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University of California  
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Modeling consumer preferences for status-signaling brands:  
branding, pricing, and product-line decisions

A dissertation submitted in partial satisfaction  
of the requirements for the degree  
Doctor of Philosophy in Management

by

Rafael Becerril Arreola

2013

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2013

## Abstract of the Dissertation

# Modeling consumer preferences for status-signaling brands: branding, pricing, and product-line decisions

by

Rafael Becerril Arreola

Doctor of Philosophy in Management

University of California, Los Angeles, 2013

Professor Dominique M. Hanssens, Chair

This dissertation introduces methods to quantitatively model the effects of human needs for social status on consumer behavior. More precisely, in this dissertation we: a) propose the first actionable metrics of the social status signaled by brands as functions of product line prices; b) use the new metrics and a new model of quality choice to show that both the ability and the motivation to pursue social status through consumption are affected by the economic resources available to consumers; c) identify the product line composition and pricing strategies that favor the sales of status-signaling products and brands under different levels of economic inequality among consumers. Important methodological and managerial contributions are drawn from the proposed metrics and models. For instance, the inclusion of the status metrics in the models allow the models to abstract rich substitution patterns. In terms of managerial implications, we find that including affordable products into a brand's product line may not harm the social status signaled by the brand as long as the median price of the line is relatively high and the most sold product is not very expensive. We also find that increasing consumer wealth inequality enhances the demand for low-end brands by increasing the dispersion of consumer preferences for status signaling and their saliency. High-end brands, in contrast to low-end brands, should adapt to increasing inequality by equalizing the social status of their product lines across product categories.

The dissertation of Rafael Becerril Arreola is approved.

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Dominique M. Hanssens, Committee Chair

University of California, Los Angeles

2013

To my parents, who gave me the best they could.  
Also to my sister, mentors, relatives, friends, foes,  
and all those who, intentionally or not, for better  
or worse, have influenced my path through life.

*Too many people spend money they haven't earned,  
to buy things they don't want,  
to impress people they don't like.*

*Will Smith*

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# CHAPTER 1

## Introduction

Preferences for status-signaling products have been identified as very important drivers of consumer behavior (Holt, 1995; Miller, 2009; Han, Nunes and Drèze, 2010; Ivanic, Overbeck and Nunes, 2011); however, to date, these preferences have not been incorporated into marketing models of demand<sup>1</sup>. As a consequence, extant models cannot: a) offer guidelines for marketers to best position their brands in terms of social status; nor b) assist policy makers in controlling consumer debt through the regulation of markets of conspicuous goods. If status-seeking consumer behavior is so important to marketing practitioners and regulators, why has it been neglected? The answer is that one can only manage what one can measure and, to date, actionable metrics of the social status that products signal are not available (Kamakura and Du, 2011). The work introduced in this doctoral dissertation overcomes this obstacle by proposing a methodology that allows us to incorporate status-seeking behaviors into available models of consumer behavior. This new methodology is used to assess the impact of economic inequality, prices, and product line composition on the sales of status-signaling products and brands.

Previous research in management, anthropology, biology, neuroscience, economics, psychology, sociology, and other disciplines has contributed to our understanding of how social processes influence consumption decisions. The proposition that consumer preferences are interdependent across consumers has already been formalized (Veblen, 1899; Duesenberry and Stemble, 1949) and supported empirically (Alessie and Kapteyn, 1991; Charles, Hurst and Roussanov, 2009; Kuhn, Kooreman, Soetevent and Kapteyn, 2011; Ordabayeva and

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<sup>1</sup>Chapter 2 will make clear that social status differs from socioeconomic status and other measures of social class previously used in marketing work (see, for instance Dominquez and Page, 1981; Coleman, 1983). Unlike socioeconomic status and social class, which are absolute measures, social status is context dependent and affected by consumer behavior.

Chandon, 2011). The biological and psychological processes underlying this form of social influence have also been explored (Ackerman, MacInnis and Folkes, 2000; Buunk and Gibbons, 2007; Chiao, Harada, Oby, Li, Parrish and Bridge, 2009; Miller, 2009; Van de Ven, Zeelenberg and Pieters, 2011). As a result, we now understand that preference interdependencies may arise because consumers use products to: a) associate with or disassociate from certain reference groups (Escalas and Bettman, 2005; White and Dahl, 2006; Muniz Jr and O’guinn, 2001; Berger and Heath, 2008; Kuksov and Xie, 2012) b) communicate their unobservable personal attributes (Sirgy, 1982; Berger and Heath, 2007; Miller, 2009); and c) legitimize their superiority over those they interact with (Berger, Cohen and Zelditch, 1972; Han et al., 2010; Rucker, Galinsky and Dubois, 2011). This third process, that of attaining social status through consumption, is the focus of this dissertation.

Within the field of quantitative marketing, most work on socially-motivated consumption has either focused on reference group effects (Amaldoss and Jain, 2005*a*; Balachander and Stock, 2009) or has aggregated multiple forms of social influence into a single process (Kuksov and Xie, 2012). For instance, the empirical studies of Joshi, Reibstein and Zhang (2009) and McShane, Bradlow and Berger (2012) showed that consumer choice can be affected by the choices of other consumers. Neither of these streams of research has however disentangled the effects of status-signaling behaviors from those of other forms of social influence. To achieve this, we must rely on our understanding of the psychological processes that underly consumers’ pursuit of social status through consumption.

To isolate the effects of the pursuit for status from the effects of other forms of social influence on consumer behavior, we propose a framework that relies on primary and secondary data, quantitative methods, and multidisciplinary theories of human behavior. We integrate theories from cultural studies, sociology, and social, evolutionary, and cognitive psychology to propose actionable metrics of the social status signaled by brands and products. We then rely on motivation theory and econometric tools to propose and test a new economic model of consumer choice that allow us to explore the conditions under which preferences for status-signaling products are revealed. Finally, we use the metrics and the new model of choice in a simulation study that investigates the determinants of the success of brands

under different levels of consumer inequality.

## 1.1 Research objectives

The main goals of this dissertation are as follows.

- 1) To propose and test metrics of the social status signaled by brands (brand status), such that:
  - the metrics represent consumer perceptions of the social status associated with brands and products
  - the metrics predict consumer behavior.
  - the metrics are robust, reliable, and objective
  - the metrics are accessible to marketing practitioners who can compute them using available secondary data
  - the metrics provide guidelines for the positioning of brands by establishing a direct link between marketing actions and consumer perceptions of the social status of brands
- 2) To use the proposed metrics of brand status to quantify the economic importance of status-seeking behavior in the consumption context.
- 3) To identify conditions that determine the strength and the exercise (as opposed to repression) of preferences for status-signaling brands. We'll focus on conditions defined in terms of:
  - consumer demographics such as income, education, ethnicity, etc.
  - consumer assets and other drivers of motivation.
- 4) To investigate how major demographic shifts affect market structure and the market performance of products and brands by changing the preferences, motivation, and ability of consumers to signal status through consumption. In particular, we investigate the effects of increasing income and wealth inequality among consumers.

## 1.2 Relationship to extant work

By pursuing the aforementioned goals, we contribute to several bodies of literature. We contribute to the consumer behavior literature on price perceptions (Petroshius and Monroe, 1987; Niedrich, Sharma and Wedell, 2001; Berger, Draganska and Simonson, 2007; Cunha Jr and Shulman, 2011) by showing that prices and product line composition determine consumer perceptions of brand and product status. In addition, we provide support to previous findings related to the roles of demographics on consumer preferences for social status (for instance Ivanic et al., 2011; Veblen, 1899). We also pioneer in the exploration of the role of demographics on consumer perceptions of the social status of products and brands. Our work on motivation provides support to motivation theories (Maslow, 1943) and show that consumer's ordering of different consumption motives can be predicted. Along these lines, we identify and test important determinants of consumption motivation. We in particular focus on the role of consumer wealth.

Our results also extend the economic literature on conspicuous consumption and social influence along several dimensions. First, we broaden the scope of the empirical work that has studied the effects of social influence on consumer expenditures (see, for instance Charles et al., 2009) to include consumer choices. We provide evidence that social influence affects not only consumer spending but also consumer choice. Second, we relax the assumption of a limited number of products needed for the theoretical analysis of status-related consumption (Hopkins and Kornienko, 2004; Bagwell and Bernheim, 1996) as we consider a real market with a large number of options. Our results can therefore be contrasted and combined with the conclusions of this previous theoretical work. Third, unlike economic models that often consider single-product firms, we consider brands and product lines. We are thus able to discuss firm decisions other than entry, exit, and the pricing of single products. Fourth, relative to relevant work in industrial organization (Gabszewicz and Thisse, 1979; Yurko, 2011), we shift the emphasis of our modeling efforts to the consumer side rather than balancing the complexity of both demand and supply models. This shift allow us to infer rather than assume properties of the decision making process of consumers.

Our contribution to the quantitative marketing literature is manifold too. An important contribution is that, by relying on theory to model the social status signaled by products, we are able to empirically isolate one of the different processes that result in social influence. Therefore, our results extend previous work on social influence (for instance McShane et al., 2012; Joshi et al., 2009) by advancing our understanding of its underlying mechanisms. Our work also complements the research that has investigated the role of prices on consumption motivated by reference-group effects (Amaldoss and Jain, 2005*b*; Amaldoss and Jain, 2010). The results make clear that one should be aware of the simultaneous repercussions of prices on reference-group effects and status-seeking behaviors. Our results also complement previous research on product line composition and pricing by showing that these marketing variables affect not only perceptions of quality (Draganska and Jain, 2006), but also perceptions of the social status conferred by the brand. An additional contribution is made to the literature that has studied how the relative position of a product within a set of vertically differentiated alternatives affects consumer behavior (Randall, Ulrich and Reibstein, 1998; Leclerc, Hsee, Nunes, Hsee and Hastie, 2005; Aribarg and Arora, 2008). We complement this work by introducing an additional dimension of vertical differentiation, namely brand status. Finally, we build on the research that has improved the realism of utility models by abstracting additional forms of consumer trade up (Allenby and Rossi, 1991; Allenby, Garratt and Rossi, 2010). Our work contributes to this body of literature by theoretically justifying and empirically testing psychological mechanisms that lead consumers to exhibit non-homothetic preferences (preferences such that marginal utilities are not constant and income elasticities are not equal to one.)

### **1.3 Dissertation roadmap**

This dissertation is composed of three self-contained essays. In Essay 1, we introduce metrics of the social status associated with brands. The metrics are constructed using the proposition that consumers use the prices of the members of a product line to infer the status signaled by brands and their products. We combine evolutionary, social comparison, range-frequency,



and categorization theories to substantiate this proposition. Having defined the metrics, we test their validity by relating them to measures of perceived brand status that were collected through an on-line survey for this purpose. The relevance of the metrics is tested through an econometric analysis carried out on secondary data of car choice. Using choice modeling techniques, we test different specifications to determine the importance of different metrics of brand status to different consumer segments. The importance of including the metrics is discussed by analyzing the ensuing price elasticities.

Essay 2 introduces a model of consumer choice that explains heterogeneity in consumer valuations of product quality. That is, the model proposes that consumers are not always willing to pay more for additional quality because their preferences for such additional quality may be repressed. This proposition leads to the formulation of a structural model of choice that allows consumer preferences for different product attributes (which address different consumption motives) to be revealed or not. The exercise of these preferences is allowed to be conditioned on sufficient levels of consumer wealth, allowing us to separately estimate the importance of income and wealth on consumer choice of status-signaling products. By estimating this new model, we investigate conditions under which preferences for status-signaling products are relevant. In particular, we investigate the roles of consumer income and wealth as separate moderators of these preferences.

In Essay 3, we combine the metrics introduced in Essay 1 and the model developed in Essay 2 to investigate the effects of increasing consumer inequality on the sales of status-signaling brands and products. We conduct a simulation study in which consumer income and wealth are redistributed so as to increase their inequality. We then look at how the redistribution of these financial assets affects: a) consumer preferences for brand status and product line composition; and b) the exercise of these preferences. Thereafter, we investigate how these changes in preferences and motivation affect consumer choices and thus the sales of different products and brands. This analysis reveals what positioning, in terms of brand status and product line consistency, favors brand sales as inequality increases. Implications for product line composition and pricing are discussed.

## CHAPTER 2

### Metrics of the perceived social status of a brand

#### 2.1 Introduction

Human behavior may be driven by a need to attain social status. A high social status allows individuals to feel superior and to be perceived as superior to others. By feeling superior, individuals experience positive affect (Buunk and Gibbons, 2007) and improved subjective well-being (Hagerty, 2000). By being perceived as superior, individuals receive preferential treatment and other social benefits (Berger et al., 1972). When individuals interact, they determine who has higher status by comparing against each other on multiple attributes, such as physical attractiveness, education, wealth, etc. Among these multiple attributes, income and wealth have been identified as the strongest correlates of subjective social status (Singh-Manoux, Adler and Marmot, 2003; Miller, 2009). However, income and wealth may not be directly observable. Consumers may then infer others' wealth and status from their observable consumption choices (Belk, Bahn and Mayer, 1982); accordingly, consumers may buy expensive products to signal high status (Ackerman et al., 2000; Rucker and Galinsky, 2008).

Brands play an important role in status signaling as brands are associated with prices, which correlate with wealth and thus with social status (Sengupta, Dahl and Gorn, 2002). Brands therefore become proxies for social status (Han et al., 2010). Though experimental research has established that social status (see, for example, Ordabayeva and Chandon, 2011) and the social status associated with brands (Han et al., 2010) are important to consumers, their effect on product demand has yet to be quantified using secondary data.

The scarcity of quantitative work in this area may ensue from the absence of actionable

metrics of the social status associated with brands. Although the social status associated with a brand can be easily measured using consumer surveys, mindset metrics of brand status cannot be mathematically explained by marketing variables and therefore their values cannot be predicted under counterfactual scenarios in which firms follow different marketing strategies. Mindset metrics cannot be used to predict the effects of, for example, a price increase on the perceived social status of a product. Therefore, mindset metrics offer no guidelines to managers on how to price their product lines so that their brands are associated with a prescribed level of social status. Mindset metrics describe the world as it is, and tell little about how the world can be under different scenarios.

To overcome the weaknesses of customer mind-set metrics, we use market outcomes and marketing actions to construct metrics of the social status associated with brands. As noted by Ailawadi, Lehmann and Neslin (2003), outcome-based metrics “...are more complete than any single customer mind-set measure because they reflect a culmination of the various mechanisms by which the brand name adds value and that they can be given a dollar value, which is appealing to senior management and is critical for financial valuation.” Because the metrics proposed herein are structurally linked to prices and product line composition, these metrics can be used to assess the market consequences of different marketing policies such as price changes, new product introductions, and vertical extensions. We refer to the social status associated with a brand as the “brand’s price status” or the “brand’s status”, for short.

Before proposing the metrics of brand status, we review the relevant literature in Section 2.2. We then explain the construction of our metrics of brand status while reviewing range-frequency and categorization theories in Section 2.3. Section 2.4 describes several datasets we rely on. Section 2.5 presents an analysis of primary data that explores the relationship between the proposed metrics of status and consumers’ actual perceptions of the status of the brand. An analysis of the robustness of the metrics is then presented in Section 2.6. Section 2.7 describes an econometric study that relies on secondary data to determine how well consumer behavior can be explained by the proposed metrics of brand status. This study makes use of a model of consumer choice that regards the status a brand

confers to the owner as a product attribute that may contribute to consumer's utility. The model is described in Section 2.7.1. The results of the estimation of the model are presented in Section 2.7.2. The implications of the results, their contribution, and limitations are discussed in Section 2.8. Conclusions are offered in Section 2.9.

## 2.2 Relevant literature

Status-seeking consumption is a particular form of culturally-motivated consumption, which has been studied in sociology (Berger et al., 1972), anthropology (Barkow, 1989), cultural studies (Dunn, 2008), economics (Leibenstein, 1950), evolutionary psychology (Miller, 2009), neuroscience (Chiao et al., 2009), consumer behavior (Holt, 1995) and other disciplines. Extant work in these areas has focused on understanding how and why humans exhibit consumption motives that are independent of the functional benefits of commodities. A central thesis underlying this research is that culture furnishes goods with meanings and that individuals may consume such goods in order to consume their meanings.

Products can convey meanings by acting as signs, symbols, or both, with the difference stemming from how the products are used (Dunn, 2008). Signs denote ideas and serve instrumental ends. Symbols connote ideas and perform expressive functions. Thus, by consuming certain products, individuals may associate themselves, in their own eyes (Sirgy, 1982) or in the eyes of others (Holt, 1995), to the meanings attached to such products. Hybrid cars, for example, are associated with clean energy and technological advancement (Ozaki and Sevastyanova, 2011) but also with prices higher than their non-hybrid counterparts. For instance, the manufacturer suggested retail price (MSRP) of the cheapest 2012 Volkswagen Touareg is 43,375USD but the MSRP of its cheapest hybrid version is 61,110USD. Thus, individuals may use hybrid cars to portray themselves as environmentally conscious and technologically savvy consumers (a symbol) but also to display wealth (a sign) (Griskevicius, Tybur and Van den Bergh, 2010).

While consumers may use a particular product as a sign, a symbol, or both, our work focuses on the consumption of a particular kind of signs. We focus on signs of wealth. As

discussed by Veblen (1899), individuals may engage in activities that signal wealth in order to attain social status and the social benefits that social status conveys. According to Veblen (1899), one such activity is the conspicuous consumption of wasteful products. We note, however, that products do not need to be wasteful to signal wealth. Consumers can signal abundant resources through costly signals of conspicuous waste (for example, a Hummer truck), conspicuous precision (a Lexus SUV), or conspicuous reputation (a BMW sedan) (Miller, 2009). To signal wealth, products only need to be relatively expensive because it is conventionally accepted that relatively expensive products can be afforded by relatively wealthy people only (Miller, 2009). Accordingly, aspects of brand prestige other than cost will not be considered here (refer to Dubois, Czellar et al., 2001, for a consumer-centered definition of brand prestige).

The relativity of the signaling meaning of conspicuous products ensues from the relative nature of social status and the comparative process that consumers use to assess it. To assess their social status when other indicators of wealth are not available, individuals compare the expensiveness of what they own against the expensiveness of what is owned by others they interact with (Ackerman et al., 2000; Ordabayeva and Chandon, 2011). This comparison is a particular form of social comparison. Many aspects of social comparisons, such as their drivers, consequences, and moderators have been widely studied in the social psychology literature (for a review, refer to Buunk and Gibbons, 2007). The more specific case of the comparison of consumption decisions has been studied in the consumer behavior literature. This body of literature has focused on questions related to consumer susceptibility to the comparison of consumption choices (Bearden and Rose, 1990) and the effects of comparisons on willingness to pay (Van de Ven et al., 2011), for example.

In the quantitative marketing literature, most work in this area has addressed consumers' need for uniqueness and the effects of reference groups (see, for example Joshi et al., 2009; Balachander and Stock, 2009). Reference group effects involve individuals' need for association with and dissociation from groups of others (Escalas and Bettman, 2005). In contrast, a need for uniqueness relates to an individuals' need to dissociate from everyone else (Snyder and Fromkin, 1980). The quantitative marketing literature has investigated how these needs

could motivate lower-status consumers to buy the products consumed by higher-status individuals. For example, a series of laboratory studies by Amaldoss and Jain (2005*b*) and Amaldoss and Jain (2010) showed that, in two-segment settings (snobs/leaders vs. conformists/followers), respondent's purchase decisions depended on whether by purchasing they became different from or similar to others. Another two-segment problem was studied by Joshi et al. (2009), who used secondary data to derive entry timing recommendations in markets subject to reference group effects. Kuksov and Xie (2012) considered a three segment market in which the ownership of two different products signals membership to either of two high-status groups and dissociates the consumer from a low-status group.

Our work differs from extant quantitative work on reference group effects in different ways. In terms of theory, our work addresses different consumption motives. The premises of most quantitative work on reference groups have been elaborated through arguments related to consumers' identity and their need for a positive self-concept (White and Dahl, 2006). By focusing on consumers' social status, we take into account a different, though overlapping, set of consumer goals that include mating (Griskevicius, Tybur, Sundie, Cialdini, Miller and Kenrick, 2007) and utilitarian benefits (Nelissen and Meijers, 2011) among others.

We also consider different information conditions. As noted by Amaldoss and Jain (2010), the research on reference groups considers situations in which group membership is directly observable to consumers. We instead consider a context in which consumers' relevant attributes are not observed and consumption is used as a proxy to determine such attributes. Our work is thus theoretically closer to the economic literature on signaling (see, for example Frank, 1985; Bagwell and Bernheim, 1996; Hopkins and Kornienko, 2004). Such body of literature is however mostly theoretical and focused on policy implications, contrasting with our empirical approach and our focus on brands and marketing implications.

Another important difference between our work and the literature on reference groups is that we are not concerned with group effects. While status groups may affect consumer behavior, other studies suggest that consumers tend to frequently compare their consumption choices against those of other individual consumers (see, for example Hyman, 1942; Ackerman et al., 2000; Van de Ven et al., 2011; Dahl, Argo and Morales, 2012). Strong competition

for status can in fact take place within groups (Anderson and Kilduff, 2009; Charles et al., 2009). For instance, by owning a luxury car, a consumer may be able to meet her goals of developing an identity (Leary and Kowalski, 1990) and enhancing her self-concept (Muniz Jr and O’guinn, 2001). In addition, the expensive durable may help the consumer maintain her self-esteem (Leary and Kowalski, 1990) by eliciting esteem-enhancing reactions from people who can only afford mainstream vehicles. However, other owners of luxury cars may not necessarily reward her with social benefits unless her choice of luxury car grants her a status higher than theirs. This example illustrates that needs for group membership and individual distinction can jointly determine consumer behavior (Chan, Berger and Van Boven, 2012); we, however, focus on the influence of individual consumers because the influence of reference groups has received more attention elsewhere. As a result, we do not need to assume that consumers can be assigned to a limited number of segments as in (Amaldoss and Jain, 2010; Joshi et al., 2009).

In addition, our work diverges from the core reference group literature in that our results are not confined to the cases of new or limited edition products. Furthermore, our results hold for any given number of brands and products. We in fact test our propositions using data from the automobile industry, which is a mature market with a large number of brands and products. Finally, our emphasis is not on forecasting nor on optimal policies. Our emphasis is on understanding, rather than assuming, the mechanism through which consumers elaborate the perception of a brand given the distribution of prices set by manufacturers.

## **2.3 Social status and brands**

### **2.3.1 Social status and consumption**

A copious body of empirical work (e.g. Alessie and Kapteyn, 1991; Charles et al., 2009) has shown that the consumption of an individual can be motivated by the consumption of others. However most of this work has assumed that consumers compare their own consumption to the average consumption of their reference groups only. Empirical evidence suggest that it is

instead the ranking of consumers' consumption levels among those of their references groups what actually drives their needs for positional consumption (Powdthavee, 2009).

According to theories of social comparison in social psychology (Wedell and Parducci, 2000) and sociology (Jasso, 2001), the status of an individual can be determined as its ranking, on a focal attribute, among a reference group. For example, range theory (Volkman, 1951) proposes that the evaluation of a stimulus is determined by its position relative to the most extreme elements within the stimulus' context. That is, the rating of, e.g., an object depends on its position relative to the most extremes values of contextual objects that are comparable to the focal one along a given dimension (price for example). Thus, the rating of a stimulus  $i$  within a context  $k$  is given by its range value

$$R_{ik} = \frac{S_i - S_{\min,k}}{S_{\max,k} - S_{\min,k}},$$

where  $S_i$  is the context invariant scale value of the stimulus, and  $S_{\min,k}$  and  $S_{\max,k}$  are the minimum and maximum values of the entities that delimit the context's range. Parducci (1965) later advanced range-frequency theory to extend range theory by including a frequency component. The frequency value of stimulus  $i$  given context  $k$  is given by

$$F_{ik} = \frac{\text{rank}_{ik} - 1}{N_k - 1},$$

where  $\text{rank}_{ik}$  is the ranking of stimulus  $i$  among all entities within context  $k$ , and  $N_k$  is the number of these contextual entities. Range frequency theory proposes that a judgment of the focal stimulus is determined as

$$J_{ik} = wR_{ik} + (1 - w)F_{ik} \tag{2.1}$$

for some weighting  $w$  that has been experimentally determined to be close to 0.5.

In terms of socioeconomic status, this implies that the status a consumer attains depends on the ranking of this consumer's wealth level among the wealth levels of all other consumers that form this consumer's reference group (Hagerty, 2000). Because wealth is not directly observable, consumption choices serve as surrogate indicators of status (Ordabayeva and Chandon, 2011). In particular, consumers may infer others' social status from the prices of the products these others own (Belk et al., 1982; Sengupta et al., 2002).



In the case of automobiles, the status of the driver could be determined by the range and frequency values of the price of the driver’s vehicle. More precisely, the status of a consumer  $i$  who buys model  $m$  and drives in population  $g$  is given by  $s_i = 0.5F_g(p_m) + 0.5(p_m - \min_{j(g)}\{p_{j(g)}\})/(\max_{j(g)}\{p_{j(g)}\} - \min_{j(g)}\{p_{j(g)}\})$ , where  $p_m$  is the perceived price of model  $m$  and  $\{p_{j(g)}\}$  is the set of the perceived prices of all models  $j$  in use in geography  $g$ .  $F_g(\cdot)$  is the perceived cumulative distribution of the prices of all the cars within the reference group  $g$ . This operationalization of status corresponds to the “judgement” of status defined in (2.1) if the consumer population  $g$  is regarded as the contextual stimuli consumer  $i$  is compared against.

