differ according to the nature of the data, with estimates derived from answers to hypothetical survey questions showing a much greater MWTP Inflation of WTP estimates in stated preference experiments is a typical result (Murphy et al., 2005) observed in many but not all WTP analyses of stated preference data (Loomis, 2014). The overall estimates from studies based on market sales data and revealed-preference surveys are similar and lower than the overall estimate from studies that used stated-preference survey data. The conditional[12] 95% confidence intervals (CCIs) for estimates from revealed- and stated-preference surveys do not overlap. The market sales CCI is much broader and has an $82 overlap of its $694 range with the stated preference CCI. Combining the studies based on market sales and revealed-preference surveys produces a meta-analysis mean of $693 (60% of the reference value) with a CCI that overlaps that of the stated preference surveys by only $1. While it is premature to draw firm conclusions, these results suggest that consumers’ stated MWTP for fuel cost reduction may be substantially higher than what is implied by their actual purchases.

The Cochrane Q test for heterogeneity rejects homogeneity at the 0.000 level for all the analyses shown in Table 6. The I-squared metric indicates that almost all of the observed variation is due to heterogeneity across studies and that 1% or less is due to estimation error (as represented in the standard errors).

Results of the metaan analysis of MWTP estimates from random coefficient models are shown in Table 7. The overall mean of the 30 estimates is $1,706, well above the reference

[11]Because the meta-analysis weights the studies – in this case, by the uncertainty metric – these values are weighted estimates of the central tendency and variation of that central tendency. In contrast, Table 53 presents unweighted estimates.

[12]We refer to the confidence intervals calculated by the metaan procedure as conditional because they are not based on true standard errors but rather on our uncertainty metric.

value ($1,150), but the range is very large, from −$450 to +$3,862. This range reflects differences in central tendency estimates across studies and not heterogeneity of preferences across the population. While there are large differences in the means and CCIs across data types, there does not seem to be a clear pattern that distinguishes stated versus revealed preference or market sales data, as seen in the fixed coefficient estimates. The only common characteristic appears to be much higher variability. The Cochrane Q and I-squared statistics again confirm extreme heterogeneity across studies.

Some studies attempted to take account of endogeneity, while others did not. Separate metaan runs for the two categories are shown in Table 8. The overall mean MWTP estimates for those that did attempt to account for endogeneity is less than half that of those that did not. The overall estimate for models that did not account for endogeneity is about 20% greater than the reference value, $1,368 versus $1,150, while the mean estimate for those that did was just under 50% of the reference MWTP value. Models assuming endogeneity tend to produce larger (absolute value) price coefficients. Since MWTP is generally the ratio of the derivative of utility with respect to an attribute to the derivative of utility with respect to price, a price coefficient with a large absolute value will, all else equal, produce a smaller MWTP estimate. The estimates shown in Table 8 appear to reflect this.

The combined meta-analysis estimate of MWTP for a $0.01/mile reduction in fuel cost is also shown in Table 8. The mean effect is 92% of the reference value, but the CCI is large (−$12 to $2,128) and includes zero. In addition, it is a consequence of averaging low MWTP estimates from studies that correct for endogeneity and studies that are based on market sales or revealed preference survey data with much higher estimates from studies based on stated preference survey data and studies that did not consider vehicle prices to be endogenous. Unfortunately, the meta-analysis seems to offer support for a wide range of conclusions about WTP for fuel cost reduction, depending on one’s beliefs about the reliability of inferences from different kinds of data and the necessity of using estimation methods that account for endogeneity of vehicle prices.

6.3.2 Performance: 1-Second Reduction in 0–60 mph Acceleration Time—

This discussion focuses on the 48 MWTP estimates that either used the metric seconds 0–60 mph or could be reasonably transformed into that metric (those metrics are seconds 0–30 mph and horsepower divided by vehicle weight). The Stata™ metaan D-L procedure was again used, and MWTP estimates were weighted by standard errors. Again, the hypothesis of homogeneity of effects across studies was rejected with a p-value less than 0.001 for both FE and D-L model tests.

For performance, the overall mean estimates of fixed and random coefficient models are $964 and $686 per second 0–60 mph, respectively. The C.I. of the estimates from random coefficient models is again larger than that of the fixed coefficient models, but the differences are not as extreme as they were for fuel cost. The C.I. of the overall mean effect for both types of models is only a little wider than +/−15%. All the metaan analyses in Table 9 reject homogeneity across studies and attribute 95% or more of the variation to heterogeneity among the estimates.

