# Does the Endowment Effect Exist in a Real Market?

June 2006
VERY PRELIMINARY

Sharon Oster
Yale School of Management

Fiona Scott Morton
Yale School of Management and NBER

Thanks to Kyle Hood for thorough research assistance. Addresses for correspondence: Yale School of Management, Box 208200, New Haven, CT 06520-8200. Email: Fiona.scottmorton@yale.edu, Sharon.oster@yale.edu.

## 1. Introduction

The endowment effect predicts that the fact of ownership by itself increases the value individuals place on objects. The fundamental theory is presented in the work of Kahneman and Tversky (1979, 1984). These papers lay out the idea that a consumer's utility depends on a reference point, and that a consumer with a reference point for consumption values losses more strongly than gains. Empirical evidence of the endowment effect has been found in the lab in numerous experiments beginning with the classic work of Kahneman, Knetsch and Thaler (1990) in which initially giving someone a mug increases his or her reservation price for that mug over someone given cash. Inducing an endowment effect seems to be remarkably easy in the laboratory setting. For example, Kahneman, Knetsch and Thaler (1990) find that traveling in an elevator for a few minutes with a mug causes participants to value the mug more highly.

From the point of view of someone working on behavioral industrial organization, anomalies like the endowment effect become most interesting when they redistribute rents in the economy relative to a pure neoclassical model. For this redistribution to be important, the biases must be significant and survive profit-seeking behavior on the part of other, potentially non-biased, agents in the market. To our knowledge, the endowment effect has not been studied outside the laboratory setting, other than in work by List (2003) in the baseball card trading market. One interpretation of his conclusions (stressed by the University of Chicago website) is that the endowment effect is not likely to be important in real markets because trading experience reduces a subject's endowment effect. Thus consumers learn from experience and their subsequently smaller bias has a minimal effect on rent distribution. However, one could imagine markets that are very large, such as those for freezers, cars, houses, and sofas, in which consumers do not typically engage in dozens of transactions in a single year. This paper examines an important market with low levels of trading to help determine the extent to which biases are manifest in markets and not just in laboratory settings.

In previous work we established that the price of a magazine subscription relative to its newsstand price reflects time-inconsistency on the part of consumers (Oster and Scott Morton (2005)). In that paper we took advantage of heterogeneity across magazines and the fact that publishers had available two pricing instruments, the spot price and the long-term contract (subscription) price, to identify the time inconsistency. Our findings in that paper indicate both that consumers are taking their behavioral anomalies to the market and that managers are choosing measurably different policies in response to that behavior. In this paper we similarly exploit difference in both product and individuals to examine whether there is any evidence that firms take the endowment effect into account as they choose the form in which they give discounts off a list price.

In laboratory studies of the endowment effect, a principal result is that fewer trades occur than one might expect. For example, Knetsch (1989) allows subjects to trade chocolate bars or mugs and finds only 10% of the sample trades, rather than the predicted 50%. Demonstrating under-trading in marketplaces is more difficult because of the need to construct an appropriate counterfactual. In this paper, we have chosen instead to focus—as we did in the magazine market—on the way in which the bias affects the optimal pricing structure chosen by sellers. In particular, we will be focusing on pricing structures that are revenue-neutral to firms, but not utility neutral to consumers.

The setting we are using in this paper is the market for new cars and used trade-in cars. There are a number of features of this market that make it attractive from our perspective. First, within years and models, cars are homogeneous in characteristics (though perhaps not in quality) with commonly-known used values. As importantly from our perspective, dealers typically have some discretion in the way in which they extract value from consumers. While most car dealers post a list price for a new car, most buyers end up bargaining for a price below list. In some cases, the buyer is simultaneously negotiating for a price for a used car trade-in. It is in this subset of car purchases that we are interested. At root, the dealer only cares about the profits he can obtain from the two linked transactions. For a new car listed at $25,000 and a trade in with a value of $5000, a dealer is indifferent between an offer of $24000 for the new car and paying $5000 for the trade-in, or an offer of $25000 for the new car while paying $6000 for the trade-in. Buyers who exhibit an endowment effect, however, may be more price elastic over the trade-in than the new car. This might allow the dealer to raise the price he offers for the trade-in and the price he asks for the new car such that he is indifferent, but the buyer feels better off. Though we focus on the used-car transaction, we will refer to the seller of the used car as the "buyer" throughout the paper.

The proposition that a used car might have an endowment effect has been suggested in the literature before. Indeed, multiple datasets have shown that the amounts car dealers offer for used trade-ins exceeds the value of those trade-ins on average, (e.g. Zettelmeyer, Scott Morton, and Silva-Risso (2001) and Goldberg (1996)). Using the subset of the data in ZSS (2001) that comprises our dataset, we find an average overpayment for a trade-in of $996. While this is certainly suggestive of an endowment effect, it is not conclusive, as there are other explanations that could be proffered.[1]

There is also experimental evidence that consumers prefer a subsidized trade-in even if it causes an equivalent increase in the price for the new car. Purohit (1995) tests precisely this proposition using a sample of MBA students. Having given them an inexpensive pen and announced a market value for it (supposedly derived from another class), he offered the students the chance to buy a more expensive pen using their endowment as partial payment. Half the students were told the trade-in value of the their pen was a dollar above market value, while the other half were told the trade-in value of their pen was a dollar below market value. The students who were given the subsidy had a higher mean *additional* willingness to pay for the expensive pen ($3.50 versus $2.50). "This suggests that subjects who are overpaid on their trade-ins (when they are sellers) experience a gain that then leads them to be more generous in determining their willingess to pay when they are buyers."

Thus far we have presented aggregate data and experimental evidence as though all buyers suffer from the endowment effect. We would rather have heterogeneity from which to tell whether all, some, or none of the buyers actually over-value their cars and by how much. The novel aspect of our approach is that we rely on previously identified demographic variation in the presence or strength of the endowment effect to identify its existence in the market for used car trade-ins. We further use existing laboratory studies to help identify which types of cars are more or less likely to induce endowment effects in their owners.

One objection that might arise in employing the used car market as a way to test for the endowment effect is the importance of asymmetric information, and therefore adverse selection, in this market. Many drivers believe they are of above-average driving ability and therefore their car has been well-treated. Alternatively, drivers may know their car has been poorly treated or has had a bad repair record. In these cases, the driver's view of the value of the trade-in may be affected both by the endowment effect *and also* by superior information. Undoubtedly the driver

[1] Note, however, that in six years of presenting car papers, the second author has been asked many times why the trade-in overallowance has a positive mean, and has never heard a convincing explanation.

does know more about her car than the dealer to whom she is selling. However, since the dealer is a professional repeat-player with sources of market information and skilled mechanics readily available to him, we expect him to get the average price right. This means that the private information of the driver will have a zero mean in expectation. Additionally, the evidence in Schneider (2006) indicates that there is no significant adverse selection in this market.

We assume that consumers are subject to both loss aversion and narrow framing. That is, individuals examine each of their transactions, the used car and the new car, in isolation. This is necessary for an endowment effect to differentially affect one transaction. Barberis and Huang (2006) discuss the role of the mix of loss aversion and narrow framing in the context of the equity puzzle. Laboratory evidence of such narrow framing is provided by Janiszweski and Cunha (2004) in looking at the way in which discounts are taken in bundled goods. They find that it matters to customers which of two products in a bundle is assigned a discount of the same dollar magnitude. Consumers prefer a bundle in which the less valued product is discounted. In our example, the bundle consists of a new car and a deal on the used car. If the consumer values the used car more, she will value a discount on the new car more than an overpayment for the used car. Yet, in our data, the latter practice is overwhelmingly common, so we conclude our bundle or setting must be significantly different from Janiszweski and Cunha (2004).

One might also be skeptical about whether one would really expect an endowment effect for the trade in car a consumer brings to the lot. Here we come up against more subtle questions of the psychology behind the endowment effect. Our model assumes that as long as one owns the car, the consumer is averse to losing it and has to be effectively bribed to do so. Another position might be that, in deciding to trade a car in, the consumer effectively shifts the car out of the "consumption" category with its attendant emotional connections into an "exchange" category, which is neutral. The recent work of Novemsky and Kahneman (2005) demonstrates that the intention of subjects moderates loss aversion. If consumers of new cars have strong enough intention to sell their old cars and have recovered from loss aversion, we will not see the expected price patterns in the data. In this case, the endowment effect can be measured only in infrequency of trades and not in pricing structures. For this reason, our test will be a relatively stringent one. Note also, that because dealers acquire cars with the explicit intention of selling them again, we assume throughout the paper that dealers do not suffer from an endowment effect in the sale of new cars.

To preview our results, we find the endowment effect is stronger in poorer consumers (keep in mind everyone in our dataset is buying a new car), less well educated consumers, consumers from poorer neighborhoods, blue collar consumers, and minorities. These results are consistent with the existing experiments on the demographics of the endowment effect.

We also find that market experience (proxied by age of the buyer) reduces the endowment effect, while length of ownership (proxied by age of the trade-in) increase the endowment effect, as predicted by the literature.

What are the welfare consequences to a consumer of having an endowment effect in this market? Our exercise may appear inconsequential because the movement of rents between new and used car does not impact the consumer in a financial way. However, because the dealer can create consumer surplus by moving rents from the new car to the used trade-in, it gives him another instrument to extract rents overall from the consumer. And we find this happens: the same people who have large endowment effects and do well bargaining over the trade-in are also those who pay more for the package of new car plus trade-in.

## 2. A Simple Model

Consider a consumer who is negotiating over a new car purchase and wants to trade-in a used car. Consumers will differ in their ability to bargain so that, holding car and dealer constant, different consumers will be able to extract better or worse deals.

Let $V_{ij}$ =the bargaining gain achieved by consumer i buying car j (and trading in car t?)

Let $V_{ij}^{u}$ = trade in price of consumer i's car less the actual value of that car

Let $V_{ij}^{n}$ = list car price to consumer i less the transaction price to consumer i

The dealer is assumed to be indifferent between $V^u$ and $V^n$ as is a consumer without an endowment effect.[2] As we suggested earlier, neither the dealer nor an unbiased consumer should care whether they negotiate a bargaining gain of $1000 more for their used car than it is worth, or

[2] The dealer is not assumed to exhibit an endowment effect on the new cars on his or her lot for example. This seems consistent with the work on List on professional baseball card traders (2003) and work by Novemsky and Kahneman (2005).

pay $1000 less for the new car. In the graph below, we represent this position as a series of equal isocost or isovalue lines, labelled $C_1 \ldots Cn$, or equivalently $V_1 \ldots Vn$ , with a slope of negative one. Cost to the dealer and value to the consumer both increase in the northeast direction.