### 2.3.2 The role of brands

When comparing the status levels of several cars, consumers may not mentally reconstruct the entire distribution of the prices of all the models available in the market as their number is too large and full information may not be available or affordable. Instead, consumers may simplify this task by breaking it down into two steps. In a first step, consumers use price information to assign levels of status to each brand under consideration (Lichtenstein, Ridgway and Netemeyer, 1993; McGowan and Sternquist, 1998). In the second step, consumers assess the status of a car by ranking the status of its brand according to the brand’s price status among the price status of all other brands. Brucks, Zeithaml and Naylor (2000) provided evidence that consumers frequently use price and brand name information to evaluate the status of a product.

How do consumers associate levels of status to brands when each brand includes products with very different prices? Consumers may regard brands as categories and thus they may infer the attributes of the brand from the attributes of the most typical of its members (Joiner and Mason, 2007; Mervis and Rosch, 1981). Thus, consumers must first determine what product is the most typical of each brand. To identify this most typical product, consumers may evaluate the coherence and the frequency-of-instantiation of the attributes of all the members of the brand (Joiner and Mason, 2007). If price is the basis of comparison,

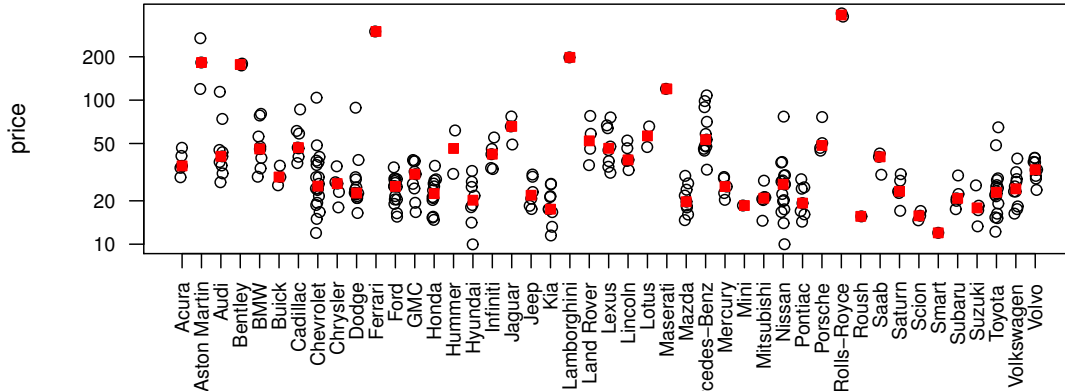


Figure 2.1: Distribution of prices (MSRP in thousands of dollars) by make. The median price appears as a square.

consumers may then first determine the typicality of the prices of each of the brand’s products and then use the most typical price to determine how expensive the brand is (Hamilton and Chernev, 2010). Because it is uncommon for a car maker to offer two or more nameplates at exactly the same price, consumers may not be able to rely on frequency-of-instantiation and coherence of prices. Instead, consumers may categorize prices into price ranges and then estimate the frequency of price instances within each range (Wedell and Parducci, 2000).

Alternatively, consumers could use a summary statistic of the prices of a brand’s products to judge how expensive the brand is. Brands can be characterized by finding the commonalities among its products, and therefore consumers may use a generalization process to infer the attributes of the brand. In fact, Cunha Jr and Shulman (2011) found that consumers rely on the summary statistics, such as the mean, of a set of prices when their goal is to find commonalities among the members of a category. Because the median is robust to outliers and thus robust to atypical exemplars, we approximate the most typical (central) price of a brand by the median of the prices of all the models within the brand. (Figure 2.1 shows the distributions of prices and their medians for the 2009 models of each make.) Alternatively, consumers could associate the brand to the the minimum or maximum price among the prices of all of its models (Leclerc et al., 2005; Hamilton and Chernev, 2010) or to the price of the most common item of the brand. Using the median, minimum, maximum, or modal price among the prices of the models of a brand, consumers may easily infer the relative status of a brand.

### 2.3.3 Metrics of brand status

The choice of a consumer to associate to a brand the minimum, median, modal, or maximum price of its products results in the consumer using one of four different metrics of product status (and consumer status), which we denote by  $s_{j,g}^{\min}$ ,  $s_{j,g}^{\text{median}}$ ,  $s_{j,g}^{\text{mode}}$  and  $s_{j,g}^{\max}$ , respectively. These metrics can be operationalized empirically as follows. Each car in a relevant population is associated with a brand and thus with the different parameters of the distribution of prices of the items within the brand's product line, such as the price of the cheapest model of the brand. For each proposed brand price (minimum, maximum, median, and mode), we rank each car within the population according to its brand price in order to obtain a frequency distribution of prices. A cumulative frequency distribution is then obtained by computing the cumulative sum of the frequencies. The cumulative frequency values are divided by the total number of cars in geography  $g$ , so as to obtain a cumulative density function that ranges from 0, for the lowest price, to 1, for the highest price. When the brand price is defined as the price of the cheapest member of the brand's product line, we denote this cumulative density function by  $F_g^{\min}(\cdot)$ . Then the local status of a given model  $m$  offered by make  $j$  is given by

$$s_{m,g} = s_{j,g}^{\min} = 0.5F_g^{\min}(p_j^{\min}) + 0.5\frac{p_j^{\min} - \min_{l(g)}\{p_{l(g)}^{\min}\}}{\max_{l(g)}\{p_{l(g)}^{\min}\} - \min_{l(g)}\{p_{l(g)}^{\min}\}}, \quad (2.2)$$

where  $p_j^{\min}$  is the price of the cheapest model offered by brand  $j$  and  $\{p_{l(g)}^{\min}\}$  is the set of minimum prices of each other brand  $l$  represented in the population of cars in circulation in geography  $g$ . Equivalent definitions can be derived when the most typical nameplate is the one with the median price  $s_{j,g}^{\text{median}}$ , the one with the highest price  $s_{j,g}^{\max}$ , and the most popular one  $s_{j,g}^{\text{mode}}$ . The most popular nameplate can be identified from the data after pooling observations across geographies. Because the ranking is geography-specific, the ensuing metric is also specific to each value of  $g$ .

In addition, we include a metric of a make's price dispersion that is operationalized as the coefficient of variation of the prices of the nameplates that belong to the make. This metric is included because the status metrics based on the most extreme prices could correlate with the dispersion of prices of the brand. Thus, by including a metric of price dispersion in our

study, we can better assess the discriminative validity of the proposed metrics of brand status. We refer to this metric as  $cv(p_j)$ .

Figure 2.2 illustrates the cumulative distributions of the four metrics of brand status for a sample of the vehicles in circulation in the metropolitan statistical area (MSA) of Washington-Arlington-Alexandria DC-VA-MDWV in 2009. These figures reveal that consumers can sometimes significantly improve their status by replacing a low-priced car for a slightly more expensive model. This is especially true for consumers who own low-priced cars. For example, if the most typical nameplate of a make is the best-selling nameplate, the plots imply that the owner of a car with a brand price of 19,000USD can improve his or her status from below 0 to a level above 0.5 by replacing the car with one of brand price above 20,000USD. However, for owners of very expensive vehicles, large status improvements involve very significant investments. For instance, the owner of a car with brand price of 40,000USD would need to buy a car with brand price of 60,000USD to improve his or her status from 0.8 to 1.

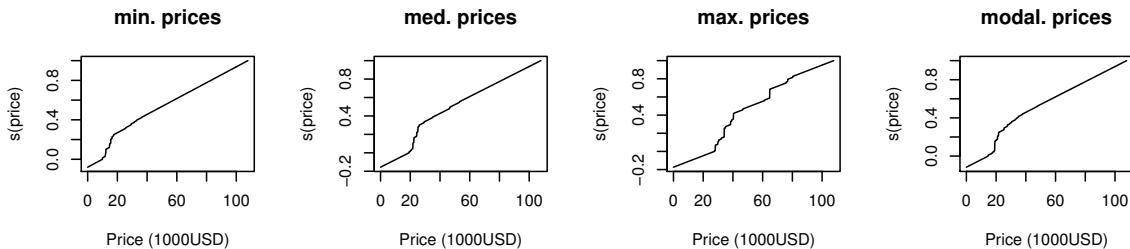


Figure 2.2: Status as a function of MSRP's (in thousands of USD) for a sample of vehicles in use in 2009

### 2.3.4 Metrics of price

The metric of status proposed in Section 2.3.3 may strongly resemble previously-proposed operationalizations of reference prices. For example, Niedrich et al. (2001) proposed that consumers' judgements of prices can be modeled using range-frequency theory. Their experimental results suggested that this range-frequency model explains subjects behavior better than other models of price references, such as those based on adaptation-level theory and

range theory. Thus, the proposed metrics of status may appear to be too closely related to perceived prices.

By definition, the proposed metric of status differs from subjective price judgements (as generated by range-frequency theory) in the following ways:

- 1) For frequently purchased goods, price judgements depend on the prices of the focal product across sellers and across time. For durable goods, reference prices are more likely determined by the prices of similar products (Mazumdar, Raj and Sinha, 2005). The prices of products that greatly differ from the focal product are not used to elaborate reference prices. In contrast, status judgments do depend on the prices of all products within the focal category.
- 2) Range-Frequency judgments of prices are based on the distribution of actual prices while range-frequency judgements of brand status are defined in terms of the distribution of perceived prices. That is, the metrics of brand status are functions of the metrics of perceived prices.
- 3) Judgments of prices are defined in terms of the distribution of all of the available instances of a price. In contrast, we define brand status in terms of the distribution of brand-specific price statistics and not in terms of the prices of each existing product member of the brand. In particular, our metrics of brand status does not consider every single available instance of price but only the minimum, maximum, median, and modal prices.
- 4) Whereas price judgments depend on a distribution of prices of items being offered for sale, status judgements depend on a distribution of prices of products owned by the population. Price judgments do not need to depend on the number of units sold nor on the number of units conspicuously used by other consumers, but status judgments do.

To ensure that the proposed status metrics in fact measure status and not perceived prices, we estimate our model using a metric of perceived prices instead of actual prices.

The perceived price of a model  $m$  is constructed as

$$p_m = 0.5F_{MSRP}(MSRP_m) + 0.5\frac{MSRP_m - \min_l\{MSRP_l\}}{\max_l\{MSRP_l\} - \min_l\{MSRP_l\}},$$

where  $MSRP_m$  is the manufacturers suggested retail price (MSRP) of model  $m$ ,  $\{MSRP_l\}$  is the set of the the MSRP's of all other new cars available, and  $F_{MSRP}(\cdot)$  is the cumulative distribution function of the elements of  $\{MSRP_l\}$ .

A plot of the perceived price  $p_m$  for a range of values of  $MSRP_m$  appears in Figure 2.3. A comparison of the plot in Figure 2.3 against the plots in Figure 2.2 suggests that perceived prices incorporate less variation than the metrics of status do. This additional variation is induced into the status metrics by the frequency of ownership of each nameplate and by the use of price statistics rather than of the entire distribution of prices. Furthermore, the status metrics vary by geography while perceived prices do not. This additional variation ensures the simultaneous identification of the two metrics in empirical studies as evidenced by the empirical results presented here.

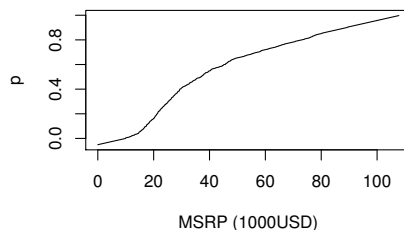


Figure 2.3: Perceived price as a function of actual price

## 2.4 Data

The proposed empirical study uses data on automobile ownership because automobiles clearly signal wealth (Belk et al., 1982; Han et al., 2010; Chiao et al., 2009; Charles et al., 2009) and thus automobiles constitute effective status signals. Data were combined from different sources, as described below.

### **2.4.1 Consumer choice data**

Car ownership and demographic data were obtained from the 2009 National Household Travel Survey (NHTS) conducted by the Federal Highway Administration. The latest survey was conducted from April 2008 to May 2009 and included 155,000 US households that, in aggregate, reported owning 309,163 vehicles. From this sample, we removed heavy trucks and observations without geographic, make, or nameplate information. Some coding errors were detected as invalid model-year combinations were reported. These observations were dropped as well. As a result, the sample was reduced to 68,552 households and 128,786 vehicles. On average, each household reported owning 1.88 vehicles.

In an initial analysis, we regarded each record of a 2009 vehicle as one observation because the record provides the information relevant to one household's car choice. This however yielded a total of 903 reported 2009 vehicles, a very small sample. Therefore, we dropped the 2009 observations and regarded the 2008 observations as the household's vehicle choice in order to enlarge our sample size. This may cause our sample of vehicles on the road to be less representative of the population because some of the 2009 vehicles we removed may have been acquired to replace older vehicles that do not appear in our final sample. The bias however can be expected to be small because the 2009 models represent only 0.8% of the entire sample (the survey was conducted early in 2009.) In fact, estimation results obtained from the two samples are qualitatively similar but we present results from the 2008 sample because these are more robust.

### **2.4.2 Reference group data**

Geographic information is necessary to define the reference groups of consumers and thus their social status and the local status of each brand. Correctly defining a consumer's reference group can be a necessary condition for the identification of social interactions in linear-in-means models (Manski, 2000). While this requirement does not necessarily apply to nonlinear models (Durlauf and Ioannides, 2010), we still need to define reference groups because the social status of a consumer is determined by the purchases of the members of the

consumer’s reference group. We define the reference group of a consumer using household location data.

The NHTS dataset includes the geographic location of each household at the Metropolitan Statistical Area (MSA) level and Core Based Statistical Area (CBSA) level. The U.S. Census Bureau defines CBSAs as follows:

“The term Core Based Statistical Area (CBSA) is a collective term for both metro[politan] and micro[politan] areas. A metro area contains a core urban area of 50,000 or more population, and a micro area contains an urban core of at least 10,000 (but less than 50,000) population. Each metro or micro area consists of one or more counties and includes the counties containing the core urban area, as well as any adjacent counties that have a high degree of social and economic integration (as measured by commuting to work) with the urban core. ”

Because the CBSAs are defined in terms of social and economic integration, they are more likely to define the reference groups within which consumers rank themselves when assessing their own social status. Empirical evidence that supports this claim was found by McShane et al. (2012), who showed that car buyers react to the purchases of other consumers living in the same, neighboring, and nearby zip codes and counties. When the authors defined reference groups at the county level rather than the zip-code level, their model yielded the best fit. Given this empirical evidence and the fact that CBSAs are defined in terms of counties, we use the CBSA geographic information to define our reference groups. Each of households in our sample is located in one of 45 different CBSAs.

The survey contained 7444 records of 2008 models with geographic information. However, we had to drop some of these observations because our estimation method requires the estimation of nameplate-specific fixed effects. Because some nameplates were seldom bought, we do not have enough observations to estimate each of these fixed effects. Accordingly, we keep those nameplates that appear in at least 16 observations. This reduces our number of observations from 7444 to 6679 (90%) and the number of nameplates reported in those observations to 118. All 45 CBSAs were represented in this sample.



### 2.4.3 Consumer demographic data

Aside from geographic information, the NHTS dataset provides a large number of demographic variables. To incorporate heterogeneity in consumer preferences for product quality and their attitude towards different metrics of status, we used a subset of these demographic variables. From eighteen reported income brackets, we computed the bracket mid-points and use them as a proxy of actual income. We refer to this variable as “Income”. We then use the reported household size and the reported number of drivers in the household to compute the number of household members who do not drive. We labeled this variable as “Passengers”. We also included a categorical variable for the educational level of the head of the household and labeled it as “Education”. Finally, we included a categorical variable that abstract the degree of urbanization of the household’s residence. This variable is denoted by “Urban”. The correlations among demographic variables appear in Table 2.1.

Table 2.1: Correlations among demographic variables.

Income	1.00			
Passengers	0.21	1.00		
Education	0.24	-0.02	1.00	
Urban	0.06	0.01	0.22	1.00
	Income	Passengers	Education	Urban

### 2.4.4 Product attribute data

Since product attributes are major determinants of a brand’s performance, we need to account for these in the model. This second dataset was obtained by crawling the web. Data on product attributes for each model and trim, such as price, dimensions, engine characteristics, warranty, etc., were collected from different online dealer websites but mainly from `consumerguideauto` and `howstuffworks.com`. This dataset includes information for 301 models, though not all variables are available for all models and thus some missing values had to be collected manually from other websites such as `edmunds.com`, `kbb.com`, and

wikipedia.org. We selected four product attributes, including engine size (henceforth referred to as “Engine.lt”), the height of the vehicle (“Height”), a dummy that equals one if the make is Asian (“Asian”), and the luxuriousness of the vehicle (“Details”). This luxury variable is an expert rating that measures the craftsmanship of the product. The aspects of craftsmanship accounted for by this expert rating are described in the reviews that consumerguideauto provide for different products. Two such reviews are:

- “Very appealing. The cabin impresses with elegant leather upholstery, expanses of wood trim, numerous padded surfaces, and top-notch workmanship. CLS63 AMG’s cabin adds sporty piano-black trim and suede accents” (2012 Mercedes-Benz CLS-Class)
- “Cabin is mostly finished in leather and soft-touch surfaces, and most switchgear works with precision. However, the upscale ambiance is compromised by some disappointing plastic trim pieces” (2012 Lincoln MKS).

We include the variable “Details” because status and luxury may correlate empirically. By including a measure of luxuriousness in our model, we can lend support to the construct validity of the proposed status metrics and better control for quality. Height is included because tall vehicles can confer a sense of power to their drivers and social status is a form of power. Thus, height and status may be correlated. The dummy for Asian origin is included because it has strong explanatory power. We include engine size for identification purposes, as discussed below.

#### **2.4.5 Instruments for marketing variables**

Because prices and the status of the brand can be determined by firms in response to demand, these product attributes can be endogenous. To correct endogeneity biases, we used an instrumental variables approach. The instrumental variables are used to instrument both for prices and for status. To generate instruments for the status variables, we computed the empirical distributions of the instrumental variables and then compute the ranking of the

Table 2.2: Correlations among vehicle attributes.  $\hat{p}_j$  is an endogeneity-corrected price variable described in Section 2.7.1.

$s_{j,g}^{\min}$	1.00									
$s_{j,g}^{\text{median}}$	0.84	1.00								
$s_{j,g}^{\max}$	0.25	0.60	1.00							
$s_{j,g}^{\text{mode}}$	0.91	0.93	0.55	1.00						
$cv(p_j)$	-0.57	-0.20	0.64	-0.27	1.00					
$\hat{p}_j$	0.61	0.64	0.40	0.60	-0.13	1.00				
Engine.lt	0.35	0.37	0.29	0.38	-0.02	0.76	1.00			
Height	-0.19	-0.19	-0.15	-0.15	0.01	0.04	0.39	1.00		
Asian	-0.37	-0.36	-0.27	-0.44	0.07	-0.18	-0.31	-0.05	1.00	
Details	0.55	0.55	0.31	0.52	-0.16	0.61	0.31	-0.24	-0.04	1.00
	$s_{j,g}^{\min}$	$s_{j,g}^{\text{median}}$	$s_{j,g}^{\max}$	$s_{j,g}^{\text{mode}}$	$cv(p_j)$	$\hat{p}_j$	Engine.lt	Height	Asian	Details

instruments for each product given by the empirical distributions. We also use the original instrumental variables to instrument for status. We denote the instrument of status by  $\tilde{s}_{j,g}$ . Price instruments are denoted by  $\tilde{p}_j$ .

We used two different instruments simultaneously. The first instrument is the average insurance premium paid for each given model, as provided by `autoinsurance.com`. We expect prices and insurance premiums to be correlated (the sample correlation equals 0.87) because prices are used by insurance companies to calculate insurance premiums. More generally, insurance premia are determined by insurance companies as functions of consumer demographics, driving records, credit scores, driving habits, and vehicle attributes such as age, cost, safety ratings, and potentially engine size (Insurance Bureau of Canada, 2012; Insurance Information Institute, 2012). While consumer-specific variable and vehicle age are not relevant here, the correlations between insurance premia and safety scores and between insurance premia and engine size can limit the validity of the proposed instrument. In particular, for an instrument to be valid, it must be uncorrelated with the unobserved product attributes. Thus, the model specification must include measures of the vehicle’s safety score and of the vehicle’s size engine so that these attributes are not lumped into the error term.

We accordingly include in our specifications the vehicle’s engine size.

We also use as instruments the nameplate’s average collision losses at the national level because of the high correlation between this variable, safety ratings, and prices. Since most consumers are unaware of the average losses of most vehicles, it is unlikely car purchases are influenced by these statistics. The unobservables affecting purchase decisions are thus very likely uncorrelated with the average losses statistics, making this variable a valid instrument. Data on different types of accident loss for different car models are available from `autoinsurance.com`. By including both average collision losses and insurance premia, we reduce the correlation between the estimation error and our instruments.

#### **2.4.6 Product category data**

We use the Environmental Protection Agency (EPA) standard to classify nameplates into categories. Because some categories contain too few models (which induces insufficient variation among alternatives within these categories), we merge “SMALL STATION WAGONS” and “MIDSIZE STATION WAGONS” into “STATION WAGONS”. Likewise, we combine all pickup trucks into “PICKUP TRUCKS”. We also merge “MINICOMPACT CARS”, “SUBCOMPACT CARS”, “MIDSIZE CARS”, and “LARGE CARS” into “CARS”. The categories “MINIVAN - 2WD”, “MINIVAN - 4WD”, “S.U.V. - 2WD”, and “S.U.V. - 4WD” are merged into “S.U.V”. Because we have a variable that classifies vehicles as “PERFORMANCE”, “LUXURY”, or neither of these, we break the “CARS” category into “CARS” and “PREMIUM CARS”. No purchases of “VANS, PASSENGER TYPE”, “VANS, CARGO TYPE”, and “TWO SEATERS” were observed. Therefore these categories were removed. This results in the following set of seven categories: “CARS”, “PREMIUM CARS”, “STATION WAGONS”, “PICKUP TRUCKS”, “PERFORMANCE”, “S.U.V.”, and “PREMIUM S.U.V.”. After discarding nameplates with too few observations (as described in Section 2.4), the observed models had the following composition: 35 cars, 16 premium cars, 6 performance cars, 11 pickup trucks, 34 SUVs, 7 premium SUVs, and 9 station wagons.

### 2.4.7 Brand perception data

To explore the internal validity of the proposed metrics of brand status, we collected measures of how consumers perceive brands. Respondents were 66 consumers who completed an brief online survey. The survey asked respondents to rate different car brands in terms of how much social status, wealth, intelligence, and refinement each brand signals. The order of the questions was randomized and so was a subset of the brands displayed. A set of least and most expensive brands in the set were used for every respondent (Chevrolet, Nissan, Porsche, and Mercedes-Benz.) Of the respondents, 36 were male and 30 female. 46 identified themselves as White, 4 as African American or Black, 8 as Asian only, 1 as Pacific Islander, 3 as Hispanic/Mexican only, 2 as White and African American, and 2 as Other. The modal household income belonged to the \$45,000 -\$49,999 bracket. The mean age was 36 years. In terms of the education, the most numerous group was the one declaring to hold a 4-year College Degree (26 respondents). 2 respondents reported a professional degree and 1 respondent reported a doctoral degree. 1 respondent reported to have completed less than high school and 9 reported to have completed high school or GED. 2 respondents regarded themselves as member of the lower lower class, 16 as members of the upper lower class, 26 as members of the lower middle class, and 22 as members of the upper middle class. Of the 66 respondents, 48 reported to have lived in one of 28 of the geographic areas for which the metrics of status were computed. The remaining 18 respondents were dropped from the sample. The survey instrument is briefly described in Appendix 2.C.

Correlations among the different perceived attributes of the brand are presented in Table 2.3. The familiarity of the respondent with the brand was measured to asses the reliability of the other measurements. The most familiar brand was Toyota with an average score of 71.31. The most unfamiliar brand was Mercury with an average score of 37.73.

Table 2.3: Correlations among perceived brand attributes.

Status	1.00				
Familiarity	0.23	1.00			
Intelligence	0.44	0.29	1.00		
Refinement	0.83	0.20	0.49	1.00	
Wealth	0.86	0.19	0.45	0.87	1.00
	Status	Familiarity	Intelligence	Refinement	Wealth

## 2.5 Validity of the metrics

To explore the internal validity of the proposed metrics of brand status, we investigate how they relate to mindset metrics of the perceived status of brands. In particular, we establish the relationship between the metrics described in Section 2.3.3 and the survey measurements described in Section 2.4.7.