The MWTP for performance estimates is analyzed by data type in Table 10. Variation in the MWTP estimates across data types is smaller than that seen in the fuel cost MWTP estimates. The meta-analysis mean MWTP estimates for performance are $949 for stated-preference surveys, $847 for revealed-preference surveys, and $685 for studies based on market sales data. The ballpark similarity of the overall estimate from stated-preference survey data ($949) to the combined market sales and revealed-preference overall estimate ($796) suggests that with respect to acceleration performance, consumers' stated preferences are relatively consistent with their actual purchase decisions.

Studies that do and do not take price endogeneity into account are compared in Table 12. Once again, the overall MWTP estimate for studies that assume endogenous vehicle prices is lower than for studies that do not, but the difference is extreme: $45 versus $1,111/s 0–60 mph.

The surprisingly low mean MWTP for studies assuming endogeneity demands explanation. A forest plot of individual MWTP values, standard errors, and D-L weights reveals that a few high MWTP values with very large standard errors have been assigned near-zero weight by the metaan D-L procedure (Figure 3). The D-L weights are represented in Figure 3 by shaded squares. Nearly all the weight is assigned to studies 2, 3, and 8 because of their very low standard errors. This contrasts with all the previously reported results, in which weights assigned by the D-L procedure are much more similar across studies. This is also the only D-L analysis in which heterogeneity is estimated to account for less than 90% of the variation among studies, also a consequence of the extreme distribution of weights. If equal weights are assigned to all studies, the overall mean MWTP estimate becomes $692 with an CCI of −$358 to $1,741. However, if the one study with a MWTP greater than $5,000 is removed, the overall mean MWTP drops to $288 with an CCI of −$42 to $617.

7. Concluding Observations

Estimating consumers' willingness to pay for vehicle attributes is a very difficult problem. Automobiles are multidimensional with dozens of relevant attributes. Researchers face challenges of variables measured with error, omitted variables, and correlations among included and omitted variables. Measuring relevant vehicle attributes is often difficult, and often only possible with a loss of precision. Consumers' preferences vary, but accurately measuring that heterogeneity remains a challenge. Finally, behavioral psychology suggests that, faced with such a complex, multidimensional choice problem (and one that most consumers do not face often), individuals may not optimize continuous trade-offs among all attributes, as assumed in the discrete choice and hedonic price models that are commonly used in these studies, but instead may use simpler decision rules.

This paper has analyzed MWTP estimates from two decades of U.S. studies. Although means and medians generally agree on signs, the variability in estimates across studies is almost always very large relative to the mean or median of the MWTP estimates for any given attribute. Although we have found some statistically significant relationships and suggested others, further analysis of existing studies is needed to more fully explain why such large differences in MWTP estimates arise.

An analysis of variance using the full set of central tendency MWTP estimates indicates that the estimates are affected by a variety of factors, some under the researchers' control and others not. Region, data type, estimation methods, model type, and even the rank of the journal in which the research was published all show statistically significant relationships with MWTP estimates. However, all the measured factors together can account for only one third of the total variation. Additional insights can be found in four studies that present results from multiple alternative models estimated on the same data set but using different variables, metrics, and estimation methods. These studies show that small changes in these factors can, but don't always, produce large changes in coefficient estimates. The evidence is indicative of several difficult statistical problems: errors in variables, omitted variables, and correlation among attributes. These difficulties have long been recognized by researchers (Brownstone et al., 1996), yet they make it difficult to find consensus among estimates of MWTP for even the most frequently included attributes.

Meta-analysis of MWTP for lower fuel cost and faster acceleration from studies that assume endogeneity versus those that do not indicates that studies assuming endogeneity tend to produce smaller MWTP values. This result may be due to a downward bias in the absolute value of price coefficients in studies that assume that prices are exogenous. Differences have also been found between studies based on stated- versus revealed-preference data and between those employing random versus fixed coefficient models. MWTP estimates for fuel cost and performance did not respond to these factors in the same way, however. Finally, the variation among our MWTP estimates is overwhelmingly due to heterogeneity across studies. This is almost certainly true despite the fact that we underestimate within-study estimation error. When heterogeneity typically accounts for 98% or more of the variance in MWTP estimates, it is even appropriate to question the logic of seeking a consensus estimate.

The large variation in existing estimates of MWTP for vehicle attributes requires that they be used with caution. The extreme heterogeneity of estimates for most attributes, at a minimum, calls for routine use of sensitivity analysis rather than a single consensus value.

Recognizing the difficulty of the problem researchers in this area face, we offer a few recommendations that might eventually lead to greater consensus.

- Routinely calculate the MWTP estimates implied by coefficient estimates and their uncertainty, and compare them with those of other studies. Because authors have the information necessary to compute superior MWTP estimates, any errors introduced by the approximate methods we have used can be avoided.

- Provide estimated covariances as well standard errors for estimated coefficients to enable other researchers to estimate mean WTP using more precise methods, such as the Delta method.

