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Modeling consumer choices between domestic and foreign automobiles

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MODELING CONSUMER CHOICES BETWEEN DOMESTIC

AND FOREIGN AUTOMOBILES

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ABSTRACT

Modeling Consumer Choices Between Foreign and Domestic Automobiles

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This paper analyzes survey data to determine the factors that impact the probability of purchasing a domestic versus foreign brand of automobile. It includes dynamic variables reflecting purchase history and thus the effect past choices may have on current behavior. Some of these factors are shown to be statistically significant. The paper also looks at key subpopulations. We see that preferences in the luxury segment are far better explained by economic, demographic, and dynamic variables than are preferences in the non-luxury market. The paper also looks at switching behavior—domestic owners who switch to foreign brands. The key finding is that loyalty to domestic brands is more a product of economic variables such as price and income, and of car attributes such as size, than it is a product of habit persistence or structural state dependence.

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CHAPTER 1

INTRODUCTION

In the five years between 1998 and 2003, while the number of vehicles sold in the U.S. increased 8% overall, the sales of American nameplate automobiles actually declined 5%. The U.S. unit market share of American brands of new cars and light trucks fell from 70% to 60%. Foreign brands sold almost 40% more cars here by 2003 than they had in 1998. (U.S. Commerce Dept. 2003)

In 2002, U.S. GDP for new cars and light trucks was over $10 Trillion. Annual employment by the industry, though declining, is still over 330,000 people. The competitiveness of American automotive brands is of concern not only to the companies directly involved, but also to their employees, suppliers, and shareholders. And to regain competitiveness, American companies will need to stem the tide pulling their consumers towards foreign brands.

The first step is to identify the factors that lead consumers to choose foreign rather than domestic brands of automobiles. It is also interesting to look specifically at consumers switching from domestic to foreign automobiles, and determine the factors that erode the retention of existing domestic buyers. Finally, it is important to look by segment and to test whether there are significant differences in consumer preferences by car class, in the luxury versus the non-luxury segments. With this kind of information, marketing and product development resources could be more effectively utilized to retain existing customers and also perhaps to attract new ones.

This paper analyzes survey data to determine the factors that impact the probability of choosing a foreign brand of automobile rather than a domestic brand. It looks at the problem in the aggregate, then examines switching behavior, and tests for differences in the luxury versus non-luxury segments. Three kinds of factors or explanatory variables are included in the study; they are 1) the characteristics of the consumers, 2) the attributes of the chosen vehicles themselves, and 3) purchase history variables. Characteristics include demographic factors such as age and place of residence. The attributes of the automobiles include the price, the size, and the power-to-weight ratio. One purchase history variable reflects whether the consumer has been loyal to domestic brands in the past. Another indicates whether the consumer, in his or her previous purchase, bought a luxury or non-luxury automobile.

Previously published models of automobile demand have generally not included dynamic variables. These studies have found various demographic factors such as age and income to be significant in consumer choices in this segment. This paper does include dynamic variables, as mentioned above, and mostly finds the demographic variables (except for income) to be insignificant at the 90% confidence level. It is also unique in that it also examines switching behavior from domestic to foreign brands. Other studies of automobile demand have focused only on general models of choice.

The primary finding of this paper relates to the issue of loyalty to domestic brands. Conventional wisdom suggests that there is a segment of consumers with demonstrated loyalty to domestic brands who are less likely to switch to foreign competition. This study suggests that this is not the case. What has been attributed to loyalty or habit persistence is actually the product of economic factors such as price and income, and of consumer preferences for particular attributes such as size.

The switching analysis shows, not surprisingly, that consumers are more likely to switch from domestic to foreign brands today than they were in the past. They are also more likely to switch if they are moving up into the luxury automobile sector from a previous non-luxury purchase. There is some evidence to suggest that gas prices were a factor in switching in the 1970s, but the analysis also shows they have not been a factor since the 1980s. The results from switching models and the aggregate, general models are for the most part similar. The factors that impact preferences for foreign versus domestic brands are price, income, car attributes, and purchase history—also all key factors in the switching sub-sample.

The final part of the study indicates that preferences in the luxury segment are different than in the non-luxury segment. Preferences in the luxury market can be to a great extent predicted given the explanatory variables in this study, whereas the factors that influence the decision to purchase foreign versus domestic in the non-luxury segment are not at all clear.

CHAPTER 2

LITERATURE REVIEW

This paper uses probit models to estimate both the general probability of choosing a domestic versus a foreign brand as well as the probability of switching from a domestic to a foreign brand of automobile. It draws on theories of product differentiation from microeconomics and industrial organization, and also on qualitative choice models from statistics and econometrics. It reflects work that has been done in the past on modeling automotive demand, yet deviates from that body of work both in that it includes explanatory variables reflecting purchase history, and in that it focuses on switching behavior as well as simple purchase behavior. The following literature review provides some background on these different areas of research.

Product Differentiation

In *Discrete Choice Theory of Product Differentiation* (hereafter referred to as *DCTPD*), Anderson, de Palma, and Thisse write "A general class of product is differentiated if any significant basis exists for distinguishing the goods (or services) of one seller from those of another. Such a basis may be real or fancied." (Anderson, de Palma, and Thisse 1992, 3-4) The premium the consumer pays for the choice best suited to his or her own tastes is the source of market power for the firm. Most products are differentiated to some extent, and automobiles are clearly so. For the purposes of this study, the key differentiating factor of interest is the nationality of the brand although size and power are also included in the analysis.

In general, there are two basic approaches to analyzing differentiation. Standard microeconomic consumer theory postulates that consumers have preferences about the commodities themselves. An alternative approach, sometimes called a hedonic approach, postulates that consumers have preferences about the attributes or characteristics of the commodities. (Carlton and Perloff 2000, 197) Because of the focus here on a particular characteristic—the nationality of the brand—this paper has an inherently hedonic approach.