First, we note, by referring to Table 2.3, that social status, refinement, and wealth are highly correlated. Intelligence, in contrast, appear to be weakly related to social status (Hyman, 1942, found intellect to be just as important as wealth but his respondents were selected from an academic environment.) Finally, familiarity is weakly but positively correlated with all other measurements. To formalize these inferences, we conducted a hierarchical factor analysis (Zinbarg, Revelle, Yovel and Li, 2005) and selected the number of factors that minimizes the Bayesian Information Criterion (BIC) of the model. The results of the factor analysis are presented in Figure 2.4 and confirm that social status, refinement, and wealth correspond to a common underlying factor while familiarity and intelligence correspond to additional factors.

To determine whether the proposed metrics of social status are good indicators of perceived status, we regressed the perceived measures on the proposed metrics of status. To account for scale usage heterogeneity, we included respondent-specific fixed effects (Rossi, Gilula and Allenby, 2001). The estimates of these fixed effects are nonetheless omitted for sake of conciseness. The results are presented in Table 2.4 and indicate that the metric  $s_{j,g}^{\min}$

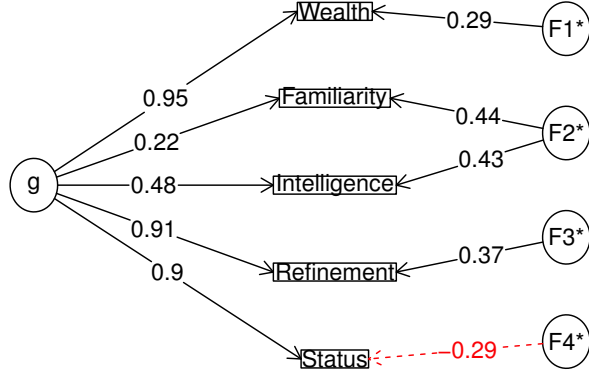


Figure 2.4: Factor analysis of perceived brand attributes. Numbers on arrows are factor loadings.

Table 2.4: Results of regressing each individual perceived brand attribute on the proposed metrics. Numbers in brackets are  $p$ -values.  $\bar{R}^2$  is the adjusted  $R^2$  when fixed effects are included.  $\bar{R}_{NFE}^2$  is computed without fixed effects.

	Explained variable				
	Status	Familiarity	Intelligence	Refinement	Wealth
$s_{j,g}^{\min}$	31.73 (0)	10.04 (0.04)	11.15 (0)	31.72 (0)	38.39 (0)
$s_{j,g}^{\text{median}}$	14.14 (0.01)	-3.47 (0.69)	8.40 (0.21)	8.26 (0.21)	12.99 (0.03)
$s_{j,g}^{\max}$	9.48 (0.18)	10.60 (0.36)	11.80 (0.19)	26.27 (0)	9.50 (0.23)
$s_{j,g}^{\text{mode}}$	-15.76 (0)	-5 (0.55)	-14.34 (0.03)	-20.37 (0)	-19.11 (0)
$cv(p_j)$	4.89 (0.26)	9.76 (0.18)	0.19 (0.97)	-4 (0.46)	7.63 (0.12)
$\bar{R}^2$	0.91	0.78	0.85	0.86	0.88
$\bar{R}_{NFE}^2$	0.91	0.77	0.83	0.86	0.89

has the most explanatory power, predicting every perceived attribute but having more weight on perceived social status, refinement, and wealth (factor F1 in Figure 2.4.)  $s_{j,g}^{\text{median}}$  explains

social status and wealth only.  $s_{j,g}^{\max}$  explains refinement, and  $s_{j,g}^{\text{mode}}$  explains all perceived attributes except familiarity (factors F1 and F2).

The regression results in Table 2.4 suggest that  $s_{j,g}^{\min}$  is a strong indicator of perceived social status but also that it associates with of other brand attributes.  $s_{j,g}^{\text{median}}$  is a more selective indicator as it only clearly explains perceived social status and wealth. Since we are concerned with only the economic aspects of social status, perceived wealth and perceived social status are indicators of our main construct and thus we conclude that  $s_{j,g}^{\text{median}}$  exhibits the best discriminant validity. The metric  $s_{j,g}^{\max}$  does not clearly explain perceived social status but does clearly explain the perceived refinement of the brand.  $s_{j,g}^{\text{mode}}$  is a strong predictor of perceived status, wealth, intelligence, and refinement. This effect is, however, negative.  $cv(p_j)$  has no clear effect on the perceived attributes of the brand. Finally, we note that the inclusion of respondent-specific fixed effects does not necessarily improve the fit of the models because the  $\bar{R}^2$  statistics do not significantly differ from the  $\bar{R}_{NFE}^2$  statistics.

Table 2.5: Results of regressing each individual perceived brand attribute on a subset of proposed metrics less affected by multicollinearity. Numbers in brackets are  $p$ -values.  $\bar{R}_{NFE}^2$  is computed without fixed effects.

	Explained variable				
	Status	Familiarity	Intelligence	Refinement	Wealth
$s_{j,g}^{\min}$	32.75 (0)	25.63 (0)	26.19 (0)	31.96 (0)	35.25 (0)
$s_{j,g}^{\text{median}}$	8.1 (0.01)	-8.35 (0.13)	3.34 (0.46)	7.43 (0.07)	5.55 (0.13)
$cv(p_j)$	15.15 (0)	34.1 (0)	26.8 (0)	13.69 (0)	13.7 (0)
$\bar{R}_{NFE}^2$	0.91	0.77	0.82	0.86	0.89

Since some of the metrics are highly correlated, their variation inflation factors were computed as  $VIF(s_{j,g}^{\min}) = 4.085$ ,  $VIF(s_{j,g}^{\text{median}}) = 7.457$ ,  $VIF(s_{j,g}^{\max}) = 7.782$ ,  $VIF(s_{j,g}^{\text{mode}}) = 6.582$ , and  $VIF(cv(p_j)) = 4.919$ . Among the different subsets of the five metrics, the largest



subset that ensures VIF's below a value of four is obtained by removing  $s_{j,g}^{\max}$  and  $s_{j,g}^{\text{mode}}$ , so that  $VIF(s_{j,g}^{\min}) = 3.029$ ,  $VIF(s_{j,g}^{\text{median}}) = 2.727$ , and  $VIF(cv(p_j)) = 1.436$ . Regression results for this subset of variables are presented in Table 2.5 and appear to be qualitatively consistent with the estimates in Table 2.4 in that both sets of estimates suggest that  $s_{j,g}^{\text{median}}$  has the best discriminant validity to measure perceived social status.

In addition, we computed standard measures of validity for the pairs formed by combining the measures of perceived status with each of the proposed metrics of status. We calculated both Cronbach's alpha and McDonald's omegas (Zinbarg et al., 2005) for these pairs, for all the proposed metrics, and for two subsets of metrics that best explain status (according to the estimates in Tables 2.4 and 2.5). When analyzing models with more than two dimensions, we computed the BIC of the models for all possible numbers of factors and chose to report the results associated with the number of factors that minimized this measure of fit. The results of these analyses are summarized in Table 2.6.

Table 2.6: Validity measures for perceived brand status and the proposed metrics.  $\alpha$  is Cronbach's alpha.  $\omega_T$  and  $\omega_H$  are McDonald's total and hierarchical omegas.

	Metrics included							
$s_{j,g}^{\min}$	x					x	x	x
$s_{j,g}^{\text{median}}$		x				x	x	x
$s_{j,g}^{\max}$			x			x		
$s_{j,g}^{\text{mode}}$				x		x	x	
$cv(p_j)$					x	x		x
Factors	1	1	1	1	1	3	1	1
BIC						4101.71	464.16	591.92
$\alpha$	0.9	0.73	0.54	0.75	0.24	0.82	0.92	0.74
$\omega_T$	0.8	0.74	0.5	0.73	0.22	0.97	0.91	0.78
$\omega_H$						0.9	0.91	0.78

The values of the Cronbach's alphas and the McDonald's omegas confirm the inferences drawn from the regression analysis. Internal consistency is low when we regard the metrics

$s_{j,g}^{\max}$  and  $cv(p_j)$  as alternative measures of perceived social status. In contrast, consistency is high when we rely on  $s_{j,g}^{\min}$ ,  $s_{j,g}^{\text{median}}$ , and  $s_{j,g}^{\text{mode}}$ . In fact, consistency is highest when we include these three metrics simultaneously. The methodological implication of these results is that we can best approximate perceived social status by using the three metrics  $s_{j,g}^{\min}$ ,  $s_{j,g}^{\text{median}}$ , and  $s_{j,g}^{\text{mode}}$  altogether. In terms of managerial implications, we have that the perceived social status of a brand is better predicted by the minimum and median prices in a product line together with the price of the most sold product of the brand. Metrics of status based on median prices have however the best discriminant validity.

## 2.6 Robustness of the metrics

We have defined the proposed metrics of status using geographical areas to define consumer reference groups. This definition assumes that consumers observe the consumption of a representative sample of the population of consumers in their geographical area. This implies both that consumers have the same reference groups and that they give equal weight to each member of the reference group.

The assumption that consumers have the same reference group could be violated because, in reality, individuals live and work close to those who are to some extent similar to them. That is, consumers may be subject to selective sampling. Selective sampling is likely to occur because high-income individuals live surrounded by high-income individuals and low-income consumers live surrounded by low-income consumers. If segregation is very high in a given geography, consumers may not be able to observe the consumption of those with very different socioeconomic background. Thus, high-income consumers may underestimate the status of the products they own while low-income consumers may overestimate the status of their consumption.

The assumption that consumers give equal weight to each member of their reference groups could be violated because individuals could give more weight to comparisons against those closer to themselves (Burger, Soroka, Gonzago, Murphy and Somervell, 2001). This form of weighted sampling could also occur because consumers may interact more often

with neighbors and other akin to themselves. If every interaction results in a comparison, consumers will undergo a larger number of comparisons against those who are similar to themselves. Thus, weighted sampling is equivalent to oversampling from a subset of consumers who are similar to the focal consumer.

The consequences of selective and weighted sampling are similar. If these processes take place, the range of variation of the actually perceived status of a product may be smaller than the range of variation of the status abstracted by the proposed metrics. Preferences for social status may then be underestimated and the measured effects may be understated. It is therefore useful to assess the magnitude of the potential bias induced by selective and weighted sampling.

While the available data does not allow us to directly observe selective and weighted sampling, we can assess whether their effects are present as well as their magnitude. We accordingly first determine how big are the differences between the status indicated by the proposed metrics and perceived status. To measure the magnitude of these differences, we compute, for all proposed metrics, the ratio  $r_{j,g(i)} = s_{j,g}^i / \text{Status}_{j,g(i)}$ , where  $i = 1, \dots, N$  indexes the survey respondents and  $\text{Status}_{j,g(i)}$  is the status of brand  $j$  as perceived by respondent  $i$  living in geography  $g$ .  $s_{j,g}^i$  represents the four proposed metrics of status. We then plot the distributions of these ratios (see Figure 2.5) and compute the distributional statistics (refer to Table 2.7.) The plots suggest that most ratios cluster together at values below two. More precisely, as suggested by the summary statistics in Table 2.7, 50% of the errors lie between 0.44 and 1.15, 75% of the errors lie between zero and 1.15, with the mean ratios lying within 15% of their desired value of one.

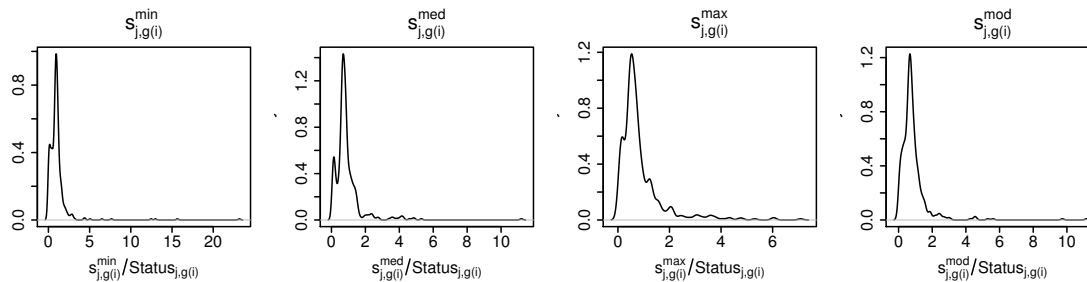


Figure 2.5: Distribution of differences between the proposed metrics and perceived status

Having estimated the magnitude of the differences between the proposed metrics of status

Table 2.7: Summary statistics of the distributions of the ratio  $r_{j,g(i)} = s_{j,g}/\text{Status}_{j,g(i)}$ .

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
$s_{j,g}^{\min}$	0.00	0.50	0.91	1.07	1.15	23.18
$s_{j,g}^{\text{median}}$	0.05	0.58	0.74	0.91	1.00	11.20
$s_{j,g}^{\max}$	0.04	0.44	0.62	0.87	0.96	7.08
$s_{j,g}^{\text{mode}}$	0.02	0.46	0.69	0.86	0.96	11.16

and perceived status, we proceed to investigate whether these differences can be explained by the variables that determine the degree to which selective and weighted sampling occur. Both consumer segregation and population size can affect how representative the reference groups of consumers are. Individual circumstances and perceptions of the self may also affect how consumers evaluate the status of others and the brands their own. Thus segregation, population size, and consumer demographics should be able to explain the magnitude of the error in the prediction of perceived status by the proposed metrics.

We test whether these variables can explain the prediction error by regressing  $r_{j,g(i)}^{\text{error}}$  on income bracket, perceived social class, age, and education as reported by respondents (refer to Section 2.4.7.) Indices of segregation and population size at the MSA level for year 2000 were obtained from the RANDs Center for Population Health and Health Disparities (CPHHD). We used population-weighted averages to obtain indices at the CBSA level. (For more details on the nature of these indices, please refer to Escarce, Lurie and Jewell, 2011). As several segregation indices are provided by the CPHHD, we present results for those that provided best statistical fit. These indices and the size of the CBSA's in number of inhabitants were included in a series of stepwise regressions that optimized the regression's Akaike Information Criterion (AIC). Regression results are presented in Tables 2.8-2.10.

The results reported in Table 2.8 indicate that self-reported social class has a positive effect in the prediction error. Consumers who regard themselves as members of a higher class are more likely to perceive the status of brands to be lower than predicted by the proposed metrics. A similar result holds for older and more educated consumers. Population size and segregation appear to have opposite effects. Respondents living in large populations

Table 2.8: Variables that determine the differences between perceived brand status and the proposed metrics. Numbers in brackets are  $p$ -values.

	$s_{j,g}^{\min}$	$s_{j,g}^{\text{median}}$	$s_{j,g}^{\max}$	$s_{j,g}^{\text{mode}}$
Int	-5.41 (6e-4)	-0.04 (0.95)	0.38 (0.73)	1 (0.31)
Income	-	-0.03 (0.11)	-0.02 (0.16)	-
Class	1.4 (8e-4)	0.6 (7e-3)	0.52 (0.01)	0.64 (6e-3)
Age	0.09 (3e-4)	-	-	0.02 (0.07)
Education	-	0.09 (0.09)	0.08 (0.07)	-
Pop. Size	-	7e-8 (0.09)	5e-8 (0.56)	6e-8 (0.11)
Segregation	-	-1.38 (0.09)	-2.02 (0.26)	-1.38 (0.11)
$s_{j,g}^{\min}$	0.37 (0.85)	0.32 (0.72)	-2.25 (0.11)	0.67 (0.56)
$s_{j,g}^{\text{median}}$	11 (4e-3)	4.91 (3e-3)	-1.56 (0.54)	5.49 (9e-3)
$s_{j,g}^{\max}$	-1.64 (0.58)	-0.5 (0.69)	3.93 (0.04)	-0.65 (0.69)
$s_{j,g}^{\text{mode}}$	-1.81 (0.64)	-2.39 (0.14)	2.73 (0.32)	-2.06 (0.34)

are also more likely to perceive brand status to be lower than as predicted by the metrics. Respondents living in highly segregated areas, on the other hand, are more likely to report higher brand status (relative to the status indicated by the metrics) than respondents living in less segregated areas. As for the effect of brand status on the prediction error, we find that brands with a high status in terms of their median prices are likely to be perceived as having less status relative to the status predicted by the metrics. One possible interpretation of this result is that the status of brands with a high median price is more likely to be

Table 2.9: Variables that determine the differences between perceived brand status and the proposed metrics (continued). Numbers in brackets are  $p$ -values.

	$s_{j,g}^{\min}$	$s_{j,g}^{\text{median}}$	$s_{j,g}^{\max}$	$s_{j,g}^{\text{mode}}$
Age $\times s_{j,g}^{\min}$	0.05 (0.14)	–	–	-2e-3 (0.89)
Age $\times s_{j,g}^{\text{median}}$	-0.16 (0.01)	–	–	-0.07 (0.02)
Age $\times s_{j,g}^{\max}$	0.04 (0.43)	–	–	0.02 (0.34)
Age $\times s_{j,g}^{\text{mode}}$	-0.03 (0.61)	–	–	0.03 (0.31)
Class $\times s_{j,g}^{\min}$	-0.22 (0.66)	-0.58 (0.03)	-0.56 (0.02)	-0.61 (0.04)
Class $\times s_{j,g}^{\text{median}}$	-2.23 (0.02)	-0.75 (0.14)	-0.37 (0.47)	-1.13 (0.04)
Class $\times s_{j,g}^{\max}$	-0.27 (0.71)	-0.13 (0.73)	-0.16 (0.64)	-0.31 (0.45)
Class $\times s_{j,g}^{\text{mode}}$	1.23 (0.20)	0.98 (0.05)	0.67 (0.15)	1.48 (6e-3)

underestimated.

The results reported in Tables 2.9-2.10 suggest that different consumer groups may perceive differently the status of brands with different status levels. The negative signs of the interaction effects between social class and the metrics indicate that self-reported higher-class consumers are more likely to perceive the status of brands favorably in relation to the status levels predicted by the first two metrics. This means that the proposed metrics can more accurately predict a) the status of high-status brands as perceived by high class consumers; and b) the status of low-status brands as perceived by low class consumers. A similar result holds for the effect of the interaction of consumer age and brand status.

We also find that population size and segregation levels interact mainly with the metric  $s_{j,g}^{\min}$  and, to some extent, with the metric  $s_{j,g}^{\text{mode}}$ . We find that the interactions with  $s_{j,g}^{\min}$  are

Table 2.10: Variables that determine the differences between perceived brand status and the proposed metrics (continued). Numbers in brackets are  $p$ -values.

	$s_{j,g}^{\min}$	$s_{j,g}^{\text{median}}$	$s_{j,g}^{\max}$	$s_{j,g}^{\text{mode}}$
Pop. Size $\times s_{j,g}^{\min}$	–	–	3e-7 (9e-3)	–
Pop. Size $\times s_{j,g}^{\text{median}}$	–	–	6e-8 (0.80)	–
Pop. Size $\times s_{j,g}^{\max}$	–	–	2e-8 (0.92)	–
Pop. Size $\times s_{j,g}^{\text{mode}}$	–	–	3e-7 (0.12)	–
Segregation $\times s_{j,g}^{\min}$	–	–	6.23 (9e-3)	–
Segregation $\times s_{j,g}^{\text{median}}$	–	–	4.34 (0.31)	–
Segregation $\times s_{j,g}^{\max}$	–	–	-2.7 (0.43)	–
Segregation $\times s_{j,g}^{\text{mode}}$	–	–	-9.31 (0.06)	–
$\bar{R}^2$	0.144	0.162	0.366	0.162

positive, indicating that. the larger and more segregated the population is, the lower the perceived status of brands with expensive cheapest vehicles will be. This implies that the metric  $s_{j,g}^{\min}$  can better predict the perceived status of brands with expensive cheapest cars in smaller and less segregated populations. This could be expected because in smaller and less segregated populations consumers are more likely to more accurately observe the actual population of vehicles on the road. Brands with expensive cheaper cars may be also more salient in the minds of consumers.

Finally, we note that the  $\bar{R}^2$  measures of explained variance are relatively low. This suggests that including variables other than the demographic and geography-specific variables considered here could help explain the differences between the proposed metrics of status

and perceived status. While this does not completely rule out the possibility that selective and weighted sampling have influenced our collected measures of perceived status, it suggests that selective sampling is not a major driver of the differences between perceived status and the status levels indicated by the proposed metrics. This follows from the fact that selective sampling can only occur in large and highly segregated geographies, but we have shown these two variables have modest explanatory power.

## 2.7 Relevance of the metrics

### 2.7.1 Model

We propose a hierarchical nested MNL model to account for rich substitution patterns and for heterogeneity in consumer preferences for different product attributes. We write the utility that a household  $i, i = 1, \dots, N$ , in geography  $g(i)$ , draws from buying a model  $j = 1, \dots, J_i$  as

$$u_{i,j} = V_{i,j} + \epsilon_{i,j} = \delta_j + \phi_{g(i)} + x_{j,i}^T \beta + \epsilon_{i,j}, \quad (2.3)$$

where  $V_{i,j}$  and  $\epsilon_{i,j}$  are the observed and unobserved components of utility, respectively. The observed utility is defined as a function of  $x_{j,i}$ , the vector that includes the interactions of the alternative-specific attribute levels and a set of consumer demographics  $d_i$ . The alternative-specific attributes,  $[s_{j,g(i)}, p_j, a_j^T]^T$ , include the car's local status  $s_{j,g(i)}$ , price  $p_j$ , and the other  $A - 2$  attributes  $a_j$  that were described in Section 2.4. The coefficients  $\beta$  are the weights of the different variables in  $x_{j,g(i)}$ . The terms  $\delta_j$  and  $\phi_{g(i)}$  are vehicle- and geography-specific fixed effects, respectively.

The inclusion of product attributes in the model may not account for all similarities among different vehicles and thus may not yield very precise substitution patterns. To address this potential source of estimation error, we implement a nested structure in which the nests are the categories described in Section 2.4. We accordingly let the unobserved shocks be of the form

$$\epsilon_{i,j} = \zeta_{i,k} + (1 - \rho)\omega_{i,j}, \quad (2.4)$$



where the random errors  $\zeta_{i.k}$  and  $\omega_{i,j}$  are distributed such that  $\epsilon_{i,j}$  are i.i.d. extreme value (Cardell, 1997). The inclusive value  $\rho$  determines the amount of within-category variance.

The average effect of price can be derived from a regression of the fixed effects  $\delta_j$  on the vector  $\hat{x}_j = [\hat{s}_j, \hat{p}_j, a_j^T]^T$ , where  $\hat{s}_j$  and  $\hat{p}_j$  are the status and prices predicted by the instruments  $z_j = [\tilde{s}_j, \tilde{p}_j, a_j^T]^T$  (described in Section 2.4). For example, the vector of projected prices is  $\hat{p} = M_p p$ , where  $\hat{p} = [\hat{p}_1, \dots, \hat{p}_J]^T$ ,  $p = [p_1, \dots, p_J]^T$ , and  $M_p = Z(Z^T Z)^{-1} Z^T$  is the projection matrix defined in terms of the matrix of instruments  $Z = [z_1, \dots, z_J]^T$ . Analogously, the average effect of status can be derived from a regression of  $\phi_{g(i)}$  on,  $\hat{s}_{g(i)}$ , the status predicted by the instrument  $\tilde{s}_{g(i)}$ . We accordingly let

$$\begin{aligned}\delta_j &= \gamma^T \hat{x}_j + \xi_j \\ \phi_g &= \alpha^T \hat{s}_{g(i)} + \psi_g\end{aligned}\tag{2.5}$$

where  $\xi_j \sim N(0, \sigma_\xi^2)$  and  $\psi_g \sim N(0, \sigma_\psi^2)$ . This is equivalent to a 2SLS regression that yields endogeneity-corrected estimates of the coefficients of the average preferences for price and status (see, e.g. Chintagunta, Dube and Goh, 2005). The matrices  $M_{s_j}$  and  $M_{s_g}$  are likewise defined as the projection matrices that map  $s_{j,g(i)}$  into  $\hat{s}_j$  and  $\hat{s}_{g(i)}$ .

Since price determines utility directly and indirectly through status, the elasticities of the proposed model are not those of the standard nested logit model. To derive price elasticities for the proposed model, we first note that the total derivative of  $P_{ik}$ , the probability of consumer  $i$  purchasing a nameplate  $l$ , with respect to  $p_j$ , the price of nameplate  $j$ , is given by

$$\begin{aligned}\frac{dP_{il}}{dp_j} &= \frac{\partial P_{il}}{\partial p_j} + \sum_{n=1}^J \frac{\partial P_{il}}{\partial \hat{p}_n} \frac{d\hat{p}_n}{dp_j} \\ &+ \sum_{n=1}^J \sum_{h=1}^H \left[ \frac{\partial P_{il}}{\partial s_{hng(i)}} + \frac{\partial P_{il}}{\partial \hat{s}_{hn}} \frac{d\hat{s}_{hn}}{ds_{hng(i)}} + \frac{\partial P_{il}}{\partial \hat{s}_{hg(i)}} \frac{d\hat{s}_{hg(i)}}{ds_{hng(i)}} \right] \frac{ds_{hng(i)}}{dp_j},\end{aligned}\tag{2.6}$$

where  $H$  is the number of status metrics and the  $h$ -th status metric of nameplate  $n$ ,  $s_{hng(i)}$ , is specific to each geography  $g(i)$ . We let  $\beta_p$  be the subvector of  $\beta$  that corresponds to the interactions of price with demographics. Likewise, we let  $\beta_h$  be the subvector of  $\beta$  coefficients that correspond to the interactions of the  $h$ -th status metric with the demographic variables. Let  $\gamma_{\hat{p}}$  be the coefficient of  $\hat{p}$  in the regression of  $\delta_j$  given by (2.5). Define  $\alpha_p$  and  $\alpha_h$  in an

analogous way.