- Pay particular attention to potential aliasing effects. Robustness checks and other measures can be used to identify which variables are aliasing other factors. Although it is frequently desirable to include these variables to obtain robust estimates of other variables, clearly distinguishing between variables that are believed to be aliasing other effects and those that are intended to accurately reflect consumers' preferences for an attribute is rarely done but could increase the likelihood of identifying consensus MWTP values for attributes. Several recent studies using very large and highly detailed data sets have included large numbers of fixed effects variables to better control for omitted variables (Leard et al., 2017).

- The units in which attributes are measured matters. For example, as Greene (2001) and Dimitopoulos et al. (2013) point out, the value of vehicle range is best represented by the inverse of range. Similarly, if fuel economy is assumed to be traded off with vehicle price, measuring it in gallons or dollars per mile is more consistent with the rational consumer model than measuring it in miles per gallon.
- Given the complexity of the vehicle-choice problem and recent insights into consumers' decision making from behavioral economics, alternatives to the continuous trade-off, rational economic model should be explored.

Over the past two decades, impressive progress has been made with respect to the sophistication of models of consumer demand and methods of estimation. In spite of this, consensus on the values consumers attach to vehicle attributes remains elusive. In part, this undoubtedly reflects the heterogeneity of consumers' preferences for vehicle attributes. It also reflects the challenges of modeling and statistically estimating the behavior of real consumers making such a complex decision. The results of our study indicate that there is still more work to do.

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Appendix B.: Attribute Groups

Group	Attribute	Count of Attribute
Comfort	air conditioning	13
	automatic transmission	9
	comfort rating	1
	FWD	6
	power steering	3
	shoulder room	12
Fuel availability	charge 10h	3
	charge 10min	2
	charge 15h	3
	charge 1h	2
	charge 20h	3
	charge 5h	2
	charge time (cont.)	2
	EV fast charge	2
	home or station refuel	1
	home refuel	4
	home refuel time	1
	PHEV fast charge	2
	Plug-in at work/other	1
	refuel 12–6am	1
	refuel any but 2–9pm	1
	station availability	12
	station availability (1/20 vs 1/50)	1
	station availability 1%	1
	station availability 10%	3
	station availability 20%	1
	station refuel time	3
	station refuel time 300h	2
Fuel costs	charger cost ($100)	1
	fuel cost	86
	gallons per mile (gpm)	20
	home refueling cost	2
	mpg	10
	operating cost	3
Fuel type	CGV	4
	diesel	2
	EV	24
	EV (V2G)	3
	flex fuel	6
	fuel cell	1
	Hybrid	27

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Group	Attribute	Count of Attribute
	methanol	5
	natural gas	7
	PHEV	5
Incentives	cashback	3
	free parking	1
	gas guzzler tax ($1000)	1
	gas guzzler tax ($1300)	1
	gas guzzler tax ($1700)	1
	gas guzzler tax ($2100)	1
	HOV access	3
	purchase subsidy	4
	tax credit	2
Model availability	number of models	14
Non-fuel operating costs	battery cost	2
	maintenance cost	3
Performance	acceleration (20% faster)	2
	acceleration (5% faster)	2
	acceleration (5% slower)	2
	acceleration (0–30)	11
	acceleration (0–60)	8
	braking distance	1
	cylinders	2
	displacement	3
	high performance	4
	horsepower	23
	hp/wt	29
	low performance	4
	top speed	9
	turning circle	1
Pollution	emissions	13
	emissions (50% lower)	2
	emissions (75% lower)	2
	emissions (95% lower)	2
Prestige	1–2 yrs	1
	3+ yrs	1
	American Motors	1
	Asian	1
	Chrysler	2
	European	3
	foreign	5
	German	1
	GM	2

Group	Attribute	Count of Attribute
	Japanese	2
	Korean	1
	luxury	1
	new	2
	Prius	6
	resale value retained	1
	used	2
Range	BEV100mi	2
	BEV150mi	2
	BEV75mi	
	PHEV10mi	
	PHEV20mi	2
	PHEV40mi	2
	range (cont.)	22
	range 125mi	3
	range 150mi	
	range 200mi	2
	range 25mi	
	range 300mi	2
	range 75mi	3
Reliability	reliability index	5
	reliability index (>=2)	1
Safety	airbags	2
	crash test rating (front & side)	1
	safety index	1
Size	footprint	17
	length	4
	length-WB	1
	luggage space	17
	size (index)	7
	volume	2
	weight	19
	wheelbase	1
	width	3
Vehicle class	compact	4
	Compact SUV	1
	Compact van	1
	Compact pickup	3
	convertible	1
	large	15
	Large van	1
	Large SUV	5