This approach often leads to the use of a spatial model of product differentiation. In this kind of model, any product can be represented by a set of axes showing the amount of each characteristic or attribute. This set of axes makes up what is called the 'characteristic space' of the product. Each brand within the product group can be located in this space according to its characteristics. (Carlton and Perloff 2000, 197) By extension, brands are closer together if they are close substitutes. Consumers also have a location in the characteristic space based on their preferences and tastes, and chose the brands that are closest to them. (Carlton and Perloff 2000, 215)

The problem is that firms cannot directly observe consumers' tastes. Spatial models are therefore not very useful in estimating aggregate market demand or individual choice probabilities. As *DCTPD* explains,

> "In practice, idiosyncratic taste parameters are unobservable. If firms know the distribution from which these taste parameters are drawn, they can forecast demand using a discrete choice model of consumer behavior. Discrete choice models start from the assumption that each consumer chooses the single option (here a variant of a differentiated product) that yields the greatest utility, while from the viewpoint of the outside observer (here firms), utility is described as a random variable reflecting unobservable taste differences... This implies that firms attribute purchase probabilities to consumers, and these probabilities depend on observable characteristics (e.g. price, location, quality) as well as on the properties of the taste distribution." (Anderson, de Palma, and Thisse 1992, 3-4)

Demographic information from the dataset defines the properties of the sample 'taste distribution'. The observable characteristics, the cars' size and nationality for example, can then be used to calculate purchase probabilities. In fact, although the consumer may be maximizing a deterministic utility function to make his or her choice, "the best that firms can do is to represent consumer decision rules by constructing choice probabilities." (Anderson, de Palma, and Thisse 1992, 4, 31-32)

As mentioned above, discrete choice models are used to construct these choice probabilities. The next step is to identify these models, and compare them to standard statistical models such as OLS or the linear probability model.

Qualitative or Discrete Choice Models Such as Probit

Standard econometric models such as OLS work with continuous dependent variables, for example wages, aggregate consumption levels, or gasoline prices. Qualitative choice situations, on the other hand are defined as those in which "a decision maker faces a choice among a set of alternatives meeting the following criteria: the number of alternatives in the set is finite, the alternatives are mutually exclusive, and the set of alternatives is exhaustive." (Train 1986, 4) As long as the first criterion holds, however, "it is usually possible to define the set alternatives in such a way that the defined set meets all three criteria... The only true restrictive criterion is the first one, namely, that the number of alternatives be finite. A distinction established by this criterion is that between continuous and discrete variables." (Train 1986, 5)The terms qualitative choice and discrete choice can therefore be used interchangeably.

In the general analyses in this paper (the aggregate as well as the luxury versus non-luxury models) the dependent variable reflects a binary qualitative choice, 0 if the purchase is domestic and 1 if the purchase is foreign. In the switching analyses, 0 indicates that the consumer again purchases a domestic vehicle whereas 1 indicates a switch to a foreign brand. In both cases, all of the criteria listed above are met.

A linear probability model can be used to address issues of binary choice, but has two key limitations. The first problem is heteroscedasticity. The second problem is that the estimated choice probabilities are not constrained to the 0 to 1 interval, generating nonsense probabilities and negative variances. (Greene 2003, 665-666) We therefore use nonlinear qualitative choice models such as logit or probit.

"All qualitative choice models are obtained by specifying some distribution for the unknown component of utility and deriving functions for the choice probabilities." (Train 1986, 12) If we assume the errors are distributed normally, the specified model is a probit. The probit equation expresses the probability that a particular choice (for example a switch to a foreign brand) is or is not chosen. It is estimated using maximum likelihood.

The probit model is often preferred over the logit, which assumes the errors are distributed as a logistic. Unlike logits, "probit models...can handle random taste variation, allow any pattern of substitution, and are applicable to panel data with temporarily correlated errors. The only limitation of probit models is that they require normal distributions for all unobserved components of utility. In many, perhaps most, situations, normal distributions provide an adequate representation of the random components." (Train 1986, 111) To summarize, "the flexibility of the probit model in handling correlations over alternatives and time is its main advantage." (Train 1986, 23) That flexibility is why probit has been chosen here.

Previous Research on Automobile Demand

Kenneth Train's book, Qualitative Choice Analysis: Theory, Econometrics, and an Application to Automobile Demand, contains a comprehensive review of research in modeling automobile demand. Train covers both disaggregate models focusing on households' behavior and preferences and aggregate models which estimate the total number of purchases in a particular market. In the sub-sample of disaggregate models, he differentiates between compensatory and noncompensatory approaches. Compensatory models assume that the high value of one product characteristic can compensate for the low value of another characteristic. (Train 1986, 113-115) Noncompensatory models, on the other hand, assume that the consumer has some minimum acceptable level for each characteristic; the characteristics are also ranked by importance. Finally, Train differentiates between analyses using real choice data versus data generated in hypothetical choice situations. (Train 1986, 126)

The data used in this paper reflects real choice situations or actual purchases. It includes variables that measure car characteristics such as size and power. The probit models applied generate probabilities for individual consumers. Train would therefore identify these models as disaggregate compensatory real choice models.

Overall, Train mentions the following variables as being potentially important in models of automobile choice: income, the age of the driver, the number of people in the household, the number of autos owned, and the price, operating cost, and size of the vehicle itself. Note that none of the projects he discusses use any explanatory variables reflecting purchase history.

The Importance of Purchase History

Including purchase history transforms models from static models to dynamic models of consumer choice. There is both theoretical and empirical evidence, at least with respect to other products, that shows that previous choices made may have a significant impact on current choices. Unfortunately, I have not been able to find dynamic models of automobile demand in the literature. This primarily reflects the difficulty of gathering data.

Consumer theory identifies variety-seeking or habit formation, state dependence, and heterogeneity as time-related factors that can impact individual's choices. "Individuals may want to consume different products on different occasions, expressing a preference for variety over time." (Anderson, de Palma, and Thisse 1992, 2) This variety-seeking behavior has a converse—habit formation; in some situations individuals seek to avoid change instead of looking for variety. A related factor is structural state dependence, or purchase feedback, which represents the "influence of observed past experience (through actual purchases) with a brand, on current choice probabilities." (Roy, Chintagunta, and Haldar 1996, 281) Finally, "individuals may also have idiosyncratic tastes about their most preferred variants," (Anderson, de Palma, and Thisse 1992, 2) in other words show unobserved heterogeneity. As explained in Roy, Chintagunta, & Haldar, each of these aspects of purchase behavior could potentially link the purchase of a brand at one point in time to its purchase (or lack thereof) on the next occasion. (Roy, Chintagunta, and Haldar 1996, 281)

Often, dynamic models of consumer choice rely on supermarket scanner data. Rossi, McCulloch, and Allenby suggest that it is the combination of purchase history and demographic information that makes these datasets interesting and useful. (Rossi, McCulloch, and Allenbv 1996, 339) Chintagunta, Erdem, Rossi, and Keane, among others, have published articles presenting dynamic analyses using panel data. Importantly, these articles demonstrate that estimated parameters become biased when dynamic effects are disregarded.