The algebraic manipulations described in Appendix 2.A allow us to break (2.6) down into the sum of two elasticity components such that  $E_{P_{il},p_j} = E_{P_{il},p_j}^D + E_{P_{il},p_j}^I$ . The first component,  $E_{P_{il},p_j}^D$ , embodies the direct effect of price on demand as described by standard models that do not include status metrics. The second component,  $E_{P_{il},p_j}^I$ , captures the indirect effect that price has on demand through brand status. The two components are accordingly given by

$$E_{P_{il},p_j}^D = p_j \frac{\partial \log P_{il}}{\partial V_{ij}} \beta_p^T d_i + p_j \sum_{n=1}^J \frac{\partial \log P_{il}}{\partial V_{in}} \gamma_p M_{p(n,j)}$$

$$E_{P_{il},p_j}^I = p_j \sum_{n=1}^J \left[ \frac{\partial \log P_{il}}{\partial V_{in}} \sum_{h=1}^H (\beta_h^T d_i + \gamma_h M_{s_{hn}(n,j)} + \alpha_h M_{s_g(n,j)}) \frac{ds_{hng(i)}}{dp_j} \right].$$

where

$$\frac{\partial \log P_{il}}{\partial V_{in}} = \begin{cases} -P_{in} - \frac{1-\rho}{\rho} P_{ik(n)} + \frac{1}{\rho} & \text{if } l = n. \\ -P_{in} - \frac{1-\rho}{\rho} P_{ik(n)} & \text{if } k(l) = k(n) \\ -P_{in} & \text{if } k(l) \neq k(n) \end{cases}$$

and  $M_{(\cdot)(n,j)}$  is the  $(n, j)$  entry of the projection matrix  $M_{(\cdot)}$ .

In order to link the thus computed elasticities with the actual prices set by manufacturers rather than with perceived prices only, these individual-level elasticities must be multiplied by the elasticities of perceived prices with respect to actual prices. This adjustment yields elasticities of purchase probabilities with respect to actual prices. Finally, individual-level elasticities must be aggregated across consumers. We follow Ben-Akiva and Lerman (1985) to write the aggregate elasticities as

$$E_{P_i,p_j} = \frac{\sum_{i=1}^N P_{il} E_{P_{il},p_j}}{\sum_{n=1}^N P_{il}}. \quad (2.7)$$

The inclusion of the status metrics into the model generates the additional elasticity component  $E_{P_{il},p_j}^I$ . This additional component is a function of the prices of all options in the choice set because a change in the price of the focal option affects the status of all other options. In a more standard model that does not include status metrics, this component does not exist and thus the link between the prices of the non-focal option  $j$  and the elasticity of

demand is weaker. Thus, this model can describe substitution patterns that are richer than those described by a model without status metrics. For example, the model allows for choice alternatives that are very different in terms of their attributes to become close substitutes if they have similar status. Changes in the prices of certain options affect the status of the entire brand and thus the elasticities between options that belong to the same brand may be strong. Furthermore, substitution patterns can be highly asymmetric because the prices of the most typical options may have a much stronger effect on status than the prices of non-typical options.

## **2.7.2 Results**

The model was estimated using Markov chain Monte Carlo (MCMC) methods. The details of the estimation procedure are presented in Appendix 2.B. To establish a benchmark, we first estimate a model specification in which we do not include any metric of status. Then, to test the relevance of the four different status metrics and a metric of price dispersion, we estimate five different specifications, each including one of the metrics. Finally, to directly compare the power of each metric, we estimate a specification that includes the five metrics. These metrics were described in detail in Section 2.3.3.

### **2.7.2.1 Preference estimates**

Estimates of the  $\lambda$  parameters appear in Tables 2.11, 2.12, and 2.13. Estimation results for the entries of the  $\gamma$  vector of each specification appear in Table 2.14. Table 2.15 presents estimates of the  $\alpha$  parameters as well as Deviance Information Criteria (DIC) (Spiegelhalter, Best, Carlin and Van Der Linde, 2002) scores for each of the specifications.

The estimation results reported in Table 2.11, Table 2.12, and Table 2.12 show that demographics are important in explaining preferences for product attributes and signals of status. As expected, higher income correlates with reduced price sensitivity and with stronger preferences for large engines. Better off households prefer more expensive and higher-performance vehicles.

Table 2.11: Estimates of  $\lambda$  coefficients. Numbers on top are posterior means (multiplied by 1000). Numbers in brackets are the probabilities of the estimate having sign different to that of its mean.

Variable	Specification						
	I	II	III	IV	V	VI	VII
$s_{j,g}^{\min}$ x Income		73 [0]					39 [0]
$s_{j,g}^{\min}$ x Passengers		-196 [0]					-403 [0]
$s_{j,g}^{\min}$ x Education		120 [0]					454 [0]
$s_{j,g}^{\min}$ x Urban		121 [0]					342 [0]
$s_{j,g}^{\text{median}}$ x Income			143 [0]				293 [0]
$s_{j,g}^{\text{median}}$ x Passengers			-188 [0]				-23 [0]
$s_{j,g}^{\text{median}}$ x Education			16 [0]				-47 [0]
$s_{j,g}^{\text{median}}$ x Urban			34 [0]				280 [0]
$s_{j,g}^{\max}$ x Income				7 [0]			376 [0]
$s_{j,g}^{\max}$ x Passengers				-118 [0]			161 [0]
$s_{j,g}^{\max}$ x Education				33 [0]			-1091 [0]
$s_{j,g}^{\max}$ x Urban				-47 [0]			-519 [0]
$s_{j,g}^{\text{mode}}$ x Income					-41 [0]		-516 [0]
$s_{j,g}^{\text{mode}}$ x Passengers					-286 [0]		-117 [0]
$s_{j,g}^{\text{mode}}$ x Education					215 [0]		599 [0]
$s_{j,g}^{\text{mode}}$ x Urban					-90 [0]		-221 [0]

Table 2.12: Estimates of  $\lambda$  coefficients (continued). Numbers on top are posterior means (multiplied by 1000). Numbers in brackets are the probabilities of the estimate having sign different to that of its mean.

Variable	Specification						
	I	II	III	IV	V	VI	VII
$cv(p_j)$ x Income						9 [0]	-433 [0]
$cv(p_j)$ x Passengers						-51 [0]	-373 [0]
$cv(p_j)$ x Education						-1 [0]	1281 [0]
$cv(p_j)$ x Urban						-59 [0]	526 [0]
Price x Income	212 [0]	189 [0]	130 [0]	148 [0]	185 [0]	197 [0]	36 [0]
Price x Passengers	74 [0]	150 [0]	125 [0]	16 [0]	188 [0]	21 [0]	206 [0]
Price x Education	13 [0]	-74 [0]	-24 [0]	92 [0]	-110 [0]	23 [0]	-58 [0]
Price x Urban	424 [0]	326 [0]	348 [0]	441 [0]	398 [0]	359 [0]	221 [0]
Engine.lt x Income	426 [0]	488 [0]	415 [0]	490 [0]	457 [0]	432 [0]	346 [0]
Engine.lt x Passengers	-89 [0]	-124 [0]	-19 [0]	32 [0]	-106 [0]	-26 [0]	-101 [0]
Engine.lt x Education	-575 [0]	-558 [0]	-541 [0]	-658 [0]	-549 [0]	-553 [0]	-361 [0]
Engine.lt x Urban	-357 [0]	-302 [0]	-325 [0]	-391 [0]	-334 [0]	-275 [0]	-148 [0]
Height x Income	-417 [0]	-478 [0]	-469 [0]	-569 [0]	-541 [0]	-475 [0]	-259 [0]
Height x Passengers	626 [0]	505 [0]	476 [0]	526 [0]	639 [0]	589 [0]	695 [0]
Height x Education	-35 [0]	26 [0]	78 [0]	119 [0]	97 [0]	-3 [0]	-267 [0]
Height x Urban	-271 [0]	-236 [0]	-241 [0]	-192 [0]	-243 [0]	-308 [0]	-405 [0]

Table 2.13: Estimates of  $\lambda$  coefficients. Numbers on top are posterior means (multiplied by 1000). Numbers in brackets are the probabilities of the estimate having sign different to that of its mean.

Variable	Specification						
	I	II	III	IV	V	VI	VII
Asian x Income	22 [0]	51 [0]	55 [0]	25 [0]	-4 [0]	21 [0]	-63 [0]
Asian x Passengers	-11 [0]	-58 [0]	-49 [0]	-18 [0]	-108 [0]	-2 [0]	-97 [0]
Asian x Education	263 [0]	296 [0]	274 [0]	247 [0]	353 [0]	268 [0]	444 [0]
Asian x Urban	118 [0]	155 [0]	130 [0]	90 [0]	82 [0]	137 [0]	123 [0]
Details x Income	87 [0]	-27 [0]	-40 [0]	22 [0]	81 [0]	42 [0]	-7 [1]
Details x Passengers	-258 [0]	-202 [0]	-207 [0]	-275 [0]	-162 [0]	-311 [0]	-103 [0]
Details x Education	75 [0]	151 [0]	207 [0]	178 [0]	78 [0]	122 [0]	36 [0]
Details x Urban	48 [0]	53 [0]	124 [0]	102 [0]	148 [0]	52 [0]	-36 [0]

Other estimates that indicate the face validity of our results are, for example, those showing that the more urban consumers prefer smaller engines and shorter vehicles. Urban consumers are also more interested in Asian cars than rural consumers are. Households with many passengers prefer tall vehicles with small engines and little luxury, such as minivans. Educated householders are more price sensitive, prefer smaller engines, and Asian brands.

The coefficients that relate income to the preferences for status are positive for all status metrics except  $s_{j,g}^{\text{mode}}$ . Because the results in Section 2.5 indicate that perceived status and  $s_{j,g}^{\text{mode}}$  are negatively correlated, these signs of the preference estimates imply that the higher the income of the household, the stronger the preference for high-status makes. These results must be interpreted together with the sign of the estimated effect of income on preferences for price dispersion, which indicates that higher income correlates with preferences for lower price dispersion (according to specification VII). This finding suggests that these preferences

for expensive cheapest and most expensive models are not simply preferences for low price dispersion but preferences for high-status brands that: a) do not dilute their status by offering affordable products; and b) offer very expensive aspirational products (products that signal refinement, as concluded from the results in Section 2.5.)

We also find that preferences for status vary with other demographics. For instance, households with large numbers of non-drivers appear to prefer brands that score low in most metrics of status. Urban households prefer brands whose minimum and median prices rank high but whose modal and maximum prices rank low (high-status and low-refinement brands). Educated households clearly prefer brands whose lowest price ranks high but whose highest price ranks not too high. That is, educated households appear to prefer brands that signal low status, low refinement, but high intelligence.

Table 2.14: Estimation results for the  $\gamma$  vector of average preferences for different car attributes. Numbers on top are means. Numbers in brackets are the probabilities of the estimate having sign different to that of its mean.

Sp.	$s_{j,g}^{\min}$	$s_{j,g}^{\text{median}}$	$s_{j,g}^{\max}$	$s_{j,g}^{\text{mode}}$	$\text{cv}(p_j)$	Price	Engine	Height	Asian	Detail	int.
I	–	–	–	–	–	-0.34	0.19	0	0.14	0.14	-0.39
	–	–	–	–	–	[0]	[0.05]	[0.49]	[0.02]	[0.03]	[0]
II	0.15	–	–	–	–	-0.4	0.25	-0.04	0.18	0.11	-0.35
	[0.06]	–	–	–	–	[0]	[0.01]	[0.37]	[0.02]	[0.05]	[0]
III	–	0.09	–	–	–	-0.34	0.19	-0.01	0.16	0.11	-0.28
	–	[0.1]	–	–	–	[0]	[0.03]	[0.41]	[0.01]	[0.09]	[0]
IV	–	–	0.11	–	–	-0.3	0.13	0.01	0.15	0.15	-0.26
	–	–	[0.05]	–	–	[0]	[0.17]	[0.4]	[0]	[0.02]	[0]
V	–	–	–	0.16	–	-0.38	0.18	0	0.19	0.12	-0.3
	–	–	–	[0.01]	–	[0]	[0.02]	[0.48]	[0]	[0.05]	[0]
VI	–	–	–	–	0	-0.3	0.19	-0.06	0.11	0.15	-0.32
	–	–	–	–	[0.53]	[0.01]	[0.02]	[0.2]	[0.07]	[0.04]	[0]
VII	-3.02	-2.61	9.14	-2.18	-8.68	-0.33	0.21	-0.07	0.14	0.19	-0.22
	[0]	[0]	[0]	[0]	[0]	[0]	[0.03]	[0.19]	[0]	[0.01]	[0]

The results of the estimation of the  $\gamma$  vector indicate that, for all specifications, price has

Table 2.15: Estimation results for the  $\alpha$  vector of geography-specific effects of status metrics. Numbers on top are means. Numbers in brackets are the probabilities of the estimate having sign different to that of its mean.

Spec.	$s_{j,g}^{\min}$	$s_{j,g}^{\text{median}}$	$s_{j,g}^{\max}$	$s_{j,g}^{\text{mode}}$	$\text{cv}(p_j)$	Int.	DIC
I	– –	– –	– –	– –	– –	0 [0.51]	66876.87
II	0 [0.43]	– –	– –	– –	– –	0 [0.5]	66905.82
III	– –	0 [0.5]	– –	– –	– –	0 [0.4]	66865.27
IV	– –	– –	0 [0.5]	– –	– –	0 [0.46]	66823.1
V	– –	– –	– –	0 [0.49]	– –	0 [0.52]	66913.1
VI	– –	– –	– –	– –	– [0.53]	0 [0.5]	66980.68
VII	0 [0.46]	0 [0.51]	0 [0.5]	0 [0.42]	0 [0.49]	0 [0.4]	66968.63

a negative average effect. In average, consumers prefer vehicles with larger engines, Asian brands, and vehicles with elaborated details (luxury). The signs of all  $\gamma$  coefficients are stable (when clearly different from zero) across specifications, including the full specification with all metrics.

The signs of the estimates also indicate that the average preference for status differs across status metrics. The estimates of the specifications with a single status metric suggest that consumers prefer high status vehicles in average. The estimates of the specification that includes all status metrics are, however, different. Because specification VII is more comprehensive, we favor the interpretation suggested by the specification that includes all the metrics. According to this specification, the coefficients of  $s_{j,g}^{\min}$ ,  $s_{j,g}^{\text{median}}$ , and  $s_{j,g}^{\text{mode}}$  are negative. This suggests that, on average, consumers prefer cars whose make does not have very expensive cheapest, median, and most sold nameplates (low status but high refinement



brands.) On the other hand, consumers prefer, on average, nameplates whose make's most expensive is expensive. This set of results would appear to suggest that consumers prefer brands with large price dispersion. However, the negative sign of the coefficient of  $cv(p_j)$  rules out this explanation. On average, consumers are averse to brands with large price dispersion but prefer brands with large status dispersion.

The estimates provided in Table 2.15 offer two insights. The first insight is that none of the geographic-specific fixed effects is statistically different from zero. The average status consumed locally does not affect consumer choices other than through the actual distribution of consumed status (as abstracted by the status metrics.) The second insight provided by Table 2.15 follows from the DIC scores presented therein. These scores indicate that two specifications that include status metrics outperform the baseline specification. These specifications are the ones that include the metrics  $s_{j,g}^{\text{median}}$  and  $s_{j,g}^{\text{max}}$ . This suggests that these two metrics do explain consumer behavior by adding explanatory power beyond that of the vehicle attributes typically reported (e.g., price, dimensions, performance, etc.)

### 2.7.2.2 Price elasticities

In what follows, we present price elasticities for a subset of selected nameplates. We compute these price elasticities using two different model specifications. First we use the specification that includes no status metric to be able to compare our price elasticities against those in the extant literature. These elasticities appear in Table 2.16. Then we use the specification that includes all the status metrics. This allows us to assess the importance of including the status metrics. We used multiple draws from the posterior distributions of the estimates to obtain multiple draws of the posterior distributions of the corresponding elasticities. The posterior means of the thus generated price elasticities appear in Tables 2.17-2.19.

The estimates on Table 2.16 reveal that the computed elasticities appear to differ from those reported elsewhere. These differences are however superficial and stem from the fact that we present conditional choice elasticities rather than choice elasticities. To derive choice elasticities using our estimates, one would need to incorporate purchase incidence elasticities

Table 2.16: Posterior means of demand elasticities  $E_{P_{il}, p_j}$  derived from a model specification that does not include any metric of social status. The elasticities correspond to a 1000USD change in the price  $p_j$  of the nameplates listed on the first column. Cars are premium cars and SUVs are premium Sports Utility Vehicles.

Class Make Nameplate	$l$							
	Car	Car	Car	Car	Car	SUV	Car	SUV
	Cadillac	M-Benz	Infiniti	BMW	Lincoln	Lincoln	Lexus	Lexus
	CTS	C-Class	G37	3-Series	MKZ	MKX	IS	RX
CTS	-1.043	0.004	0.01	0.012	0.002	0.002	0.009	0.014
C-Class	0.007	-0.965	0.01	0.011	0.003	0.002	0.009	0.013
G37	0.006	0.002	-0.899	0.01	0.001	8e-04	0.007	0.012
3-Series	0.006	0.002	0.008	-0.941	0.001	0.001	0.008	0.012
MKZ	0.007	0.004	0.01	0.011	-0.993	0.002	0.009	0.013
MKX	0.008	0.005	0.011	0.012	0.003	-1.248	0.01	0.041
IS	0.005	0.002	0.008	0.009	0.001	0.001	-0.855	0.012
RX	0.005	0.002	0.008	0.009	0.001	0.004	0.007	-1.092

into the estimates on Table 2.16. Own-price and cross-price elasticities of purchase incidence in the new automobile industry in 1989 were reported to be close to -0.87 and 0.82, respectively (McCarthy, 1996). If one added these average incidence elasticities to the estimates on Table 2.16, one would obtain choice elasticities that are closer to those derived from models similar to ours (see, for example, Goldberg, 1995).

Having shown that the computed elasticities are reliable because they are consistent with previous work, we proceed to assess the effects of brand status on elasticities. To this end, we present the elasticities that we compute using the full specification with all status metrics. Tables 2.17-2.19 present the direct ( $E_{P_{il}, p_j}^D$ ), indirect ( $E_{P_{il}, p_j}^I$ ), and total ( $E_{P_{il}, p_j}$ ) elasticities that were introduced in Section 2.7.1. To assess whether these elasticities are statistically different from those presented in Table 2.16, we compute the differences between the chains of elasticities that correspond to the chains of estimates of the models with and without

status metrics. We then investigated whether the posterior distributions of these differences of elasticities include zero or not. For sake of convenience, we say that two elasticities are statistically different at the 10% level if no more than 10% of the posterior distribution of their differences has sign opposite to the sign of the posterior mean.

Table 2.17: Posterior means of the direct elasticities ( $E_{P_{il}, p_j}^D$ ) of the demand of the nameplates listed on the first row with respect to a 1000USD increase on the prices of the nameplates listed on the second column. In bold, elasticities that are statistically different from those listed in Table 2.16 at the 10% level.

Make	Cadillac	M-Benz	Infiniti	BMW	Lincoln	Lincoln	Lexus	Lexus
Nameplate	CTS	C-Class	G37	3-Series	MKZ	MKX	IS	RX
CTS	-1.003	<b>0.006</b>	0.015	0.013	0.004	0.003	<b>0.016</b>	<b>0.022</b>
C-Class	0.008	-0.955	0.014	0.012	0.003	0.003	<b>0.015</b>	<b>0.021</b>
G37	<b>0.008</b>	<b>0.006</b>	-0.919	<b>0.012</b>	<b>0.003</b>	<b>0.003</b>	<b>0.015</b>	<b>0.021</b>
3-Series	0.008	<b>0.006</b>	<b>0.014</b>	-0.922	<b>0.003</b>	<b>0.002</b>	<b>0.015</b>	<b>0.021</b>
MKZ	0.008	0.006	0.013	0.012	-0.905	0.002	<b>0.014</b>	0.02
MKX	0.008	0.006	0.014	0.012	0.003	-1.042	<b>0.015</b>	0.044
IS	<b>0.008</b>	<b>0.006</b>	<b>0.013</b>	0.012	<b>0.003</b>	<b>0.003</b>	-0.885	<b>0.02</b>
RX	<b>0.009</b>	<b>0.006</b>	<b>0.014</b>	0.012	<b>0.003</b>	0.006	<b>0.015</b>	-1.025

The computed direct elasticities ( $E_{P_{il}, p_j}^D$ ) represent the effect that price has on sales through affordability. These elasticities are very similar to those presented in Table 2.16 and abstract conventional substitution patterns. For instance, these elasticities suggest that substitution within categories can be stronger than substitution across categories. This is indicated by the relatively-larger value of the elasticities of the sales of the Lexus RX with respect to an increase in the price of the Lincoln MKX.

The indirect elasticities ( $E_{I_{il}, p_j}^D$ ) represent the effect that price has on sales through the social status of the brand. These elasticities are, relative to the direct elasticities, more diverse. For instance, we find that the own price elasticity of the Mercedes-Benz C-Class is positive and large. This implies that, by increasing the price of this nameplate, Mercedes-

Table 2.18: Posterior means of the indirect elasticities ( $E_{P_{i},p_j}^I$ ) of the demand of the nameplates listed on the first row with respect to a 1000USD increase on the prices of the nameplates listed on the second column. All posterior distributions exclude zero.

Make	Cadillac	M-Benz	Infiniti	BMW	Lincoln	Lincoln	Lexus	Lexus
Nameplate	CTS	C-Class	G37	3-Series	MKZ	MKX	IS	RX
CTS	-0.034	-0.059	-0.152	-0.082	0.01	0.055	-0.198	-0.155
C-Class	0.109	0.159	0.272	0.176	0.036	-0.062	0.322	0.256
G37	-0.106	-0.319	-0.883	-0.401	0.178	0.456	-1.266	-0.955
3-Series	-0.054	-0.026	-0.069	-0.071	-0.053	-0.049	-0.024	-0.037
MKZ	0.129	0.142	0.189	0.156	0.093	0.029	0.162	0.144
MKX	-0.047	-0.022	-0.054	-0.06	-0.047	-0.045	-0.014	-0.027
IS	0.109	0.148	0.238	0.163	0.049	-0.034	0.269	0.218
RX	-0.057	-0.018	-0.056	-0.069	-0.062	-0.064	0.006	-0.016

Table 2.19: Posterior means of total elasticities ( $E_{P_{i},p_j}$ ) of the demand of the nameplates listed on the first row with respect to a 1000USD increase on the prices of the nameplates listed on the second column. Elasticities not statistically different from those reported in Table 2.16 at the 0% level appear in italics.

Make	Cadillac	M-Benz	Infiniti	BMW	Lincoln	Lincoln	Lexus	Lexus
Nameplate	CTS	C-Class	G37	3-Series	MKZ	MKX	IS	RX
CTS	<i>-1.037</i>	-0.052	-0.137	-0.069	0.013	0.058	-0.182	-0.132
C-Class	0.118	<i>-0.796</i>	0.286	0.188	0.039	-0.059	0.337	0.277
G37	-0.098	-0.313	-1.803	-0.389	0.181	0.459	-1.251	-0.934
3-Series	-0.046	-0.02	-0.056	<i>-0.993</i>	-0.049	-0.046	-0.009	-0.016
MKZ	0.137	0.147	0.202	0.167	<i>-0.812</i>	0.031	0.176	0.164
MKX	-0.039	-0.016	-0.041	-0.048	-0.044	<i>-1.087</i>	0.001	<i>0.017</i>
IS	0.117	0.153	0.252	0.175	0.052	-0.032	<i>-0.616</i>	0.238
RX	-0.048	-0.012	-0.042	-0.057	-0.058	-0.058	0.022	<i>-1.041</i>

Benz could increase its social status and favor the sales of this product. Similarly, we find that an increase in the price of the Lexus IS favors the sales of both the Lexus IS and the Lexus RX because it benefits the social status of Lexus as a brand. This pattern is however not generalizable. An increase in the price of the Infiniti G37 actually harms the perceived social status of Infiniti. Overall, consideration of the indirect component of elasticity induces additional variation in the total elasticities. This can be clearly observed if we compare the elasticities in Table 2.16 against the total elasticities reported in Tables 2.17 - 2.19.

## 2.8 Discussion

### 2.8.1 Implications

**Theoretical implications.** The analysis of primary data revealed that consumers rely mostly on the median price of a brand, and the prices of the cheapest and most-sold products within a line to infer the social status of a brand. While the price of the cheapest product of the brand is strongly associated with brand status, it is also associated with other brand attributes. The median price, in contrast, appears to have better discriminant validity. We also found that the price of the most expensive product within a line also affects consumer perceptions of the brand, but it appears to affect the perceived refinement of the brand more than its perceived status. These results reveal a complex network of relationships among different product-line prices and different perceived brand attributes.