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Group	Attribute	Count of Attribute
	luxury	9
	luxury/sport	1
	Medium SUV	3
	midsize	3
	Mid-size cross-utility SUV	1
	mini	6
	mini-SUV	3
	minivan	22
	non-compact	1
	pickup	7
	sedan	1
	small	7
	Small cross-utility car	1
	Small cross-utility SUV	1
	Small SUV	4
	sport	11
	station wagon	5
	subcompact	4
	SUV	20
	truck	16
	two-seater	2
	van	6
Grand Total		**777**

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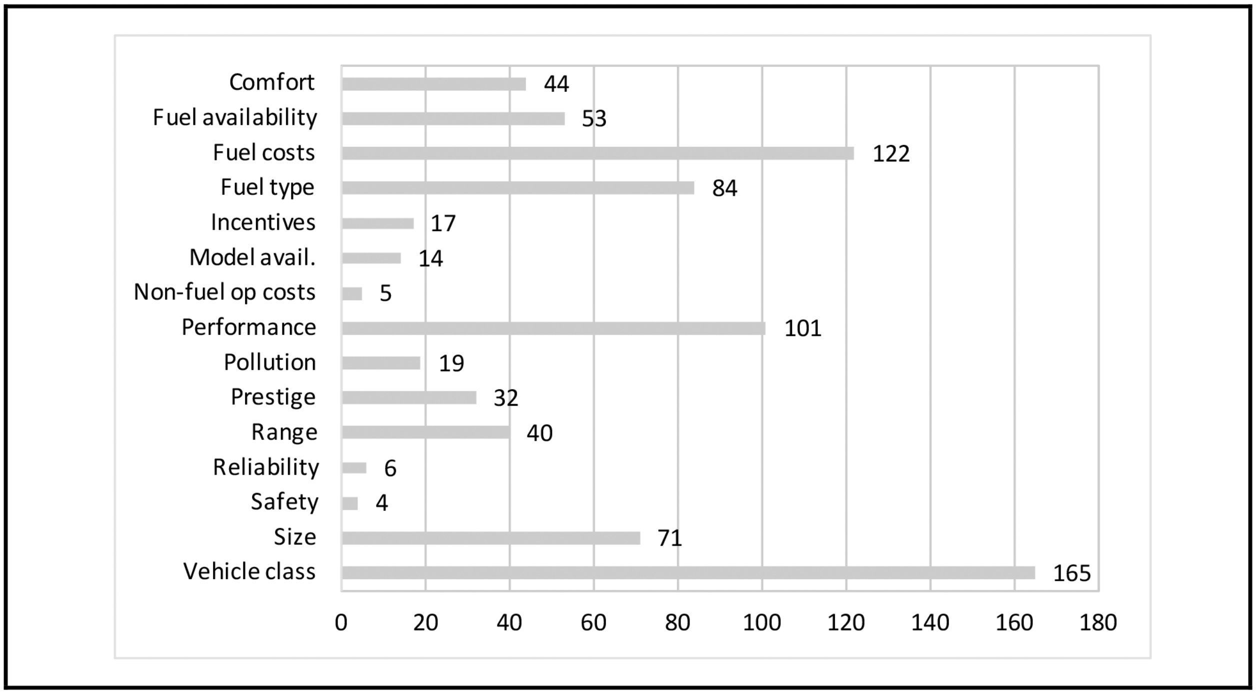

Figure 1.
Number of MWTP Observations by Attribute Group

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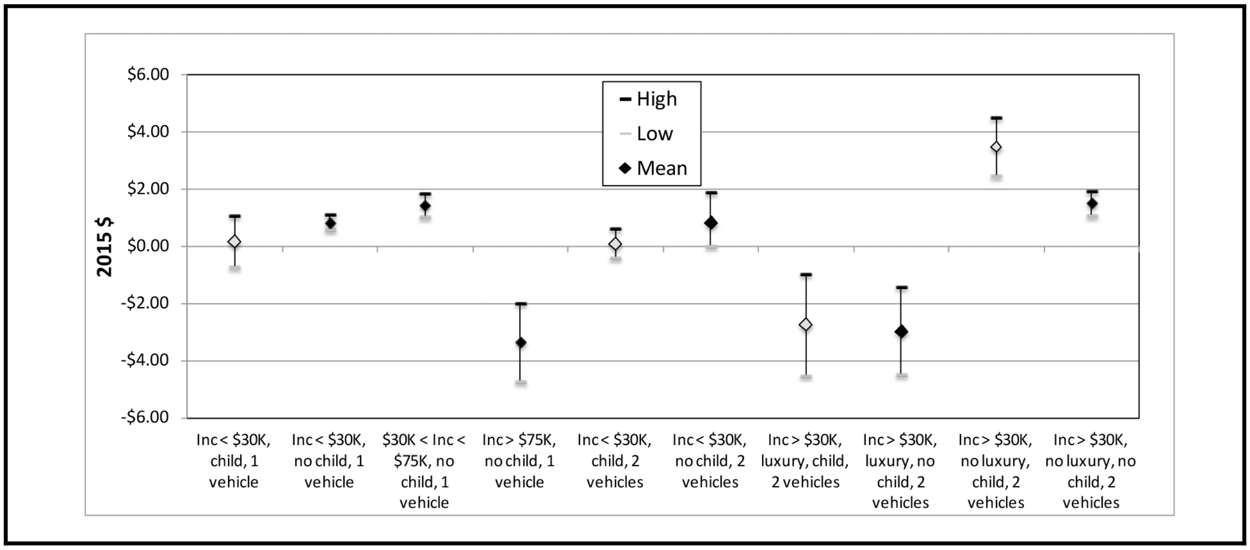