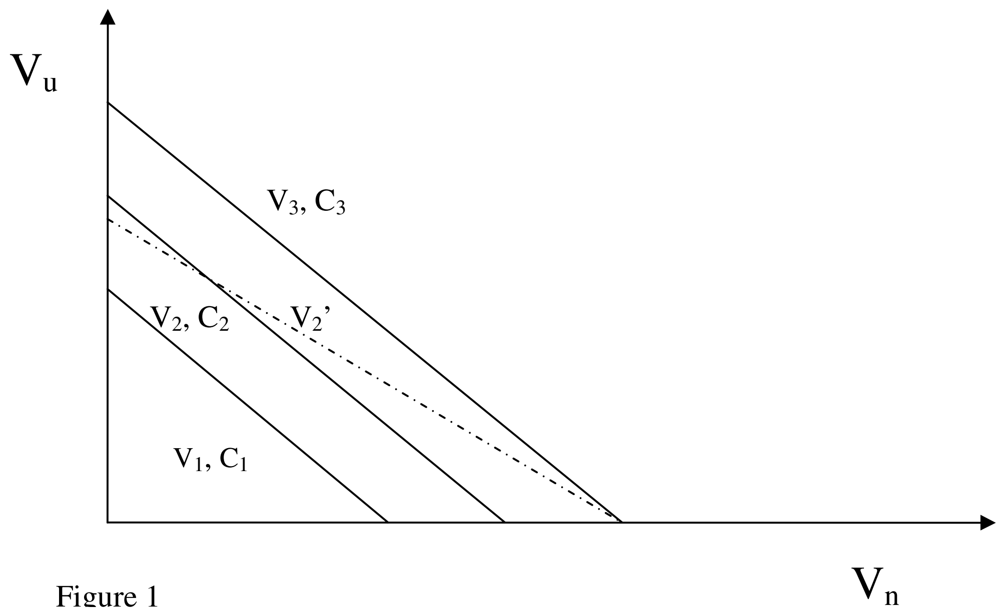


Figure 1

The dealer's problem is to achieve the deal at the lowest cost, while the consumer is interested in pushing for the highest V. With unbiased consumers and dealers, we will not be able to predict where on any given isocost / isovalue line we will end up. All we can predict is that as consumer bargaining power rises, we move to a higher V (C).

For a consumer with an endowment effect, however, the value line is no longer coincident with the isocost line. Now we expect the V lines to be flatter than the C lines, as in $V_2$ in our example above. Using our earlier notation, we can represent the endowment effect most simply as:

$$V_{ij} = \alpha V_{ij}^{u} + V_{ij}^{n} \qquad (4)$$

where $\alpha>1$.

It follows simply that the optimal strategy for a dealer faced with a consumer with an endowment effect will be to put all the bargaining value on to the trade-in, since value there is “multiplied up” by the endowment parameter. That is, in Figure 1, the equilibria will all lie on the corner along the y-axis.

In practice, the distortion away from a reasonable new car price will get too large and noticeable for all the bargaining value to be taken in this form. Nevertheless, the general proposition should hold that all else equal consumers with endowment effects should take a greater portion of their gains in $V^u$. This is the position tested in this paper.

## 3. Data and Estimation Strategy

The dataset we use comprises approximately one million new car purchases at a sample of new car dealerships across the US in 1999. The observations were collected by a market research firm, hereafter referred to as MRF. Some 40% of these purchases were accompanied by a trade-in transaction and it is this part of the data set we will focus on.

The dataset contains a great deal of detailed information about both the new car and the trade-in. For the new car, we have data on both the transaction price and the average sales price for that same make and model at a very precise level (including, for example, the engine type, number of doors, transmission and trim level). These data will allow us to construct a variable measuring how “good a deal” the buyer got on his or her new car purchase. Our data also report both the transaction price of the trade-in and also the amount at which the dealer’s internal accounting system values the car.

The timing of the different steps of the transaction is important. Typically the consumer who wants a new car brings her used car to the dealership. The dealer’s mechanics look at the exterior of the car, see its age, mileage, options, and perhaps raise the hood for a visual examination. Then the dealer offers the consumer a trade-in value for the car. This is the “transaction price” we measure for the trade-in. After the transaction is successfully consummated, mechanics at the dealership examine the car carefully. At this point, its value is entered into the dealer’s accounting system; this is the “value” of the traded car we use in our analysis. We assume this value is correct and there is no further unobserved quality. In fact, it is in the interest of the dealership to correctly measure the car's value, as often a salesman's commission depends on the net profit of the transaction. Thus, we are able to measure the transaction price relative to the dealer valuation to discover how well the consumer did on the sale of the trade-in. Clearly, a consumer will do better by our measure if the defects on her car are hidden from casual inspection but revealed in the full inspection. We will return to this issue later in the paper.

In the estimation, we will use two different dependent variables derived from the transactions prices. The simplest is the negotiated value of the trade-in relative to its booked value, which we name *TradeRatio*. We construct this measure directly from the original data and delete the top and bottom 5% of observations because they appear to be typos.[3] The mean of the truncated variable is 1.16 with a standard deviation of .33 and a median of exactly 1. As a consumer becomes more successful in her negotiation, the value of *TradeRatio* increases. The flaw in this measure is that it does not account for any surplus that may exist in the new car portion of the transaction. We will supplement our findings from *TradeRatio* with results from previous work using this dataset that provides information on the new car results of various groups.

The second measure we construct attempts to capture the proportion of the buyer's total surplus in the deal that is represented by the used car transaction. This measure more closely matches the concepts $V_u$ and $V_n$ in our model. We construct the average sales price (not including any margin on the trade-in) for each car type. Then we normalize the price an individual buyer paid for her new car by that average and call this $V_n$. Thus a buyer who bargained well for her new car pays a below average price, resulting in a ratio below one. We take the reciprocal of *TradeRatio* and name that $V_u$, so that the better the buyer is at negotiating over her trade-in, the lower the value of $V_u$. We convert these ratios back into dollars by multiplying each one by the sample mean of new car or used car prices, respectively. The common dollar unit allows us to add the new and used surplus measures to form a denominator, while the numerator is the used surplus only. We will call this variable *TradeinSurplusShare* The mean of this variable is .21 and its standard deviation is .03.

The data just described allow us to capture the extent to which a buyer strikes an advantageous bargain in both the new and used car part of the transaction. We use two types of

[3] The dropped values of *TradeRatio* range from 2.7 to 19,817 and 0 to 0.857.

data to predict when the endowment effect will be strongest for buyers and thus when more of the value will be loaded onto the trade-in piece: car characteristics and buyer characteristics.

**Buyer Characteristics**

One of the early results of Knetsch and Sinden (1984) in an experimental setting is that when individuals make choices on behalf of other people, they do not display the endowment effect. In the case of car deals, it is clear that there are times in which someone in a family other than the principal driver actually negotiates the deal. Unfortunately in our data set, we do not know whether the car traded in was driven by the buyer or someone else in the family. However, we can assume that the frequently the two will be the same – in single-person households, for example, and some substantial fraction of the time in a typical married household. We also separately examine the results for female buyers as compared to male. For example, casual observation of household behavior would suggest that when the buyer is female, it will disproportionately be the case that she is trading in her own car; i.e. wives are less likely to negotiate on behalf of their husbands but the converse is often true. Thus, when the buyer is male, he could be trading in a car he usually drove, or a car his wife usually drove. This suggests, all else equal, that the endowment effect will be stronger for the female buyer since the probability is higher that the trade-in is her own. To get at this a second way, we exploit variation in car type ownership by gender. For example, minivans are almost exclusively owned by married couples, whereas small sporty cars are majority-owned by single people. Thus, small sports car trade-ins are also expected to be more often own trade-in and thus should exhibit more of an endowment effect. Our dataset measures gender by analyzing the first name of the buyer.

There is surprisingly little experimental work on the demographic characteristics that minimize or accentuate behavioral biases. Recent work by Chen et al (2006) on loss aversion in Capuchin monkeys suggests that biases may be at least to some extent built into the brain rather than socially learned. However, there is a small literature on the relationship of demographics to behavioral biases.

Papers by List (2003) and List (2004) show that market experience is important in reducing the endowment effect. The more often a consumer has traded in the past, the more able he or she is to identify gains from trade and trade accordingly. The best measure we have for market experience is age. In the US, where car-ownership is almost universal, age is likely to be highly correlated with the number of cars a person has owned, and perhaps transacted over, in the past. (CES EVIDENCE HERE). The transaction dataset provides the age of the buyer. We include age as a spline, as we have no pre-existing view on the functional form it should take. The groups are 25 and below, 26-34, 35-45, 46-55, and 56-65. The omitted group is 66 and above**.**

List (2004) studies the impact of other demographic characteristics on willingness to trade (lack of endowment effect). He finds no significant effect of demographics: no gender effect, no age effect, and no effect of education.

We also draw on work that suggests that impulsive instincts in general may be partly overcome by cognitive reasoning, suggesting that phenomena like loss aversion might be more modest in individuals with higher cognitive skills (Loewenstein and O'Donoghue (2004)). Recent work by Benjamin and Shapiro (2006) finds laboratory evidence that both small stakes risk aversion and short run discounting are less common among students with higher standardized test scores. One might similarly predict that greater cognitive skills might moderate endowment effects.

The dataset does not, of course, have data on the cognitive abilities of the buyers. We do, however, have data on the census block group of the buyer which allows us to use the census to extract neighborhood data for each buyer. Variables include percent of the population with a college degree, percent who are high school dropouts, percentage blue collar, professional, executive, and averages such as household size, house value, and income. Achievement in the US has been shown to depend both on native ability of the person in question and, of course, on the resources provided by the person's family (CITE). Thus we do not assert that average neighborhood income, for example, is an accurate measure of the SAT scores of all of the residents of the neighborhood. However, despite the family component, income will be correlated with cognitive ability due to the financial returns to ability in the economy. Likewise, we are helped by the substantial social and geographic mobility in the US, which causes people to sort into neighborhoods with residents of similar characteristics (Pat Bayer CITE).

The ethnicity frequencies large enough to analyze are Hispanic and Asian. Additional information on race is taken from the census block data. We have no prediction concerning race and ethnicity and the endowment effect. However, in the US, race and ethnicity are correlated with other demographic variables such as education and income, so we expect to see coefficients on race and ethnicity variables that mirror those patterns.

**Characteristics of the Trade-in**

Strahilevitz and Loewenstein (1998) find that the longer individuals are endowed with an object, the higher their valuation of that object, suggesting that long ownership might accentuate the endowment effect. Thus, we suggest that the length of time the seller has owned the trade-in will be an important factor in whether or not the person feels the endowment effect. We do not know this fact, unfortunately, but we do know the age of the trade-in. At least some of our buyers will have bought their trade-in as a new car. We include the age of the trade-in as a spline as we do not want to impose a linear functional form on the data. Zero to three years is the first category because this is the period when the warrantee holds. A person who always wants a car under warrantee will trade-in at this point. Three to seven years old is the next group, followed by eight to ten. The omitted category is over ten years old. Our expectation is that the endowment effect and thus the amount of value captured by the trade in will increase with the age of the car.

