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Exploring the Nature of Loss Aversion[1]

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Abstract

Loss aversion, the fact that losses have a greater impact than gains, is a fundamental property of behavioral accounts of choice. In this paper, we suggest four possible characterizations of the relative impact of losses and gains: (1) It could be a constant, such as the much cited value of 2, as in losses have twice the impact of gains. (2) It could be a systematic individual difference, with some individuals more or less loss aversion, (3) it could be a property of the attribute, or (4) a property of the different processes used to construct selling and buying prices.

We examine the behavior of a large sample of auto buyers using an experiment which allows us to measure loss aversion, at the individual level for several different attributes. A set of hierarchical linear models shows that to understand loss aversion, one must consider the process used to construct prices. Interestingly, we show that knowledge of the attribute lowers loss aversion and that age and attribute importance increases loss aversion.

Introduction

Imagine you were shopping for a new car, and had your eye on a model with safety features such as a front and side airbags for all passengers and integrated safety bars in the door. However, you now see a car that is identical in every respect, but without the airbags and safety bars. How much cheaper would this second car need to be for you to choose the less safe car? Now imagine you had instead, tentatively chosen a car without these safety features and were offered a choice between keeping your original choice and an amount of cash or getting the safer car. How much cash would you want to stay with the car you had chosen?

Standard economic theory and common sense suggest that the amount of money that you would demand in each case should be identical. The two situations have identical outcomes; the only difference is how they are framed. In the first scenario, you are giving up safety for cash; in the second scenario, you are choosing between amounts of cash and added safety. However, we suspect the reader shares the intuition that the amount required in each case would differ, and that we would demand more money to give up the additional safety features than we would be willing to pay for them.

This contrast in value, between a selling price and the economically equivalent choice, is one of the better documented departures from the standard economic analysis. It originates in observations of gaps between buying and selling prices in studies of the value of non-market goods, and in experimental demonstrations of an endowment effect. In these studies people who are randomly assigned possession of a simple commonplace good, such as a pen, mug or keychain, value it about twice as much as those who were not given the object, but given the opportunity to purchase it.

Why are these asymmetries in value important? First, they contradict an important principle used in applications of economic theory, the Coase Theorem. Simply stated, the Coase Theorem says that value is independent of initial assignment, so that as long as the opportunity to trade exists, goods will end up with those who value them the most. This has been an important rationale in the regulation of air pollution, the allocation of stocks in antitrust regulation, and in use of defaults in public policy. For consumer choice, these asymmetries have pervasive implications, suggesting that elasticities for product attributes will differ for increases and decreases from current levels, and that there will be less trading and more loyalty than would be suggested by a standard value maximization model.

In marketing, most examination of these asymmetries has focused on pricing and concentrated on demonstrations of the impact of reference prices upon choice. However, such effects should not be limited to price alone, and have been demonstrated for many attributes, suggesting that understanding the nature and origin of this kind of state dependence is essential for explaining and predicting consumer choice.

The most frequent explanation for these differences is loss aversion, the observation that losses from a reference point have a greater impact upon choices than the equivalent sized gain from the same reference point. This is usually modeled by adding a multiplier, λ_i, for each attribute, X_i, which is applied to deviations below the reference point, increasing their impact. Following Tversky and Kahneman (1991), we write:

$R_i(x_i) = u_i(x_i) - u_i(r_i)$ if $x_i \geq r_i$ and $R_i = \lambda_i(u(x_i) - u(r_i))$ if $x_i < r_i$.

Despite its broad impact, we know less, perhaps, than we might like about the nature of loss aversion and how it might vary across people, attributes and measures. In this paper, we discuss possible characterizations of loss aversion and examine a large survey of consumers for evidence which might help us understand the nature of loss aversion.

Characterizing Loss Aversion

Is Loss Aversion Constant?

While it is clearly an oversimplification, a useful baseline model would be to suggest that loss aversion is a constant, across people and attributes. However, such a view does appear in textbooks, for example Hastie and Dawes (2001, p. 216) write: "Losses hurt more than gains satisfy; most empirical estimates conclude that losses are about twice as painful as gains are pleasurable." And "The coefficient λ indexes the difference in slopes of the positive and negative arms of the value function. A typical estimate of λ is 2.25, indicating that losses are approximately twice as painful and gains are pleasurable (p. 294)."

Is Loss Aversion a Trait?

An alternative characterization of loss aversion would be that it might be a stable individual difference, much like a personality trait, that exists across attributes. By analogy to risk aversion, we might characterize individuals as more or less loss averse. While the extant data suggest that risk attitude does differ across domains, there is little evidence examining loss aversion. However, this characterization of loss aversion would seem to have a clear prediction, that loss aversion should be correlated across attributes: One who is loss averse for money should be loss averse for other attributes such as the fuel consumption of a car. This could be quite useful in applications. For example, Fehr and Goette (2002) use an individual difference measure of loss aversion to predict how long bicycle messengers will work, once a target wage has been reached. Thus, a person-specific measure of individual loss aversion across attributes λ_j might be a useful predictor of individual behavior.

Is Loss Aversion a Characteristic of an Attribute?

The use of a subscripted λ_i in Tversky and Kahneman's reference dependence model (1991) suggests that loss aversion might vary systematically across attributes. Empirically, there is evidence of large differences in the degree of loss aversion associated with different attributes. Sayman and Oncular (2005), in a meta-analysis of the ratio between buying and selling prices, report a range from 1 (equality) to over 100. Their meta-analysis identifies attributes which help determine the level of loss aversion: goods related to health, the environment, or trade in goods not legitimately bought or sold. Another line of reasoning is suggested by Dhar and Wertenbroch (2000), who argue that hedonic attributes possess more loss aversion than do utilitarian attributes. Similarly, Heath et al. (2000) argue that loss aversion for quality attributes is greater than that for price, a result supported as well by Hardie, Johnson and Fader (1993). Finally, Tversky and Kahneman speculate that loss aversion is a function of attribute importance.

Loss aversion as an attribute characteristic has an appealing simplicity. The technology exists for estimation both in scanner (Hardie et al. 1993; Putler 1992) and survey data (Fehr and Goette 2002), and if loss aversion is largely determined by the nature of the attribute, the use of a representative loss averse consumer in analytic modeling is much simplified. Clear support for an attribute based view of loss aversion would come from data showing that the variability in λ across attributes is large, relative to individual differences in λ.

Is Loss Aversion the Result of a Process?

A fourth alternative is that loss aversion reflects neither a characteristic of the person nor attribute, but reflects the process used to construct judgments of value. In this view, loss aversion is not as much an inherent parameter of preferences, but a robust outcome of the way values are constructed (Fischer et al. 1999; Fischhoff 1991; Payne et al. 1992; Slovic 1995). Work in characterizing the processes that generate loss averse preferences is just beginning, but there seem to be two candidates, one based on the interplay between memory and value construction, the other based on the role of affect in value construction.