Unfortunately, the theoretical and computational difficulties of most of the dynamic models are daunting. I do not, in this paper, attempt to measure state dependence, heterogeneity, or habit formation. In a previous paper entitled "Modeling Brand Choice in the Luxury Autos Product Group" using the same dataset, I was able to determine that purchase history is a significant factor in consumer choice in this sector. If there is no connection between past and current purchases, we say that consumer choice behavior is 'zero order'. Using simple dummy variables for past purchases and looking at the significance of those coefficients, I was able to reject the null hypothesis that consumer choices in automobiles are zero order. I did not determine the specific cause of the dynamic link (for example state dependence versus habit formation), only determined that history is in fact important. There is therefore both significant theoretical and some empirical work that suggests that history will be important in this analysis as well.

Modeling Switching Behavior

So far all of the work that has been mentioned in this literature review encompasses models of choice, specifically of consumers' choices about whether to purchase or not purchase a particular product. For automobile marketers trying to stop defections from domestic brands to foreign brands of automobiles, the answer to a more specific question may be more useful. It may be important to identify the factors that cause consumers to switch.

Many of the practical elements of the analysis remain the same. Again, we have a discrete model of qualitative choice. The probit remains the most appropriate form to apply. However, just as I have not been able to find any published dynamic models of automobile choice, I have found no switching models of automobile demand. I would expect many of the same factors to be significant here as was the case in aggregate models of consumer choice in this product group. Purchase history should also still be important. I have not, however, been able to find any theoretical discussion or outside analysis confirming that this is in fact the case.

It is important here to differentiate between the approach in this paper and what are sometimes called 'switching regression models'. Switching regression models are systems of equations used when there are binary explanatory variables and concerns about self-selection bias. (Woolrdige 2002, 603-612) They are too advanced an application in this context, and this paper does not attempt such an analysis. By 'switching model', I mean a simple, single-equation probit model where the dependent variable represents the probability of switching from one product to another.

There is at least one example of such an analysis in the insurance industry. In "Consumer Information and Decisions to Switch Insurers", Schlesinger and von der Schulenburg examine the interaction of various factors such as insurer quality attributes, price, search costs, and switching costs in an individual's decision to switch insurers. (Schlesinger and von der Schulenburg 1993, 591) They run probit models to examine how such factors affect the probability of a consumer's changing insurers. They also compare results from sub-samples of informed and uninformed consumers. They find that search activity (becoming informed) increases both the likelihood of switching and the importance of price variables in the switching decision.

They do not include demographic factors, which they generally label 'random noise factors', although they do mention in their conclusion that events such as changes in marital status can trigger a switch in insurers. They do not include any dynamic factors, but again mention that "dynamic effects, together with the experienced-good nature of the insurance product, make it difficult to predict switching with much precision". (Schlesinger and von der Schulenburg 1993, 612) This differs from the analysis in this paper, where demographic factors are included, and there is an attempt to capture some of the dynamic effects. Otherwise, however, the analyses are similar, suggesting that this is an appropriate structure with which to approach this question of switching from domestic to foreign brands of automobiles.

Clearly, there is large body of academic work spread across many fields that is relevant to this project. This body of work indicates the use of a discrete choice model, and specifically suggests use of the probit. It highlights the importance of dynamic factors in analyses of this kind, and offers some guidance as to how to model switching behavior. It also identifies the factors that are most likely to significantly influence consumer choices about automobiles. This paper brings together the various theories and methods, and applies them to the issue of switching behavior from domestic to foreign brands and also to the issue of general preferences in the automobile product group. The results are significant, and potentially could be of interest to the automobile industry.

CHAPTER 3

THEORETICAL MODEL

As stated earlier, "Discrete choice models start from the assumption that each consumer chooses the single option… that yields the greatest utility." (Anderson, de Palma, and Thisse 1992, 3-4) However, "the utility of any alternative is best viewed as a random variable." (Ben-Akiva and Lerman 1985, 58) These two ideas are the basis of the Random Utility Model, which forms the theoretical foundation for this paper.

In a binary choice situation, the probability that an individual *n* chooses alternative *i* is the probability that the utility from alternative *i* is greater than the utility from alternative *j*. That probability is:

$$P_n(\, i \,)=\Pr(U_{in} \geq U_{jn})$$

To make random utility theory operational, total utility is separated into deterministic and random components. The error term is the random component and represents all factors and aspects of utility unknown by the researcher. The deterministic component is a function of the observed factors (characteristics and attributes) times a vector of parameters to be estimated. (Train 1986, 10) Where V_{in} and V_{jn} are the deterministic components, and ε_{in} and ε_{jn} are the random error terms, (Ben-Akiva and Lerman 1985, 61)

$$P_n(\, i \,)=\Pr(V_{in}+ \varepsilon_{in} \geq V_{jn}+ \varepsilon_{jn})$$

$$P_n(\, i \,)=\Pr(\varepsilon_{jn}- \varepsilon_{in} \leq V_{in} - V_{jn})$$

In this paper, I assume errors are normally distributed. The difference of two normal random variables is itself a normal random variable. The difference $(V_{in} - V_{jn})$, on the other hand, is not a random variable at all—it is the difference of two deterministic functions. The choice probability in this probit model is therefore easily calculated as the probability that a normally distributed variable is less than a particular value $(V_{in}- V_{jn})$.

In the initial model in this paper, $P_n(\, i \,)$ reflects the probability that the utility of purchasing a foreign brand of automobile is greater than the utility of purchasing a domestic brand. This is also the case in the luxury versus non-luxury analyses. The difference here, however, is that I hypothesize that there are two separate choice probabilities to be calculated rather than one:

$$P_{\text{luxury } n}(i) = \Pr(\varepsilon_{\text{luxury } jn} - \varepsilon_{\text{luxury } in} \leq V_{\text{luxury } in} - V_{\text{luxury } jn}) \text{ and}$$

$$P_{\text{nonluxury } n}(i) = \Pr(\varepsilon_{\text{nonluxury } jn} - \varepsilon_{\text{nonluxury } in} \leq V_{\text{nonluxury } in} - V_{\text{nonluxury } jn})$$

I do this because I suspect that (and test whether) the parameters in the deterministic portion of the utility function may not be the same for the two subpopulations.