The analysis of secondary data provided evidence that all four proposed metrics could affect consumer choice but suggest that in particular two of them have significant explanatory power, namely the metrics that assume that the most typical product within a brand is the product whose price is the median or the maximum prices of all the products of the brand. Because the median price exhibits better divergent validity and also influences consumer choice, the best metric of brand status is the one defined by this median price.

**Methodological implications.** Our results indicate that the inclusion of status metrics largely affects the estimated price elasticities. By considering the effects of price on status

and the effects of status on purchase probabilities, the proposed model is able to reproduce complex substitution patterns that similar models without status metrics cannot recreate (see, for example, Goldberg, 1995). First, such substitution patterns are more heterogeneous than those computed without status metrics. Weaker own-price elasticities follow from price increases leading to enhancements of the status of the brand. Stronger own-price elasticities follow from price increases hurting the status of the brand. Second, by including status metrics, we are also able to obtain larger than conventional cross-price elasticities among products belonging to the same brand. Large cross-price elasticities emerge from spillovers of brand status across the products of a brand and from strong substitution among products with similar status independently from their similarity in terms of other product attributes.

**Managerial implications.** The tests that explored the validity of the proposed metrics offer important implications. By revealing the relationships between the different prices of the product line and the perceived attributes of the brand, the results offer insights as to how to effectively position a brand. In particular, managers can manipulate the median price of a product line to position the brand at a desired level of perceived status because the metric defined in terms of the median price strongly correlates with perceived status and strongly explains consumer behavior. For instance, to increase the perceived status of the brand, managers could increase the prices of several items in the line without changing the prices of the most sold product nor the minimum and maximum prices. If managers want to reposition the brand in terms of refinement, they can manipulate the price of the most expensive product of the line. This follows from the fact that the metric defined in terms of the maximum price strongly correlates with the brand's perceived refinement and also explains consumer choice.

Manipulation of the cheapest price and the price of the most sold product is more complicated because these prices affect multiple perceived attributes simultaneously. For instance, because the price of the most commonly sold item in the product line negatively correlates with the perceived status of the brand, brands can increase their perceived status by reducing the prices of their most sold products. This would however harm the perceived intelligence

and refinement of the brand. An optimization algorithm could be used to reposition the brand in the space spanned by all the attributes under consideration.

The analysis of secondary data also offers important managerial insights. Its results explain how demographics moderate consumer preferences for different aspects of the distribution of the prices of a brand. The role of consumer heterogeneity (individual differences) has been largely neglected by previous work on how product line prices affect brand perceptions (e.g., Petroschius and Monroe, 1987; Randall et al., 1998; Leclerc et al., 2005). Heterogeneity, however, is very important for brands that seek to position their products within specific market segments.

Consider, for instance, the case of the Cadillac CTS. This is the cheapest member of the Cadillac's product line and caters consumers whose household income lies well above the mean but whose education level is below that of the owners of other luxury brands (Naughton, 2010). Because both high income and high education levels imply preferences for brands whose cheapest product is expensive, Cadillac faces a difficult challenge pricing the CTS. A price increase may have a positive effect on high-income consumers but a negative effect on less educated consumers. The negative indirect elasticity indicates that the later effect dominates the former one. The sales of the Cadillac CTS could then possibly be enhanced by reducing the price of this nameplate, but Cadillac should also consider whether and how a change in the price of the CTS may affect the sales of other members of the product line. This will strongly depend on the demographics of the Cadillac's target segments.

The link between prices and brand status can, on the other hand, favor some brands. Such is the case of Lexus. By increasing the price of its nameplate IS, Lexus can improve the perceived status of both the IS and the RX. This follows from the facts that: a) the IS is the cheapest product in the Lexus lineup; b) Lexus is favored by highly educated individuals (Naughton, 2010); and c) highly educated consumers prefer brands whose cheapest product ranks higher (refer to Table 2.11). An increase in the price of the Lexus IS thus results in an increase of the appeal of the entire Lexus product line. We accordingly see that the indirect own-price elasticity of the IS is positive and so is the cross-price elasticity between the IS and the RX.

## 2.8.2 Contribution to literature

Overall, this study contributes to the literature on vertical differentiation by demonstrating that product line pricing is important not only because it allows for price discrimination but also because it affects how the entire brand is perceived by consumers. Previous work in this area has shown, for instance, that vertical differentiation may affect brand preferences more than horizontal differentiation and has also assessed the profitability of pricing strategies (Draganska and Jain, 2006). Most studies in this area are typically concerned with consumer packaged goods. For non-positional products, social status may not be a major influence on consumer behavior and thus prices may affect choice mainly through budget constraints. In contrast, the prices of status-signaling products do have an additional effect on brand choice because they define the social status of brands. By demonstrating this, we highlight the need for incorporating the effect of price on perceived status into current models of vertical differentiation.

This study also contributes to the literature on the effects of product line prices on brand equity. In particular, our results complement Randall et al.'s (1998) work on how a brand's price premium relates to the prices of the least and most expensive products of the brand's product line. The two projects are complementary for two major reasons. First, Randall et al. (1998) study price premia as a consequence of brand equity. We, in contrast, study brand status as a source of brand equity. The second reason is that Randall et al. (1998) focused on brand heterogeneity by differentiating between low-end and high-end brands, without considering consumer heterogeneity. On the other hand, we allow for consumer heterogeneity while accounting for heterogeneity in brand positioning through the proposed metrics of brand status.

Further research is required to clarify the relationship between our results and those in the brand equity literature. Such additional research could, for example, relate brand status and price premia in a single product category so as to control for category effects and consumer heterogeneity. Studying a single category is important because the prices of, for instance, new bicycles and new automobiles lie in very different ranges and (at least



in the U.S.) automobiles could be considered more of a necessity than bicycles. Consumer heterogeneity may be important as well if the demographics of car buyers are significantly different from the demographics of bicycle buyers. By controlling for category effects and consumer heterogeneity, one could then establish the relationship between brand status, brand equity, and product line prices.

### **2.8.3 Limitations**

In order to define actionable metrics of the social status signaled by brands, we have made some simplifying assumptions. The most significant assumptions and their consequences are discussed next.

**Irrelevance of fleet size.** We have assumed that consumers observe only the vehicle driven by others and not the entire fleets owned by their comparison targets. Consumers could however signal wealth by owning several inexpensive vehicles rather than a single expensive car. The potential biases induced by the potential use of fleet size as an alternative signal of wealth and status are however mitigated by the fact that the individuals tend to compare to strangers very frequently (Hyman, 1942). The only occasions in which a consumer can observe the entire fleet of another consumer is when the two are neighbors or otherwise close. Therefore, owning expensive products is more often a clearer signal of status than owning many products. A large number of products does not fully substitute for expensive products and therefore neglect of fleet size does not necessarily bias the estimated preferences for status signaling. In fact, by neglecting fleet size we define the estimated preferences as preferences for status-signaling products rather than preferences for status-signaling product stocks.

**Irrelevance of other product categories.** Our analysis is restricted to the study of one product category. Consumers may however chose to use different product categories as status signals and substitution across product categories may arise because of status seeking behavior. The effect of preference for status-signaling products on the allocation of

a household's budget across product categories is an important problem and it is studied elsewhere (Becerril-Arreola, 2011). We currently focus on an analysis at the product level because it generates important implications for brand management. While a complete model considering both brand choice and category incidence would be definitely very interesting, we first need to generate the building blocks that will later allow us to answer more complex research questions.

**Reduced-form specification of status.** To be able to estimate our model, we have assumed that social status enters utility directly. Previous theoretical work has proposed that status is valued because of the social benefits it conveys and that therefore utility should be specified as a function of such benefits through a structural specification (see, for example Truys, 2009). Empirical work has however shown that social status has a strong non-instrumental value (Huberman, Loch and Öncüler, 2004), therefore suggesting that status contributes to utility directly. We do not rule out the instrumental utility of social status, but let it be confounded with the direct utility through our reduced-form specification (2.3). Structural models that abstract the instrumental utility of status are circumscribed to very specific contexts because of their assumptions. For instance, Truys's (2009) model exclusively focuses on the mating utility of social status.

**Aggregation bias.** The NHTS survey collected data on the make and nameplate of the vehicles reported by respondents but it offers no information about the trims of the vehicles. While the prices and attributes of a nameplate may vary significantly among trims, using trims as choice alternatives is not statistically feasible. Nameplates like the Ford F-150 are available as dozens of trims. Furthermore, each trim can be offered with combinations of multiple options. Considering each trim and option for a given nameplate thus leads to an explosion of choice alternatives and to a very reduced number of observed choices for each choice alternative. To avoid this problem, we have chosen to use nameplates as choice alternatives and use the attributes of the trim with the smallest MSRP or the lowest attributes levels. This implies that the actual sale prices and product attributes exhibit

larger variation than our measures. Accordingly, our estimates may be biased towards zero.

An additional source of aggregation bias can emerge if consumers do not regard makes as brands, but attribute perceived status to other groupings of products. For example, consumers could attribute independent status levels to Ford SUVs and Ford pick up trucks. To assess the robustness of the proposed metrics of status to this potential misspecification, we estimated the model with alternative metrics of status computed at the make/category level. The results are qualitatively equivalent and therefore we present one set of results only. We present the results related to metrics defined at the make level because a smaller level of categories simplifies the collection of survey data and generates more robust estimates.

## 2.9 Conclusions

We have constructed four metrics of brand status and tested their validity, robustness, and relevance to consumer choice. The results of the study make multiple contributions. In terms of theory, the results support the proposition that consumers rely on the prices of the most typical products within a brand to assess the social status conferred by the brand. Furthermore, we find that a given consumer may construct inferences of social status using the prices of not only one but multiple typical products.

In terms of methodology, our results indicate that estimation of models that do not include status metrics can lead to biased estimates of price elasticities. The elasticities generated by a model that accounts for brand status suggest that substitution patterns are much richer than those derived from standard models that do not include brand status. Status metrics thus appear to be useful in improving the realism of choice models of consumer demand for status-signaling products.

In terms of managerial implications, our work clarified how pricing strategies may affect the perceived status of brands and estimated the preferences for status-signaling products among different consumer groups. These results can thus be very helpful in improving a manufacturer's pricing and segmentation strategies. Segmentation is in fact of great importance for firms that attempt to position their brands as signals of social status. Our results

indicate that, for example, while the average consumer seems to prefer low price dispersion and inexpensive bottom-of-the-line models, high-income households seem to prefer low price dispersion and expensive bottom-of-the-line vehicles. Brands that target these wealthy consumers should then offer expensive options only. Having an expensive most-sold product may however hurt the appeal of the brand among this selective consumer group.

Finally, because our approach yields estimates of consumer preferences for both status and other product attributes, manufacturers could use our approach to determine the importance of status relative to quality for particular market segments. The interplay between status and quality is of great importance. A brand may suffer significant performance loss by claiming high status without providing high quality (Silverstein, Fiske and Butman, 2003).

## Appendix 2.A Derivation of Elasticities

The price elasticities are given by

$$\begin{aligned}
E_{P_{il}, p_j} &= \frac{dP_{il}}{dp_j} \frac{p_j}{P_{il}} \\
&= \left[ \sum_{n=1}^J \sum_{h=1}^H \frac{\partial P_{il}}{\partial s_{hng(i)}} \frac{ds_{hng(i)}}{dp_j} + \frac{\partial P_{il}}{\partial p_j} + \sum_{n=1}^J \frac{\partial P_{il}}{\partial \hat{p}_n} \frac{d\hat{p}_n}{dp_j} \right] \frac{p_j}{P_{il}} \\
&= p_j \sum_{n=1}^J \left[ \frac{\partial \log P_{il}}{\partial V_{in}} \sum_{h=1}^H \left( \frac{\partial V_{in}}{\partial s_{hng(i)}} + \frac{\partial V_{in}}{\partial \hat{s}_{hn}} \frac{d\hat{s}_{hn}}{ds_{hng(i)}} + \frac{\partial V_{in}}{\partial \hat{s}_{hg(i)}} \frac{d\hat{s}_{hg(i)}}{ds_{hng(i)}} \right) \frac{ds_{hng(i)}}{dp_j} \right] \\
&\quad + p_j \frac{\partial \log P_{il}}{\partial V_{ij}} \frac{\partial V_{ij}}{\partial p_j} + p_j \sum_{n=1}^J \frac{\partial \log P_{il}}{\partial V_{in}} \frac{\partial V_{in}}{\partial \hat{p}_n} \frac{d\hat{p}_n}{dp_j} \\
&= p_j \sum_{n=1}^J \left[ \frac{\partial \log P_{il}}{\partial V_{in}} \sum_{h=1}^H (\beta_h^T d_i + \gamma_h M_{s_{hn}(n,j)} + \alpha_h M_{s_g(n,j)}) \frac{ds_{hng(i)}}{dp_j} \right] \\
&\quad + p_j \frac{\partial \log P_{il}}{\partial V_{ij}} \beta_p^T d_i + p_j \sum_{n=1}^J \frac{\partial \log P_{il}}{\partial V_{in}} \gamma_p M_{p(n,j)},
\end{aligned} \tag{2.8}$$

## Appendix 2.B Estimation procedure

Estimation is carried out using a Bayesian algorithm

- 1) for each  $i$ , draw  $\beta_i | \delta_j, \phi_g, \rho, V_\beta, \Lambda$  using a Metropolis-Hastings (M-H) step

- 2) draw  $V_\beta, \Lambda | \beta_i$  using a Gibbs-sampler step
- 3) for each  $j$ , draw  $\delta_j | \beta_i, \phi_g, \rho, V_\beta, \Lambda$  using a M-H step
- 4) draw  $\sigma_\xi^2, \gamma | \delta_j$  using a Gibbs-sampler step
- 5) for each  $g$ , draw  $\phi_g | \beta_i, \delta_j, \rho, V_\beta, \Lambda$  using a M-H step
- 6) draw  $\sigma_\psi^2, \alpha | \phi_g$  using a Gibbs-sampler step
- 7) draw  $\rho | \beta_i, \delta_j, \phi_g, V_\beta, \Lambda$  using a M-H step

The implementation of the Metropolis-Hasting steps is similar to those described by Rossi, Allenby and McCulloch (2005) and Lahiri and Gao (2002) with semi-flat priors for  $\rho$  given by

$$f(\rho_k) = \begin{cases} 0 & \text{if } \rho \leq 0, \\ \lambda & \text{if } 0 < \rho < 1, \\ \lambda e^{\frac{\lambda}{1-\lambda}(1-\rho)} & \text{if } \rho \geq 1 \end{cases}$$

with  $\lambda = 0.8$ . The M-H chains for the inclusive value  $\rho$  followed a hybrid of the independence and random-walk methods. We used a proposal gamma distribution with scale parameter  $0.0005/\rho$  and shape parameter  $\rho^2/0.0005$ . This distribution is to some extent equivalent to a random walk because it is (almost) symmetrical and its mean is located at  $\rho$ . However, it also ensures that  $\rho > 0$ .

## Appendix 2.C Survey instrument

All respondents were shown the following text at the beginning of the survey:

“In the following screens you will be asked to rate different brands in terms of how much social status, wealth, and style (taste, refinement, sophistication) they show. To answer these questions, imagine you hear that Mr. A owns a car of brand X but that is all you know about Mr. A. You, however, want to know how wealthy Mr. A is. Then you use your knowledge of brand X to make a guess of

how wealthy Mr. A is. Similarly, you try to guess what is the social status of Mr. A and how stylish (refined, sophisticated) or smart he is by just knowing he owns a car of brand X.”

After that, they were asked to rate different aspects of the brand in randomized order. For instance, the question about status read as follows:

“What would you think the social status of Mr. A would be if you knew that the car he owns was made by each of the following brands?”

Respondents had to slide a bar thus assigning to each of ten brands a score that ranged from 0 to 100. Every brand had to be scored before respondents could proceed. Finally, respondents were requested to provide their demographics including their geographic location in 2009.

## CHAPTER 3

### Social status as a motive for consumer trade-up

#### 3.1 Introduction

Some product attributes offer universal value that is not subject to satiation; yet, their value is not reflected in the behavior of every consumer. Such is the case of, for instance, the social status conferred by status-signaling products. Social status offers universal value in the form of health and economic benefits (Berger et al., 1972; Sapolsky, 2004), among others, and is not subject to satiation because it always pays off to increase one's ranking (J. Solnick and Hemenway, 1998; Hopkins and Kornienko, 2004). Nonetheless, some wealthy individuals forgo the benefits of signaling social status through consumption even if they can afford it. Less well-off individuals, at the same time, may spend a disproportionate share of their resources on signaling status (Silverstein et al., 2003). Evidence is provided by the facts that: a) 61% of people with incomes above 250,000USD buy mainstream rather than luxury cars (Muller, 2011); and b) more than 5% of U.S. households facing bankruptcy and about 8% of households filing for Chapter 13 own luxury cars (Zhu, 2011). Given these facts, economic models that assume that wealthier consumers are always willing to pay more for additional quality (for instance, Gabszewicz and Thisse, 1979; Shaked and Sutton, 1987; Hopkins and Kornienko, 2004) may lead to inaccurate predictions.

We explore one source of this heterogeneity in trade up and trade down behaviors. As solid evidence has been advanced that consumer assets affect consumer spending (see, for example, Paiella, 2009), we introduce a new model of consumer choice that accounts for the potential effect of wealth on consumer motivation. The model relies on the proposition that some consumers are not willing to pay more for additional quality because their motivation to

consume such additional quality is suppressed. In particular, the model allows consumption motives to be heterogeneously suppressed or revealed conditional on consumer wealth. After justifying this proposition through human motivation theory (Vinson, Scott and Lamont, 1977; Brehm and Self, 1989; Diener and Fujita, 1995; Kenrick, Griskevicius, Neuberg and Schaller, 2010), we incorporate it into a model of non-homothetic utility. The ensuing indirect utility model allows consumer choice to depend both on wealth, through the saliency of preferences, and on income, through budget constraints. We test the validity of this model through an empirical study.

The paper is organized as follows. We start by reviewing the literature that explains trade up behaviors in Section 3.2. An exploratory analysis of car expenditure and choice is presented in Section 3.3 to motivate the structure of the model proposed herein. The psychological theory that supports our model is presented in Section 3.4 and then translated into an economic model in Section 3.5. From the economic model, we derive an econometric specification. We estimate this econometric model using data on car choices, as discussed in Section 3.6. Results are presented and discussed in Sections 3.6.4 and 3.6.5. Conclusions are offered in Section 3.7.

## **3.2 Relevant literature**

The study of how inequality affects consumer behavior requires a clear understanding of how income and wealth influence consumer decisions. The role of income on purchase incidence and expenditure has been the focus of multiple studies (see, for example, Levedahl, 1980; Bernanke, 1984). We, in contrast, focus on the effects of both income and wealth on brand choice with a particular interest in the choice of vertically-differentiated products. That is, we focus on consumer choice among low-end and high-end brands (trade down and trade up, respectively) and pay special attention to the new car market. The implications can however be extended to other product categories.

The choice of high-end products is an interesting topic because it is difficult to model empirically. The difficulty follows in part from the fact that preferences for high-end products



cannot be completely explained in terms of functional dimensions of quality. The choice of high-end products is, in fact, also motivated by less tangible product and brand attributes. Since these less tangible aspects of quality are not easily measured, it is difficult to incorporate them into econometric models of consumer behavior. Extant models that consider functional product attributes only cannot accurately explain nor predict consumer preferences for high-end products.

To see how functional quality cannot always fully explain preferences for high-end products, consider the value per dollar offered by low-end and high-end options. Consider, for example, a choice between two twin cars: the 2012 Toyota Camry XLE (MSRP 24,725USD, gross weight 4630lbs) and 2012 Lexus ES350 (MSRP 36,725USD, gross weight 4680lbs). Miller's (2009) argument applied to these figures leads to the result that the Camry XLE sells at 5.34USD/lb and the ES350 sells at 7.85USD/lb. That is, the more prestigious Lexus ES350 is sold at a higher price per pound than the Camry XLE is. This difference between the prices per pound of the two products could be justified, from the perspective of the manufacturer, by differences in the costs of designing and producing the two vehicles. Producing high-end models involves higher fixed costs per unit produced partly because low-end vehicles sell many more units than high-end options do. Also, high-end brands often offer more product-mix variety and therefore face higher operational complexity and costs per unit (MacDuffie, Sethuraman and Fisher, 1996). It follows that high-end vehicles must command higher percentage markups. This was shown explicitly by the empirical studies of Bresnahan (1981) and Goldberg (1995), and implicitly by the results of Bordley (2003).

From the perspective of the utility-maximizing consumer, however, paying for these larger percentage markups may sometimes seem harder to justify. The Lexus ES350 and the Toyota Camry XLE offer similar levels of reliability because both vehicles are designed and manufactured by the same firm. Furthermore, a comparison of the technical specifications of the two cars suggest that they deliver almost the same levels of functionality. It would seem then that the Lexus ES350 offers slightly higher functional utility than the Toyota Camry XLE does, but the unit price of this additional quality is significantly higher than the unit price of the quality offered by the low-end option. Thus, some consumers' willingness to pay

for additional quality appears to be larger for high-end products. That is, some consumers exhibit non-constant marginal utility. Why is it so?

Previous research has offered multiple explanations to the fact that some consumers are willing to pay higher price premia for high-end products. Among these explanations we have that consumers: a) prefer high-end products whose brands, prices, and variety signal higher quality; b) are unaware that high-end products command higher mark-ups; c) face high search costs that prevent them from finding options with high value per dollar ratio; d) value the social meanings associated with high-end products; and e) have stronger preferences for quality.

The roles of brand, price, and variety as signals of unobserved quality have been extensively studied. It has been shown, for example, that consumers could be more willing to pay for high-end products when more options are available because they interpret product proliferation as a signal of greater category expertise and competency (Berger et al., 2007) or as a signal that quality is very important (Bertini, Wathieu and Iyengar, n.d.). Evidence has also been advanced, however, to show that marketing variables are not very useful signals in the new car market. For instance, Bearden, Carlson and Hardesty (2003) found non-significant effects of MSRP on the perceived quality of automobiles. Consumer surveys also repeatedly report that the perceived quality of mainstream car makes is at least as good as the perceived quality of luxury brands (see, for example, Automotive Lease Guide, 2009*b*; ConsumerReports.org, 2010). Furthermore, the perceived quality of cars is strongly correlated with their residual value (Automotive Lease Guide, 2009*b*) and the residual values of mainstream nameplates are at least as good as those of luxury nameplates (Kelley Blue Book, 2009; Automotive Lease Guide, 2009*a*; Edmunds, 2009). This lack of correlation between prices and perceived quality could be explained by availability of detailed automobile specifications and expert evaluations, as well as by the possibility of test-driving the products. Thus, in the new cars market, quality and its importance can be easily diagnosed (accurately or not) by consumers.

Even if consumers can diagnose the quality of a product, lack of accurate pricing information could prevent them from inferring the product's percentage mark-up. This was shown

by Verboven (1999) for the new car industry and under the assumptions that: a) consumers only know the price of the cheapest model of each of two makes under consideration; and b) consumers need to visit dealers to learn about the prices of other models. In a similar vein, Ellison (2005) proposes a pricing strategy that allows firms to charge higher markups for products with “add-ons”. The effectiveness of the proposed pricing strategy requires that the prices of the add-ons be unobserved by consumers. While the assumptions of incomplete pricing information may be credible in the case of add-ons, they are harder to justify in the case of vehicle-brand choice. The empirical work by Moorthy, Ratchford and Talukdar (1997) in fact showed that on average consumers visit over three different dealers and consider more than three different brands before purchasing a new car. Likewise Lapersonne, Laurent and Le Goff (1995) showed that (in France) consideration sets for new vehicle purchases include one single brand in about 20% of the cases only. The incomplete information explanation is therefore unlikely to hold for the automobile industry.

A similar explanation to the larger percentage margins commanded by high-end automobiles follows from the assumption that consumers face high search costs that prevent them from accurately assessing the value of different alternatives. For instance, mattress manufacturers and credit cards firms may frame product information in ways that make hard for consumers to assess the value and cost of their offerings (Ellison, 2006). However, regulations in industries such as the new car industry make sure that pricing and performance information is accurately provided. Information is furthermore made available not only by manufacturers but also by experts. For instance, Consumer Guide Automotive rates each vehicle according to it compares in terms of its “value within class” and other attributes. Therefore, it seems unlikely that consumers cannot judge the value of new cars.

The higher percentage mark-ups of high-end products can be explained as well by considering the symbolic value they provide in a social context. For example, Amaldoss and Jain (2008) showed that consumers may prefer high-end products if they experience needs for uniqueness and conformism. In Amaldoss and Jain’s (2008) framework, the need for uniqueness is experienced by a group of leaders and the need to conform is experienced by a group of followers, who try to imitate the leaders. Under this setting, and for a range of

values of marginal cost, the profits of a monopoly are increasing on the marginal cost and thus the firm offers more costly products that are not necessarily functionally superior. The high cost of the more expensive products makes them less appealing to the followers and thus more appealing to the leaders, who try to differentiate themselves from the followers. This results in higher demand for the higher-cost product, which however command lower margins (because of higher marginal costs). The needs for uniqueness and conformism may then explain consumers preferences for high-end vehicles but cannot explain why these products command larger percentage margins than low-end cars do.