Building on work that suggest that loss aversion and difference in buying and selling prices shift the focus of decision makers (Birnbaum and Stegner 1979; Carmon and Ariely 2000), Johnson, Häubl and Kienan (2005) propose a query theory account of the endowment effect. The basic idea is that the request for valuation, for example a selling price, is decomposed into two queries: Why the trade should be made, and why the trade should not be made. A second assumption is that these queries are executed sequentially, but in different orders for sellers and choosers. Finally, Johnson et al. argue that retrieval of the first category interferes with retrieval from the second category, resulting in a richer representation for the first category and the resulting differences in value. Evidence for this is provided in a series of experiments which shows that (1) the buyers and chooser do generate aspects of the trade in the hypothesized manner; (2) changing the query order generates changes in what is generated, and hence the subsequent value for the good, inducing an endowment effect without endowment; and (3) changing the query order can eliminate the endowment effect.

Because this account is memory-based, it can leverage the existing literature describing interference and inhibition to make several predictions (Weber and Johnson 2004). In particular, since the mechanism described by Johnson et al. is related to interference in part list cuing and inhibitory mechanisms in retrieval induced forgetting (Anderson et al. 1994; Anderson and Neely 1996; Perfect et al. 2002), variables which affect interference may affect the degree of loss aversion.

Past research suggests that two types of variables seem particularly relevant. The first is the degree to which knowledge is well structured. For example, one may possess many facts about a domain, but they may be structured in a well-organized hierarchy. Because experts' knowledge is better organized and less prone to interference (Alba and Hutchinson 1987), we expect knowledge of the attributes to lead to decreases in interference and accompanying decreases in loss aversion. A good example of this principle is demonstrated in research on the "fan effect" (Anderson 1974), in which learning a larger set of facts about a particular category typically *increases* the amount of time it takes to verify later on whether any one fact is true of the category (Anderson, 1974; (Anderson and Reder 1999; Lewis and Anderson 1976). These effects are reduced, however, when the facts which one learns are organized into subcategories (McCloskey and Bigler 1980) – a type of organization that is particularly likely when an individual has expert knowledge in a given domain (Chase and Ericsson 1981).

A second variable known to affect the degree of interference is age. Increases in interference are well documented for older adults, and it has even been argued that many deficits in memory that accompany aging are due in fact to increases in interference. In particular, research has shown that older adults relative to younger adults show greater inability to avoid interference on short-term memory and Stroop tasks (Hedden & Park, 2001; Spieler, Balota, & Faust, 1996); to engage in directed forgetting (Zacks et al. 1996) and to ignore irrelevant information on reading tasks (Connelly et al. 1991). Not surprisingly, then, research has also shown a tendency for older adults to be more susceptible than younger adults to part-set cuing effects. In one particularly rigorous set of studies, Marsh, Dolan, Balota, and Roediger (2004) produced part-set cuing effects in older adults that did not occur in younger adults: Just 1 cue in a 9-item set was sufficient to induce a part-set cuing effect in the older age group. Because we believe that interference plays an important part in generating loss aversion, we would expect increases interference with age to produce increases in loss aversion.

A second stream of research examining the origins of loss aversion focuses on the feelings of sellers and choosers. Reported affect concerning ownership predicts, in part, differences in the valuations (Peters et al. 2003), and it has been demonstrated that different types of induced negative affect can increase or reverse the endowment effect (Lerner et al. 2004). Camerer (2005) has speculated that fear may underlie the endowment effect. To maximize sample size, external validity, and number of variables we examine, we used a large market research survey. We will not focus on affect-based explanations of the endowment effect in this research because of the difficulty of conducting either affect manipulations or using sensitive measures of affect in a survey setting.

Is Loss Aversion Real?

Finally, several skeptical economists have recently called into question the robustness of loss aversion. One stream of research has suggested that loss aversion is limited to those inexperienced with markets. For example, List (2003; 2004) examines gaps between selling and buying for inexperienced and experienced traders of sports memorabilia and argues that loss aversion disappears when experienced traders are buyers and sellers. In addition, he presents evidence that loss aversion is reduced across rounds of a laboratory repeated market. Even less skeptical economists propose effects of experience, suggesting that loss aversion is limited to less experienced subjects—see the field studies of New York taxi drivers (Camerer et al. 1997) and real estate markets (Genesove and Mayer 2001). However, more research seems necessary, since Haigh and List (2005) provide experimental evidence that experienced options traders show *more* loss aversion than students do.

A more serious critique is provided by Plott and Zeiler (2005), who argue that loss aversion is a result of miscomprehension of the experimental situation by respondents and who demonstrate that, with significant instruction and experience, gaps in evaluation between sellers and choosers disappear. One critique of this work is that the levels of instruction are extraordinary and unlikely to appear in real world settings. A stronger criticism is that this work suffers from demand effects, since the intent of the experimenter may be obvious to respondents. Despite the large number of field studies demonstrating loss aversion (Camerer 2000), there seems to be some value in examining the existence of loss aversion in experienced consumers. In addition, to the extent that miscomprehension is a factor in loss aversion, we might want to examine the effects of education or variables which might minimize miscomprehension.

The Data

Overview

We will explore these issues by asking a series of questions about the size and nature of the coefficient of loss aversion λ_{ij}, for various attributes, *i,* and consumer, *j,* characteristics. We used a survey of 360 people conducted by personal interviews by a professional market research company. These consumers had recently purchased a mid-sized family sedan. They participated in two interviews, held several weeks apart, in return for 50€. All were German-speaking and resided in one of thirty cities in Austria, Germany and Switzerland.

Using data like this has several advantages: All consumers are familiar with the product and have just made a substantial purchase in the product class, and the use of non-student subjects provides substantial variance on many of the independent variables of interest. At the same time, there are constraints and limitations: We are limited to pencil and paper instruments, and some results, particularly the intercorrelation between demographic variables, may not be typical of other populations and samples.

Experimental Design and Questionnaire

All substantive experimental factors were varied within subjects. They included our main concern a 2 (selling vs. choosing) by 4 (attribute) factorial which elicited indifference prices. The questions closely paralleled the situation we presented at the beginning of this paper. Our goal was to estimate λ both within attributes and individuals. We did this by asking both choice and selling questions, counterbalancing for order. To make these as independent as possible, we positioned these questions some distance apart in the questionnaire, but also tested for any possible order effects. Appendix 1 provides an English translation of the relevant sections of the questionnaire.

Order and Level Controls

To assess the generality of our estimates, we collected them using three different levels of each attribute as shown in the appendix.[1] We did this because any simple comparison of Selling and Choice prices reflects both loss aversion and possible diminishing sensitivity of the attribute (see Köbberling and Wakker 2005 for a discussion). By comparing the aggregate estimates of λ across the three possible comparisons, we can examine the robustness of our results.