In the switching model, on the other hand, we are again calculating just one choice probability. However, it is a particular conditional probability

$$P_n(i|D_n) = \Pr(U_{in} \geq U_{jn}, \forall n \in D_n)$$

where D_n is the subset of consumers who chose *j* (domestic) in the previous period. In other words, we calculate the probability of choosing to switch to a foreign brand given that the previous purchase was domestic.

The switching probability could be expressed in the same form as the probabilities for the luxury versus non-luxury segments. The two analyses are similar in that they both look at subpopulations within the data. However, whereas we are able to look at both sides of the coin in the luxury versus non-luxury segments, it is not possible using this dataset to examine switching behavior to domestic brands as well as from them. This is why the switching analysis is presented differently. In either case, however, it is important to note that the unit of analysis is the purchase decision, not the individual.

CHAPTER 4

SURVEY AND DATASET

The dataset used in the analysis was generated by a telephone survey conducted in 1997 of 100 car owners throughout the country. It includes the gender of the respondents as well as their age, martial status, size of household, place of residence, and income at each purchase occasion throughout their car ownership history. From the make and model of the car, each purchase is identified as luxury or non-luxury, domestic or foreign, and by car class. Foreign here refers to the nationality of the manufacturer or nameplate. For example, Mercedes cars are classified as foreign, regardless of the place of manufacture.

In the sub-sample used for this analysis, the earliest purchase is from 1977. Sixty-four percent of the purchases used are from the 1990s. Thirty-two percent are from the 1980s. Just four percent are from the 1970s. The youngest age at which a car was bought is 19, the oldest is 85. Thirty-six percent of the purchase occasions represent women respondents. The longest history in terms of number of purchases is from a gentleman who reports on the 12 cars he bought from 1973 to 1995. There are, of course, survey responses in which there is only one entry.

The full survey (when purchases made while living abroad and those missing key demographic information have been removed from the dataset) contains 442 cars. The first car purchase from each survey is sacrificed when purchase history is used as an explanatory variable. This reduces the data set to 365 purchases. For the switching analyses, looking at the sample of those who had chosen a domestic vehicle in the previous purchase further reduces the dataset to 210 observations.

Price and characteristic information for the cars was collected from back issues of the *Consumer Reports* "Car Buying Guides". In some cases, survey respondents only provided the brand name but not the model of the car purchased (for example, "Lincoln" as opposed to "Lincoln Town Car"). In these cases, price and attribute information was entered in assuming the model was the cheapest model offered by that brand in that particular year. (I do test and discuss the sensitivity of the analyses to this assumption in the

Results section of the paper.) In some cases, no *Consumer Reports* information was available about the cars in the survey. Those observations were dropped. There are, therefore, 328 purchases included in the aggregate analyses and 178 in the switching models.

Table 1 in the Appendix, titled "Variables Used in Analysis by Category and Type, with Descriptions" contains more specific details about the dataset. Table 2, "Summary Statistics, Aggregate Models", presents the mean, standard deviation, and minimum and maximum values for each variable in the aggregate choice and luxury versus non-luxury regressions while Table 3 does the same for the switching models.

As shown in Tables 1, 2, and 3, there are five categories of potential explanatory variables: Purchase Characteristics, Demographic, Time Trend, Purchase History, and Gasoline Prices. Demographic variables include characteristics such as age, income, and place of residence. The Time Trend captured by the variable *year* proxies shifting preferences over time. Purchase Characteristics variables include the price of the purchased car as well as measures of the car's size and power. One Purchase History variable of note is *loyalty*. It indicates whether the consumer has been loyal to domestic brands, and over how many purchases. Another is the variable *switchtoluxury*, which indicates whether the consumer is moving from a previous non-luxury purchase to a luxury auto. Finally, the Gasoline Prices category includes three variables that test whether real gas prices have had different effects in different decades.

There are two more issues of note regarding the data. The first has to do with the *realincome* variable. Survey respondents were asked to identify their income at the time of purchase by picking from a list of brackets, for example "$20,001 to $40,000". The mean of the upper and lower bounds of each bracket was used to generate an estimate of income. For example, for a respondent choosing the "$20,000 to $40,000" bracket, income would be entered as $30,001. These nominal numbers were then deflated using the Consumer Price Index-All Urban Consumers, Base Period 1982-84=100 to get real income values.

The second issue has to do with gasoline prices. Data for this category of variables was collected from the U.S. Department of Energy publication "Annual Energy Review 2001", available online at http://www.eia.doe.gov/emeu/aer/petro.html. Until 1975, only the price of leaded regular gasoline is available. From 1976 until 1990, prices for both leaded and unleaded gasoline are reported. From 1991 on, only unleaded gasoline prices are available. To get a consistent series, a regression was performed on the data from 1976 to 1990 to determine the relationship between leaded and unleaded prices. The equation estimated by standard OLS is as follows: unleaded=-0.29 + 1.06*leaded. The regression, using 15 observations, has an R^2 value of 99.4%. The variable *gasprice* indicates the price in real cents per gallon of regular unleaded gasoline, where the values before 1976 are estimates based on the price of regular leaded gasoline at the time. The variables *gas70s*, *gas80s*, and *gas90s* are interaction variables of *gasprice* with the appropriate decade indicators.

Finally, I would like to emphasize that this paper focuses on brands, not on place of manufacture. 'Foreign' and 'domestic' refer to the nationality of the automobile brands, not to their import status or even the current location of their parent company. The analysis has a marketing focus.

Also, in order to better understand defections or switching behavior from domestic to foreign brands, the switching analyses look at individuals whose previous purchase was a domestic brand of automobile. The results from these switching analyses apply to an interesting but very specific sample of consumers. The aggregate analyses are more broadly applicable.

CHAPTER 5

RESULTS

The goal of this study is to determine how consumers choose between domestic and foreign brands of automobiles. The first analysis below develops a general choice model using the full sample from the survey; this is also referred to as the aggregate model. The next analysis examines a sub-sample of automobile sales where the consumers' previous purchase was of a domestic brand. This "switching" analysis attempts to identify the factors that lead domestic buyers to switch to foreign brands. Finally, the last analysis tests whether there are differences in purchasing behavior by car class, specifically differences between luxury and non-luxury purchases.