One more explanation of why high-end products command higher percentage mark-ups is offered in the industrial organization literature. This explanation relies on the heterogeneity of consumer valuations for quality, nonlinear pricing policies, and market structures that mitigate competition. For example, Tirole (1994) showed that under heterogeneous consumer taste for quality and monopolistic nonlinear prices the firm draws larger mark-ups from high quality products. The monopolistic results can be extended to the competitive case if cooperation between firms takes place. However, a study by Sudhir (2001) showed that cooperation may take place in the mid-range automobile market but not in the low-end and high-end markets. It is thus unlikely that nonlinear pricing and collusion can explain the higher percentage margins of high-end cars.

Consumer heterogeneity does nonetheless seem to be important in explaining consumer willingness to pay for higher percentage mark-ups. In the particular case of the automobile industry, Verboven (2002) showed that heterogeneity in the number of miles driven by consumers accounts for 75% to 90% of the difference between the markups of diesel-based (high-quality) and gasoline-based (low-quality) automobiles. Although these results rely on the simplifying assumption that consumer preferences for other product attributes are homogeneous, they do lend support to the conjecture that stronger preferences for one aspect of quality (fuel-efficiency in this case) may explain consumers' willingness to pay higher markups.

The heterogeneity in the preferences for quality has been shown to be at least partially explained by the heterogeneity of consumer financial resources. For instance, Dubé (2004)

found that households with higher income have a higher taste for the quality of carbonated drinks. A multinational multicategory study by Steenkamp, Van Heerde and Geyskens (2010) likewise revealed that higher self-reported social class is positively correlated with the willingness to pay for national brands over private labels and that this relationship is mediated by the perceived quality gap. Departing from the assumption that high-income consumers value quality more than low-income consumers, Allenby and Rossi (1991) built a model of consumer choice and fitted it to data on consumer packaged goods. The authors thus showed that their proposed model outperforms standard economic models because, by abstracting nonhomothetic preferences, their model is able to explain how higher consumption-levels correlate with stronger preferences for superior brands.

The model first proposed by Allenby and Rossi (1991) and then extended by Allenby et al. (2010) is perhaps the model in the extant marketing literature that describes the most general patterns of trade up behavior. Just like these authors, we relax the assumption of constant marginal utility so as to allow for non-homothetic preferences. Unlike Allenby and Rossi (1991) and (Allenby et al., 2010), however, we do not depart from the assumption that the marginal utilities of consumers with large budgets are larger than the marginal utilities of consumers with small budgets. We instead use psychological theories of human motivation (Maslow, 1943; Vinson et al., 1977; Brehm and Self, 1989; Diener and Fujita, 1995; Kenrick et al., 2010) to explain how wealth and income determine consumers' marginal utility for different product attributes.

The proposed theoretical framework also differs from the work of Allenby and Rossi (1991) in that it postulates that marginal utility is a function of household's wealth rather than of the household's total expenditure in the product category. As a result, we are able to differentiate the effects of income on consumption from those of wealth. We attempt to clarify how wealth moderates the relationship between revealed preferences and underlying preferences for different dimensions of quality, such as those associated with functional and social value.

### 3.3 Exploratory analysis

To offer some intuition on how income and wealth affect consumer behavior, we offer an exploratory analysis of consumer behavior data. We use data from the new car market because for this product category budget constraints play a clear and important role and because cars cater a broad range of consumption motives. By empirically identifying the role of budget constraints, we can focus on additional effects of income and wealth on consumer behavior. By considering multiple consumption motives, we can more clearly observe identify the effects of wealth on different dimensions of quality. The exploratory analysis thus aims at empirically motivating the structure of the model proposed below.

To gain intuition on the relationship between consumer resources (income/wealth) and vehicle consumption (expenditure/holdings), we start by plotting the Engel curves of vehicle consumption. Engel curves are typically of one of two types. Engel curves of the first type describe the variation in the share of budget allocated to a particular good as a function of household income or total expenditures. We use data from the Consumer Expenditure Survey (CEX) carried out by the Bureau of Labor Statistics to compute budget shares allocated to the purchase of new cars conditional on a purchase taking place. We then plot these shares against the households' annual incomes and against the households' total expenditures. The plots appear in Figure 3.1 and show both individual observations and a smoothed mean of vehicle holdings value. The plots in this figure show that the budget share allocated to new vehicles is decreasing on income and total expenditure for households with income below approximately 70,000USD but not necessarily for higher-income households. The classical interpretation of this result is that vehicles are considered “necessities” by households with lower income but at the same time are considered “luxuries” by households with higher income.

Engel curves of a second type describe how the actual expenditures on a particular good vary as a function of household income or total expenditure. To plot these curves, we use data from the 2009 wave of the Panel Study of Income Dynamics (PSID). Plots of the reported value of a household's vehicle holdings versus the household's income and wealth

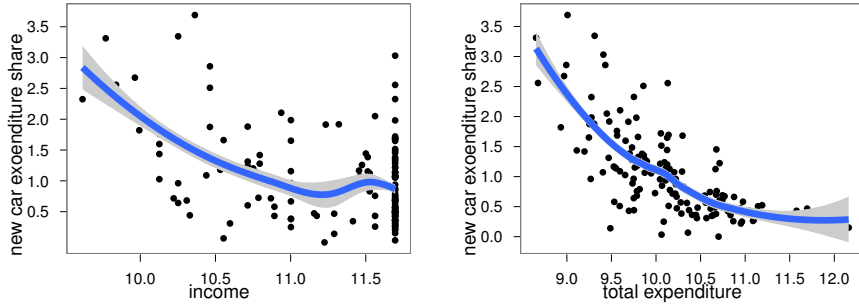


Figure 3.1: Budget share of new vehicle expenditures versus income and total expenditures. Data source: Consumer Expenditure Survey, Bureau of Labor Statistics.

(computed as the sum of assets minus the sum of liabilities minus the value of vehicles owned by the household) appear in Figure 3.2. The first plot suggests that the value of vehicles owned is slightly decreasing in income when income lies below a threshold of approximately 70,000USD. The average value of vehicle holdings does however clearly increase as income grows above this threshold. The classical interpretation of this result is that, for lower-income households, vehicles are not necessities but inferior goods. The second plot in Figure 3.2 shows that the value of vehicles owned by households does grow with wealth and that the rate of growth is larger for wealth levels beyond 170,000USD.

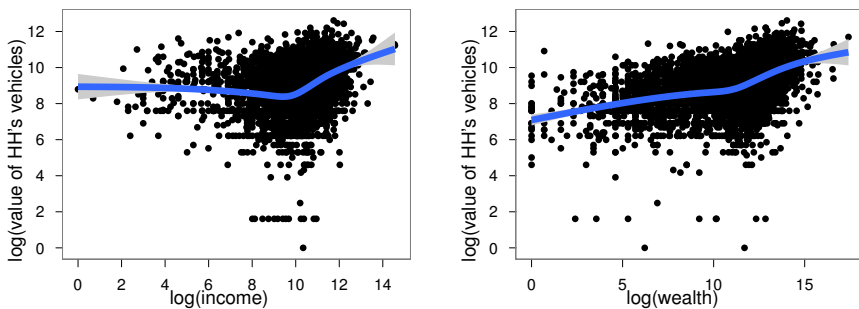


Figure 3.2: Value of vehicle holdings versus wealth and income. Data source: Panel Study of Income Dynamics.

An increase in the value of vehicle holdings could reflect an increase in the prices of the vehicles owned or an increase in the number of vehicles owned. To clarify to what extent each of these two explanations holds, we use data from the 2009 National Highway Transportation Survey (NHTS) and plot kernel estimates of the distribution of the number of

vehicles as function of income levels. A first plot appears in Figure 3.3(a) and shows that the median number of vehicles owned is two for households with income under approximately 70,000USD and three for households with income above 70,000USD. This increase in the number of vehicles seems to be associated with the change in the slopes of the graphs in Figure 3.2 but does not necessarily imply that the increase in holdings value is due to a larger fleet only. Even for households with income well above 70,000USD, it is common to own only one vehicle. Thus many of these households trade up rather than purchase multiple cars.

To gain further insight, we plot, for different income levels, the distribution of the number of vehicles per driver in each household. The plot appears in Figure 3.3(b) and indicates that the median number of vehicles per driver remains constant at one across all income groups. Excepting the case of the group with income above 100,000USD (the highest income group), most households own one car per driver. Then, a major reason for the increase on expenditures among households with income above 70,000USD is the choice of more expensive vehicles. In other words, a large number of households with income above 70,000USD trade up to higher-end options instead of buying multiple vehicles per driver.

A general relationship between income and brand choice can be revealed by analyzing the relationship between the MSRPs of vehicles owned by a household versus the household's income. To carry out this analysis, we complement the data from the 2009 National Highway Transportation Survey (NHTS) with pricing data obtained from internet specialty websites. We first categorize a make as either low or high end according to whether the median of the prices of all the make's nameplates falls above or below the median of the prices of all nameplates available in the market. We then compute the proportion of high-end vehicles owned by the households within each income bracket. The plot appears in Figure 3.4 and suggests that the relationship between income and the proportion of high-end vehicles is different for incomes below and above 60,000USD. While the relationship appears to be concave for lower incomes, it seems to be linear for higher incomes. This suggests that income affects the behavior of low-income and high-income households differently. In addition, Figure 3.4 reveals that the proportion of high-end vehicles owned is modest at every income



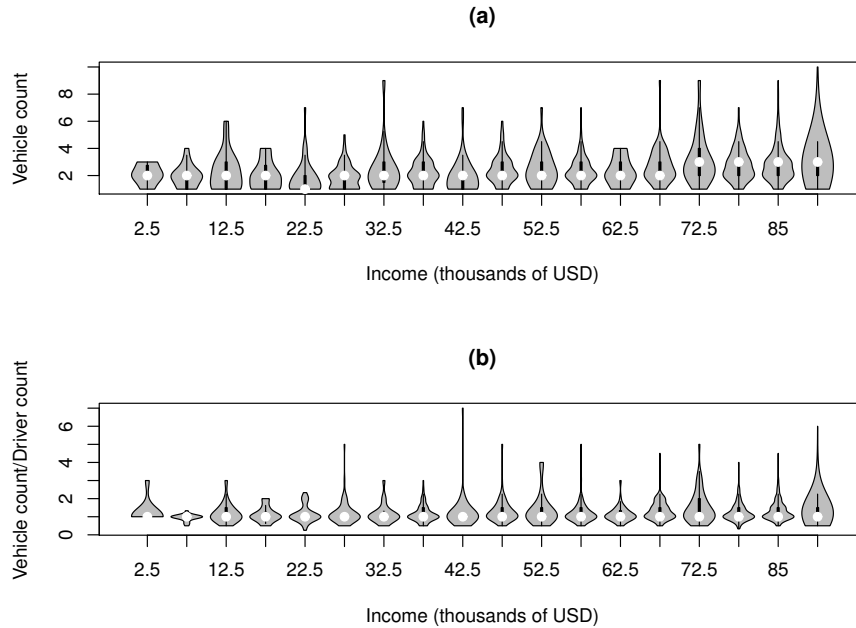


Figure 3.3: Number of vehicles owned and ratio of vehicles to drivers versus household income (in thousands of USD). Data source: National Highway Transportation Survey, Federal Highway Administration.

level, thus confirming that many well-off households prefer not to trade up.

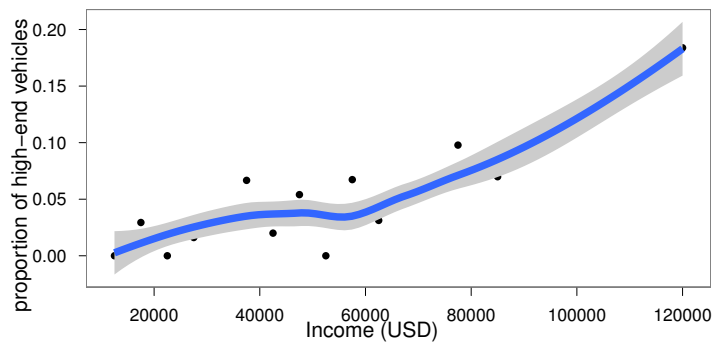


Figure 3.4: Proportion of high-end vehicles owned by households in each income group. The blue line is a smoothed mean and the gray envelope is its standard error. Data source: National Highway Transportation Survey, National Highway Administration.

In conclusion, the above plots suggest that the behavior of well-off households (those with income above 70,000USD and wealth above 170,000USD) differs from the behavior of less wealthy households. Motivated by this difference and by extant theories of human motivation, we propose that some higher-income households have stronger preferences for

some attributes that only high-end products can provide. In other words, we propose that differences in behavior result not only from budget differences but also from income affecting the importance of underlying preferences.

## **3.4 Psychological model**

### **3.4.1 Wealth, motives, and brand choice**

We propose that individuals behave as if they ranked different consumption motives in terms of their importance and that, holding other demographics constant, resource availability determines how many of these motives are aroused. In other words, wealth levels moderate the relationship between consumption motives and revealed preferences as wealth levels determine what less important motives are suppressed and what more important motives drive behavior. Low resource availability is associated with a large number of suppressed motives and high resource availability is associated with a large number of fulfilled motives. For instance, income affects the importance of preferences for different food attributes. A survey conducted by Steptoe, Pollard and Wardle (1995) indicated that, after controlling for price (and thus for budget constraints), the reported importance of preferences for good taste and smell in food is lower for low-income individuals than for high-income consumers.

The fundamental premise that human motives can be suppressed or aroused finds support in different theories of motivation. According to Brehm and Self (1989), potential motivation and motivation arousal interact to generate instrumental behavior. Motivation is qualified as potential because its magnitude can be affected by a number of factors that include internal states such as needs, potential outcomes, and the perceived probability of successfully satisfying needs or controlling outcomes. Motivational arousal is moderated by the difficulty, affordability, and justifiability of the instrumental behavior required to cater a motive. Therefore, we have that (potential) motivation may be present without being reflected in (instrumental) behavior. Empirical evidence that consumer behavior can be significantly affected by the saliency of motives was provided by Ordabayeva and Chandon (2011), who

showed that the saliency of social competition may elicit status seeking behaviors.

Theoretical support for the statement that human motives are prioritized follows from previous work on human motivation and values (see, e.g. Maslow, 1943; Vinson et al., 1977). Empirical support has also been advanced to show that different individuals prioritize their values differently (Kamakura and Mazzon, 1991) and evolutionary theory has been used to explain that environmental factors may determine the importance of different motives (Kenrick et al., 2010). An example of this heterogeneous prioritization of motives in the consumption context is provided by Kamakura and Mazzon (2012), who find that social class determines consumption priorities. An example of the role of environmental factors was studied by Yang, Allenby and Fennell (2002), who showed that people consume different brands of beer depending on the consumption motives triggered by the consumption environment.

Given a hierarchy of consumption motives, a consumer allocates his or her resources to first fulfill the most important or salient motives (Maslow, 1943; Earl, 1990). The number of motives that can be addressed depends on the amount of available resources such as intelligence, physical attractiveness, income, and wealth. If a goal is not attainable given the consumer's resources, the goal may be devalued (Brehm and Self, 1989; Diener and Fujita, 1995). We apply this framework to the consumption context and focus on the resources of income and wealth. Accordingly, we propose that wealth determines what consumption motives individuals and households pursue. The consumption of low-wealth households may address only important motives, while the consumption of wealthy households may fulfill less vital motives as well.

By moderating the saliency of consumption motives, wealth may determine consumers' choices between low-end and high-end brands. The austerity of low-end brands enables them to address consumers' basic motives only (Yalch and Brunel, 1996). Mainstream car brands, for example, affordably provide transportation but not much social status. On the other hand, premium brand vehicles can signal higher social status and offer more varied designs that allow consumers to better express their personality traits and values. Thus, consumer may trade up from low-end brands to high-end brands to fulfill additional goals when their

income and wealth allows them to.

### 3.4.2 Social status as consumption motive

The proposition that status signaling is a consumption motive has been advanced before (Silverstein et al., 2003; Miller, 2009; Han et al., 2010). Empirical evidence has been provided as well. For instance, Silverstein et al. (2003) surveyed consumers and grouped their reported reasons to trade up into four categories: a) time for the self, convenience, and reward (hedonic benefits); b) attracting, nurturing, and belonging (social bonding facilitation); c) adventure, learning, and play (mental stimulation); and d) self-expressing, self-branding, and signaling (self-concept maintenance, self expression, identity signaling, and social status signaling). The hedonic and stimulative benefits conferred by luxury brands stem from the higher quality of their products, such as the additional comfort provided by leather seats and the excitement associated with the high acceleration provided by a large engine of a car. The service that luxury goods provide in facilitating bonding depend a lot on their power to signal identities and social status, which perform assortative functions by allowing consumers to identify others with similar or desired interests (see, for example, Sundie, Kenrick, Griskevicius, Tybur, Vohs and Beal, 2011). We focus on three of the four categories identified by Silverstein et al. (2003) and reduce them to two groups of motives that correspond to two types of product attributes. These two types are: a) product functional and hedonic attributes; and b) status-signaling attributes.

As explained by Han et al. (2010), consumers choose car makes according not only to the functional quality of the models they offer but also because brands allow them to signal social status. The more expensive the brand purchased, the higher the wealth signaled by the driver. Thus, high-end brands signal higher social status and entail consumers with a diverse set of benefits such as better mating partners, longer life-expectancy, better health, preferential treatment, and better outcomes in economic transactions (see, for example, Berger et al., 1972; Nelissen and Meijers, 2011). Consumers may then choose an option with lower value per dollar in order to obtain the benefits of enhanced social status.

Social status was classified by Maslow (1943) as a higher-level need, implying that individuals first address more basic needs such as shelter, nourishment, and transportation. Evidence that social status can be devalued when resources are scarce can be found in the literature on power, which proposes that social status is a form of social power (Lammers, Stoker and Stapel, 2009). Work in this body of literature has found that socioeconomic status (that is, a consumer's relative wealth) is a structural determinant of power and that consumers with low generalized sense of power may not be very motivated to acquire high-status objects (Rucker et al., 2011). That is, individuals who's resources are very limited may not be concerned about using consumption to signal social status.

If wealth determines whether individuals devalue or pursue the signaling of social status through consumption, their choices of new cars should reflect this moderating role of wealth because automobiles are products that consumers use to signal social status (Chiao et al., 2009). More precisely, wealth-deprived consumers would buy automobiles that provide transportation and convenience at affordable prices. In contrast, wealthy consumers would reveal preferences for automobiles that allow them to signal social status.

In summary, extant theoretical and empirical results suggest that wealth levels may determine whether consumers pursue the fulfillment of only basic motives, such as transportation, or also less vital motives, such as social status. Given that the prominence of these motives may depend on wealth levels, high levels of wealth may lead to stronger revealed preferences for social status. This in turn may result in wealthy consumers trading up to higher-end brands.

### **3.5 Economic model**

In what follows, we extend the traditional compensatory utility model by letting the marginal utilities of attributes be moderated by wealth. We then show that this model is able to abstract non-homothetic preferences and predict trade ups.

In the traditional compensatory utility model, we write the indirect utility of consuming

product  $j$  as

$$u_j = \log(y - p_j) + X_j^T \beta, \quad (3.1)$$

where  $y$  is income. The vector  $\beta = [\beta_1, \dots, \beta_a, \dots, \beta_A]^T$  determines the importance of each of  $a = 1, \dots, A$  product attributes included in the vector  $X_j$ . That is, the  $\beta$  coefficients are the marginal utilities of consumer additional units of their respective product attributes. The term  $\log(y - p_j)$  embeds the budget constraint into the model and accounts for a diminishing marginal return of money (Easterlin, 2005). This simple model has been widely used in econometric work because of its simplicity. However, if used to predict both choice and quantity decisions, the model cannot reproduce all instances of trade up as it may predict that higher income induces consumers to buy multiple units of a given product (Allenby and Rossi, 1991).

Trade up can be modeled by allowing the marginal utility of consuming a product attribute to increase with consumption. Thus, and in agreement with the psychological model presented in Section 3.4, we let revealed marginal preferences for product attributes to be functions of consumer wealth  $w$ . In particular, we let the revealed preference weights  $\beta_a$  be zero when wealth is below or equal to a threshold  $\tau_a$ . If wealth is greater than this threshold, the revealed preference weights will equal some underlying preference weights  $\hat{\beta}$ . Accordingly, we let

$$\beta_a = \hat{\beta}_a I(w > \tau_a), \quad (3.2)$$

where  $I$  represents an indicator function that equals 1 when its argument is true. Thus, the underlying preference  $\hat{\beta}_a$  is revealed only if wealth is higher than the threshold  $\tau_a$ . This specification of the preference weights implies that consumers with wealth above the threshold  $\tau_a$  derive higher levels of utility than consumers with wealth below the threshold do. A low threshold  $\tau_a$  implies that the household will address the associated motive even if wealth is low. A high threshold  $\tau_a$  implies that the household will fulfill the associated motive only if wealth is high. If we define the vector  $\tau = [\tau_1, \dots, \tau_A]^T$ , then the smaller entries of  $\tau$  correspond to the attributes that the household prioritizes more.

The proposed model differentiates between income and wealth because empirical work

has shown that these two variables affect consumer behavior differently. Macroeconomic and microeconomic studies of the relationship between wealth and consumption have found that the marginal propensity to spend real estate and stock market assets is very low compared to the marginal propensity of spending earnings (Elliott, 1980; Paiella, 2009). This violation of the fungibility of money has been explained as a consequence of mental accounting; that is, the tendency of individuals to allocate different forms of wealth to different mental categories (Shefrin and Thaler, 1988). Accordingly, we let the budget constraint be defined by income rather than wealth.

Although wealth may not directly determine budget constraints, it does determine consumption. As reported by Paiella (2009), empirical work has generally found a positive and significant correlation between wealth and consumption. We focus our attention on the effect that wealth may have on the saliency of consumption motives. This effect could be the result of different mechanisms. For instance, the wealth of a household determines its social class and thus the social norms that the household is subject to. These social norms could determine what products households should consume (Bourdieu, 1979). Likewise, wealth could allow consumers to shift their attention from basic motives to less vital ones. Owning a home allows a household not to worry about housing and focus on the consumption of other goods.

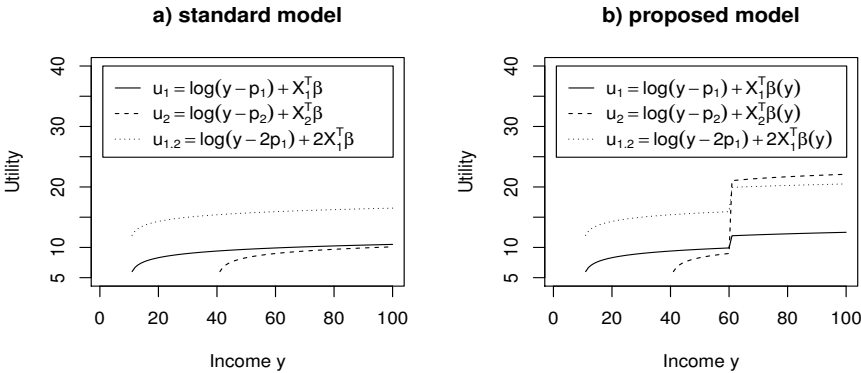


Figure 3.5: Utilities of buying product 1 ( $u_1$ ), product 2 ( $u_2$ ), and two units of product 1 ( $u_{1,2}$ ) as functions of income and wealth.

To illustrate how the proposed model predicts trade ups, we consider the choice between two substitute products that are perceived by consumers in terms of two attributes. For sake

of illustration and without loss of generality, this example assumes that wealth equals income ( $w = y$ ). We let the prices of the two products be  $p_1 = 10$  and  $p_2 = 40$ . The attributes of product 1 are such that  $X_1^T = [2, 1]$  and the attributes of product 2 are  $X_2^T = [2, 6]$ . For the standard model we let preferences be given by  $\beta^T = [3, 2]$ . For the proposed model we let  $\hat{\beta}^T = [3, 2]$  and  $\tau^T = [0, 60]$  so that preferences for attribute 2 are revealed only when wealth (income) exceeds the value of  $\tau_2 = 60$ . Preferences for attribute 1 are revealed for all non-negative levels of wealth (income). These parameter values produce the utility functions depicted in Figure 3.5. The plots show that for income levels satisfying  $y \leq 60$ , one or two units of product 1 provide more utility than product 2. However, for income levels satisfying  $y > 60$ , product 2 provides higher utility than product 1 and even than two units of product 1. Thus, trade up occurs when income surpasses the value  $y = 60$ .

## 3.6 Empirical study

### 3.6.1 Data

As described in Section 3.4, the proposed theoretical model predicts heterogeneity in the consumption motives of individuals. We therefore test the model empirically using individual-level data. In particular, we use individual-level automobile data because automobiles satisfy multiple consumption motives. This allows us to measure how much consumers prioritize social status over other consumption motives. Furthermore, the expensiveness of products in this category ensures that the income constraint plays a significant role as well.