Other Measures

Respondents were asked for buying and selling prices for a small replica of the car that they had purchased using a strategy method. This replica usually retailed for 15 €. These transactions were actually carried out at the end of the session. We also asked respondents to indicate which of the following set of lotteries they would play, fashioned after the gambles used by Fehr and Goette (2002), and these were played out at the end of the session as well. These lottery choices arguably measure loss aversion. For detailed analysis of these measures from the larger set of respondents see Gächter, Herrmann and Johnson (2005).

Preliminary Data Analysis

We present our results using a mix of descriptive statistics for clarity, but also using a random coefficient model to provide a nested structure for the major hypotheses test. Intuitively, this can be seen as a test of a series of more complex models, starting with the simplest of all possible regressions, using only a constant, and then introducing random effects representing subject differences, attribute differences, and various predictor variables which we hope both predict loss aversion and potentially diminish individual and attribute differences.

Results

Is Loss Aversion a Constant?

While the idea of loss aversion as a constant is clearly greatly simplified, it does serve as a baseline for subsequent tests. The overall mean estimated λ in this sample is 1.85, and a simple regression model, estimating just this constant, serves as a baseline as shown in the first row of Appendix 2, Table 1.

Is Loss Aversion a Trait?

Loss aversion as a characteristic of the individual is tested in Table 1, which shows the inter-attribute correlations among the four car attributes which are the primary focuses of this paper. The relevant intercorrelations are bolded in the table. None of these correlations reach significance. In contrast, we include the two measures, reported in the Gächter et al. paper, which are more direct measures of loss aversion for money: Setting actual buying and selling prices for a model replica of the purchased car, and choices among actual gambles. In contrast to the car attributes, these two methods correlate quite highly, $r = .59$, $p < .0001$. This suggests that it is possible for measures of loss aversion to agree, and that the lack of correlation we see is not due to response error. In fact, the correlation between these two measures is impressive, since the buying and selling prices are judgments of riskless value, while the gambles are risky choices. While these measures of monetary loss aversion have some modest correlation with loss aversion for the car attributes, there seems little evidence for the description of global loss aversion across attributes.

We provided a more formal test, by adding a random effect representing individual differences (See Table 1, Model 2, Appendix 2) in loss aversion to the model describing loss aversion for the car attributes as a constant. In essence, it is the equivalent of a repeated measures ANOVA, allowing for personal overall levels of loss aversion. This model shows little improvement in fit, and the variance component representing individual differences does not reach significance. Thus the idea that loss aversion is a trait across attributes has little support in this data.

Is Loss Aversion a Characteristic of an Attribute?

Prior research describes attribute differences in loss aversion, as measured by the ratio of selling to choosing (or buying) prices, and there has been significant theorizing about the origin of these differences. This data allows us to examine these differences across a set of attributes and to contrast these effects with other sources of variance, such as individual differences. Further, we can examine some of the determinants of these differences.

We start by looking at the dispersion of loss aversion across people and attributes. Figure 1 displays the distribution of λ_{ij}'s for each of the four attributes that we used, calculated simply by: Selling Price/Choice Equivalence. As can be seen in the Figure, the vast majority (greater than 93% in each case) of the λ_{ij}'s are greater than 1, consistent with individuals being, for the most part, loss averse. As can also be seen, there is significant heterogeneity in loss represented by the considerable variance in λ_{ij}s. The coefficients of loss aversion also differ across the attributes, $\lambda_{\text{Fuel Consumption}} = 1.66$, $\lambda_{\text{comfort}} = 1.89$, $\lambda_{\text{safety}} = 1.89$, and $\lambda_{\text{information}}=1.94$, with median values of 1.56, 1.68, 1.83, and 1.80 respectively. These differences, however, seem much smaller than the appreciable variation in the loss aversion within each attribute. [2]

What determines these differences, and the marked variance? One possibility is that individuals' perceptions of the characteristics of the attributes determine loss aversion. In other words, the distributions in Figure 1 may really reflect attribute differences, but that people differ in their perception of the attributes For example, Tversky and Kahneman's (1991) speculation that attribute importance determines loss aversion requires that we include a measure of individual perceptions of attribute importance. Similarly Dhar and Wertenbroch (2000) suggest that the hedonic nature of an attribute leads to loss aversion. Fortunately, we can test these ideas by including individual ratings of importance and of the hedonic nature of each attribute which were collected at the same time as the pricing judgments.

We first portray the effects of importance and attribute hedonics by examining the level of loss aversion for the levels of the response scale, shown in Figure 2. The figures portray the mean level of λ for each level of the 7-point rating scale, with the height of each diamond representing the error around the mean and the width representing the number of observations corresponding to that mean. Since each graph shares the same x-axis scale, we can compare the effects of different variables upon loss aversion. For example, in Figure 2 it is clear that attribute importance affects loss aversion, but that respondents' ratings of an attribute as hedonic or utilitarian do not. This latter result is contrary to the idea that hedonic attributes are more loss averse (Dhar & Wertenbroch, 2000; see also Horowitz, 2002), at least given our measures. The right hand of the figure also suggests that very few respondents considered these attributes to be very hedonic, since almost all of their responses were below 4 on the seven point scale, as shown by the broad diamonds for those scale values.

To test these observations more formally, we estimated two hierarchical models (see Appendix 2), the first of which allows attributes to have different degrees of loss aversion. The resulting model (Model 3) allows attributes to differ in loss aversion, provides a significant increase in fit, $p < .0001$, and a lower BIC. [3] The effect of attribute is significant, $F(3, 1077) = 11.65$, $p < .0001$. This model confirms that the $\lambda_{\text{Fuel Consumption}}$ is significantly less than that for the other attributes, which do not differ from each other.

However the real story is contained in a model (Model 4) which includes importance and hedonics in an attempt to explain the considerable variation within the attributes. The regression shows that the attribute's importance rating is a strong predictor of loss aversion, but that the relationship between the perception of an attribute as hedonic and loss aversion is not. To characterize the relationship with importance, we note that for every point increase in rated importance (on a 7 point scale), λ_{ij} increases by

.26. We also estimated a more complex model (Model 5) which nests the attribute characteristics within each attribute. This allows us to assess the degree to which the effect of these attribute characteristics differs across attributes. This results in a significant increase in fit, but produces largely the same story: The perception of an attribute as hedonic does not predict the degree of loss aversion, but perception of the attribute as important does. The nested model simply indicates that the effect of importance is greater for comfort and information systems, but that the effect is significant for all attributes.

While the effect of attribute importance is large, we offer two observations. First, it does not account for much of the variation in the attribute differences, since the attribute differences remain significant. Second, while the effect of importance is large, its theoretical role seems unclear: What exactly is reflected by a respondent's rating of attribute importance? We will return to this point in the discussion.

Is Loss Aversion the Result of a Process?