The age of the trade-in may also measure a second effect which has been established in the experimental literature by Chapman (1998). This paper shows that the more similar the traded objects are (e.g. two kinds of pen rather than mug and chocolate), the lower the endowment effect. In our setting a person is trading in an old car for money, but may perceive she is trading in an old car for a new car (and some negative money). If this is the case, then perhaps newer trade-ins will show less of an endowment effect compared to older trade-ins that are less good substitutes for the new car. Novemsky and Kahneman (2005) refer to this effect and use traded-in cars as their example of similar goods. Clearly a newer used car will be a closer substitute to a brand new car, in terms of the benefits it can deliver, than an older used car, and so may show less endowment effect. The two age effects operate in the same direction, so we will not be able to distinguish them in our results. An off-setting effect mentioned by Purohit (1995) concerns the subsidy as a proportion of market price. As the trade-in gets older, it is worth less, and a subsidy of a particular dollar size becomes an ever larger proportion of its market price, while remaining unchanged as a proportion of the new car price. Thus, if the consumer is convinced by proportion, rather than absolute dollar amounts (in contrast to our model), as the car ages, less subsidy might be as effective in generating a transaction compared to a case where the trade-in was newer.

Just as we observe that behavioral biases can be mitigated by higher level reasoning, so one might expect emotional connections to accentuate these effects. Lerner, Small, and Loewenstein (2004) find that some emotional states like disgust can eliminate the endowment effect. We hypothesize that emotional connections are likely to be positive and strongest for an individual's first car. While we do not have information on whether or not a trade in is a first car, we do know the age of the car buyer. Thus, we judge that any car traded in by a driver under 25 years of age is likely to be trading in his or her first car. We would expect endowment effects to be stronger for these younger drivers.

Likewise, the endowment effect might differ across car subsegment because of the different purposes for which different subsegments are used and therefore the different emotions they arouse. A fun, sporty car might have a different endowment effect than a boring minivan. Okada (2001) finds evidence that frequent pleasant use of a durable good leads the owner to reduce her mental book value of the durable, relative to a good with negative associations. An object with a lower mental book value will be willingly traded at a lower price. Under this theory, the effect of the pleasurable emotion will be to reduce the endowment effect and reduce the price requested for the trade-in (and increase trading in used cars). We assign the traditional subsegments used by the industry to three categories: fun, luxury, and other.

## 4. Results

We estimated our Value equations using OLS, with the two variants of the dependent variable, *Traderatio* and *TradeinSurplusShare*. The results for a series of specifications are given in the Tables below. Besides the variables of interest, we control for the region of the transaction, and include end of month, end of year, and weekend indicators.

In specifications 1a and 1b *TradeRatio* and *TradeinSurplusShare* are in turn the dependent variables. We discuss them together because the results are nearly identical. Keep in mind that doing better on the trade-in is indicated by a positive coefficient in 1a but a negative coefficient in 1b. We will focus on coefficient magnitudes from specification 1a because they are easier to understand, being based around the ratio one (the tradein price/ tradein book value). The net effect of income is negative, as is percent with a college degree, homeownership, median housevalue, and percent with executive occupation. Percentage of residents with blue collar or technical occupations, percent black, and percent Hispanic all have positive coefficients. The effects are substantial in size. A standard deviation increase in house value lowers the expected *TradeRatio* by 2%, while a standard deviation increase in income lowers *TradeRatio* by 2%. Moving from zero to one hundred percent blue collar increases *TradeRatio* by 5%. Moving from a neighborhood with zero to one hundred percent college educated lowers *TradeRatio* by 4%.We see in these specifications, buyers with arguably lower cognitive skills, the less educated and those living in poorer neighborhoods, extract a relatively high value from their trade-ins.

Interestingly, previous results from this dataset analyzing the combined transactions (Zettelmeyer, Scott Morton, and Silva-Risso (2003)) show that these characteristics are associated with worse overall prices for the total package, including the margin on the trade-in. Thus, while the uneducated may be doing well with the trade-in, they are more than making up for this bargaining success by overpaying for the new car. Further, information about the new car is arguably easier to get, and it is easier to collect competing price quotes because the new car is a homogenous object. Therefore, it seems as if these consumers are doing well at the harder piece of the bargaining task.

The estimated coefficient on *female* is positive and significant; women do relatively well bargaining over a trade-in (1%). This may be a pure gender effect or may simply represent the stronger endowment effect in the subsample of buyers who are trading in their own cars rather than their partners' cars. However, similar to the demographics above, the positive coefficient can be contrasted with results from the same data set (Zettelmeyer, Scott Morton, and Silva-Risso (2003)) showing that women get overall worse deals in the car market. However, all of these results are consistent with our expectations about the endowment effect, suggesting that even relatively poor bargainers with these demographics get reasonably good trade-in deals because they are loading so much of the value they do get on to the trade-in (moving towards a corner in our earlier picture).

We further find strong evidence that market experience reduces the endowment effect. The coefficients on the age spline are monotonically decreasing: the youngest age group does best on the trade-in, 11% more than the omitted group, followed by a steady decline (6%, 4%, 2%, 1%) until the 66 and over group.

Our results also show a significant effect of the age of the trade-in vehicle. Buyers do better negotiating for older trade-ins. This is consistent both the endowment effect increasing with the length of ownership and also with the old and new cars being worse substitutes as the trade-in ages. The effect is quite strong, with a coefficient of -7% on 0-3 year old tradeins. The next group has a coefficient of -3%, followed by +1% for the age 8-10 category. The omitted category of really ancient trade-ins (more than 10 years old) are intermediate in magnitude with an implied coefficient of zero.

Our measure of whether the car is a 'first car' has a negative and significant coefficient, which is the opposite of our theoretical prediction that positive emotion enhances the endowment effect. It is consistent with Okada (2001). Recall his theory is that pleasurable use lowers the mental accounting value of the durable good, making an owner more willing to trade.

We now return to the issue of unobservable quality. Recall that in our setting, the dealer learns about all unobservable quality upon carrying out a full inspection. The final booked value of the car in the denominator contains all information about the value and condition of the car. A buyer with a car that looks good on the outside, but has a ruined transmission, might be offered an average price for the car, but then the dealer would revise down the booked value upon inspection. Then this consumer's *TradeRatio* would be relatively high due to the new information. Our empirical findings are consistent with this story, in the sense that the highest values of *TradeRatio* are earned by the socio-economically most disadvantaged buyers. Thus it would not be surprising if these cars were discovered to have below average condition after trade-in offers were made.

Of course, if this were an empirical regularity, we would expect the salesman to correct for it in the average level of his offers. He is able to observe the socio-demographic status of the buyer with some accuracy due to her presence at the dealership and the fact that car salesmen are selected to have this kind of observational skill. He can adjust his offers downwards if he suspects low condition that will be discovered *ex post*. Secondly, the salesman is typically compensated by a percentage of the net margin on the deal. The margin on the deal is calculated using the booked value of the trade-in. Thus if the trade-in is worth less than the salesperson thought, his financial reward falls. So it is not in the interest of the salesman to make persistent *mistakes* about the value of the car – though of course he may choose to offer more than the trade-in is worth if it creates a deal where there would not otherwise be one, as in our model above.

Note also that any feature of the car or buyer that is observable to the dealer when he makes the trade-in offer cannot be information learned from the inspection that lowers the booked value of the car. The trade-in's age, for example, and the age and gender of the buyer are fully known at the time of the trade-in offer.

We briefly engage in some robustness checks by running the same regression on different sub-samples of the data. A key feature of our setting is the flexibility of both transaction prices, which allows the endowment effect to have an impact. This flexibility will not exist in negotiations where the two parties first agree on the new car price before discussing the trade-in. With this timing, the dealer commits to a price at which he will sell the new car and cannot raise that price. Only later does the consumer physically arrive at the dealership with her trade-in, and at that point the dealer can examine the trade-in and make an offer. (Note that dealers will not make binding trade-in offers without physical inspection of the used vehicle for obvious reasons.) Buyers who have used the Internet to get a price quote would be an example of a group where the bargaining over the trade-in might be independent of the new car price because that has been fixed in a previous negotiation. In our results thus far we have found that the groups least likely to use the Internet (socio-economically disadvantaged) are the ones who get the most for their trade-ins. Our concern is that perhaps every consumer has the same endowment effect but the Internet shoppers do not show it because the dealer can not trade off between the two prices. Thus, the next specification uses a subsample consisting only of buyers who used Autobytel.com before buying a new car. As one can see in Specification 2, the same pattern of results hold, though naturally they are weaker due to the much reduced sample size (265,000 down to 12,000). Housing values, income, being from a black neighborhood, age of the buyer and trade-in age all show the same pattern as before. College, homeownership, executive, technical, and Hispanic are no longer significant. Female is also no longer significant. However, this variable is mis-measured in our dataset, so it is not surprising it suffers attenuation bias in a smaller sample.[4]

We also limit the sample to those who paid cash because of given our demographic findings and known discrimination in lending rates (CITE Ayres). Restricting the sample to

[4] MRF takes the first name on the purchase contract and uses it as the buyer's first name, which creates a problem in the case of joint ownership. Thus if the buyers are Jane and John Doe, the buyer is coded as female. If the buyers are John and Jane Doe, the buyer is coded male.

transactions with no financing through the dealership limits the sample to buyers who are likely to be more financially sophisticated. They have either saved enough money to pay cash for their car or they have obtained financing through a bank or other institution. Nonetheless, this sophisticated group generates similar results (Specification 3). Perhaps because of the smaller sample size, we lose significance of college, homeownership, technical, and Hispanic. Interestingly, the coefficients on percent black and female are approximately half the size of those in specification 1a. However, the coefficients on age of the buyer and age of the trade-in are comparable in magnitude. 74% of transactions with a trade-in obtain financing from the dealer, so our sample size for this specification is about 72,000.

Likewise, restricting the sample to female buyers (Specification 4) yields the same results as Specification 1, without an estimate for the coefficient on *female*, clearly (95,000 observations). We do not see any interesting or significant differences in the pattern of estimated coefficients across gender. Because female is so poorly measured in these data, we also examine the results if we restrict the specification to buyers of vans (24,000 observations) as compared to sporty cars. Vans are disproportionately bought by married couples (95%) and so we conjecture a man was likely to be involved in the negotiation at some point. As we expected, female is no longer significant in this specification, but the results concerning race, age, and the age of the trade-in are unchanged (specification 5). The majority of sporty cars are bought by single buyers. In this specification (43,000 observations), many of the estimated coefficients drop in magnitude. In contrast to the 'van' results, the *female* coefficient in the sporty sample is larger than the estimate in the base specification. This pattern is consistent both with a) women having a larger endowment effect and measuring *female* accurately, and b) with the endowment effect being stronger for a car the buyer has driven herself.