Figure 2.

Willingness to Pay for a $1 Present Value Decrease in Operating Cost: 1- and 2-vehicle Households. Estimates derived from Brownstone et al. (1996).

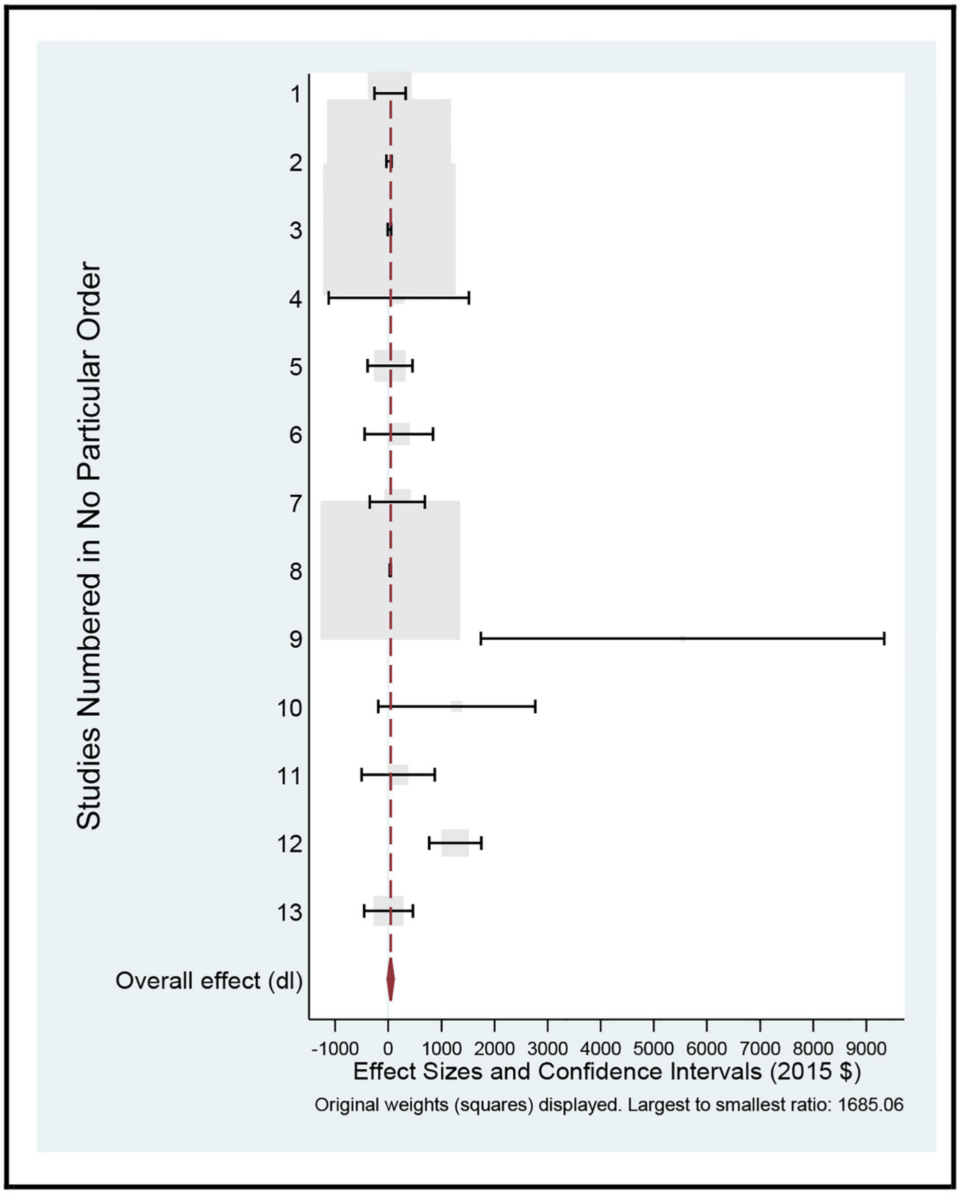

Figure 3.