We use data from the 2009 National Highway Transportation Survey that collected rich demographic and vehicle data from a large sample of car owners in the United States. Respondents in this nation-wide survey reported the year model, nameplate, and make of the vehicles they own as well as their income brackets and other household-specific variables such as the number of drivers, household size, etc. Because this is not transaction data, we consider the reporting of each vehicle of model 2008 as an observation of a new-car purchase. (We discard 2009 models as they represent less than 0.8% of the usable sample.) For sake



of statistical accuracy, we reduced the number of choice alternatives by focusing on the car market. That is, we removed SUV's, station wagons, and vans from the sample. We then randomly split the sample into two. The first subsample is used for estimation and the second subsample is used for out-of-sample hit-ratio tests. We then remove observations related to nameplates observed less than 45 times in the estimation subsample because we need to estimate nameplate-specific fixed effects. This results in a total of 3690 estimation observations and 912 test observations that span 31 different nameplates, or 75% of observations in the sample.

### **3.6.1.1 Consumer variables**

To characterize households, we used demographics such as the number of vehicles per driver (referred to as "VEHDRVRRATIO"), the number of non-drivers in the household ("NON-DRIVERS"), a dummy indicating whether the head of household belongs to the Black or Hispanic minority groups ("MINORITY"), and a coded variable indicating the education level of the the head of household (referred to as "EDUC"). We use the minority status of the household because race was shown to strongly correlate with willingness to pay for status-signaling products (Ivanic et al., 2011). Likewise, we include education because previous research showed that social class predicts the saliency of the need for self expression (Munson, 1973). We also compute a dummy variable ("HIGHOCC") that indicates whether the household's head practices a high-prestige occupation. Consistently with the classification proposed by Ganzeboom and Treiman (1996), this dummy variable equals one when the head's occupation is "professional, managerial, or technical" and zero when the occupation is "sales/service", "clerical/admin support", or "manufacturing, construction, maintenance, or farming". Other demographics considered are the age ("AGE") of the head of the household, the degree of urbanization ("URBAN") of the location of the household's home, an dummy that indicates if the household is in the midwest ("MIDWEST"), and the number of yearly miles driven by the head of household ("YEARMILE").

**Metric of income:** We constructed a measure of permanent income because permanent income has been shown to be more influential of vehicle choice than current income (Levedahl, 1980). A study by R.L Polk & Co. (2012*b*) reported that in 2009 households keep their new cars for about five years in average. We use this figure as a proxy for the length of the average planning horizon of vehicle purchases. This implies that the income that determines the transportation budget is the income perceived within five years. We accordingly let the permanent income of a household be  $y_h = 5HI$ , where  $HI$  is the current income reported by the household. We then use this metric of income to compute the utility of the outside good by subtracting the price  $p_j$  of each alternative  $j$  from the income variable  $y_h$ . This variable representing the outside good was labeled as “oGoods”.

**Metric of wealth:** Previous work has proposed different methods to measure wealth according to data availability. For instance, principal components analysis can be used to uncover wealth as component underlying households durable assets or consumption. As explained by Sahn and Stifel (2003), estimates of wealth obtained from asset ownership are better than estimates obtained from consumption. Because the NHTS includes enough data on home and automobile ownership, we simply approximate a household’s wealth as the sum of the estimated market values of the household’s real estate and car stocks.

In average, real estate is the single most important component of wealth. The value of a household’s primary residence accounts on average for 30% of the household’s wealth. Other components of wealth, such as the value of additional real state and diverse financial assets, account for at most 20% each (Keister and Moller, 2000). The NHTS does not collect information on the value of a household’s primary residency but provides an indicator of whether the household owns a home or not and an indicator of the type of the home. We accordingly used these indicators to approximate the real estate assets of each household. To better approximate the heterogeneity of household wealth, we used data on the metropolitan median area prices provided by the National Association of Realtors (NAR). This dataset provides the median price of extant single-unit and multiple-unit houses for the Metropolitan Statistical Areas included in the NHTS. We accordingly matched the type of home reported

in the NHTS with the prices reported by the NAR if the NHTS household reported owning the home it inhabits.

Automobile stocks are another important component of household wealth. Because households participating in the NHTS report the make and age of each single vehicle they own, we can approximate the market value of each of these vehicles accounting for its depreciation. We assign to each vehicle a value given by the median price of the 2009 models offered by the manufacturer of the vehicle under consideration. We then depreciate this value using an exponential depreciation rate because this rule was shown to be accurate in practice (Storchmann, 2004). Following the results by Storchmann (2004), we use an exponential yearly depreciation rate of 15%. Having computed the depreciation-adjusted value of each vehicle owned by the household, we sum across vehicles to obtain an estimate of the market value of the household's car stock.

Both metrics of permanent income and wealth were adjusted to account for differences in the cost of living across the different metropolitan areas in the sample. To this end, we relied on the ACCRA Cost of Living Index (COLI) published by the Council for Community and Economic Research (C2ER).

### **3.6.1.2 Product attributes**

The respondents of the NHTS do not report the sale price nor the attributes of the vehicles they own. We accordingly merge the NHTS data with pricing and attribute data collected from specialty Internet websites such as `consumerguideauto`. The lowest Manufacturer Suggested Retail Price (MSRP) among all trims of a nameplate is used to proxy for the transaction price. This approximation is not without problems but circumvents: a) the difficulty of not knowing the household-specific transaction prices of the alternatives not chosen; as well as b) the endogeneity induced by the correlation between the individual transaction price and other household-specific variables such as bargaining power (Goldberg, 1995).

To characterize the attributes of each option in the choice set, we use a reduced set of both

objective and subjective variables. For the objective attributes, we used raw data on engine size in liters (“Power”), vehicle height (“Height”), and its seating capacity (“Seats”). We also include a dummy variable that indicates whether the brand of the vehicle is Asian (“Foreign”). For the subjective attributes, we use expert ratings reported by `consumerguideauto`. We focus on the quality of the details of a car because it determines the luxuriousness of the vehicle. This variable was labeled as “Luxury”. We also compute metrics of the status and product-line variety of each vehicle as described below. We then computed a dummy variable that equaled one when the household owned another vehicle of the same make and zero otherwise. We labeled this variable “hasMake”, or  $v_{hj}$  because it is specific to household  $h$  and to the brand of option  $j$ . This variable was included to a) mitigate potential heterogeneity biases (Allenby and Rossi, 1991); and b) improve the predictive power of the model.

In addition to the aforementioned product attributes, we compute a measure of the variety in the product line of each make. Two well established metrics of the variety of an assortment are the dispersion and dissociation of attributes (Van Herpen and Pieters, 2002). We estimated the models using metrics of dispersion and dissociation to find that they produce qualitatively identical results. Since the metric of dissociation produced more significant estimates, we only report results for this metric.

To build a metric of attribute dissociation (or the opposite of product line consistency), we subtracted from one the median of the elements of the correlation matrix that we computed from the data of the attributes of the vehicles offered in a category by each make. That is, we computed

$$\text{attrVar}_{jk} = 1 - \text{median}\{VAR(X_l)_{aa}\}, l \in b(j, k), a = 1, \dots, A$$

where  $b(j, k)$  is the brand/category to which product  $j$  belongs (e.g. Toyota/SUV) and  $X_l$  are a vector of attributes for product  $l$ , which are indexed by  $a$ . According to this metric, the smaller (more negative) the median correlation, the more different the nameplates offered by the make are.

An additional dataset was obtained from the Environmental Protection Agency (EPA).

This dataset was used to classify each nameplate into one of the several categories designed by the EPA. To ensure that each category includes multiple nameplates, several categories were merged to obtain four groups, namely “Compact cars”, “Midsize cars”, “Large cars”, and “Premium cars”, to the subcompact cars category was merged into the compact cars group. These new categories included ten, nine, six and six nameplates, respectively.

**Metric of the social status of a product:** For each brand/category combination we computed the metric of brand status proposed in Chapter 2. Relying on social comparison theory, we proposed that the status that brands signal depend on how expensive the brands are perceived to be. The expensiveness of a brand in turns depends on the prices of the members of the brand, whose distribution is processed by consumers to generate the price of the brand (a measure of how expensive the brand is perceived to be). The status of a focal car will then depend on the position of its brand’s price relative the prices of the brands of all the vehicles owned by the consumers that constitute the reference group of the driver of the focal car.

We follow the framework proposed in Chapter 2 and let the price of a brand be given by the price of the most typical nameplate offered by the car make. Since we reported that the median price among the prices of the members of the product line signals status for a large number of consumers, we let the product with the median price be the most typical member of the product line. We accordingly extracted the median price across the nameplates of a make and then build a distribution of median prices for all makes. The status of the make was giving by the range-frequency value (Wedell and Parducci, 2000) associated with its median price and the distribution of the median prices for all makes owned by the relevant consumer population.

Accordingly, we compute  $F_g(\cdot)$ , the cumulative density function of the brand prices of all the vehicles in geography  $g$ . Then the local status of a given model  $j$  offered by brand  $b$  is given by

$$s_{j,g} = 0.5F_g(p_{b(j)}) + 0.5\frac{p_{b(j)} - \min_{l(g)}\{p_{b(l(g))}\}}{\max_{l(g)}\{p_{b(l(g))}\} - \min_{l(g)}\{p_{b(l(g))}\}},$$

where  $p_{b(j)}$  is median of the prices of the products  $j$  offered by brand  $b$  and  $\{p_{b(l(g))}\}$  is the

set of median prices of each brand  $l$  represented in the population of cars in circulation in geography  $g$ . In the subsequent analysis, we refer to this variable as “status”.

**Instruments:** Because prices, the status of the brand, and product-line attributes are determined by the firms in response to demand, these product attributes are endogenous. We accordingly need instruments to induce exogenous variation into our model. To instrument for prices, status, and attribute variation, we use the average insurance premium paid for each nameplate in 2010. Insurance rates are highly correlated with vehicle prices. More generally, insurance premia are determined by insurance companies as functions of consumer demographics, driving records, credit scores, driving habits, and vehicle attributes such as age, cost, safety ratings, and potentially engine size (Insurance Bureau of Canada, 2012; Insurance Information Institute, 2012). While consumer-specific variable and vehicle age are not relevant here, the correlations between insurance premia and safety scores and between insurance premia and engine size can limit the validity of the proposed instrument. In particular, for an instrument to be valid, it must be uncorrelated with the unobserved product attributes. Thus, the model specification must include measures of the vehicle’s safety score and of the vehicle’s size engine so that these attributes are not lumped into the error term. We accordingly include in our specifications the vehicle’s engine size and the nameplate’s average collision losses are the national level (highly correlated with safety ratings). This way, we ensure that the correlation between the estimation error and our instrument is negligible.

### 3.6.2 Econometric Models

#### 3.6.2.1 Proposed model

To model consumer choice, we propose a nested multinomial logit specification in which the utility that household  $h = 1, \dots, H$  draws from purchasing nameplate  $j = 1, \dots, J$  is given by

$$u_{hj} = \alpha_1 \log(y_h - p_j) + \sum_{l=2}^{n_v} \alpha_l v_{hjl} + \sum_{a=1}^A \psi_{ha} \lambda_a x_{hja} + \delta_j + \epsilon_{hj}, \quad (3.3)$$

where  $y_h$  is the income of household  $h$  and  $x_{hja}$  are the  $a = 1, \dots, A$  interactions of product attributes with household demographics. The parameters  $\delta_j$  are option-specific fixed effects used to separate the utility of unobserved attributes from other unobservables that are lumped into  $\epsilon_{hj}$ , as in (Chintagunta et al., 2005). In agreement with a nested logit specification, we let this unobserved component  $\epsilon_{hj}$  be given by

$$\epsilon_{hj} = \zeta_{hk} + (1 - \rho)\zeta_{hj}, \quad (3.4)$$

where the error components  $\zeta_{h,k}$  and  $\zeta_{h,j}$  satisfy the conditions described by Cardell (1997) and the term  $\rho$  determines the importance of each error component. The variable  $k$  indexes the  $K$  vehicle classes defined in Section 3.6.1.

The coefficients  $\alpha_l, l = 1, \dots, n_v$  represent the weights that consumers give to  $n_v$  variables that are both household-specific and product-specific. The first one,  $\alpha_1$ , determines the importance of the income left for spending in other goods  $y_h - p_j$ . The second one,  $\alpha_2$ , determines the importance of previous experience with the brand of option  $j$  as operationalized by the variable  $v_{hj2}$ . Additional  $v_{hjl}$  variables can be added to control for additional unobserved heterogeneity. The coefficients  $\lambda_a$  represent the importance of each of the  $a = 1, \dots, A$  covariates  $x_{hja}$ .

The model accounts for the saliency of consumption motives through the coefficients  $\psi_{ha}, a = 1, \dots, A$ , which relate to  $M$  motive-specific coefficients  $\psi_{hm}, m = 1, \dots, M$  through a linear mapping  $\psi_{ha} = G\psi_{hm}$ . In other words, each of the  $\psi_{hm}$  coefficients embodies the saliency of a single consumption motive associated with a single product attribute such as the product's social status or its self-expressiveness. The  $G$  matrix thus maps the saliency coefficients of the  $M$  consumption motives into the saliency of the  $A$  covariates  $x_{hja}$ . These coefficients of the saliency of each consumption motive are defined as

$$\psi_{hm} = \begin{cases} 1 & \text{if } \mu_{hm} \geq \tau_m \\ 0 & \text{otherwise,} \end{cases} \quad (3.5)$$

where the coefficients  $\tau_m, m = 1, \dots, M$  represent thresholds of above which the consumption motives are salient. The parameters  $\mu_{hm}$  are therefore measures of the motivation of

household  $h$  to pursue motive  $m$ . This motivation is consumer specific and therefore can be written as a function of consumer-specific variables, such that

$$\mu_{hm} = q_h^T \theta_m + \kappa_{hm}, \quad (3.6)$$

where the vector  $q_h$  may include measures of the household's wealth,  $w_h$ , and its square,  $w_h^2$ , to allow for some motives to be overlooked above certain levels of wealth.

We assume that the unobservables  $\kappa_{hm}$  follow a multivariate normal distribution such that the vectors  $\boldsymbol{\kappa}_h = [\kappa_{h1}, \dots, \kappa_{hM}]^T$  are distributed as  $\boldsymbol{\kappa}_h \sim N(0, \Sigma)$ . This specification of a full covariance matrix enables the model to capture correlations across motives and within households. As a result, the specification (3.5) is that of a multivariate ordered probit model in which the parameters  $\theta_m$  and the thresholds  $\tau_m$  must be simultaneously estimated. Because ordered probits are not fully identified, we impose an identifying restriction by setting to zero the intercepts in the specification of  $\mu_{hm}$ . We use a multivariate Hastings-within-Gibbs estimation algorithm to accelerate the convergence of the chains, according to the method proposed by Cowles (1996). We likewise rely on the method of Smith and Kohn (2002) to estimate  $\Sigma$  through the decomposition  $\Sigma^{-1} = BCB^T$ , where  $B$  is a lower-triangular matrix with 1's in the diagonal and  $C$  is a diagonal matrix. This specification is preferred to the more standard inverted Wishart because it allows for more flexibility. The details of the estimation algorithm are presented in Appendix 3.A.

The coefficients  $\lambda_a$  can be used to compute a household-specific weight  $\beta_{hm}$  that measures the strength of the  $h$ -th household's preferences for the product attribute that satisfies the  $m$ -th consumption motive. If we denote  $\beta_h = [\beta_{h1}, \dots, \beta_{hM}]^T$  and  $\lambda = [\lambda_1, \dots, \lambda_A]^T$ , then we can express a household's preferences as

$$\beta_h = G^T \text{diag}(\lambda) d_h, \quad (3.7)$$

where  $d_h$  is a vector of demographic variables and  $G$  is the transformation matrix defined above.

To estimate the across-population average preferences for different product attributes, we regress the fixed effects  $\delta_j$  on the product attributes  $\mathbf{x}_{hj} = [x_{hj1}, \dots, x_{hjA}]^T$ . We follow



Chintagunta et al. (2005) and use the equivalent of a two-stage least squares procedure to carry out this regression. The choice of instruments is discussed in the data section. Accordingly, we let the product-specific fixed effects be given by

$$\delta_j = \gamma^T \hat{z}_j + \xi_j, \quad (3.8)$$

where  $\xi_j$  are the unobserved attributes of option  $j$  and  $\hat{z}_j$  is the 2SLS projection of the alternative attributes  $\mathbf{x}_{hj}$  on the instruments  $z_j$ . The vector  $\gamma$  is to be estimated and represents a form of average preferences.

### 3.6.2.2 Benchmark models

Aside from the econometric model proposed above, we estimate two less structured models that we use as benchmarks to assess the benefits of modeling motivation. This first benchmark model does not account for the role of wealth on preferences, while the second benchmark model does consider wealth but in more “reduced form”.

Benchmark model I allows us to compare the performance of the proposed utility model against that of more standard utility models the benchmark model is akin to. In particular, Benchmark model I is similar in structure to that of Chintagunta et al. (2005) but differs in that it incorporates consumers’ budget constraints. The benchmark specification mimics these extant models in that it assumes that preferences are unaffected by wealth. In particular, the benchmark model replaces the definition of utility in (3.3) by the simpler formulation given by

$$u_{hj} = \alpha_1 \log(y_h - p_j) + \alpha_2 v_{hj} + \sum_{a=1}^A \lambda_a x_{hja} + \delta_j + \epsilon_{hj}. \quad (3.9)$$

The third model used in our analysis, Benchmark model II, does incorporate the effect of wealth on consumer preferences but avoids the structure imposed in the proposed model by letting wealth enter linearly into the utility function, such that

$$u_{hj} = \alpha_1 \log(y_h - p_j) + \alpha_2 v_{hj} + \sum_{a=1}^A [\lambda_{a0} x_{hja} + \lambda_{a1} x_{hja} w_h] + \delta_j + \epsilon_{hj}. \quad (3.10)$$

That is, this specification assumes that the preference weights can be rewritten as  $\tilde{\lambda}_a =$

$\lambda_{a0} + \lambda_{a1}w_h$ . This functional form lets preferences be given by a baseline level  $\lambda_{a0}$  and a component that increases with wealth. Therefore, this specification of preferences allows wealthier households to have stronger (or weaker) taste for different forms of quality.

### 3.6.3 Identification

The model given by (3.3)-(3.8) is an extension of a homogeneous choice model that has been extensively used to model car choice. Accordingly, the identification of the parameters  $\rho$ ,  $\lambda$ ,  $\alpha$ ,  $\delta$ , and their variances has been discussed elsewhere and is omitted here. Given that the coefficients  $\psi_{ha}$  described in (3.5) are a new feature introduced here, their identification does deserve some discussion.

We first note that the  $\psi_{ha}$  coefficients are household specific parameters that follow a Bernoulli distribution. These parameters are identified together with the  $\tau_m$  coefficients from observing household with similar demographics but different revealed preferences. For sake of illustration, consider a hypothetical scenario in which products can be characterized by one single attribute that measures, for instance, the luxury of the product. This implies that our model requires one single threshold parameter  $\tau_1$ . Assume also that each of the observed households belongs to one of two groups of households that are identical in terms of the distributions of all of their demographics except wealth. If we estimate the effect on observed choices of the product attribute and the demographics using a conventional model of compensatory utility (in which  $\psi_{h1} = 1$ ), the estimated weights  $\lambda_a$  would attempt to best explain the behavior of the two groups of households simultaneously. However, the different choices of the two groups can be better explained by letting each group have their own weights  $\lambda_a$  such that the preferences for luxury of the households buying luxury cars are stronger than the preferences for luxury of the households buying compact cars. This difference in preferences is introduced into the model through the  $\psi_{h1}$  coefficients, which induce zero  $\lambda_a$  weights for the buyers of mainstream cars and non-zero  $\lambda_a$  weights for the buyers of luxury cars. Thus, the  $\psi_{hm}$  parameters are identified by the improvement of fit that results from using group-specific preference weights instead of homogeneous preference weights. The

identification of the  $\psi_{hm}$  parameters is, in some sense, similar to the identification of a latent-class model.

Identification of the  $\tau_1$  parameter follows from the identification of the  $\psi_{h1}$  parameters. Given the realized values of the  $\psi_{h1}$  parameters, the population of consumers is categorized into two groups (one group with  $\psi_{h1} = 1$  and the other group with  $\psi_{h1} = 0$ .) The parameters  $\tau_m$  are identified from differences in the wealth levels of the two groups as determined by the  $\psi_{hm}$ . Put differently, the estimation of the  $\tau_1$  parameter is akin to a discriminant analysis in which wealth is the basis of classification. The  $\tau_1$  parameter defines the sizes of the two populations of households by providing a classification rule for the  $\psi_{h1}$  parameters. On such classification rule could, for example, be one that maximizes the likelihood of the observed purchases. Because the  $\tau$  parameters are estimated jointly with the  $\psi_{hm}$  parameters, the variation in  $q_h$  helps the identification of the  $\psi_{hm}$  parameters.

In addition, we note that the coefficients  $\psi_{ha}$  are by definition correlated with each other because they are linear functions of the parameters  $\psi_{hm}$ . Thus, the correlations of the  $\lambda_a$  parameters, as observed in the data, are partly attributed to the correlations of the  $\psi_{ha}$  parameters. This attribution favors the identification of  $\psi$  the parameters as well.

### 3.6.4 Results

In what follows we first present model-fit statistics to show that the proposed model outperforms the benchmarks. We then present parameter estimates and discuss their implications. Estimation is performed using Markov Chain Monte Carlo (MCMC) methods as described in Appendix 3.A. We therefore present the posterior means of the estimates as well as the probabilities that the sign of the estimates differs from the sign of the posterior mean. A zero probability indicates that the posterior distribution does not include zero and therefore that the estimate is statistically different from zero.

Table 3.1: Model fit statistics. DIC stands for Deviance Information Criteria. LL stands for log likelihood and Hel. stands for Hellinger distance. The slope and the  $\bar{R}^2$  are the posterior means of the parameters of the regressions of the predicted sample shares on the actually observed nameplate shares.

Model	in-sample					out-of-sample				
	DIC	LL	slope	$\bar{R}^2$	Hel.	DIC	LL	slope	$\bar{R}^2$	Hel.
Bench. I	22647	-11420	1.39	0.71	0.435	5700	-2849	1.34	0.742	0.411
Bench. II	21826	-11489	1.35	0.634	0.401	5774	-2886	1.24	0.641	0.371
proposed	23748	-11868	1.09	0.701	0.325	5807	-2902	1.11	0.742	0.321

### 3.6.4.1 Model fit and predictive power

We compare the three models in terms of fit and predictive power using several measures. First, we compute each model’s Deviance information Criterion (DIC) (Spiegelhalter et al., 2002), as explained in Appendix 3.B, and report it in Table 3.1. We use the DIC rather than the more common Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC) because the number of parameters in hierarchical models is not well defined. According to the DIC scores, the proposed model does not fit the data better than the other two models. In fact, the DIC of Benchmark model II is smaller than the DIC of benchmark model I in the in-sample test. This suggests that wealth has explanatory power beyond that of other demographic variables but the amount of information in the data may not always compensate for the additional model complexity.

A more detailed interpretation of the DIC scores follows from a comparison of the log-likelihoods of the models. These are reported in Table 3.1 as well. Keeping in mind that the models with wealth nest Benchmark model I but the proposed model does not nest Benchmark model II, we note that both models with wealth have lower log-likelihoods than

Benchmark model I. Since the definition of the DIC can be rewritten as

$$\begin{aligned} DIC &= 2\overline{D(\theta)} - D(\bar{\theta}) \\ &= -4E_{\theta}[\log\{p(y|\theta)\}] + 4E_{\theta}[\log\{f(y)\}] + 2\log\{p(y|\bar{\theta})\} + 2\log\{f(y)\}, \end{aligned}$$

where  $D$  is the Bayesian deviance and  $y$  is the data, we have that the DIC increases with the log-likelihood  $-\log\{p(y|\theta)\}$  and decreases with the “plug-in” estimate  $\log\{p(y|\bar{\theta})\}$ . This plug-in estimate can be regarded as a measure of how well the posterior estimates  $\bar{\theta}$  re-predict the data and therefore relates to the predictive power of the estimates. From these observations, we conclude that the negative effect of a lower likelihood on the DIC scores of the models with wealth can be mitigated by the models’ improved predictive power.

We further explored this conclusion by directly analyzing the predictive ability of the three models. To this end, we first computed the probabilities of each household choosing each vehicle in the sample and used these probabilities to draw a choice from the respective multinomial distribution. We did this for each set of estimates in the chain so as to obtain a large sample of choices for each household. We used these predicted choices to compute the predicted shares of each nameplate and regressed these predicted shares on the shares actually observed in the sample (without an intercept). Table 3.1 reports the posterior means of the slope of this regression as well as the posterior means of the adjusted  $R^2$  statistics to provide measures of how closely the predicted shares follow the actual shares. The regression slopes indicate that the proposed model generates less biased predictions of the sales of each product. The  $\bar{R}^2$  statistics indicate that the predictions drawn from each of three models are able to explain a large portion of the variation in the actual shares.