In specification 6 we add the indicators *fun* and *luxury* which refer to the sub-segment of the traded-in car. Sporty categories form the first variable and the union of all the luxury categories forms the second. Buyers do less well trading in a fun car and better trading in a luxury car. Since these categories of vehicle are alleged to induce pleasurable emotions in their drivers, we expected stronger endowment effects for both categories of cars relative to others. Only the coefficient on *luxury* matches the prediction.

**5. Conclusion**

We find that, in bargaining over a trade-in vehicle, a consumer does better if she has owned the car for a longer time (proxied by car age) and if she is young and therefore without much market experience buying and selling cars. These results are consistent with the endowment effect affecting trade in the market for used cars. Car dealers will shift money between new and used car prices in order to create utility for the consumer. Consumers who appear to have a strong endowment effect and therefore desire this shift are lower income, blue collar, minority, non-college educated, and who live in poorer neighborhoods. Women may exhibit a stronger endowment effect but in our data we cannot separate the differences between genders and the "driver" effect.

Our setting has advantages for studying endowment effects because of the ease with which the salesman can move money from one product to the other. However, that ease arises from the underlying fact that the two sources of money are identical for the dealer and for the consumer's bank account, though not perhaps for the consumer's utility. Given the potential lack of financial effects from an endowment effect in our setting, what can we conclude concerning welfare in the presence of the endowment effect in real markets? First, we measure the correlation between ratio earned on trade-in and total surplus overall. This is strongly negative (-.17) and significant. That is, those buyers who do well bargaining over the trade-in have a positive error term – they pay too much – in the overall price of the package. This indicates that the endowment effect has consequences for welfare and profits. Because the dealer can move money between two goods that the consumer values differently, he can create utility for the consumer. However, as one might expect, the dealer also captures some of that surplus for himself and therefore redistributes rents from consumers to the retail auto industry.

Second, we infer from the fact that the dealer adjusts the price of the trade-in that he gains from doing so – he reduces the probability of losing the combined deal and induces consumers to trade. If there is no such margin to adjust, some owners of used cars would not upgrade their used car to a new car. Our results provide predictions for which subsegments of the used car market will be disproportionately active in the absence of the ability to subsidize the trade-in: cars owned by older people, younger cars, cars driven by men, and cars owned by wealthier and better educated people. We find the car segments that require the most cross-subsidy by the dealer, the highest Vu/(Vu+Vn), to be 'entry compact,' 'premium compact,' and 'lower midsize.'

The market for cars is not one in which most consumers trade frequently. For example, a baseball card collector probably trades many more cards in a five year span than a typical new-car consumer trades cars. This leads us to reconcile the difference between our findings and List (2004) by pointing to differences between consumers' market experience in the two contexts. Of course, we also find that market experience is important, but this is only one component of the endowment effect and it takes 40 years of market experience for it to disappear. Our findings demonstrate that the endowment effect remains a significant feature of one important real-world market, and suggests to us that is perhaps a feature of other markets where the frequency of trading is not high.

*References*


Barberis, Nicholas and Ming Huang (2006) "Loss Aversion / Narrow Framing Approach to the Equity Premium Puzzle" draft Yale School of Management

Benjamin and Shapiro (2006) "Title?" draft, University of Chicago.

Chapman, Gretchen (1998) "Similarity and Reluctance to Trade" *Journal of Behavioral Decision-making*: 11:1 (December) 47-58.

Chen, M. Keith, Vankat Lakshimarayanan, and Laurie Santos (2006) "How Basic are Behavioral Biases? Evidence from Capuchin Monkey Trading Behavior" forthcoming *Journal of Political Economy.*

Janiszweski, Chris and Marcus Cunha (2004) "The Influence of Price Discount Framing on the Evaluation of a Product Bundle" *Journal of Consumer Research*, 30 (March) 534-546.

Khaneman, Daniel, Jack Knetsch, and Richard Thaler (1990), "Experimental Tests of the Endowment Effect and the Coase Theorem," *Journal of Political Economy*, 98 (December) 1325-48.

Khaneman, Daniel and Amos Tversky (1979) "Prospect Theory: An Analysis of Decision Under Risk" *Econometrica* 47 (March): 263-91

--------- and -------- (1984) "Choices, Values, and Frames," *American Psychologist*, 39 (April) 341-50.

Knetsch, Jack (1989) "The Endowment Effect and Evidence of Noreversible Indifference Curves" American Economic Review, 79 (December), 1277-84.

Knetsch, Jack and J.A. Sinden (1984) "Willingness to Pay and Compensation Demanded: Experimental Evidence of an Unexpected disparity in Measures of Value" *Quarterly Journal of Economics*: 99 (3): 507-521.

Lerner, Jennifer, Deborah Small, and George Loewenstein (2004) "Heart Strings and Purse Strings: The Carry-Over of Effects of Emotions on Economic Transactions" *Psychological Science:*15:5:337-341

List, John (2003) "Does Market Experience Eliminate Market Anomalies?" *Quarterly Journal of Economics* (Feb) 41-71.

List, John (2004) "Neoclassical Theory versus Prospect Theory: Evidence from the Marketplace" *Econometrica*: 72:2:615-25.

Loewenstein and O'Donoghue (2004) "Animal Spirits: Affective and Deliberative Processes in Economic Behavior" draft, Carnegie Mellon University, Cornell University.

Novemsky, Nathan and Daniel Kahneman (2005) "The Boundaries of Loss Aversion," *Journal of Marketing Research*, Vol 42 (May), 119-128.

Okada, Erica (2001) "Trade-ins, Mental Accounting, and Product Replacement Decisions" *Journal of Consumer Research*: 27: 433-446.

Oster, Sharon and Fiona Scott Morton (2005) "Behavioral Biases Meet the Market: the Case of Magazine Subscription Prices" *Berkeley Electronic Journals in Economic Analysis & Policy Advances*:5:1

Purohit, Devavrat (1995) "Playing the Role of Buyer and Seller: The Mental Accounting of Trade-ins" *Marketing Letters*:6:2:101-110.

Strahilevitz and Loewenstein (1998) "The Effect of Ownership History on the Valuation of Objects" *Journal of Consumer Research*, 25: 276-289

Scott Morton, Fiona, Florian Zettelmeyer, and Jorge Silva-Risso (2001) "Internet Car Retailing" *The Journal of Industrial Economics*:49:4

Zettelmeyer, Florian, Fiona Scott Morton, and Jorge Silva-Risso (2003) "Consumer Information and Discrimination: Does the Internet Affect the Pricing of New Cars to Women and Minorities?" *Quantitative Marketing and Economics*:1:1:65-92, 2003.

Specification 1a

```
. reg traderat regiona-regiono endofmo endofyr weekend income inc2 college
less
> hs hsown hsval prof exec blue tech pctas pctbl pcthis female age25 age34
age4
> 5 age55 age65 trage03 trage47 trage810 firstcar if anytr==1

      Source |       SS       df       MS              Number of obs =  266821
-------------+------------------------------           F( 42,266778) =  360.71
       Model |  1448.32601    42  34.4839525           Prob > F      =  0.0000
    Residual |   25504.255266778  .095601043           R-squared     =  0.0537
-------------+------------------------------           Adj R-squared =  0.0536
       Total |   26952.581266820  .101014096           Root MSE      =  .30919

------------------------------------------------------------------------------
    traderat |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
                  -- region effects --

     endofmo |   -.000869   .0014943    -0.58   0.561    -.0037978    .0020598
     endofyr |  -.0058427   .0046348    -1.26   0.207    -.0149268    .0032413
     weekend |   .0028309   .0014728     1.92   0.055    -.0000557    .0057174
      income |  -1.26e-06   1.37e-07    -9.15   0.000    -1.53e-06   -9.87e-07
        inc2 |   6.88e-12   8.33e-13     8.26   0.000     5.25e-12    8.51e-12
     college |  -.0003956   .0000918    -4.31   0.000    -.0005754   -.0002157
      lesshs |  -.0000983   .0001148    -0.86   0.392    -.0003233    .0001267
       hsown |  -.0001548   .0000418    -3.70   0.000    -.0002367   -.0000728
       hsval |  -2.26e-07   1.39e-08   -16.29   0.000    -2.53e-07   -1.99e-07
        prof |  -.0000363    .000136    -0.27   0.790    -.0003029    .0002304
        exec |  -.0005013   .0001415    -3.54   0.000    -.0007786   -.0002239
        blue |   .0004913   .0000904     5.43   0.000     .0003141    .0006685
        tech |   .0006766    .000324     2.09   0.037     .0000416    .0013115
     pctasia |   .0000416   .0001069     0.39   0.697     -.000168    .0002512
      pctblk |   .0011225   .0000483    23.24   0.000     .0010278    .0012171
     pcthisp |   .0006804   .0000943     7.21   0.000     .0004955    .0008653
      female |   .0108651   .0012629     8.60   0.000     .0083899    .0133402
       age25 |   .1116296   .0046226    24.15   0.000     .1025695    .1206898
       age34 |    .064053   .0024604    26.03   0.000     .0592306    .0688754
       age45 |    .038877   .0022085    17.60   0.000     .0345483    .0432057
       age55 |   .0243999   .0023072    10.58   0.000     .0198778    .0289219
       age65 |   .0116333   .0025674     4.53   0.000     .0066012    .0166654
     trage03 |  -.0690683    .002044   -33.79   0.000    -.0730745    -.065062
     trage47 |  -.0275436   .0019731   -13.96   0.000    -.0314108   -.0236764
    trage810 |   .0105034   .0022814     4.60   0.000     .0060319    .0149748
    firstcar |  -.0167638   .0036043    -4.65   0.000    -.0238281   -.0096995
       _cons |   1.243825   .0112332   110.73   0.000     1.221808    1.265842
------------------------------------------------------------------------------
```