Aggregate Model Results

Table 4-Column 1 presents the results of the aggregate model. The dependent variable is *usvforeign*. We see that the variables *previousforeign*, *realincome*, *realprice*, *loyalty*, *switchtoluxury*, *lengthxwidth*, and *gender* are statistically significant 90% confidence or better. The variables *year*, *hpweight*, *householdsize*, *gas70s*, *gas80s*, *gas90s*, *age*, *married*, *ne*, *s*, and *mw* are statistically insignificant. Can we therefore omit some of these variables from the analysis? In other words, how confident are we that the coefficients on these variables equal zero? A likelihood ratio test determines the answer to these questions.

Table 4-Column 2 shows the results of a probit model that omits *hpweight*, *householdsize*, *gas70s*, *gas80s*, *gas90*, *age*, *married*, *ne*, *s*, and *mw* from the analysis. *Year* is not omitted even though it was not statistically significant in the first model; we want to continue to test for a time trend. The results are similar to those from the previous model; all of the variables except *gender* are statistically significant. As shown in Table 5, a likelihood ratio test fails to reject the null hypothesis that the coefficients of all of the omitted variables are equal to zero. We can therefore focus our attention on the results from Table 4-Column 2.

These results, however, are somewhat hard to interpret as the coefficients do not reflect the marginal effect of each variable on the probability of switching to a foreign brand. STATA can simply transform these coefficients, using bootstrapping, into marginal effects form; the results from such a transformation are presented in Table 4-Column 3. The results are as follows. Not surprisingly, if the previous car purchased was a foreign brand, the probability that the consumer again chooses a foreign car increases by 0.26. Each $1,000 increase in income increases the probability of purchasing a foreign brand car by 0.02. Each $1,000 increase in price increases the probability of purchasing a foreign brand car by 0.04. Price therefore has a greater impact than income.

Each passing year increases the probability of choosing a foreign brand rather than a domestic by 0.03. A switch into the luxury segment increases the probability of choosing a foreign brand car by 0.22. Only the choice of a larger car increases the probability of choosing a domestic brand.

As mentioned earlier, the price and attribute data on the cars purchased was collected from *Consumer Reports* magazine. In some cases, survey respondents only provided the brand name but not the model of the car purchased (for example, "Lincoln" as opposed to "Lincoln Town Car"). In these cases, price and attribute information was entered in assuming the model was the cheapest model offered by that brand in that particular year. This may bias the price data downwards. Table 4-Column 4 presents the switching model applied only where such an assumption was not necessary, dropping entries with price estimates. The results are very similar to those in Table 4-Column 2. The only major impact is that the *switchtoluxury* variable is no longer statistically significant. Based on these results, we can be cautiously optimistic that the price estimates are not unduly disrupting the analysis.

Switching Model Results

As mentioned above, the results from the switching model should be similar to those from the aggregate models above, and they mostly are. The switching model evaluates a conditional probability—the probability that the choice will be a foreign brand given that the previous purchase was domestic. It is in essence a sub-sample of the aggregate model.

It is not, however, directly a nest of the aggregate model. The variable *previousforeign* cannot be used in the switching analysis—its value would always equal zero. However, a new variable *loyalty* is introduced. *Loyalty* measures how many domestic brands the consumer has bought in a row, including the current purchase. In the aggregate analysis, *loyalty* would be closely correlated with *previousforeign* and cause problems in estimation. For these reasons, *previousforeign* is included in the aggregate analysis while *loyalty* is included in the switching analysis.

The results of the initial switching probit model are presented in Table 6-Column 1. The dependent variable is *toforeign.* We see that the variables *realincome, realprice, year, switchtoluxury, lengthxwidth, hp/weight,* and *householdsize* are significant. The variables *loyalty, gas70s, gas80s, gas90s, age, gender, marital, ne, s,* and *mw* are statistically insignificant. Again, we turn to a likelihood ratio test to test a simpler form of the model.

To apply the test, we run a new model that omits *age, gender, marital, ne, s,* and *mw* from the analysis. *Loyalty* remains because it is one of the key variables of interest. The gasoline price variables are also kept; anecdotal evidence would suggest that the gas crisis in the 1970s caused some consumers to switch to gasoline-efficient imports. Table 6-Column 2 shows the results of this model. The likelihood ratio test presented in Table 7 evaluates the restriction that the coefficients for *age, gender, marital, ne, s,* and *mw* are all equal to zero. The test probability is 79%; we therefore fail to reject the null hypothesis. These demographic variables do not have a statistically significant impact on the probability of switching. The rest of the analysis will therefore build on the results presented in Table 6-Column 2, with the restrictions in effect.

Table 6-Column 3 presents the marginal effects coefficients generated from the model in Column 2. Key findings are as follows. The existence of a time trend is confirmed. Each additional year increases the probability of switching from domestic to foreign by almost 0.01. If the purchase represents a switch into the luxury segment, the probability increases by almost 0.03. Also, buyers choosing a bigger car are less likely to switch. In a perhaps related finding, each additional member of the household has a -0.013 impact on the probability of switching (in other words, larger families are more likely to stay domestic). Buyers choosing an auto with a high horsepower to weight ratio are also less likely to switch.

Each \$1,000 increase in income increases the probability of switching by 0.0004. Each \$1,000 increase in the price of the car increases the probability of switching to a foreign brand by 0.004. Again, price has a greater impact than income. Gas prices, on the other hand, are not statistically significant here. This result does not appear to be caused by multicollinearity problems. Note that the demographic variables *age*, *gender*, and *marital* were eliminated based on the likelihood ratio test results, and are also not statistically significant. This is also the case for the region indicators, *ne*, *s*, and *mw*. Most surprisingly, the *loyalty* variable does not have a statistically significant impact on the probability of switching. Note that *loyalty* reflects the number of purchases over which the consumer has been loyal to domestics. This finding suggests that a history of loyalty to domestic brands does not influence the decision to stay domestic or defect.

One potential explanation for this is that a pattern of loyalty is less a reflection of habit persistence or structural state dependence than it is a product of economic factors and preferences for particular vehicle attributes. A previous version of this study that did not yet include price, income or car characteristic information did find *loyalty* to be strongly significant. In fact, if we omit the *realincome*, *realprice*, *lengthxwidth*, and *hp/weight* variables here, loyalty does again become strongly significant. The results from this regression are presented in Table 6-Column 4. A statistically significant result for *loyalty* supports an argument for strong habit persistence or structural state dependence. With the inclusion of *realincome*, *realprice*, *lengthxwidth*, and *hp/weight* as in columns 1 and 2, *loyalty* is no longer statistically significant. The statistical significance of *loyalty* in Table 6-Column 4, therefore, seems to be caused by misspecification in the model.