While we obviously do not directly observe the processes used to generate these loss averse valuations, process based theories do make predictions concerning the relationship between loss aversion and individual characteristics. One set of predictions concerns the effect of age, the other knowledge of the attributes.

Age and other Demographic Differences

We first examined the ability of the demographic differences to explain the variance in the individual level coefficients of loss aversion seen in Figure 1. Recall that our questionnaire collected information about the respondents' gender, age, income, occupation, education, and household wealth.

Figure 3 plots the average λ_{ij} across the variables gender, age, income, wealth education and occupation; for one attribute, fuel consumption. This pattern is similar for all four attributes, but Table 2 reports the λ_{ij} for all attributes and demographics. Concentrating first on Age, in the upper right hand of the figure, we see, as expected, a rather strong effect: The youngest respondents in our sample have an average loss aversion coefficient of 1.4, the oldest, 2.4. Thus age seems to be an important moderator of loss aversion.[4]

Surprisingly, there are large and systematic differences for many other demographic measures. For the nominal variables of gender and occupation, we present histograms with error bars; for the ordinal variables of age, education, income and wealth, we again present a mean diamond, whose height contains confidence intervals around the mean, and whose width indicates the size of the group.

What emerges then is a surprisingly strong and systematic pattern. Our theorized effect of age is accompanied by a large effect for education, which decreases loss aversion, and effects of income and wealth which increase loss aversion. Occupations seem best described by two groups: Unemployed, Students, People working at home, and Workers/Farmers; who are more loss averse than Managers and Entrepreneurs. Finally, there are no systematic gender differences.

Of course these variables are interrelated, and what appears to be an effect of one variable, say income, could be due to correlated differences in other variables, such as age. Since age is of theoretical interest, we explore this possibility by estimating a hierarchical model (Model 6) described in Appendix 2, using all the demographics in

Figure 3 as predictors. Although our data set has a fairly large number of respondents, we collapse across several infrequent categories to increase statistical power. The result simplifies the picture: age and income are still significant predictors of loss aversion. Education is no longer significant, and wealth and occupation are now only marginal predictors, $p = .1$ and $.07$ respectively. Gender remains an insignificant predictor. We can also test whether these demographic differences differ across attributes by examining the attribute by demographic interactions. This shows no differences in the pattern of demographic effects among the attributes.

To summarize, our analysis shows the effect of age predicted by a memory based account of loss aversion: Older people are more loss averse. There is also an unexpected effect: Those with higher levels of income display greater loss aversion.

Knowledge Differences

Recall that query theory predicted that an increase in knowledge of an attribute may lead to a decrease in loss aversion. If we believe that increases in knowledge are accompanied by increases in the structure of that knowledge, we would expect inhibition to have less effect and for loss aversion to diminish with knowledge. Initial evidence is provided in the first panel of Figure 4, which depicts the mean amount of loss aversion for each point in the knowledge scale. Clearly knowledge of the attribute has an effect.

We examined this hypothesis more formally by predicting loss aversion using an attribute-specific rating of knowledge, as well as self-ratings of overall knowledge and interest in cars, and two measures based on a laddering exercise (Jolly et al. 1988). These laddering exercises, common in commercial marketing research, are thought to assess aspects of the overall representation of the product. The overall fit (see Model 7,

Appendix 2, Table1) is slightly better than that provided by the ratings of importance and attribute hedonics. Only knowledge of the specific attribute predicts loss aversion, $F(1, 1076) = 693.7$, $p < .00001$. We can further improve the fit of the model by allowing the weights of the knowledge variables to vary by attributes (Model 8).

To explore this more closely, we performed simple regressions on the loss aversion measures for each of the four attributes, using the self ratings of knowledge of each of the attributes as well as overall measures of the knowledge of cars and laddering measures. To test the specificity of each predictor, we included not only the individual coefficient for the specific attribute but also for the knowledge ratings of the other attributes. Thus for the individual λ for comfort we include as predictors, not only the self rating of knowledge for comfort, but also that for fuel consumption, safety and information, with the expectation that the coefficients for comfort would far exceed the predictive power of other coefficients. As can be seen in Appendix 2, Table 1, attribute-specific ratings of knowledge produced significant decreases in loss aversion, as can be seen by the diagonal of coefficients, and were much larger effects than any others. On average, a 1 point increase in the self-rating of attribute-specific knowledge reduces λ for that attribute by .16 for Fuel Consumption, .32 for comfort, .18 for Safety and .23 for Information Systems. An important result of this analysis is that the effect of knowledge is largely attribute-specific; coefficients on the diagonal (bolded in the figure) are always significant and much larger than those off the diagonal. In addition, self ratings of knowledge, the results of a laddering exercise, and self reports of overall interest had little systematic effect upon loss aversion. Thus, as suggested by query theory, specific knowledge of the attribute reduces loss aversion. Because this reduction is attribute-specific, and not due to other measures of general knowledge and interest, it seems less likely that a non-memory based, motivational explanation would apply.

Experience Differences

Recall that prior research has argued that experience in markets diminishes loss aversion. While we do not have direct measures of experience in making sales and purchases of automobiles, we do have several self report measures of experience, and can therefore test the related hypothesis that product experience affects loss aversion. As seen in the second and third panels of Figure 4, an increase in experience with this product class and usage decreases loss aversion. Note, however, that these decreases seem more modest than those we have seen for knowledge or importance.

We examined this more formally using the hierarchical model employing the self report measures of car usage, and experience with cars described in Appendix 2. This model (Model 10 in Appendix 2, Table1) provides a significant decrease in loss aversion. Both the self report measure of experience and usage are significant predictors, $p < .0001$. Of course, experience and usage may be correlated with other factors, which lead us to our last model.

Joint Prediction

We have examined many different predictors of loss aversion. Some are based on prior speculation about attributes; these include attribute importance or the hedonic nature of the attribute. Others follow from speculations about the nature of the decision-maker and their experience with the transaction. Finally, others follow from a memory-based view of loss aversion, termed query theory, which focuses on knowledge of the attribute and the age of the decision maker. We are cautious conducting a ‘horse race’ evaluating these predictors because the results may be fairly limited to this product class and measures, and because these constructs have different theoretical status. However, we did tentatively explore the ability of variables that have been shown to be good predictors of loss aversion as parts of specific tests to explain loss aversion in the context of other variables.

We examined our attribute-specific self-ratings of knowledge, importance and whether the attribute was hedonic, along with individual-specific measures and age--all had either been significant predictors of loss aversion in more specific tests, or predicted by other research. While there is some correlation among these variables, the highest correlation was .59, and remaining were less than .3, suggest that multicollinearity was not an overwhelming challenge for this analysis.