Specification 1b: Dependent variable is proportion earned on used car

```
. reg Vunorm regiona-regiono endofmo endofyr weekend income inc2 college
lesshs
>  hsown hsval prof exec blue tech pctas pctbl pcthis female age25 age34 age45
> age55 age65 trage03 trage47 trage810 firstcar if anytr==1

      Source |       SS       df       MS              Number of obs =  266821
-------------+------------------------------           F( 42,266778) =  378.46
       Model |  17.8037239    42  .423898187           Prob > F      =  0.0000
    Residual |  298.808801266778  .001120065           R-squared     =  0.0562
-------------+------------------------------           Adj R-squared =  0.0561
       Total |  316.612525266820  .001186615           Root MSE      =  .03347

------------------------------------------------------------------------------
      Vunorm |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
                 - - region effects - -
     endofmo |   .0003817   .0001617     2.36   0.018      .0000646    .0006987
     endofyr |   .0025428   .0005017     5.07   0.000      .0015595    .0035261
     weekend |  -.0002724   .0001594    -1.71   0.088     -.0005848    .0000401
      income |   1.55e-07   1.49e-08    10.45   0.000      1.26e-07    1.84e-07
        inc2 |  -9.12e-13   9.01e-14   -10.12   0.000     -1.09e-12   -7.35e-13
     college |   .0000386   9.93e-06     3.89   0.000      .0000192    .0000581
      lesshs |  -.0000132   .0000124    -1.06   0.288     -.0000376    .0000111
       hsown |   .0000189   4.53e-06     4.17   0.000      9.99e-06    .0000277
       hsval |   3.00e-08   1.50e-09    19.99   0.000      2.71e-08    3.30e-08
        prof |   2.18e-06   .0000147     0.15   0.882     -.0000267     .000031
        exec |   .0000436   .0000153     2.85   0.004      .0000136    .0000736
        blue |  -.0000437   9.79e-06    -4.47   0.000     -.0000629   -.0000245
        tech |  -.0000583   .0000351    -1.66   0.096      -.000127    .0000104
     pctasia |  -4.86e-06   .0000116    -0.42   0.674     -.0000276    .0000178
      pctblk |   -.000141   5.23e-06   -26.98   0.000     -.0001513   -.0001308
     pcthisp |  -.0000874   .0000102    -8.56   0.000     -.0001074   -.0000674
      female |  -.0016294   .0001367   -11.92   0.000     -.0018974   -.0013615
       age25 |  -.0131376   .0005004   -26.26   0.000     -.0141183   -.0121569
       age34 |  -.0070134   .0002663   -26.33   0.000     -.0075353   -.0064914
       age45 |  -.0044371   .0002391   -18.56   0.000     -.0049056   -.0039685
       age55 |  -.0032675   .0002497   -13.08   0.000      -.003757    -.002778
       age65 |  -.0017888   .0002779    -6.44   0.000     -.0023335   -.0012441
     trage03 |     .00311   .0002212    14.06   0.000      .0026764    .0035436
     trage47 |   .0003489   .0002136     1.63   0.102     -.0000697    .0007675
    trage810 |  -.0014579   .0002469    -5.90   0.000     -.0019419   -.0009739
    firstcar |   .0029722   .0003901     7.62   0.000      .0022075    .0037368
       _cons |   .2123342   .0012159   174.63   0.000      .2099511    .2147174
------------------------------------------------------------------------------
```

```
Specification 2a Internet Users
.
. reg traderat regiona-regiono endofmo endofyr weekend income inc2 college
less
> hs hsown hsval prof exec blue tech pctas pctbl pcthis female age25 age34
age4
> 5 age55 age65 trage03 trage47 trage810 firstcar if ABT==1 & anytr==1

      Source |       SS       df       MS              Number of obs =   12595
-------------+------------------------------           F( 42, 12552) =   15.67
       Model |  50.3805701    42  1.19953738           Prob > F      =  0.0000
    Residual |  960.909556 12552  .076554299           R-squared     =  0.0498
-------------+------------------------------           Adj R-squared =  0.0466
       Total |  1011.29013 12594  .080299359           Root MSE      =  .27668

------------------------------------------------------------------------------
    traderat |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
                 -- region effects  --
     endofmo |  -.0026076   .0060762    -0.43   0.668    -.0145179    .0093028
     endofyr |  -.0192228   .0171852    -1.12   0.263    -.0529084    .0144628
     weekend |   .0058869    .006102     0.96   0.335     -.006074    .0178478
      income |  -1.41e-06   5.63e-07    -2.51   0.012    -2.51e-06   -3.07e-07
        inc2 |   7.11e-12   3.17e-12     2.24   0.025     8.89e-13    1.33e-11
     college |  -.0004428   .0003669    -1.21   0.227     -.001162    .0002763
      lesshs |  -.0004543     .00055    -0.83   0.409    -.0015323    .0006237
       hsown |  -.0000864   .0001738    -0.50   0.619    -.0004271    .0002543
       hsval |  -1.93e-07   5.08e-08    -3.79   0.000    -2.92e-07   -9.31e-08
        prof |   .0000212   .0005268     0.04   0.968    -.0010114    .0010538
        exec |   .0001867   .0005637     0.33   0.741    -.0009183    .0012916
        blue |   .0005028   .0004076     1.23   0.217    -.0002962    .0013019
        tech |   -.000554    .001294    -0.43   0.669    -.0030903    .0019823
     pctasia |   .0003569   .0004152     0.86   0.390    -.0004569    .0011707
      pctblk |   .0008242   .0002592     3.18   0.001     .0003161    .0013323
     pcthisp |  -.0003163   .0004445    -0.71   0.477    -.0011875     .000555
      female |   .0058871   .0052932     1.11   0.266    -.0044884    .0162625
       age25 |    .059857   .0196917     3.04   0.002     .0212582    .0984558
       age34 |    .027483   .0129015     2.13   0.033     .0021942    .0527718
       age45 |   .0170091   .0122042     1.39   0.163    -.0069129    .0409311
       age55 |   .0050398   .0126885     0.40   0.691    -.0198316    .0299112
       age65 |   .0051386   .0141604     0.36   0.717     -.022618    .0328951
     trage03 |  -.0395788   .0087502    -4.52   0.000    -.0567304   -.0224271
     trage47 |   -.018078   .0080803    -2.24   0.025    -.0339166   -.0022394
    trage810 |  -.0013188   .0090813    -0.15   0.885    -.0191196     .016482
    firstcar |   .0081625   .0130239     0.63   0.531    -.0173664    .0336913
       _cons |   1.326846   .0524586    25.29   0.000     1.224019    1.429673
------------------------------------------------------------------------------
```

Specification 2b: Internet Users

```
 reg Vunorm regiona-regiono endofmo endofyr weekend income inc2 college lesshs
>  hsown hsval prof exec blue tech pctas pctbl pcthis female age25 age34 age45
> age55 age65 trage03 trage47 trage810 if ABT==1 & anytr==1

      Source |       SS       df       MS              Number of obs =   12595
-------------+------------------------------           F( 41, 12553) =   17.28
       Model |  .672679742    41  .016406823           Prob > F      =  0.0000
    Residual |  11.9192428 12553  .000949513           R-squared     =  0.0534
-------------+------------------------------           Adj R-squared =  0.0503
       Total |  12.5919226 12594  .000999835           Root MSE      =  .03081

------------------------------------------------------------------------------
      Vunorm |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
                 - - region effects - -
     endofmo |  -.0003538   .0006767    -0.52   0.601    -.0016802    .0009726
     endofyr |   .0039616   .0019137     2.07   0.038     .0002105    .0077127
     weekend |  -.0003842   .0006796    -0.57   0.572    -.0017162    .0009478
      income |   1.65e-07   6.27e-08     2.64   0.008     4.24e-08    2.88e-07
        inc2 |  -9.38e-13   3.53e-13    -2.65   0.008    -1.63e-12   -2.45e-13
     college |    .000063   .0000409     1.54   0.123    -.0000171    .0001431
      lesshs |   .0000317   .0000612     0.52   0.605    -.0000884    .0001517
       hsown |   .0000109   .0000194     0.56   0.575    -.0000271    .0000488
       hsval |   2.57e-08   5.66e-09     4.55   0.000     1.47e-08    3.68e-08
        prof |  -.0000618   .0000587    -1.05   0.293    -.0001768    .0000532
        exec |  -.0000612   .0000628    -0.98   0.329    -.0001843    .0000618
        blue |  -.0000676   .0000454    -1.49   0.137    -.0001566    .0000214
        tech |  -.0000109   .0001441    -0.08   0.940    -.0002933    .0002716
     pctasia |  -6.69e-06   .0000462    -0.14   0.885    -.0000973    .0000839
      pctblk |  -.0001018   .0000289    -3.53   0.000    -.0001584   -.0000452
     pcthisp |    .000024   .0000495     0.49   0.628     -.000073     .000121
      female |  -.0014841   .0005895    -2.52   0.012    -.0026396   -.0003286
       age25 |  -.0077084   .0016194    -4.76   0.000    -.0108827   -.0045341
       age34 |  -.0036298   .0013899    -2.61   0.009    -.0063543   -.0009053
       age45 |  -.0023349    .001359    -1.72   0.086    -.0049988    .0003289
       age55 |  -.0012906    .001413    -0.91   0.361    -.0040604    .0014791
       age65 |  -.0014092    .001577    -0.89   0.372    -.0045004    .0016819
     trage03 |  -.0001441   .0009505    -0.15   0.879    -.0020073     .001719
     trage47 |  -.0005862   .0008775    -0.67   0.504    -.0023061    .0011338
    trage810 |   .0000758   .0010014     0.08   0.940    -.0018872    .0020387
       _cons |   .1992569    .005841    34.11   0.000     .1878077     .210706
------------------------------------------------------------------------------
```

Specification 3a: No dealer financing

```
. reg traderat regiona-regiono endofmo endofyr weekend income inc2 college
less
> hs hsown hsval prof exec blue tech pctas pctbl pcthis female age25 age34
age4
> 5 age55 age65 trage03 trage47 trage810 firstcar if anyfin==0 & anytr==1

      Source |       SS       df       MS              Number of obs =   71830
-------------+------------------------------           F( 42, 71787) =  139.39
       Model |  408.788911    42  9.73306931           Prob > F      =  0.0000
    Residual |  5012.73394 71787  .069827879           R-squared     =  0.0754
-------------+------------------------------           Adj R-squared =  0.0749
       Total |  5421.52285 71829  .075478189           Root MSE      =  .26425

------------------------------------------------------------------------------
    traderat |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
                  - - region effects - -
     endofmo |    .003734   .0024529     1.52   0.128    -.0010737    .0085416
     endofyr |  -.0092959   .0074256    -1.25   0.211      -.02385    .0052582
     weekend |   .0095841   .0026122     3.67   0.000     .0044641    .0147041
      income |  -1.02e-06   2.11e-07    -4.83   0.000    -1.43e-06   -6.04e-07
        inc2 |   4.70e-12   1.19e-12     3.94   0.000     2.36e-12    7.03e-12
     college |  -.0000535   .0001472    -0.36   0.716    -.0003421     .000235
      lesshs |  -.0002944   .0002034    -1.45   0.148     -.000693    .0001042
       hsown |   .0000903   .0000709     1.27   0.203    -.0000487    .0002293
       hsval |  -1.48e-07   2.19e-08    -6.77   0.000    -1.91e-07   -1.05e-07
        prof |  -.0001103   .0002116    -0.52   0.602    -.0005249    .0003044
        exec |  -.0005148   .0002236    -2.30   0.021     -.000953   -.0000766
        blue |   .0003887   .0001462     2.66   0.008     .0001022    .0006752
        tech |   6.14e-06   .0005198     0.01   0.991    -.0010126    .0010249
     pctasia |    .000172   .0001926     0.89   0.372    -.0002055    .0005494
      pctblk |   .0006056   .0000944     6.42   0.000     .0004206    .0007906
     pcthisp |   .0001285   .0001706     0.75   0.451    -.0002059    .0004629
      female |   .0046598   .0020944     2.22   0.026     .0005549    .0087648
       age25 |   .0900183   .0089803    10.02   0.000     .0724169    .1076197
       age34 |   .0195308   .0039134     4.99   0.000     .0118604    .0272011
       age45 |  -.0058163   .0029941    -1.94   0.052    -.0116848    .0000522
       age55 |   -.011806   .0030639    -3.85   0.000    -.0178113   -.0058007
       age65 |  -.0040715   .0032463    -1.25   0.210    -.0104342    .0022913
     trage03 |  -.1196354   .0033992   -35.20   0.000    -.1262978   -.1129731
     trage47 |  -.0658979   .0032002   -20.59   0.000    -.0721702   -.0596255
    trage810 |    .008008   .0036639     2.19   0.029     .0008269    .0151892
    firstcar |  -.0348227   .0072898    -4.78   0.000    -.0491106   -.0205348
       _cons |   1.363747    .019292    70.69   0.000     1.325934    1.401559
------------------------------------------------------------------------------
```