Note that the regressions in Columns 1 and 2 are clearly superior to the model presented in Column 4. From a theoretical economics perspective, it is critical to include the price and income variables. As we would expect, explanatory power, as reflected by the Pseudo-R-squared statistics, increases dramatically with the inclusion of the economic and attribute variables. The point therefore is not to suggest equivalence between the different models. The interesting finding is that behaviors the automotive industry is inclined to attribute to habit persistence may in fact be a product of economic factors and specific consumer needs.

It is also interesting to note more specifically the differences in the Pseudo-R-squared statistics. The Pseudo-R-squared statistic reflects the percentage of variation in the dependent variable that is explained by the explanatory variables. The model that does not include price and income data or the car's characteristics only explains 29% of the variation in the probability of switching from domestic to foreign brands. When *realprice*, *realincome*, *lengthxwidth*, and *hp/weight* are included, that percentage increases to 74%. Not only is that a dramatic improvement, the 74% figure is quite good for discrete choice model with a dataset this size.

Finally, again we test whether price estimates have disrupted the results of these models. Table 6-Column 5 presents the switching model applied only where price estimates were not necessary, dropping the entries with price estimates. There are two key discrepancies between these results and those from the previous discussion. First, *switchtoluxury* is no longer statistically significant here. Second, *gas70s* is statistically significant, suggesting that rising gas prices did increase the probability of switching to foreign brands during the 1970s.

Luxury versus Non-Luxury Segment Results

The final question here is whether there are differences in purchasing behavior in the luxury versus the non-luxury segments. First, we perform a likelihood ratio test to determine whether in our sample parameters are the same for the luxury and non-luxury subpopulations. See Table 8 for the results from this test. First, we return to our aggregate model from Table 4-Column 1 and run a version of it including only the luxury purchase sub-sample; we call the log likelihood statistic from this model LLlux. We then run a model including only the non-luxury sub-sample and call the log likelihood statistic from this model LLnonlux. The log likelihood for the unrestricted model (LLunrest) is equal to LLlux + LLnonlux. The restricted model is the original aggregate or general model presented in Table 4-Column 1. This likelihood ratio test strongly rejects the null hypothesis that the parameters are the same for the two subpopulations.

This result suggests that we should run separate models for the luxury and non-luxury populations. The results of the luxury segment model are presented in Table 9-Column 1. First note the extraordinarily high Pseudo-R-squared value, 0.89. This suggests that the model is able to account for most of the variation in the probability of purchasing domestic versus foreign brand cars in the luxury segment. By comparison, the Pseudo-R-squared value in Table 4-Column 1, the first aggregate model regression, is 0.65. We can therefore see that the explanatory variables in this study are much better able to explain domestic versus foreign brand choice in the luxury auto segment than they are in the auto market as a whole.

Still, the results for the luxury segment are generally similar to those from the models above, just have more explanatory power. The variables *previousforeign*, *realincome*, *realprice*, and *lenghtxwidth* are statistically significant, and the coefficients have the same signs as above. Note that the *gas70s* variable drops out because this sample does not include any luxury cars bought in the 1970s.

While the luxury segment model has a very high Pseudo-R-squared value, the non-luxury segment model performs relatively poorly. See Table 9-Column 2. The Pseudo-R-squared value is just 0.38, the lowest in the study. Furthermore, the only explanatory variables that are statistically significant are *lengthxwidth* and *gender*. Multicollinearity does not appear to be the culprit, as there are no unusually high correlations between the explanatory variables. The problem may in part be the size of the sample; there are only 93 observations. What is clear is that while this set of explanatory variables does a fantastic job of predicting foreign versus domestic brand choice in the luxury segment, preferences are much harder to explain in the non-luxury auto market. Unfortunately, there is no way to determine whether this pattern holds in the switching analysis as well—the dataset is not large enough to run separate models for luxury and non-luxury purchases in the switching sub-sample.

CHAPTER 6

CONCLUSION

This paper is unique in a number of ways. First, it includes dynamic variables whereas previously published models of automobile demand generally have not done so. Habit formation, state dependence, and heterogeneity are time-related factors that have been shown in other studies to be critical in consumers' purchasing decisions with regard to consumer packaged goods like yogurt. We might expect these factors to be even more important in the purchase of durable goods such as automobiles, given their higher cost and longer lifespan. Data to test this hypothesis has, however, has not usually been available.

Although it doesn't differentiate between habit formation, state dependence, and heterogeneity, this paper is able to test whether purchase history is statistically significant in the automobile market. It finds that purchase behavior in this segment is not zero order—purchase history does matter. For example, a buyer may be more likely to buy a foreign brand if the purchase represents a step up into the luxury automobile segment.

While income is important, surprisingly the study finds that demographic factors such as age and region do not have a statistically significant impact on the probability of choosing a foreign brand. This contradicts results cited by Kenneth Train in his comprehensive review of automobile demand literature. The dynamic variables may be partly responsible for this difference. This study does find a time trend—consumers are more likely to buy foreign brands rather than domestic brands today than they were in the past. Furthermore, there is only mixed evidence that fluctuations in gas prices have ever had a significant impact on the probability of switching or generally of choosing domestic versus foreign brands.

This paper is also unique in its examination of various subpopulations. It finds that there may be substantial differences in the luxury versus non-luxury segments. The variables available here do a much better job of explaining preferences in the luxury segment and, in fact, do a very poor job of explaining behavior in the non-luxury market. It may therefore be problematic to group these two segments together when performing analyses, as has often been done.

Furthermore, the study asks specifically about switching behavior from domestic to foreign brands of automobiles. It is therefore able to test whether there is such a thing as "domestic loyalty". The key finding in the paper is that there may be no such thing as loyalty to domestic brands. The study finds evidence that behavior that has been attributed to loyalty (some combination of habit persistence and structural state dependence) may in fact be a reflection of economic factors such as price and income and car characteristics such as size and power.