Forest Plot of Weights Assigned to Each Study, Assuming Endogenous Prices by the D-L Meta-analysis of MWTP for Performance.

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Table 1.

Literature Summary Statistics Based on Our Main Sample

Paper count	52
Observation count	777
Unique attribute count	142
Literature type	
Peer-reviewed	86.4%
Grey	13.6%
Data type	
Revealed-preference (RP) survey	19.6%
Stated-preference (SP) survey	38.6%
Market data	29.3%
Other	12.5%
Model type	
Hedonic price	8.8%
Multinomial logit (MNL)	30.1%
Nested multinomial logit (NMNL)	13.6%
Mixed logit (MXL)	29.3%
Berry-Levinsohn-Pakes (BLP)	6.8%
Other	11.3%

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Table 2.

Count by Type of Data and Vehicle Market (one study that presented results from two different surveys is counted twice in this table, and the two literature reviews are not included).

Vehicles Included	Revealed Preference	Stated Preference	RP & SP	Market Individual	Market Aggregated	Total
New	5	14	3	15	3	40
Used	0	0	0	2	0	2
Both	4	2	0	3	0	9
Total	9	16	3	20	3	51

Table 3.

Summary Statistics from Pooled Central MWTP Estimates (2015 $). (Vehicle class estimates have been omitted because they are not comparable across studies due to differing class definitions and base vehicles. Values in italics are based on observations converted to a common metric.)

					Raw				Trimmed						
Grouping	Attribute	N	Units	Out-liers	Mean	SD	Min	Max	Mean	SD	Min	Max	Median	Inter-quartile Range	Skew
Comfort	Auto-transmission	9	0/1	1	1,818.8	3,739.3	−2,987.0	9,260.6	888.6	2,660.8	−2,987.0	5,321.4	1,090.3	3,262.9	0.8
	Rear-wheel drive	6	0/1	0	32,030.9	18,030.7	10,069.8	62,928.8	32,030.9	18,030.7	10,069.8	62,928.8	26,778.8	16,189.4	1.2
	Air conditioning	13	0/1	0	3,484.2	9,627.1	−15,380.0	19,818.5	3,484.2	9,627.1	−15,380.0	19,818.5	3,961.6	7,474.0	0.9
	Shoulder room	12	$/inch	1	1,085.1	1,393.7	178.4	5,266.6	705.0	478.7	178.4	1,800.1	545.9	764.2	1.3
Fuel availability	Recharging time	27	$/hr	0	2,194.8	2,923.1	−227.4	11,947.1	2,194.8	2,923.1	−227.4	11,947.1	930.9	2,689.9	2.4
	Fuel availability	18	$/%	2	834.5	2,133.1	48.8	9,133.3	227.8	201.4	48.8	789.6	161.7	166.7	1.9
Fuel costs (value of reduction in costs)	**Aggregate fuel cost per mile**	**117**	**$/cpm**	**7**	**−8,330.7**	**97,820.1**	**−1,052,470**	**64,499.0**	**1,879.7**	**6,875.4**	**−7,425.0**	**64,499.0**	**990.6**	**2,194.2**	**1.9**
	Cost per mile	*60*	*$/cpm*	*0*	*1,366.3*	*3,318.0*	*-7,425.0*	*19,415.1*	*1,366.3*	*3,318.0*	*-7,425.0*	*19,415.1*	*1,146.5*	*2,546.5*	*1.2*
	Cost per year	*15*	*$/($/yr)*	*1*	*-63,204.0*	*274,176.8*	*-1,052,470*	*64,499.0*	*7,457.8*	*17,256.0*	*-3,224.1*	*64,499.0*	*1,133.9*	*4,723.8*	*6.6*
	Gallons per mile	*24*	*$/0.01 gpm*	*3*	*46.1*	*3,090.7*	*-7,472.2*	*4,701.1*	*1,066.3*	*1,483.6*	*-1,094.8*	*4,701.1*	*1,027.1*	*1,816.8*	*1.0*
	Miles per dollar	*8*	*$(10mi/$)*	*3*	*-14,917.7*	*20,600.8*	*-59,618.7*	*-676.5*	*-2,328.4*	*1,795.8*	*-4,985.1*	*-676.5*	*-2,097.0*	*2,349.3*	*1.1*
	Miles per gallon	*7*	*$/mpg*	*0*	*991.4*	*1,404.0*	*-325.2*	*3,848.9*	*991.4*	*1,404.0*	*-325.2*	*3,848.9*	*800.3*	*1,451.5*	*1.2*
	Other converted units	*3*	*$/GGE or $/gallon*	*0*	*896.4*	*702.1*	*115.6*	*1,475.9*	*896.4*	*702.1*	*115.6*	*1,475.9*	*1,907.6*	*1,360.3*	*0.8*
Fuel type	Electric vehicle	27	0/1	1	−10,525.6	22,711.8	−77,780.3	30,651.0	−7,938.8	18,670.1	−43,983.9	30,651.0	−8,454.0	28,385.9	0.9
	Hybrid	27	0/1	2	−12,671.0	44,878.6	−180,394.4	18,860.1	−1,436.6	18,573.8	−55,816.5	18,860.1	2,374.7	11,880.8	−0.6
	Flex fuel	6	0/1	0	5,166.3	5,692.3	−4,409.9	10,975.3	5,166.3	5,692.3	−4,409.9	10,975.3	6,114.4	6,298.4	0.8
	PHEV	5	0/1	0	12,337.8	12,061.0	−7,959.3	23,809.8	12,337.8	12,061.0	−7,959.3	23,809.8	14,740.0	4,877.4	0.8
	Methanol	5	0/1	0	11,134.3	2,884.9	6,989.4	13,962.7	11,134.3	2,884.9	6,989.4	13,962.7	12,587.2	3,461.5	0.9
	Natural gas	7	0/1	2	−5,619.6	23,691.2	−55,978.3	12,956.4	6,187.4	3,850.6	3,295.7	12,956.4	5,006.2	439.2	1.2
Model Availability	Make-model availability	14	$/# of models	2	898.8	2,281.3	0.5	6,841.5	5.9	7.6	0.5	22.1	2.1	8.2	2.8
Performance	**Aggregate acceleration (0–60) time reduction**	**48**	**$/s**	**0**	**953.7**	**1,259.2**	**−1,546.9**	**5,543.5**	**953.7**	**1,259.2**	**−1,546.9**	**5,543.5**	**1,004.9**	**1,199.5**	0.9
	Acceleration (0–30) time reduction	*11*	*$/s*	*0*	*1,045.2*	*1,122.8*	*-1,546.9*	*3,287.5*	*1,045.2*	*1,122.8*	*-1,546.9*	*3,287.5*	*1,140.6*	*608.9*	*0.9*
	Acceleration (0–60) time reduction	*8*	*$/s*	*0*	*1,095.6*	*627.4*	*34.6*	*2,200.1*	*1,095.6*	*627.4*	*34.6*	*2,200.1*	*1,182.7*	*497.8*	*0.9*
	Horsepower/weight	*29*	*$/0.01hp/lb*	*0*	*879.8*	*1,448.5*	*-860.4*	*5,543.5*	*879.8*	*1,448.5*	*-860.4*	*5,543.5*	*198.4*	*1,558.1*	*4.4*