In this multivariate analysis, all the predictors that were significant--age, importance and knowledge--are still significant predictors, in the same direction as before; and the hedonic nature of the attribute continues not to predict loss aversion. Most importantly, much but not all of the attribute differences in loss aversion is explained by these effects. Looking at the fifth column on Appendix 2, Table1, we see that the variance due to attribute differences is reduced by about 70%, from .163 in the baseline Model 3, to .047 in the joint estimation in Model 10. Much of this reduction is due to two variables predicted by query theory, Age and Attribute knowledge. The third major predictor was anticipated by prior research, Attribute importance.

Summary and Conclusions

Contributions

While much of this paper has concentrated on the substantive analysis of loss aversion, we also demonstrate a method for measuring loss aversion at the individual level. By using choice and selling response modes, and by spacing the questions in different parts of the questionnaire, we were able to derive individual level estimates that were systematically related to variables that we predicted would affect loss aversion, such as knowledge, importance and age. This method could be of use in the analysis of loss aversion in consumer behavior in other settings.

More substantively, we have explored the nature of loss aversion in one purchase domain, albeit one that is substantial: expenditures made by actual consumers. Our basic result is that loss aversion is not simply a constant, a characteristic of an attribute or an individual. Instead, we find that a substantial amount of loss aversion can be explained by the decision maker's knowledge of the attribute, the attributes' importance to the decision-maker and finally, the individual's age. This result also has implications for the application of loss aversion, suggesting who will be the most loss averse. In particular, it emphasizes the role of specific product knowledge and suggests that some individuals, particularly those who are older or less educated, may be more likely to be loss averse.

Further Research

While we believe that this sample has much more variance along many of the predictor variables than a student sample would, and that it is more knowledgeable of the task than most, we believe that it is important to replicate these results with other products, cultures, and methods. It is comforting, however, that our results in the aggregate for the buying and selling prices for the model car, and for the lottery choice, are similar to those obtained by others. A final important step would be to relate these estimates of loss aversion to the product choices made by these decision-makers.

The Status of Loss Aversion

What is the status of loss aversion after we have examined this data set? Recall that skeptical economists have recently argued that Loss Aversion and the Endowment Effect are phenomena that are restricted to certain lab settings and that their importance for actual markets is questionable. Our data have two answers to these questions. The first, which is quite supportive of the usefulness of loss aversion, is that we find significant degrees of loss aversion in a sample that has recently made a substantial purchase in this product class. Thus while extreme degrees of instruction and experience may limit or eliminate loss aversion, our data indicate that loss aversion is an important factor in understanding these real world consumers. On the other hand, we do find that loss aversion is moderated by several variables, including attribute knowledge and importance. While loss aversion still typifies consumers, the amount of loss aversion varies greatly among them. Thus, we suggest that the question should not be whether or not loss aversion is important, but rather how important loss aversion is, and for which attributes and consumers.

The Why of Loss Aversion

We started by describing four different conceptualizations of loss aversion: as a constant, a trait, an attribute characteristic, or the result of the preference construction process.

We argue that the view of loss aversion as the result of a process seems best supported by this data. In particular, one explanation of loss aversion, query theory, predicts that loss aversion will increase with age, and decrease with specific knowledge of the attributes, results which are supported by this data. At the same time, other factors, in particular attribute importance, seem to be important in loss aversion. Importance by itself does not seem to shed much light on the cause of loss aversion. One must ask what it is about important attributes that increases loss aversion. This is clearly a question for further research, but seems consistent with the idea that emotional reactions or anticipated regret may play a role. Since we know that emotions of disgust and sadness can moderate loss aversion, we suspect that future research exploring this connection will be fruitful. A more important question, it would seem, is the connection between such emotion-based and memory based explanations.

In conclusion, a final observation seems relevant. Much of the research that has been conducted establishing loss aversion has been done with young people enrolled in college. While some people have suggested that this results in larger demonstrations of loss aversion, our data suggest the opposite: In our data, respondents who are older and have less education show *more* loss aversion, suggesting that research based on students may underestimate the importance of loss aversion.

Notes

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[1] Note that many contemporary studies, including ours, contrast selling and choice prices, and not buying and selling prices, since the latter confound loss aversion with possible wealth effects.

[2] It is noteworthy that, while these means far exceed 1, they are lower than the prototypical value of 2 commonly reported for loss aversion. One possibility is that selling-choice estimates of λ are often smaller than those estimated by buying and selling prices. Indeed, a measure of buying and selling prices that was gathered from the same sample (Gächter et al., 2005) also shows a λ of above 2, but otherwise behaves like the λs that we observed. In other work, we have observed similar differences between choice-selling and buying-selling in between subjects estimates of loss aversion (Johnson et al., 2004).

[3] We can also test whether there are significant correlations among these variance components. Not surprisingly, given the results of Table 1, modifications such as allowing for correlation among the λ's does not improve the fit of the model.

[4] This contrasts with the results of Kavalchik et al (2005) who, using a similar procedure to Plott and Zeiler, fail to find loss aversion for either older or younger adults.

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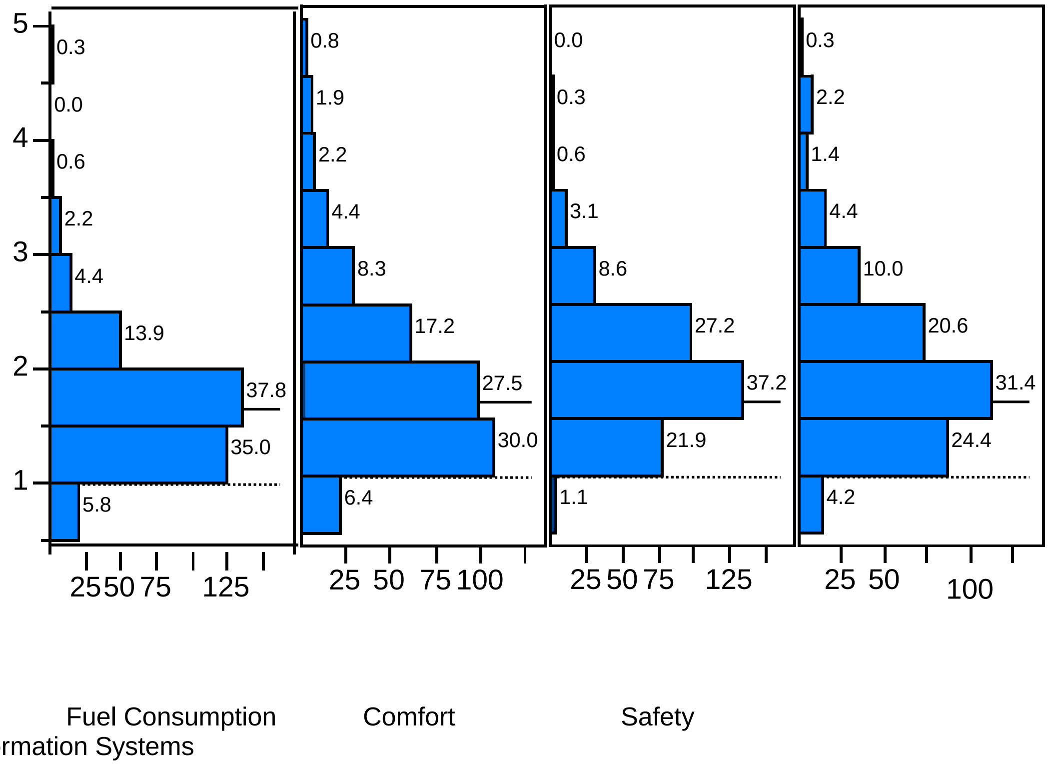

Figure 1 Distribution of Loss Aversion by Attribute. The solid line is the mean loss aversion for each attribute and the dotted line shows λ=1. Bars are labeled by the percentage of respondents represented by each bar, and the x axis represents the number of respondents.