The key asset in this study is the unique data set, which includes both demographic and purchase history information from the automobile market. This presents a special opportunity to evaluate a more complete model of consumer preferences. Unfortunately, the study is also limited by the size of the data set. More observations would most probably improve the results for the non-luxury segment. A larger data set would also make it possible to apply more advanced methods to estimate habit persistence, structural state dependence, and unobserved heterogeneity. Despite this size limitation, this project has yielded interesting results—especially with regards to the importance, or lack thereof, of "loyalty" to domestic brands in the automobile market.

APPENDIX

Table 1: Variables Used in Analyses by Category and Type, with Descriptions

Category	Variable	Binary?	Desription
Dependent Variables	Toforeign	Yes	0: Stays with domestic brand 1: Switches to foreign brand
	Usvforeign	Yer	0: Domestic brand 1: Foreign brand
Purchase Characteristics	Realprice		Real price of the car (nominal value from *Consumer Reports*)
	Lengthxwidth		Length of the car x the width (from *Consumer reports*, in inches)
	Hp/weight		Horsepower / weight (from *Consumer Reports*)
Demographic	Age		
	Gender	Yes	0: Male; 1: Female
	Married	Yes	0: Not Married; 1: Married
	Hshldsize		Number of people in the household
	Realincome		Real Income (from midpoint of survey category indicated)
	NE	Yes	Northeast Region
	S	Yes	South Region
	MW	Yes	Midwest Region
Time Trend	Year		
Purchase History	Switchtoluxury	Yes	1 if switch from non-luxury to luxury
	Plux	Yes	0: Current car (before purchase) is not luxury 1: Current car (before purchase) is luxury
	Loyalty		Length of purchase stream showing loyalty to domestic brands: neverforeign*carnumber
Gasoline Prices	Gas70s		0 if not in 1970s real gas price if in 1970s
	Gas80s		0 if not in 1980s real gas price if in 1980s
	Gas90s		0 if not in 1990s real gas price if in 1990s

Table 2: Summary Statistics, Aggregate models

Category	Variable	Mean	Std. Dev.	Minimum	Maximum
Dependent Variable	Usvforeign	0.48	0.50	0.0	1.0
Purchase Characteristics	Realprice *(1000s)*	18.46	7.29	1.9	40.5
	Lengthxwidth	13879.02	1944.17	9982	18640
	Hp/weight	0.05	0.01	0.02	0.09
Demographic	Age	47.74	13.90	19.0	85.0
	Gender	0.36	0.48	0.0	1.0
	Married	0.79	0.40	0.0	1.0
	Hshldsize	2.56	1.17	1.0	6.0
	Realincome *(1000s)*	72.33	43.75	6.6	224.5
	NE	0.39	0.49	0.0	1.0
	S	0.20	0.40	0.0	1.0
	MW	0.32	0.47	0.0	1.0
Time Trend	Year	1990	5.31	1977	1997
Purchase History	Switchtoluxury	0.31	0.46	0.0	1.0
	Previousluxury	0.50	0.50	0	1
	Loyalty	1.95	2.58	0.0	12.0
Gasoline Prices	Gas70s	6.08	30.15	0.0	172.8
	Gas80s	48.92	74.37	0.0	220.9
	Gas90s	78.10	58.80	0.0	134.6

Number of Observations: 328

Table 3: Summary Statistics, Switching models

Category	Variable	Mean	Std. Dev.	Minimum	Maximum
Dependent Variable	Toforeign	0.29	0.45	0.0	1.0
Purchase Characteristics	Realprice *(1000s)*	18.64	6.66	4.9	35.1
	Lengthxwidth	14454.45	1986.82	9982	18640
	Hp/weight	0.05	0.01	0.02	0.09
Demographic	Age	51	14.07	20.0	79.0
	Gender	0.13	0.34	0.0	1.0
	Married	0.75	0.44	0.0	1.0
	Hshldsize	2.45	1.19	1.0	6.0
	Realincome *(1000s)*	63.21	40.80	8.1	224.5
	NE	0.38	0.49	0.0	1.0
	S	0.13	0.34	0.0	1.0
	MW	0.41	0.49	0.0	1.0
Time Trend	Year	1989	5.39	1977	1997
Purchase History	Switchtoluxury	0.36	0.48	0.0	1.0
	Loyalty	3.33	2.63	0.0	12.0
Gasoline Prices	Gas70s	8.01	35.07	0.0	172.8
	Gas80s	61.03	79.01	0.0	220.9
	Gas90s	67.57	61.07	0.0	134.6

Number of Observations: 178

Table 4: Aggregate Models – Probit, Dependent Variable Usvforeign

	1	2	3	4
Variable	Aggregate[a]	Aggregate, Restricted[a]	Marginal Effects[b]	No Price Estimates[a]
Previousforeign	**0.91 (3.4)**	**0.81 (3.2)**	**0.26**	**0.88 (2.5)**
Realincome	**0.01 (3.3)**	**0.07 (2.6)**	**0.02**	**0.06 (1.7)**
Realprice	**0.13 (5.3)**	**0.12 (5.4)**	**0.04**	**0.15 (4.4)**
Year	0.09 (1.3)	**0.08 (2.9)**	**0.03**	**0.12 (3.5)**
Switchtoluxury	**0.68 (2.4)**	**0.63 (2.3)**	**0.22**	0.20 (0.4)
Lengthxwidth	**-0.001 (-8.3)**	**-0.001 (-8.5)**	**-0.36**	**-0.001 (-7.2)**
Hp/weight	-11.88 (-0.9)			
Householdsize	-0.19 (-1.4)			
Gas70s	0.005 (0.4)			
Gas80s	-0.001 (-0.2)			
Gas90s	-0.0004 (-0.6)			
Age	0.01 (1.1)			
Gender	**0.41 (1.7)**	0.32 (1.4)	0.11	0.23 (0.8)
Married	-0.18 (-0.5)			
NE[c]	0.01 (0.1)			
S[c]	-0.03 (-0.1)			
MW[c]	-0.26 (-0.6)			
Constant_term	-158.25 (-1.2)	**-137.87 (-2.7)**		**-225.58 (-3.4)**
Log Likelihood	-79.91	-85.04		-53.59
Pseudo-R^2	0.65	0.63		0.69
Sample size	328	328	328	254

Notes:
a: Coefficient (Z-statistic) **[Bold font indicates statistically significant at 90% confidence)**
b: Coefficient only (refer to Z statistics from Switching, Restricted)
c: Regional coefficients are relative to the West.