Grouping	Attribute	N	Units	Out-liers	Raw				Trimmed						
					Mean	SD	Min	Max	Mean	SD	Min	Max	Median	Inter-quartile Range	Skew
	Horsepower	11	$/hp	0	53.6	108.8	0.0	355.0	53.6	108.8	0.0	355.0	9.2	38.2	5.8
	Top speed	9	$/mph	0	100.1	58.3	27.6	209.7	100.1	58.3	27.6	209.7	54.2	86.5	1.8
Pollution	Emissions reduction	19	$/10%	0	48,007.8	69,595.8	−66,982.0	168,535.7	48,007.8	69,595.8	−66,982.0	168,535.7	1,491.3	132,083.1	32.2
Range	Range	40	$/mi	0	86.3	51.5	−20.1	242.6	86.3	51.5	−20.1	242.6	87.3	62.5	1.0

* Attributes in italics are combined into aggregate measures.

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Table 4.

Summary of MWTP for Different Performance Metrics: mph = miles per hour

MWTP for Attribute	N	Mean	S.D.	Minimum	Maximum	Median
Converted to second 0–60 mph						
Acceleration (seconds 0–30 mph)	11	1,045	1,122	−1,547	3,288	1,141
Acceleration (seconds 0–60 mph)	8	1,096	627	35	2,200	1,183
Horsepower/pound	29	880	1,449	−860	5,544	198
All converted (secs. 0–60 mph)	48	954	1,259	−1,547	5,543	1,005
Metrics not converted						
Horsepower	11	54	109	0	355	9
Top speed (mph)	9	100	58	28	210	75

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Table 5.

Analysis of Variance: All MWTP Estimates (Excluding Outliers).