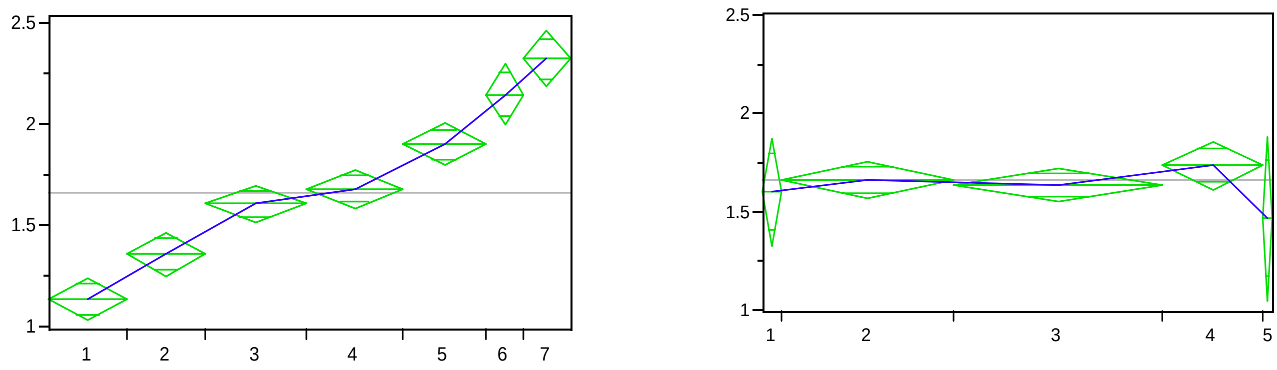

Figure 2 Loss Aversion by Ratings of Importance and Hedonic-Utilitarian, 1 = least important, and least hedonic

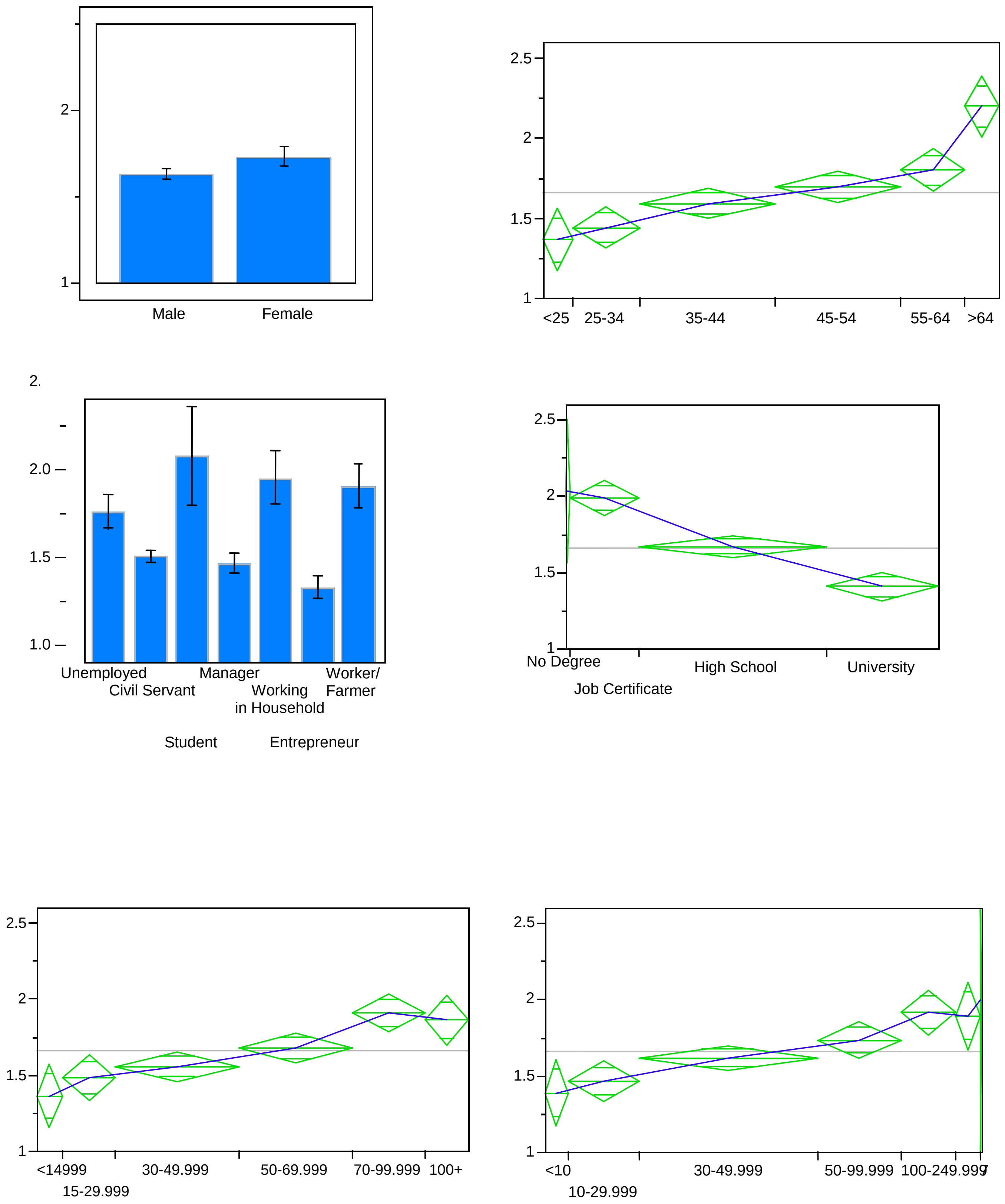

Figure 3 Loss Aversion for Fuel Consumption by Gender, Age, Occupation, Education, Income (thousands) and Net Worth (thousands)