Table 5: Likelihood Ratio Test Results, Aggregate Models

Model	Omitted Variables	Log Likelihood	Number of Restrictions	Probability[a]	Conclusion[b]
Unrestricted (Column 1)		-79.91			
Restricted (Column 2)	age, married, ne, s, mw, gas70s, gas80s, gas90s, hp/weight, householdsize	-85.04	10	0.51	Fail to Reject

Notes:
a: Probability refers to the probability that the critical value exceeds the test statistic.
b: Conclusion refers to Null Hypothesis that the coefficients of all of the omitted variables are equal to zero.

Table 6: Switching Models – Probit, Dependent Variable toforeign

	1	2	3	4	5
Variable	Switching[a]	Switching, Restricted[a]	Marginal Effects[b]	Test, Habit Persistence[a]	No Price Estimates[a]
Realincome	**0.02 (3.3)**	**0.02 (3.3)**	**0.0004**		**$2.4 x 10^{-5}$ (3.1)**
Realprice	**0.23 (3.6)**	**0.21 (3.8)**	**0.004**		**$2.6 x 10^{-4}$ (3.6)**
Year	**0.45 (2.8)**	**0.41 (2.8)**	**0.008**	0.09	**0.52 (3.0)**
Loyalty	-0.13 (-0.7)	-0.10 (-0.6)	-0.002	**-0.3 (-3.7)**	-0.11 (-0.6)
Switchtoluxury	**0.93 (1.7)**	**0.88 (1.8)**	**0.026**	**1.1 (4.5)**	0.66 (1.2)
Lengthxwidth	**-0.002 (-4.8)**	**-0.002 (-5.2)**	**$-3.4 x 10^{-5}$**		**-0.002 (-4.8)**
Hp/weight	**-42.53 (-1.6)**	**-47.22 (-2.1)**	**-0.916**		**-47.22 (-2.1)**
Householdsize	**-0.60 (-1.7)**	**-0.66 (-2.6)**	**-0.013**	0.04 (0.3)	**-0.66 (-2.4)**
Gas70s	0.03 (1.3)	0.02 (1.2)	$4.4 x 10^{-4}$	0.009 (0.8)	**0.04 (1.7)**
Gas80s	0.01 (0.8)	0.01 (0.5)	$1.4 x 10^{-4}$	0.006 (0.9)	0.02 (0.3)
Gas90s	0.003 (0.2)	0.003 (0.2)	$5.4 x 10^{-6}$	0.004 (0.6)	0.004 (0.3)
Age	0.02 (1.1)				
Gender	0.21 (0.5)				
Married	-0.23 (-0.3)				
NE[c]	-0.45 (-0.6)				
S[c]	0.20 (0.2)				
MW[c]	-0.27 (-0.4)				
Constant_term	**-866.56 (-2.8)**	**-796.22 (-2.8)**		**-170.10**	**-1006.30 (-3.0)**
Log Likelihood	-26.33	-27.90		-75.86	-24.23
Pseudo-R^2	0.75	0.74		0.29	0.76
Sample size	178	178	178	178	170

Notes:
a: Coefficient (Z-statistic) **[Bold font indicates statistically significant at 90% confidence)**
b: Coefficient only (refer to Z statistics from Switching, Restricted)
c: Regional coefficients are relative to the West.

Table 7: Likelihood Ratio Test Results, Switching Models

Model	Omitted Variables	Log Likelihood	Number of Restrictions	Probability[a]	Conclusion[b]
Unrestricted (Column 1)		-26.33			
Restricted (Column 2)	age, gender, married, ne,s,mw	-27.90	6	0.79	Fail to Reject

Notes:
a: Probability refers to the probability that the critical value exceeds the test statistic.
b: Conclusion refers to Null Hypothesis that the coefficients of all of the omitted variables are equal to zero.

Table 8: Likelihood Ratio Test Results, Luxury vs Nonluxury Segment

Statistic	Description	Log Likelihood	Number of Restrictions	Conclusion
LLlux	Model as in Table 4-Column 1, with only luxury subpopulation	-35.58		
LLnonlux	Model as in Table 4-Column 1, only non-luxury subpopulation	-11.26		
LLunrest	LLlux + LLnonlux	-46.84		
LLrestricted	Table 4-Column 1	-79.91	18	Reject

Note: Conclusion refers to Null Hypothesis that the parameters are the same for the two subpopulations.
The test statistic equals 2*(LLrestricted-LLunrest) = 66.14
The critical value of the Chi-squared distribution with 95% confidence, given the number of restrictions, is 28.87.

Table 9: General Models (Luxury versus Non-Luxury), Probit
Dependent Variable Usvforeign

	1	2
Variable	General, Luxury Only[a]	General, Non-Luxury Only[a]
Prevoiusforeign	**1.81 (2.3)**	0.47 (0.8)
Realincome	**$3.7 x 10^{-5}$ (2.9)**	$1.6 x 10^{-6}$ (0.3)
Realprice	**$3.1 x 10^{-4}$ (3.0)**	$-2.0 x 10^{-6}$ (0.3)
Year	0.16 (1.0)	-0.003 (0.0)
Previousluxury	-0.29 (-0.4)	-0.35 (-0.7)
Lengthxwidth	**-0.003 (-3.7)**	**$6.6 x 10^{-4}$ (3.1)**
Hp/weight	35.81 (0.8)	-42.98 (1.6)
Householdsize	-0.44 (-1.4)	-0.08 (-0.4)
Gas70s		
Gas80s	-0.01 (-0.3)	-0.01 (-0.8)
Gas90s	0.002 (0.1)	-0.008 (-0.7)
Age	$4.4 x 10^{-4}$ (0.0)	0.03 (1.3)
Gender	0.60 (0.9)	**0.70 (1.8)**
Married	-1.35 (-1.3)	0.48 (0.7)
NE[b]	0.12 (0.1)	0.48 (0.6)
S[b]	0.82 (0.5)	0.47 (0.6)
MW[b]	-1.12 (-1.0)	-0.11 (-0.2)
Constant_term	-280.36 (-0.9)	-280.36 (-0.9)
Log Likelihood	-17.79	-35.69
Pseudo-R^2	0.89	0.38
Sample size	230	93

Notes:
a: Coefficient (Z-statistic) **[Bold font indicates statistically significant at 90% confidence)**
b: Coefficient only (refer to Z statistics from Switching, Restricted)

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