Number of observations =	717			R-squared =		0.41
Root Mean Square Error =	14099			Adj. R-squared =		0.33
Source		Partial Sum Sq.	df	Mean Sq.	F	Prob>F
Model		8.56E+10	86	9.96E+08	5.01	0.0000
Data Type		3.65E+08	3	1.22E+08	1.83	0.1626
Statistical Model		2.17E+09	5	4.34E+08	6.54	0.0003
Assume Endogeneity		8.43E+08	1	8.43E+08	12.7	0.0012
Preferred Form		6.97E+07	1	6.97E+07	1.05	0.3134
Interaction Variable		2.18E+09	4	5.45E+08	8.22	0.0001
Choice Level		6.40E+08	3	2.13E+08	3.22	0.0367
Sample Region		4.23E+09	5	8.86E+08	13.4	0.0000
Journal Rank		1.20E+09	4	2.99E+08	4.51	0.0057
Date		3.28E+07	1	3.28E+07	0.49	0.4873
Group#Date		2.12E+10	14	1.52E+09	22.8	0.0000
Data Type#Assume Endog.		2.83E+09	1	2.83E+09	42.7	0.0000
Group		2.14E+10	14	1.53E+09	23.0	0.0000
Metric|Group		1.99E+09	30	6.63E+07	0.33	0.9997
Residual		1.25E+11	630	1.99E+08		
Total		2.11E+11	716	2.94E+08		

[#] indicates interaction between two factors.

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Table 6.

D-L Random Effects Analysis: Mean MWTP for Fuel Cost Reduction of $0.01/mile and Conditional 95% Confidence Intervals from D-L Meta-analysis—Models with Fixed Coefficients (weighted by uncertainty metric)

	$				
Data Type	**Mean**	**CCI Low**	**CCI High**	**p-value**	**Count**
Market Sales	678	330	1,024	0.000	37
Revealed-Preference Survey	549	325	773	0.000	11
Stated-Preference Survey	1,225	942	1,509	0.000	20
Market + Revealed Preference	693	444	943	0.000	48
All	853	636	1,071	0.000	68

Table 7.

D-L Random Effects Analysis: MWTP for Fuel Cost Reduction of $0.01/mile and 95% Conditional Confidence Intervals from D-L Meta-analysis—Models with Random Coefficients (weighted by uncertainty metric)

	2015 $				
Data Type	**Mean**	**CCI Low**	**CCI High**	**p-value**	**Count**
Market Sales	−760	−4,300	2,742	0.000	12
Revealed-Preference Survey	4,140	−186	8,465	0.000	2
Stated-Preference Survey	2,866	1,824	3,908	0.000	13
All	1,706	−450	3,862	0.000	27

Table 8.

D-L Random Effects Analysis: MWTP for Fuel Cost Reduction of $0.01/mile and 95% Conditional Confidence Intervals from D-L Meta-analysis—Methods That Did and Did Not Correct for Endogeneity (weighted by uncertainty metric)

	2015 $				
Price Endogenous?	**Mean**	**CCI Low**	**CCI High**	**p-value**	**Count**
Yes	569	369	770	0.000	36
No	1,368	−14	2,752	0.000	59
All	1,057	−12	2,128	0.000	95

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Table 9.

D-L Random Effects Analysis: MWTP for a 1 Second Reduction in 0–60 mph Acceleration and Conditional 95% Confidence Intervals—Random and Fixed Coefficient Models (weighted by uncertainty metric)

	2015 $				
Coefficient Type	**Mean**	**CCI Low**	**CCI High**	**p-value**	**Count**
Random	686	403	970	0.000	20
Fixed	964	830	1,098	0.000	28
All	845	713	977	0.000	48

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Table 10.

D-L Random Effects Analysis: MWTP for a 1 Second Reduction in 0–60 mph Acceleration and 95% Conditional Confidence Intervals—Alternative Data Types (weighted by uncertainty metric)

	2015 $				
Data Type	**Mean**	**CCI Low**	**CCI High**	**p-value**	**Count**
Market Sales	685	392	979	0.000	23
Revealed-Preference Survey	847	684	1,011	0.000	10
Stated-Preference Survey	949	570	1,328	0.000	15
Market + Revealed Preference	796	592	1,000	0.000	33
All	845	713	977	0.000	48

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Table 11.

D-L Random Effects Analysis: MWTP for a 1 Second Reduction in 0–60 mpg Acceleration and 95% Conditional Confidence Intervals—Methods That Did and Did Not Correct for Endogeneity (weighted by uncertainty metric)

	2015 $				
Price Endogenous?	**Mean**	**CCI Low**	**CCI High**	**p-value**	**Count**
Yes	45	−8	99	0.000	13
No	1,111	930	1,292	0.000	35
All	845	712	977	0.000	48