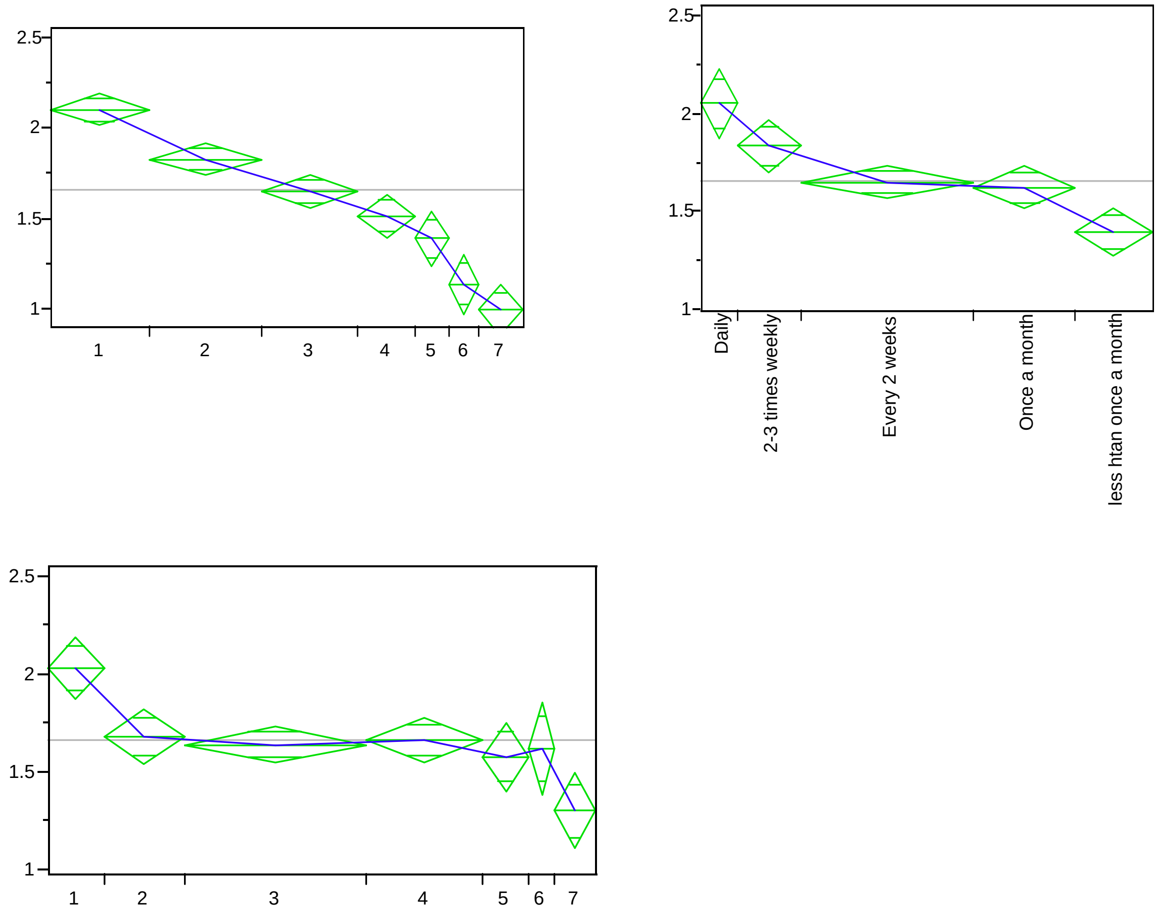

Figure 4 Loss Aversion for Ratings of Knowledge, Auto Usage and Experience.

	$\lambda_{\text{Fuel Consumption}}$	λ_{Comfort}	λ_{Safety}	$\lambda_{\text{Information Systems}}$	$\lambda_{\text{Model Car}}$	$\lambda_{\text{Gamble Choice}}$
$\lambda_{\text{Fuel Consumption}}$	1.00					
λ_{Comfort}	**.05**	1.00				
λ_{Safety}	**-.07**	**.03**	1.00			
$\lambda_{\text{Information Systems}}$	**-.00**	**-.05**	**-.08**	1.00		
$\lambda_{\text{Model Car}}$	.41	.18	.28	.05	1.00	
$\lambda_{\text{Gamble Choice}}$	.34	.14	.35	.11	.59	1.00

Table 1 Loss Aversion: Correlation among Attributes

	N	Fuel Consumption	Comfort	Safety	Information Systems
Gender					
Male	266	1.63	1.91	1.84	1.91
Female	94	1.73	1.84	2.03	2.03
Age	.	.	.	.	.
<25	24	1.37	1.47	1.51	1.80
25-34	53	1.44	1.60	1.81	1.71
35-44	107	1.59	1.92	1.86	1.87
45-54	99	1.70	1.88	1.93	2.01
55-64	51	1.80	2.07	1.98	2.14
>64	26	2.20	2.45	2.12	2.21
Education	.	.	.	.	.
No Degree	4	2.04	1.93	2.23	2.13
Job Certificate	67	1.99	2.10	2.08	2.37
High School	181	1.67	1.95	1.95	1.84
University	108	1.41	1.65	1.65	1.83
Income	.	.	.	.	.
<14999	22	1.36	1.55	1.50	1.64
15-29.999	44	1.48	1.58	1.72	1.65
30-49.999	103	1.56	1.87	1.79	1.96
50-69.999	95	1.68	1.86	1.89	1.95
70-99.999	61	1.91	1.95	2.01	2.06
100+	35	1.86	2.55	2.39	2.20
Net Worth	.	.	.	.	.
<10	20	1.39	1.59	1.32	1.66
10-29.999	58	1.47	1.69	1.93	1.89
30-49.999	147	1.62	1.83	1.89	1.93
50-99.999	69	1.74	1.98	1.87	1.89
100-249.999	45	1.92	2.28	1.96	2.08
250+	20	1.90	2.05	2.12	2.38
Occupation	.	.	.	.	.
Unemployed	28	1.86	2.11	2.02	2.18
Working in Household	13	2.05	1.75	1.93	2.51
Student	10	2.18	1.96	2.02	2.27
Worker/Farmer	22	2.01	2.24	2.12	2.30
Civil Servant	178	1.61	1.89	1.84	1.88
Manager	77	1.57	1.90	1.87	1.88
Entrepreneur	32	1.43	1.51	1.84	1.68

Table 2 Lambdas for each Attribute by Demographic Variables

	Fuel Consumption	Comfort	Safety	Information Systems
Intercept	2.11***	3.15***	2.49***	2.72***
Fuel Consumption Knowledge	**-0.16***	0.02	0.04**	0.04
Comfort Knowledge	0.02	**-0.32***	0.02	0.03
Safety Knowledge	0.04**	-0.02	**-0.18***	0.09***
Information Systems Knowledge	-0.01	0.06**	0.01	**-0.23***
Car Knowledge	-0.01	-0.04	-0.05**	0.01
Overall interest	-0.02	-0.00	-0.04**	-0.04
Ladder Depth	0.01	-0.02	0.02	-0.00
Number of Laddered Attributes.	-0.01	-0.00	-0.01	-0.04

Table 3 Loss Aversion by Attribute Knowledge

*** p< .001
** p < .01
* p < .05

Appendix 1: Questionnaire.