Specification 3b: No financing

```
. reg Vunorm regiona-regiono endofmo endofyr weekend income inc2 college
lesshs
>  hsown hsval prof exec blue tech pctas pctbl pcthis female age25 age34 age45
> age55 age65 trage03 trage47 trage810 if anyfin==1 & anytr==1

      Source |       SS       df       MS              Number of obs =  194991
-------------+------------------------------           F( 41,194949) =  264.04
       Model |  12.7406823    41  .310748349           Prob > F      =  0.0000
    Residual |  229.438084194949  .001176913           R-squared     =  0.0526
-------------+------------------------------           Adj R-squared =  0.0524
       Total |  242.178766194990  .001242006           Root MSE      =  .03431

------------------------------------------------------------------------------
      Vunorm |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
                 - - region effects - -
     endofmo |   .0005296   .0001942     2.73   0.006     .0001489    .0009103
     endofyr |   .0023506   .0006081     3.87   0.000     .0011588    .0035423
     weekend |   .0003495   .0001866     1.87   0.061    -.0000163    .0007153
      income |   1.63e-07   1.87e-08     8.70   0.000     1.26e-07    2.00e-07
        inc2 |  -1.00e-12   1.19e-13    -8.43   0.000    -1.24e-12   -7.69e-13
     college |   .0000551   .0000121     4.57   0.000     .0000315    .0000788
      lesshs |  -.0000165   .0000146    -1.13   0.259    -.0000452    .0000122
       hsown |   .0000246   5.39e-06     4.57   0.000      .000014    .0000352
       hsval |   2.99e-08   1.84e-09    16.31   0.000     2.63e-08    3.35e-08
        prof |  -.0000197   .0000181    -1.09   0.277    -.0000551    .0000158
        exec |   .0000359   .0000187     1.92   0.055    -6.99e-07    .0000725
        blue |  -.0000455   .0000118    -3.84   0.000    -.0000687   -.0000223
        tech |  -.0000997   .0000425    -2.35   0.019     -.000183   -.0000164
     pctasia |   1.29e-07   .0000135     0.01   0.992    -.0000263    .0000266
      pctblk |  -.0001443   5.98e-06   -24.13   0.000     -.000156   -.0001326
     pcthisp |  -.0000817    .000012    -6.83   0.000    -.0001051   -.0000583
      female |  -.0017208   .0001636   -10.52   0.000    -.0020415   -.0014001
       age25 |  -.0081387   .0004133   -19.69   0.000    -.0089488   -.0073285
       age34 |  -.0046487   .0003639   -12.77   0.000     -.005362   -.0039354
       age45 |  -.0032036   .0003541    -9.05   0.000    -.0038976   -.0025095
       age55 |   -.002424   .0003665    -6.61   0.000    -.0031423   -.0017057
       age65 |  -.0010616   .0004052    -2.62   0.009    -.0018557   -.0002675
     trage03 |   .0009576   .0002583     3.71   0.000     .0004514    .0014639
     trage47 |  -.0014112   .0002512    -5.62   0.000    -.0019035   -.0009189
    trage810 |  -.0013052   .0002969    -4.40   0.000    -.0018871   -.0007233
       _cons |   .1881795   .0014302   131.58   0.000     .1853764    .1909826
------------------------------------------------------------------------------
```

Specification 4a: Women only

```
. reg traderat regiona-regiono endofmo endofyr weekend income inc2 college
less
> hs hsown hsval prof exec blue tech pctas pctbl pcthis female age25 age34
age4
> 5 age55 age65 trage03 trage47 trage810 firstcar if female==1 & anytr==1

      Source |       SS       df       MS              Number of obs =   94995
-------------+------------------------------           F( 41, 94953) =  131.67
       Model |  568.402286    41  13.8634704           Prob > F      =  0.0000
    Residual |  9997.88644 94953  .105293002           R-squared     =  0.0538
-------------+------------------------------           Adj R-squared =  0.0534
       Total |  10566.2887 94994  .111231117           Root MSE      =  .32449

------------------------------------------------------------------------------
    traderat |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
                  - - region effects - -
     endofmo |  -.0015224   .0026243    -0.58   0.562    -.0066659    .0036212
     endofyr |  -.0037125   .0082471    -0.45   0.653    -.0198768    .0124518
     weekend |   .0009694   .0025821     0.38   0.707    -.0040914    .0060303
      income |  -1.33e-06   2.44e-07    -5.45   0.000    -1.81e-06   -8.52e-07
        inc2 |   6.86e-12   1.49e-12     4.60   0.000     3.94e-12    9.79e-12
     college |  -.0003389   .0001612    -2.10   0.035    -.0006548    -.000023
      lesshs |  -.0002536   .0002013    -1.26   0.208    -.0006482     .000141
       hsown |  -.0000945    .000072    -1.31   0.189    -.0002357    .0000466
       hsval |  -2.34e-07   2.43e-08    -9.63   0.000    -2.81e-07   -1.86e-07
        prof |   .0000603   .0002396     0.25   0.801    -.0004092    .0005298
        exec |  -.0004064   .0002495    -1.63   0.103    -.0008954    .0000825
        blue |   .0006848   .0001592     4.30   0.000     .0003727     .000997
        tech |   .0010749   .0005647     1.90   0.057     -.000032    .0021818
     pctasia |   .0001643   .0001891     0.87   0.385    -.0002063    .0005349
      pctblk |    .001448   .0000741    19.55   0.000     .0013029    .0015931
     pcthisp |   .0005143    .000165     3.12   0.002     .0001909    .0008376
      female |  (dropped)
       age25 |   .1061334   .0079342    13.38   0.000     .0905824    .1216844
       age34 |   .0617175   .0045687    13.51   0.000     .0527629    .0706721
       age45 |   .0420679   .0041693    10.09   0.000     .0338962    .0502397
       age55 |   .0209127   .0043386     4.82   0.000     .0124091    .0294162
       age65 |   .0089618   .0048823     1.84   0.066    -.0006075    .0185311
     trage03 |  -.0626204   .0036476   -17.17   0.000    -.0697697   -.0554712
     trage47 |  -.0214436   .0034752    -6.17   0.000     -.028255   -.0146321
    trage810 |   .0115531   .0039494     2.93   0.003     .0038124    .0192938
    firstcar |  -.0169261   .0060991    -2.78   0.006    -.0288803   -.0049719
       _cons |   1.259828   .0211664    59.52   0.000     1.218342    1.301314
------------------------------------------------------------------------------
```

Specification 4b: Women only

```
. reg Vunorm regiona-regiono endofmo endofyr weekend income inc2 college
lesshs
>  hsown hsval prof exec blue tech pctas pctbl pcthis female age25 age34 age45
> age55 age65 trage03 trage47 trage810 if female==1 & anytr==1

      Source |       SS       df       MS              Number of obs =   94995
-------------+------------------------------           F( 40, 94954) =  144.00
       Model |  6.81728859    40  .170432215           Prob > F      =  0.0000
    Residual |   112.38064 94954  .001183527           R-squared     =  0.0572
-------------+------------------------------           Adj R-squared =  0.0568
       Total |  119.197929 94994  .001254794           Root MSE      =   .0344

------------------------------------------------------------------------------
      Vunorm |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
                 - - region effects - -
     endofmo |   .0004697   .0002782     1.69   0.091    -.0000756     .001015
     endofyr |   .0020517   .0008743     2.35   0.019      .000338    .0037654
     weekend |  -.0001385   .0002738    -0.51   0.613    -.0006751     .000398
      income |   1.74e-07   2.59e-08     6.74   0.000     1.24e-07    2.25e-07
        inc2 |  -1.01e-12   1.58e-13    -6.37   0.000    -1.32e-12   -6.97e-13
     college |   .0000352   .0000171     2.06   0.039     1.71e-06    .0000687
      lesshs |  -7.72e-07   .0000213    -0.04   0.971    -.0000426    .0000411
       hsown |   .0000138   7.63e-06     1.81   0.070    -1.13e-06    .0000288
       hsval |   3.08e-08   2.57e-09    11.99   0.000     2.58e-08    3.59e-08
        prof |  -4.95e-06   .0000254    -0.19   0.845    -.0000547    .0000448
        exec |     .00003   .0000264     1.13   0.257    -.0000218    .0000818
        blue |  -.0000591   .0000169    -3.50   0.000    -.0000922    -.000026
        tech |  -.0001193   .0000599    -1.99   0.046    -.0002366   -1.94e-06
     pctasia |  -.0000164     .00002    -0.82   0.412    -.0000557    .0000229
      pctblk |  -.0001688   7.85e-06   -21.51   0.000    -.0001842   -.0001535
     pcthisp |  -.0000695   .0000175    -3.97   0.000    -.0001038   -.0000352
      female |  (dropped)
       age25 |  -.0089144   .0005207   -17.12   0.000    -.0099349   -.0078938
       age34 |  -.0055992   .0004596   -12.18   0.000       -.0065   -.0046985
       age45 |  -.0045298   .0004418   -10.25   0.000    -.0053956   -.0036639
       age55 |  -.0026931   .0004598    -5.86   0.000    -.0035944   -.0017919
       age65 |   -.001217   .0005176    -2.35   0.019    -.0022314   -.0002026
     trage03 |   .0014391   .0003787     3.80   0.000     .0006968    .0021814
     trage47 |  -.0009545   .0003603    -2.65   0.008    -.0016608   -.0002482
    trage810 |  -.0015842   .0004154    -3.81   0.000    -.0023984     -.00077
       _cons |   .2092234   .0022438    93.25   0.000     .2048256    .2136213
------------------------------------------------------------------------------
```

Specification 5a: Vans only

```
. reg traderat regiona-regiono endofmo endofyr weekend income inc2 college
less
> hs hsown hsval prof exec blue tech pctas pctbl pcthis female age25 age34
age4
> 5 age55 age65 trage03 trage47 trage810 firstcar if van==1 & anytr==1

      Source |       SS       df       MS              Number of obs =   23624
-------------+------------------------------           F( 42, 23581) =   39.68
       Model |  160.626866    42  3.82444919           Prob > F      =  0.0000
    Residual |  2272.76881 23581  .096381358           R-squared     =  0.0660
-------------+------------------------------           Adj R-squared =  0.0643
       Total |  2433.39567 23623  .103009596           Root MSE      =  .31045

------------------------------------------------------------------------------
    traderat |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
                  - - region effects - -
     endofmo |   .0037099   .0049978     0.74   0.458    -.0060862    .0135059
     endofyr |  -.0057004   .0151447    -0.38   0.707    -.0353849    .0239841
     weekend |   .0079262   .0048777     1.62   0.104    -.0016344    .0174868
      income |  -2.10e-06   4.77e-07    -4.40   0.000    -3.04e-06   -1.16e-06
        inc2 |   1.12e-11   2.92e-12     3.83   0.000     5.48e-12    1.69e-11
     college |  -.0002833   .0003168    -0.89   0.371    -.0009043    .0003377
      lesshs |  -.0000846   .0003985    -0.21   0.832    -.0008657    .0006966
       hsown |  -2.12e-06   .0001532    -0.01   0.989    -.0003023    .0002981
       hsval |  -2.15e-07   5.11e-08    -4.22   0.000    -3.16e-07   -1.15e-07
        prof |   .0006922   .0004709     1.47   0.142    -.0002308    .0016152
        exec |  -.0005032   .0004864    -1.03   0.301    -.0014567    .0004503
        blue |   .0011896   .0003138     3.79   0.000     .0005745    .0018046
        tech |  -.0003624   .0011153    -0.32   0.745    -.0025485    .0018237
     pctasia |   .0008198    .000357     2.30   0.022       .00012    .0015195
      pctblk |   .0008217   .0001868     4.40   0.000     .0004555    .0011879
     pcthisp |   .0007311   .0003327     2.20   0.028      .000079    .0013832
      female |   .0010632   .0044634     0.24   0.812    -.0076854    .0098118
       age25 |   .1050987   .0269796     3.90   0.000      .052217    .1579805
       age34 |   .0871427   .0093902     9.28   0.000     .0687373    .1055481
       age45 |   .0398467   .0075843     5.25   0.000      .024981    .0547123
       age55 |   .0310991   .0080529     3.86   0.000      .015315    .0468833
       age65 |   .0227407   .0091254     2.49   0.013     .0048543     .040627
     trage03 |  -.1041091   .0092591   -11.24   0.000    -.1222574   -.0859607
     trage47 |  -.0420865   .0088399    -4.76   0.000    -.0594134   -.0247597
    trage810 |  -.0005706   .0096159    -0.06   0.953    -.0194183    .0182771
    firstcar |   .0114009   .0166887     0.68   0.495      -.02131    .0441118
       _cons |   1.420554   .0431968    32.89   0.000     1.335886    1.505223
------------------------------------------------------------------------------
```

Specification 5b: Vans only

```
. reg Vunorm regiona-regiono endofmo endofyr weekend income inc2 college
lesshs
>  hsown hsval prof exec blue tech pctas pctbl pcthis female age25 age34 age45
> age55 age65 trage03 trage47 trage810 if van==1 & anytr==1

      Source |       SS       df       MS              Number of obs =   23624
-------------+------------------------------           F( 41, 23582) =   39.65
       Model |  1.85270242    41  .045187864           Prob > F      =  0.0000
    Residual |  26.8737619 23582  .001139588           R-squared     =  0.0645
-------------+------------------------------           Adj R-squared =  0.0629
       Total |  28.7264644 23623  .001216038           Root MSE      =  .03376

------------------------------------------------------------------------------
      Vunorm |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
                  - - region effects - -
     endofmo |  -.0000998   .0005434    -0.18   0.854    -.0011649    .0009654
     endofyr |   .0032795   .0016468     1.99   0.046     .0000517    .0065073
     weekend |  -.0007539   .0005304    -1.42   0.155    -.0017935    .0002857
      income |   2.39e-07   5.19e-08     4.60   0.000     1.37e-07    3.41e-07
        inc2 |  -1.36e-12   3.18e-13    -4.27   0.000    -1.98e-12   -7.35e-13
     college |   9.96e-06   .0000345     0.29   0.772    -.0000576    .0000775
      lesshs |  -.0000538   .0000433    -1.24   0.214    -.0001387    .0000311
       hsown |   5.74e-06   .0000167     0.34   0.730    -.0000269    .0000384
       hsval |   2.55e-08   5.55e-09     4.60   0.000     1.46e-08    3.64e-08
        prof |  -.0000749   .0000512    -1.46   0.143    -.0001753    .0000254
        exec |    .000053   .0000529     1.00   0.316    -.0000507    .0001567
        blue |  -.0001224   .0000341    -3.59   0.000    -.0001893   -.0000555
        tech |   .0000128   .0001213     0.11   0.916    -.0002249    .0002506
     pctasia |  -.0000919   .0000388    -2.37   0.018     -.000168   -.0000158
      pctblk |  -.0001117   .0000203    -5.50   0.000    -.0001516   -.0000719
     pcthisp |   -.000111   .0000362    -3.07   0.002    -.0001819     -.00004
      female |  -.0004407   .0004853    -0.91   0.364    -.0013919    .0005106
       age25 |   -.012179   .0023306    -5.23   0.000    -.0167471   -.0076109
       age34 |  -.0093954   .0009799    -9.59   0.000    -.0113161   -.0074747
       age45 |  -.0045203   .0008247    -5.48   0.000    -.0061367   -.0029039
       age55 |  -.0036457   .0008756    -4.16   0.000    -.0053619   -.0019296
       age65 |  -.0032819   .0009922    -3.31   0.001    -.0052268   -.0013371
     trage03 |   .0057584   .0009886     5.82   0.000     .0038206    .0076961
     trage47 |   .0012744   .0009446     1.35   0.177    -.0005772    .0031259
    trage810 |  -.0001042   .0010455    -0.10   0.921    -.0021534     .001945
       _cons |   .1896626   .0046951    40.40   0.000     .1804599    .1988653
------------------------------------------------------------------------------
```

Specification 6a: Fun/Sporty cars only

```
. reg traderat regiona-regiono endofmo endofyr weekend income inc2 college
less
> hs hsown hsval prof exec blue tech pctas pctbl pcthis female age25 age34
age4
> 5 age55 age65 trage03 trage47 trage810 firstcar if fun==1 & anytr==1

      Source |       SS       df       MS              Number of obs =   43314
-------------+------------------------------           F( 42, 43271) =   59.35
       Model |  177.112177    42   4.2169566           Prob > F      =  0.0000
    Residual |  3074.66487 43271  .071056016           R-squared     =  0.0545
-------------+------------------------------           Adj R-squared =  0.0535
       Total |  3251.77705 43313  .075076237           Root MSE      =  .26656

------------------------------------------------------------------------------
    traderat |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
                  - - region effects - -
     endofmo |  -.0042665   .0032405    -1.32   0.188     -.010618     .002085
     endofyr |   .0035709   .0098212     0.36   0.716    -.0156788    .0228207
     weekend |   .0047169   .0031787     1.48   0.138    -.0015134    .0109472
      income |  -8.76e-07   3.13e-07    -2.80   0.005    -1.49e-06   -2.62e-07
        inc2 |   5.11e-12   2.06e-12     2.48   0.013     1.07e-12    9.14e-12
     college |  -.0000681   .0002015    -0.34   0.735     -.000463    .0003268
      lesshs |  -.0000918   .0002368    -0.39   0.698    -.0005558    .0003722
       hsown |  -.0001423   .0000902    -1.58   0.115    -.0003191    .0000344
       hsval |  -1.82e-07   3.09e-08    -5.90   0.000    -2.43e-07   -1.22e-07
        prof |   -.000195   .0003047    -0.64   0.522    -.0007921    .0004022
        exec |  -.0001323   .0003117    -0.42   0.671    -.0007433    .0004786
        blue |   .0003225   .0001912     1.69   0.092    -.0000522    .0006972
        tech |    .000753   .0006992     1.08   0.282    -.0006174    .0021234
     pctasia |  -.0001764    .000238    -0.74   0.459    -.0006428    .0002901
      pctblk |   .0006914   .0001167     5.92   0.000     .0004626    .0009203
     pcthisp |   .0004564    .000199     2.29   0.022     .0000663    .0008465
      female |   .0152491   .0028581     5.34   0.000     .0096472     .020851
       age25 |   .0803855   .0104463     7.70   0.000     .0599107    .1008604
       age34 |   .0513053    .007055     7.27   0.000     .0374773    .0651333
       age45 |   .0277548   .0068211     4.07   0.000     .0143853    .0411243
       age55 |   .0133602   .0069798     1.91   0.056    -.0003204    .0270407
       age65 |  -.0046989   .0075767    -0.62   0.535    -.0195494    .0101517
     trage03 |  -.1024735   .0049928   -20.52   0.000    -.1122594   -.0926876
     trage47 |   -.060174   .0050304   -11.96   0.000    -.0700338   -.0503143
    trage810 |  -.0168918   .0055898    -3.02   0.003    -.0278479   -.0059357
    firstcar |    .001754   .0072195     0.24   0.808    -.0123964    .0159044
       _cons |   1.230569   .0228949    53.75   0.000     1.185695    1.275444
------------------------------------------------------------------------------
```