In this appendix, we list the measures used in the instrument. The questionnaire included measures of gender, age, family status, number of children, occupation, education, household income, net worth, size of town, frequency of auto use, self-ratings of knowledge of the four auto attributes.

Attribute	Level		
	Low	**Medium**	**High**
Fuel Consumption	EPA fuel economy estimates (mpg) 18 (city), 28 (highway)	EPA fuel economy estimates (mpg) 14 (city), 21 (highway)	EPA fuel economy estimates (mpg) 10 (city), 14 (highway)
Comfort	Regular seats	12-way power driver and front passenger seats including 4-way power lumbar adjustment and lockable head restraints	12-way power driver and front passenger Recaro sport seats including 4-way power lumbar adjustment and lockable head restraints, memory function, leather upholstery, including door panel inserts
Safety	No airbags	Full size airbags and sideguard head protection airbags for front and rear passengers	Full size airbags and sideguard head protection airbags for front and rear passengers, rear side airbags, driver and front occupants seat mounted chest side airbags
Information	No information or telematics system	Backlit instrument cluster, onboard computer, driver information display with radio display, auto check system, service interval indicator	Backlit instrument cluster, onboard computer, driver information display with radio display, auto check system, service interval indicator, Audi telematics (emergency services, accident assist, convenience services, route suppo stolen vehicle tracking, ride assist)

Appendix 1 Table 1: Low, Medium, and High Levels, by Attribute, used in eliciting choice and selling prices

Levels of comparison	Attribute			
	Consumption	Comfort	Safety	Information
Low - medium	Group 1	Group 2	Group 3	Group 2
Medium - high	Group 2	Group 1	Group 2	Group 3
Low - high	Group 3	Group 3	Group 1	Group 1

Appendix 1 Table 2: Counterbalanced Groups

Selling Question for group 1 (consumption: low - medium)						
After a comprehensive search and evaluation process, you are about to buy a new Audi A4. For the car you have in mind (car A), Audi reports fuel economy estimates (mpg) of 14 (city) and 21 (highway). Just before the purchasing decision is made, another A4 comes across (car B), which is totally identical to your favorite A4 (car A) with one exception: The consumption of car B is 18 mpg in the city and 28 on highways. How much lower should the price for car B be, so that you prefer car B over car A?						
500 Euro and less	1000 Euro	1500 Euro	2000 Euro	2500 Euro	3000 Euro	3500 Euro and more
Choice Question for group 1 (consumption: low - medium)						
You are about to buy a new Audi A4 and you have two specific cars (A and B) in mind. For car A Audi reports fuel economy estimates (mpg) of 14 (city) and 21 (highway). For the car you have in mind (car A) Audi reports fuel economy estimates (mpg) of 14 (city) and 21 (highway). Car B is totally identical to car A, however its consumption is 18 mpg in the city and 28 on highways. Both cars have the same price, but the dealer offers a discount on car B. Please indicate for which discount for car B you would still prefer car A over car B.						
500 Euro and less	1000 Euro	1500 Euro	2000 Euro	2500 Euro	3000 Euro	3500 Euro and more

Appendix 1 Table 3 Example of Questions used for Selling and Choice.

Appendix 2: A random coefficients model of loss aversion.

Our models of loss aversion--as a constant, an individual difference, a characteristic of an attribute, or a product of some underlying process--can be represented as a series of nested models, some allowing for heterogeneity across people using random coefficients. Tests of significance can be provided both by tests of additional variance accounted for and by likelihood statistics. The basic model (Verbeke and Molenberghs 2000) is:

$Y_i = X_i \beta + Z_i b_i + \varepsilon_i$

where Y_i is the observed degree of loss aversion, the X_i are the usual predictors in a regression framework and β is a vector of regression coefficients and Z_i are the subject specific effects with estimates provided by b_i.

Obviously the loss aversion as a constant model (Model 1) has only a single X_i representing the intercept; the individual difference model (Model 2) estimates a random coefficient for that effect. Similarly, an attribute characteristic model specifies a fixed effect representing the attribute being assessed; that is, an additional 4 X_i's ,one for each of the attributes. This model is not reported here since it is subsumed in Model 3, and does not increase the fit of Model 2.

To model heterogeneity in the effects of attributes (Model 3), we introduce a random effect for attributes, which provides a subject-specific intercept for each attribute effect in the Z_is.

Finally tests of possible process mediators of the effects of loss aversion are conducted by introducing additional variables as fixed effects in X_i's, and success in accounting for attribute variability is demonstrated by a reduction of the variance in the on-diagonal elements in b_is. For example, Model 4 adds two X_is representing the subjects' ratings of attribute importance and the attributes' hedonic nature. As can be seen in the 5th column in Appendix 2, Table1, these two variables reduce the random effect of the attributes by more than half, from .164 to .073. Similarly, Model 5 allows the β_is to vary across attributes, changing the two additional β_is in Model 4, to a 8 (2 predictors x 4 attributes). In addition to the usual tests of fit offered by the Log Likelihood, the Bayes Information Criterion (columns 3 and 4, respectively) we can test several nested models. These tests are reported in columns 6-9.

	Model	Log Likelihood	BIC	Respondent Specific Variance in Attributes	Nested Models Tests			
					Contains Model..	Incre-mental χ^2	Addit-ional d.f.	*p* for incre-mental fit
1	Constant λ	3110.5	3117.7	----	---			
2	Individual Difference[1]	3108.2	3120.0	----	1	2.24	1	.135
3	Attribute Differences with a random effect	3088.7	3100.5	.1639	3	21.8	4	.0002
4	Importance + Hedonics (Overall)	2481.4	2493.1	.0732	3	607.3	2	< .0001
5	Importance + Hedonics (Attribute Specific)	2425.8	2437.6	.0783	4	55.6	6	< .0001
6	Demographics	3015.7	3026.9	.1431	3	73.0	13	< .0001
7	Knowledge (Overall)	2445.3	2457.0	.0730	3	643.4	5	< .0001
8	Knowledge (Attribute Specific)	2413.4	2425.2	.0689	7	21.9	3	< .0001
9	Experience (Overall)[2]	3011.7	3023.5	.1457	3	77.0	5	< .0001
10	Joint Estimation	2158.6	2170.3	.0476	3	930.1	19	< .0001

Appendix 2, Table 1: Fit of Various Accounts of Loss Aversion.

[1] This model cannot be estimated since the variance in slopes in negligible, yielding negative variance estimates An alternative marginal model can be specified, however, see Verbeke and Mohlenberghs (2000, pp. 52-54 and 117-118) for a discussion.

[2] Allowing the effect of experience to vary across attribute did not result in an improvement of fit.