Specification 6b: Fun/sporty only

```
. reg Vunorm regiona-regiono endofmo endofyr weekend income inc2 college
lesshs
>  hsown hsval prof exec blue tech pctas pctbl pcthis female age25 age34 age45
> age55 age65 trage03 trage47 trage810 if fun==1 & anytr==1

      Source |       SS       df       MS              Number of obs =   43314
-------------+------------------------------           F( 41, 43272) =   58.46
       Model |  2.18191168    41  .053217358           Prob > F      =  0.0000
    Residual |  39.3927657 43272  .000910352           R-squared     =  0.0525
-------------+------------------------------           Adj R-squared =  0.0516
       Total |  41.5746774 43313  .000959866           Root MSE      =  .03017

------------------------------------------------------------------------------
      Vunorm |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
                 - - region effects - -
     endofmo |   .0008416   .0003668     2.29   0.022     .0001227    .0015605
     endofyr |    .000498   .0011117     0.45   0.654    -.0016809    .0026768
     weekend |  -.0006207   .0003598    -1.73   0.085    -.0013259    .0000845
      income |   1.25e-07   3.54e-08     3.54   0.000     5.60e-08    1.95e-07
        inc2 |  -7.93e-13   2.33e-13    -3.40   0.001    -1.25e-12   -3.36e-13
     college |   8.78e-06   .0000228     0.39   0.700    -.0000359    .0000535
      lesshs |   .0000314   .0000268     1.17   0.241    -.0000211    .0000839
       hsown |   .0000204   .0000102     2.00   0.046     3.96e-07    .0000404
       hsval |   2.76e-08   3.50e-09     7.89   0.000     2.07e-08    3.44e-08
        prof |   .0000142   .0000345     0.41   0.681    -.0000534    .0000818
        exec |  -.0000158   .0000353    -0.45   0.655    -.0000849    .0000534
        blue |  -.0000512   .0000216    -2.37   0.018    -.0000937   -8.83e-06
        tech |  -.0000585   .0000791    -0.74   0.460    -.0002137    .0000966
     pctasia |   .0000443   .0000269     1.65   0.100    -8.46e-06    .0000971
      pctblk |  -.0000967   .0000132    -7.32   0.000    -.0001226   -.0000708
     pcthisp |  -.0000823   .0000225    -3.65   0.000    -.0001265   -.0000382
      female |  -.0018785   .0003235    -5.81   0.000    -.0025126   -.0012444
       age25 |  -.0084244   .0008442    -9.98   0.000     -.010079   -.0067698
       age34 |  -.0046546   .0007791    -5.97   0.000    -.0061817   -.0031275
       age45 |  -.0025578    .000772    -3.31   0.001    -.0040709   -.0010447
       age55 |  -.0013799   .0007899    -1.75   0.081    -.0029282    .0001684
       age65 |   .0007019   .0008576     0.82   0.413     -.000979    .0023827
     trage03 |   .0060569   .0005452    11.11   0.000     .0049884    .0071255
     trage47 |   .0026234   .0005475     4.79   0.000     .0015502    .0036967
    trage810 |   .0003399   .0006291     0.54   0.589    -.0008931    .0015729
       _cons |   .2149807   .0025898    83.01   0.000     .2099047    .2200568
------------------------------------------------------------------------------
```

Specification 7a: Subsegment types

```
. reg traderat regiona-regiono endofmo endofyr weekend income inc2 college
less
> hs hsown hsval prof exec blue tech pctas pctbl pcthis female age25 age34
age4
> 5 age55 age65 trage03 trage47 trage810 firstcar fun lux if anytr==1

      Source |       SS       df       MS              Number of obs =  266821
-------------+------------------------------           F( 44,266776) =  360.63
       Model |  1513.14375    44  34.3896306           Prob > F      =  0.0000
    Residual |  25439.4372266776  .095358793           R-squared     =  0.0561
-------------+------------------------------           Adj R-squared =  0.0560
       Total |   26952.581266820  .101014096           Root MSE      =   .3088

------------------------------------------------------------------------------
    traderat |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
                 - - region effects - -
     endofmo |  -.0011069   .0014925    -0.74   0.458     -.0040321    .0018183
     endofyr |  -.0056473   .0046289    -1.22   0.222     -.0147199    .0034252
     weekend |   .0024168    .001471     1.64   0.100     -.0004662    .0052999
      income |  -1.24e-06   1.37e-07    -9.08   0.000     -1.51e-06   -9.76e-07
        inc2 |   6.67e-12   8.32e-13     8.02   0.000      5.04e-12    8.30e-12
     college |  -.0004158   .0000917    -4.54   0.000     -.0005955   -.0002362
      lesshs |   -.000118   .0001147    -1.03   0.303     -.0003427    .0001067
       hsown |  -.0001444   .0000418    -3.46   0.001     -.0002263   -.0000625
       hsval |  -2.27e-07   1.39e-08   -16.40   0.000     -2.54e-07   -2.00e-07
        prof |  -8.23e-06   .0001359    -0.06   0.952     -.0002745    .0002581
        exec |  -.0004932   .0001413    -3.49   0.000     -.0007702   -.0002162
        blue |   .0005695   .0000903     6.30   0.000      .0003924    .0007465
        tech |   .0006902   .0003236     2.13   0.033       .000056    .0013243
     pctasia |   .0000237   .0001068     0.22   0.825     -.0001857     .000233
      pctblk |   .0010851   .0000483    22.48   0.000      .0009905    .0011797
     pcthisp |    .000626   .0000942     6.64   0.000      .0004413    .0008107
      female |   .0084306   .0012662     6.66   0.000      .0059488    .0109123
       age25 |   .1166729   .0046215    25.25   0.000      .1076148    .1257309
       age34 |   .0697605   .0024676    28.27   0.000      .0649241    .0745968
       age45 |   .0432503   .0022122    19.55   0.000      .0389146    .0475861
       age55 |     .02852   .0023097    12.35   0.000       .023993     .033047
       age65 |   .0144973   .0025668     5.65   0.000      .0094665    .0195281
     trage03 |  -.0662673   .0020483   -32.35   0.000     -.0702819   -.0622528
     trage47 |  -.0267177   .0019732   -13.54   0.000     -.0305851   -.0228503
    trage810 |   .0109763   .0022814     4.81   0.000      .0065047    .0154478
    firstcar |  -.0158401    .003601    -4.40   0.000      -.022898   -.0087821
         fun |   -.038287   .0016999   -22.52   0.000     -.0416188   -.0349552
         lux |   .0118247    .001515     7.81   0.000      .0088554     .014794
       _cons |   1.242532   .0112243   110.70   0.000      1.220533    1.264532
------------------------------------------------------------------------------
```

Specification 7b: Subsegment types

```
. reg Vunorm regiona-regiono endofmo endofyr weekend income inc2 college
lesshs
>  hsown hsval prof exec blue tech pctas pctbl pcthis female age25 age34 age45
> age55 age65 trage03 trage47 trage810 firstcar fun lux if anytr==1

      Source |       SS       df       MS              Number of obs =  266821
-------------+------------------------------           F( 44,266776) =  372.76
       Model |  18.3377957    44  .416768083           Prob > F      =  0.0000
    Residual |  298.274729266776  .001118072           R-squared     =  0.0579
-------------+------------------------------           Adj R-squared =  0.0578
       Total |  316.612525266820  .001186615           Root MSE      =  .03344

------------------------------------------------------------------------------
      Vunorm |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
                 - - region effects - -
     endofmo |   .0004025   .0001616     2.49   0.013     .0000858    .0007193
     endofyr |   .0025247   .0005012     5.04   0.000     .0015423    .0035071
     weekend |  -.0002338   .0001593    -1.47   0.142     -.000546    .0000784
      income |   1.55e-07   1.48e-08    10.41   0.000     1.25e-07    1.84e-07
        inc2 |  -8.96e-13   9.01e-14    -9.95   0.000    -1.07e-12   -7.19e-13
     college |   .0000405   9.93e-06     4.08   0.000      .000021      .00006
      lesshs |  -.0000116   .0000124    -0.94   0.349     -.000036    .0000127
       hsown |   .0000181   4.52e-06     4.01   0.000     9.26e-06     .000027
       hsval |   3.01e-08   1.50e-09    20.03   0.000     2.71e-08    3.30e-08
        prof |  -4.81e-07   .0000147    -0.03   0.974    -.0000293    .0000284
        exec |   .0000429   .0000153     2.80   0.005     .0000129    .0000729
        blue |  -.0000507   9.78e-06    -5.18   0.000    -.0000698   -.0000315
        tech |  -.0000594    .000035    -1.70   0.090    -.0001281    9.26e-06
     pctasia |  -3.44e-06   .0000116    -0.30   0.766    -.0000261    .0000192
      pctblk |  -.0001379   5.23e-06   -26.38   0.000    -.0001481   -.0001276
     pcthisp |  -.0000826   .0000102    -8.09   0.000    -.0001026   -.0000626
      female |  -.0014232   .0001371   -10.38   0.000    -.0016919   -.0011545
       age25 |  -.0136121   .0005004   -27.20   0.000    -.0145929   -.0126313
       age34 |  -.0075402   .0002672   -28.22   0.000    -.0080639   -.0070165
       age45 |  -.0048289   .0002395   -20.16   0.000    -.0052984   -.0043595
       age55 |  -.0036429   .0002501   -14.57   0.000    -.0041331   -.0031528
       age65 |  -.0020551   .0002779    -7.39   0.000    -.0025999   -.0015104
     trage03 |   .0028284   .0002218    12.75   0.000     .0023937    .0032631
     trage47 |   .0002528   .0002137     1.18   0.237    -.0001659    .0006716
    trage810 |  -.0015261    .000247    -6.18   0.000    -.0020103   -.0010419
    firstcar |   .0028686   .0003899     7.36   0.000     .0021044    .0036329
         fun |   .0036505   .0001841    19.83   0.000     .0032897    .0040112
         lux |  -.0007471    .000164    -4.55   0.000    -.0010686   -.0004256
       _cons |   .2123753   .0012154   174.74   0.000     .2099932    .2147575
------------------------------------------------------------------------------
```

Summary Statistics

```
. sum traderat endofmo endofyr weekend income inc2 college lesshs hsown hsval
p
> rof exec blue tech pctas pctbl pcthis female age25 age34 age45 age55 age65
tr
> age03 trage47 trage810 firstcar

    Variable |       Obs        Mean    Std. Dev.       Min        Max
-------------+-----------------------------------------------------------
    traderat |    281784    1.156226    .3311844          0   2.691143
    Vunorm        266821      .213756     .034447     .0807        .3691

     endofmo |    744571    .2243601    .4171605          0          1
     endofyr |    744571     .018972    .1364261          0          1
     weekend |    744571    .2276653    .4193257          0          1
      income |    744571    56820.99    24980.24      10403     150000
-------------+-----------------------------------------------------------
        inc2 |    744571    3.85e    3.59e   1.08e   2.25e
     college |    744571    31.17249    17.76198          0        100
      lesshs |    744571      12.334    10.44367          0        100
       hsown |    744571    73.09979    22.38617   .1372119        100
       hsval |    744571    164587.8    99670.01       7500     500000
-------------+-----------------------------------------------------------
        prof |    744571    16.51362    8.451952          0        100
        exec |    744571    17.48105    8.061972          0        100
        blue |    744571    26.06533    14.92308          0        100
        tech |    744571    2.987941    1.971384          0        100
     pctasia |    744571    4.875911    7.869873          0        100
-------------+-----------------------------------------------------------
      pctblk |    744571    5.905225    14.42766          0        100
     pcthisp |    744571    8.119791    10.19073          0   55.32995
      female |    744571    .3583083    .4795037          0          1
       age25 |    744571    .0865331    .2811498          0          1
       age34 |    744571     .197683     .398252          0          1
-------------+-----------------------------------------------------------
       age45 |    744571    .2933904    .4553161          0          1
       age55 |    744571    .2255258    .4179284          0          1
       age65 |    744571    .1126595    .3161763          0          1
     trage03 |    744571    .1137151    .3174652          0          1
     trage47 |    744571    .1558334    .3626975          0          1
-------------+-----------------------------------------------------------
    trage810 |    744571    .0685697    .2527211          0          1
    firstcar |    744571    .0665618    .2492618          0          1
```