Finally, we computed metrics of distance between the distribution of actual choices and the distributions of predicted choices. We, in particular, compute the Hellinger distance, which, for two discrete distributions  $P = (p_1, \dots, p_k)$  and  $Q = (q_1, \dots, q_k)$ , is defined as

$$H(P, Q) = \frac{1}{\sqrt{2}} \sqrt{\sum_i^k (\sqrt{p_i} + \sqrt{q_i})^2}. \quad (3.11)$$

The computed statistics appear in Table 3.1 and indicate that the distribution of choices predicted by the proposed model is more similar to the distribution of observed choices than

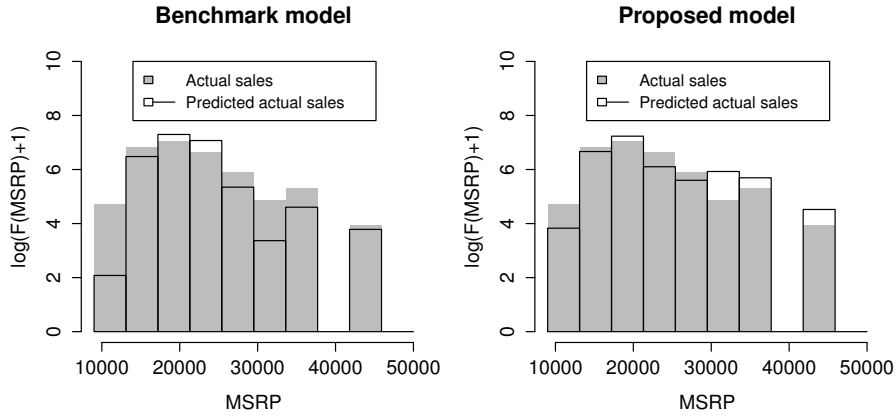


Figure 3.6: Actual and predicted distributions of prices.

the distributions of choices predicted by the benchmark models. This result is supported by the plots presented in Figure 3.6. These plots present the distribution of the prices of the vehicles chosen by the households as they were recorded in the survey and as they are predicted by Benchmark model I and by the proposed model.

### 3.6.4.2 Consumer preferences and their saliency

Table 3.2: Posterior means of the estimates of the  $\alpha$  utility weights for spending income on other goods (oGoods) and purchasing vehicles of a make already owned (hasMake). Numbers in brackets are the probabilities of the estimate having sign different to that of its mean.

Estimate	Model	
	Benchmark I	proposed
oGoods	0.11 [0]	0.72 [0]
hasMake	0.56 [0]	0.61 [0]

As the analysis of fit showed that both wealth and motivation add value to our model of consumer choice, the subsequent discussion will compare the estimation results generated by Benchmark model I and by the proposed model only. We omit the estimation results generated by Benchmark model II to reduce clutter.

Posterior means of the estimates of the  $\alpha$  coefficients for the two models of interest appear in Table 3.2. In general, the estimates are consistent across specifications. Preferences for having money left for spending on other goods are positive, as one would expect. The positive sign of the coefficient for “hasMake” implies that households tend to be brand loyal as they have positive preferences for buying car makes they already own. We notice that the inclusion of motivation into the model dramatically increases the importance of money spent on other goods.

Posterior means of the estimates of the  $\lambda$  coefficients for the two models of interest appear in Tables 3.3 and 3.4. The figures these tables show that, while there are some remarkable differences, a large number of the coefficient signs are consistent across specifications. A major difference of interest is that the estimates of the proposed model are about one order of magnitude larger than the estimates of Benchmark model I.

The signs of some of the estimates lend some face validity to the results. For example, according to the proposed model, the sign of the coefficient of the interaction between the demographic “NONDRIVERS” and engine power is positive. This positive sign indicates that households with more members who do not drive prefer more powerful cars, arguably because these households need to transport heavier passenger loads. Likewise, the negative sign of the coefficient of “YEARMILE x Power” indicates that heavy user households prefer smaller engines. The more a household drives, the smaller the engine it prefers so as to reduce fuel expenses.

Of particular interest is the sign of the estimated coefficient that relates “MINORITY” to “Status”; that is, the effect of belonging to a minority group on the preferences for vehicles that signal high social status. The estimates generated by the benchmark and proposed models are positive, though not statistically different from zero. In terms of the

Table 3.3: Posterior means of the estimates of the  $\lambda_a$  weights (for the benchmark and proposed models) and of the  $\lambda_{a1}$  weights (for the reduced-form model with wealth). Numbers in brackets are the probabilities of the estimate having sign different to that of its mean.

Estimate	Model		Estimate	Model	
	Benchmark I	proposed		Benchmark I	proposed
AGE x Status	1.79 [0]	-4.16 [0]	URBAN x Power	-0.29 [0]	-0.61 [0]
EDUC x Status	0.39 [0]	16.3 [0]	YEARMILE x Power	-0.08 [0]	-1.66 [0]
HIGHOCC x Status	-0.1 [0]	-1.2 [0]	MINORITY x Power	0.54 [0]	1.49 [0]
MINORITY x Status	0.1 [0.14]	0.07 [0.22]	NONDRIVERS x Power	-0.44 [0]	2.24 [0]
VEHDRVRRATIO x Status	-0.94 [0]	5.06 [0]	VEHDRVRRATIO x Power	0.31 [0]	-9.03 [0]
AGE x attrVar	-0.71 [0]	-3.32 [0]	EDUC x Height	-1.01 [0]	-20.61 [0]
EDUC x attrVar	0.22 [0]	2.15 [0]	URBAN x Height	0.78 [0]	-0.63 [0]
HIGHOCC x attrVar	0.05 [0]	0.56 [0]	MINORITY x Height	0.24 [0]	3.9 [0]
MINORITY x attrVar	-0.3 [0]	-0.13 [0.04]	VEHDRVRRATIO x Height	-0.16 [0]	-1.24 [0]
VEHDRVRRATIO x attrVar	-0.03 [0.14]	-5.2 [0]			

interaction between “AGE” and “Status”, the two models make opposite predictions. While the estimates of Benchmark model I suggest that older householders have stronger preferences



Table 3.4: Posterior means of the estimates of the  $\lambda_a$  weights (for the benchmark and proposed models) and of the  $\lambda_{a1}$  weights (for the reduced-form model with wealth). Numbers in brackets are the probabilities of the estimate having sign different to that of its mean.

Estimate	Model		Estimate	Model	
	Benchmark I	proposed		Benchmark I	proposed
AGE x Luxury	-1.91 [0]	-3.46 [0]	NONDRIVERS x Seats	-0.1 [0]	-6.07 [0]
EDUC x Luxury	0.35 [0]	2.85 [0]	VEHDRVRRATIO x Seats	0.26 [0]	10.64 [0]
HIGHOCC x Luxury	0.32 [0]	1.67 [0]	AGE x Foreign	0.41 [0]	4.48 [0]
MINORITY x Luxury	-0.17 [0]	1.8 [0]	URBAN x Foreign	-0.14 [0]	2.32 [0]
VEHDRVRRATIO x Luxury	0.29 [0]	-8.71 [0]	MIDWEST x Foreign	-0.23 [0]	0.3 [0]

for high-status products, the proposed model suggest it is younger households who have stronger preferences for status.

We do find agreement in the estimates of the preferences of educated households, concluding that education levels positively correlate with preferences for status. The estimates of the preferences of households with high occupational prestige for status-signaling vehicles suggest an negative interaction between these two variables. That is, consumers with prestigious occupations prefer lower status products.

High occupational-prestige and highly educated households both have stronger preferences for specific combinations of product attributes, as suggested by the positive sign of the coefficient of the interactions “EDUC x attrVar” and “HIGHOCC x attrVar”. These

preferences dwindle as the head of the household ages, as suggested by the negative sign of the coefficient of the “AGE x attrVar” interaction. Minority households also appear to have weaker preferences for specific attribute combinations, as do households that own a large number of vehicles relative to the number of drivers. This could reflect the fact that, the more cars per driver the household owns, the more personalized the vehicles can be to specific drivers within the household and thus the weaker the needs to match the combined preferences of multiple household members.

The positive signs of the estimates of the interaction “HIGH OCC x Educ” indicate that the more educated the household, the stronger its preferences for luxury are. On the other hand, the older the householder, the weaker the preferences for luxury. According to the estimates of the proposed model, the higher the occupational prestige of the household, the stronger the preferences for luxury. Minority households appear to have stronger preferences for luxury as well.

The estimates of the average motivation levels,  $\tau_m$  at which preferences for the different product attributes are elicited are reported in Table 3.5. The estimates indicate that the motivation to purchase a foreign vehicle is the one that arises first, followed by the motivation to care about height and power. As their wealth increases, households become more likely to exercise their preferences for specific attribute combinations, luxury, specific seating capacity levels, and social status.

The estimates of the  $\theta$  coefficients offer interesting insights as well. We note that wealth has a positive first order effect on the motivation to consume high status products, but a negative second order effect. This implies that, although motivation to consume status increases with wealth, it does so at a diminishing rate. The wealthiest households are less likely to express their preferences for social status and households near the center of the wealth scale. Householders who practice high-prestige occupations are less motivated to pursue status through consumption, just like highly educated households. Belonging to a minority group appears to have little influence in the motivation to consume status.

We find that wealth also has a positive but declining effect on the motivation to pursue

Table 3.5: Posterior means of the estimates of the motivation thresholds  $\tau_m$  and the coefficients  $\theta_{mq}$ . Numbers in brackets are the probabilities of the estimate having sign different to that of its mean.

		$\tau_m$	$\theta_{mq}$						
			Demographic $q$						
			WEALTH	WEALTH <sup>2</sup>	HHSIZE	MINORITY	HIGHOCC	EDUC	NONDRIVERS
Motive $m$	Status	0.77 [0]	0.18 [0]	-0.12 [0.08]	-0.09 [0.1]	0 [0.38]	-0.05 [0.02]	-0.15 [0]	-0.11 [0]
	attrVar	0.56 [0]	0.26 [0]	-0.24 [0]	-0.12 [0]	-0.02 [0.24]	-0.04 [0.04]	0.04 [0.06]	0.08 [0]
	Luxury	0.62 [0]	0.07 [0.1]	-0.09 [0.08]	0.04 [0.12]	0.01 [0.42]	-0.04 [0.04]	-0.07 [0]	-0.09 [0.02]
	Power	0.41 [0]	-0.25 [0]	0.3 [0]	0.11 [0]	0.04 [0.02]	0.03 [0.12]	0.03 [0.08]	0 [0.56]
	Height	0.41 [0]	-0.01 [0.52]	0.02 [0.4]	0.15 [0]	0.09 [0]	0.08 [0]	0.35 [0]	-0.09 [0]
	Seats	0.74 [0]	-0.2 [0]	0.18 [0.04]	0.12 [0.04]	0.01 [0.4]	0.08 [0.02]	0.52 [0]	0.17 [0]
	Foreign	-0.07 [0]	-0.06 [0.12]	0.14 [0.02]	0.12 [0]	-0.08 [0]	0.11 [0]	0.16 [0]	-0.07 [0.04]

preferences for specific combinations of product attributes. This motivation is more likely to be effective for smaller and educated households with low occupational prestige and a

larger number of non-drivers. The motivation to consume luxury appears to be affected by demographics very similarly to how the motivation for status is.

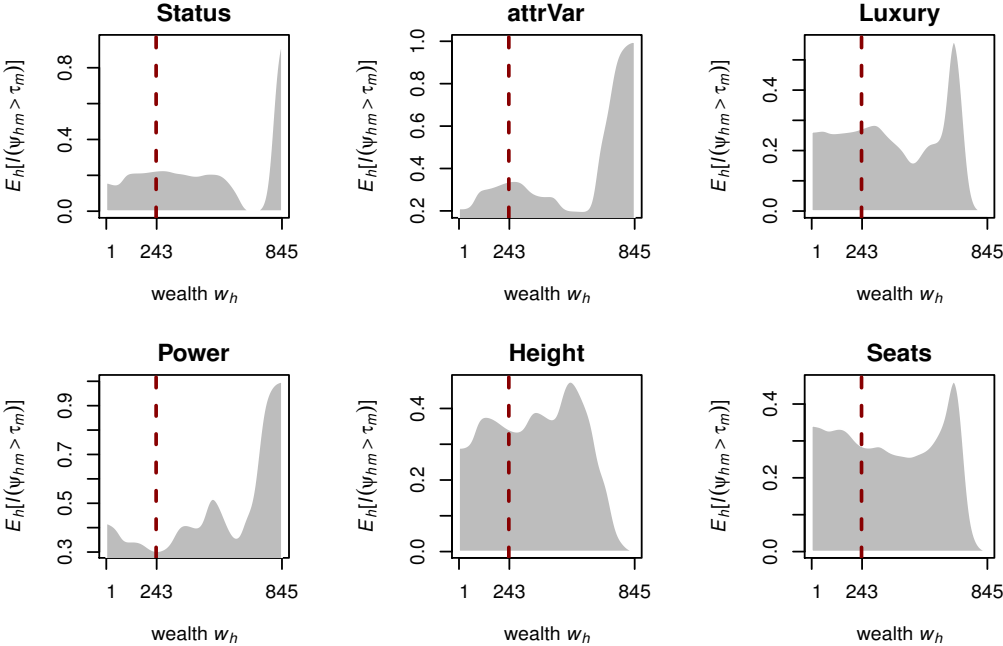


Figure 3.7: Probabilities that a household reveals its preferences for different consumption motives at different wealth levels. Wealth is given in thousands of dollars.

The probabilities that a household exercises its preferences for each product attribute are depicted in Figure 3.7 as functions of wealth. We note that the shapes of these curves can be affected by the shape of the distribution of wealth.

### 3.6.5 Discussion

#### 3.6.5.1 Methodological contribution

Our work contributes to the methodological literature on models of consumer heterogeneity. We show that consideration of the saliency of consumption motives can improve the predictive power of models of consumer demand. The proposed model outperforms the more standard benchmark model in terms of predictive ability in in-sample and out-of-sample tests. This improvement is due to the introduction of wealth into the model but also to the structure imposed on the proposed model. This conclusion follows from the fact that

the out-of-sample predictions made by Benchmark model II are better than those made by Benchmark model I but more biased than those made by the proposed model.

A comparison of the magnitudes of the coefficients generated by Benchmark model I against those generated by the proposed model suggests that, by accounting for wealth and motivation, the proposed model is able to identify a stronger effect of the budget constraints (refer to Table 3.2). Likewise, a comparison of the magnitudes of the estimates in Table 3.3 reveals that, by accounting for the possibility that preferences may be suppressed, the proposed model allow us to better estimate the actual importance of these preferences. Accounting for the heterogeneity in motivation, we can mitigate the effects of aggregation bias.

Another stream of methodological research we contribute to is the one that has focused on relaxing the assumptions imposed on traditional utility models. Because the psychological theory that underlies the proposed model leads to an economic model of non-homothetic preferences, we advance the line of research on non-homothetic demand models that was established by Allenby and Rossi (1991) and Allenby et al. (2010). We extend this line of research by empirically showing that the consideration of motivation and wealth can improve the predictive performance of the choice models. Models that account for both wealth and the saliency of consumption motives may be able to better forecast demand. Even accurate wealth data is seldom available, rough proxies of wealth (like the one used in our study) can improve predictive power.

### **3.6.5.2 Theoretical contribution**

This study presents a new explanation to observed trade down and trade up behaviors. Because the proposed framework can incorporate multiple consumption motives, the proposed model unifies several of the previously proposed explanations of consumers' choice of low-end and high-end products. Our model can incorporate, for instance, heterogeneous valuations of quality, consumer needs for social status and any other consumption motive that can be satisfied by a measurable product attribute. In this sense, the proposed theoretical model

represents a step towards a richer theory of preferences for quality.

The proposed theoretical framework finds support in the reported empirical study as the proposed model predicts product sales better than a standard empirical model of choice does. That is, we provide support to the external validity of models of human motivation that posit that human motives may be revealed or suppressed (Kenrick et al., 2010). Our results also support the contention that this saliency of motives may depend on the availability of resources and that different levels of resources are required for different motives to be salient. For example, we find that preferences for status-signaling products are elicited at much higher motivation (and wealth) levels than preferences for imported cars. These results thus extend the findings of Kamakura and Mazzon (1991) by showing that hierarchies of motives are relevant in the consumption context and that wealth moderates how consumers prioritize their motives.

The estimates that reflect the importance of product attributes to different demographic groups are consistent with previous findings. First, the result that minority households could exhibit stronger preferences for high-status products is consistent with the findings of Ivanic et al. (2011). Second, the result that educated households also have stronger preferences for status products is consistent with the observations of (Veblen, 1899). Third, the result that household with high occupational prestige care less about status can be explained in terms of the finding that individuals holding managerial positions (high occupational prestige) have more power and perceive themselves as more powerful (Rucker et al., 2011). Because individuals in high-power states focus more on the utilitarian aspects of products, they may be less concerned with status (Rucker et al., 2011).

### **3.6.5.3 Robustness**

Because the proposed metrics of permanent income and wealth are crude, we attempted to assess how much their specification affects the results. We estimated the model using different metrics of permanent income and different metrics of wealth. For example, knowing that the average lifetime of vehicles in 2009 was eight years (R.L Polk & Co., 2012*a*), we also

computed permanent income as eight times current income. These robustness tests revealed that the choice of metrics affected the absolute bias of the slope estimates in the regression of predicted shares to actual shares. However, the choice of metrics did not meaningfully affect how the models compared.

#### **3.6.5.4 Limitations**

The nature of the problem studied herein conveys certain limitations. The choice of an expensive durable for the empirical application of our model implies that frequent purchases cannot be observed. Even if panel data is available, durables like cars are not purchased frequently. This poses a challenge because consumer preferences and circumstances can vary significantly across repeated purchases. Households also intend different vehicles for different uses and thus their preferences may be radically different across purchase occasions even if these occur simultaneously. These difficulties prevent us from being able to identify household specific parameters and thus limit the accuracy of our model. The choice of such product category is however justified by: a) the goal of considering products that cater consumer preferences for social status; and b) the need for the income constraint to be binding. Frequently purchased goods are unlikely to meet these two conditions and thus cannot help answer our research question.

The limited size of our dataset affected our results too. A larger dataset could allow us to include more explanatory variables to improve the predictive power of our models. A larger number of demographics and psychographics could help us improve the fit of the models. The NHTS has however important advantages. Rich individual-level data are required for our model to better abstract heterogeneity as demographics play an important role in modeling consumer motivation and preferences. Because most other available datasets do not include the number of demographics included in the NHTS dataset, it is unlikely these other datasets could help us demonstrate the importance of wealth and the saliency of needs. These other datasets could be used in practice, but may be not be able to support a theoretical contribution.

## 3.7 Conclusions

We have investigated how income and wealth affect the demand for status-signaling products and other consumption motives in vertically-differentiated markets. To this end, we have proposed a new model of consumer choice that, by relying on human motivation theory, incorporates consumer wealth to produce more realistic trade-up behaviors. An econometric study on secondary data provided support to our model by showing that it predicts sales better than more standard choice models do. That is, the empirical results support the proposition that wealth influences the choice between low-end and high-end products by determining what consumption motives are aroused or suppressed. While income affects consumer behavior through budget constraints, wealths affect behavior by moderating the elicitation of preferences.

## Appendix 3.A Estimation

The estimation of the Nested logit is not as straightforward as that of the multinomial logit (MNL). Full information maximum likelihood (FIML) and limited information maximum likelihood (LIML) methods may generate different estimates because the likelihood surface of the nested logit can be very irregular (Lahiri and Gao, 2002). Navigation across the multiple modes of the likelihood surface can be attained using MCMC methods and heating (Lahiri and Gao, 2002; Liu, 2008). Because a closed form for the posterior distribution of the parameters does not exist, we heavily rely on the Metropolis-Hastings (MH) algorithm to estimate the first-level parameters of the model (i.e.,  $\rho$ ,  $\alpha$ ,  $\lambda$ ,  $\delta$ ,  $\psi$ .) We are nonetheless able to exploit the conjugacy of the second level of the model to estimate the  $\gamma$ ,  $\sigma_\xi$ ,  $\theta$ ,  $B$  and  $C$  parameters using Gibbs samplers. A Hastings-within-Gibbs step (Cowles, 1996) is used to speed up the estimation of the parameters  $\tau$  and  $\mu$ . We implement these estimation strategies by writing custom R code for each of the models considered. The algorithm used to estimate the proposed model is different from that one used to estimate the benchmark models only in that additional steps were included to estimate the additional parameters.



To draw MCMC chains for the parameters in (3.3), we use MH steps. Accordingly, we need to define the likelihood of the nested logit model. If we denote the model parameters by  $\Omega = \{\alpha, \lambda, \delta, \tau, \psi, \mu, \rho, \varphi, \sigma_\xi, \gamma, \theta, B, C\}$ , and the data as  $D = \{X, V, y, G, Q, Z, \bar{r}\}$ , then we can write the log-likelihood of the nested logit as

$$LL(\bar{r}|\Omega) = \sum_{h=1}^N \sum_{j=1}^J P_{hj}^{\bar{r}_{hj}},$$

where the  $\bar{r}_{hj}$  variables are dummies indicated whether household  $h$  was observed to own product  $j$ . Letting  $\bar{u}$  be the observable component of utility, we have

$$P_{hj} = \frac{\left[ \sum_{i \in \{k(j)\}} \exp \frac{\bar{u}_{hi}(\alpha, \lambda, \delta, \psi)}{\rho_{k(j)}} \right]^{\rho_{k(j)}} \exp \frac{\bar{u}_{hj}(\alpha, \lambda, \delta, \psi)}{\rho_{k(j)}}}{\sum_{l=1}^K \left[ \sum_{i \in \{l\}} \exp \frac{\bar{u}_{hi}(\alpha, \lambda, \delta, \psi)}{\rho_l} \right]^{\rho_l} \sum_{i \in \{k(j)\}} \exp \frac{\bar{u}_{hi}(\alpha, \lambda, \delta, \psi)}{\rho_{k(j)}}}, \quad (3.12)$$

where  $\{l\}$  denotes the set of choice alternatives that belong to category  $l$  and  $k(j)$  denotes the category to which alternative  $j$  belongs. Accordingly,  $\{k(j)\}$  denotes the set of alternatives in the same category as alternative  $j$ .

Having thus defined the likelihood of the nested logit, we iterate over the following steps.

**STEP 1** We first estimate the preference weights  $\alpha$  using a MH step that relies on a normal approximation of the posterior distribution of  $\alpha$  (Rossi et al., 2005). We use a prior  $MVN(\alpha_0, A_\alpha)$  and draw the MH candidates using a standard random walk with the variance-covariance matrix of the innovation term given by a multiple of the Hessian of the MNL (Koop and Poirier, 1993). In particular, we let  $\alpha^{new} \sim MVN(\alpha^{old}, H_\alpha^{-1}t_\alpha)$ , where

$$H_\alpha(\Omega, D) = - \sum_{h=1}^N \sum_{j=1}^J P_{hj} (v_{hj} - \bar{v}_h)(v_{hj} - \bar{v}_h)^T$$

$$\bar{v}_h = \sum_{i=1}^J P_{hi} v_{hi},$$

the vectors  $v_{hj} = [v_{hj1}, v_{hj2}]^T$  have as first element  $v_{hj1} = \log(y_h - p_j)$ ,  $t_\alpha$  is a tuning parameter, and  $P_{hj}$  is given by (3.12).

**STEP 2** We assume a prior  $MVN(\lambda_0, A_\lambda)$  and draw  $\lambda$  using a random-walk MH step such that  $\lambda^{new} \sim MVN(\lambda^{old}, H_\lambda^{-1}t_\lambda)$ ,  $t_\lambda$  is a tuning parameter, the Hessian of the normal

approximation is,

$$H_\lambda(\Omega, D) = - \sum_{h=1}^N \sum_{j=1}^J P_{hj} (x_{hj} - \bar{x}_h)(x_{hj} - \bar{x}_h)^T$$

$$\bar{x}_h = \sum_{i=1}^J P_{hi} x_{hi}.$$

and  $x_{hj} = [x_{hj1}, \dots, x_{hjA}]^T$ .

**STEP 3** We draw each of the indicators  $\psi_{hm}$  independently using a MH step and a Bernoulli trial in which the probability of success is a function of demographics (correlations among the  $\psi_{h1}, \dots, \psi_{hM}$  arise because all of them depend on  $q_h$ .) In particular, we take draws  $\nu_{hm} \sim N(q_h^T \theta_m, \sigma_\psi^2 t_\psi)$  and let  $\psi_{hm} = 1$  if and only if  $\nu_{hm} > \tau_m$ . The candidate is accepted or rejected according to the MH algorithm.

**STEP 4** For each  $j = 2, \dots, J$ , we use a random walk MH step to draw  $\delta_j$  from a univariate random walk with a prior  $N(\delta_0, \sigma_\xi^2 t_\delta)$ . That is, we let  $\delta_j^{new} \sim N(\delta_j^{old}, \sigma_\xi^2 t_\delta)$  with a standard acceptance probability.

**STEP 5** We use data augmentation and a Hastings-within-Gibbs step (Cowles, 1996) to draw  $\tau_m$  and  $\mu_{hm}$  conditional on  $\theta_m$  and  $\psi_{hm}$ . Because the marginal distributions of these parameters are

$$p(\tau_m | \theta_m, \psi_{hm}) \propto \prod_{h:\psi_{hm}=0} \Phi(\tau_m - q_h^T \theta_m) \prod_{h:\psi_{hm}=1} [1 - \Phi(\tau_m - q_h^T \theta_m)]$$

$$p(\mu_{hm} | \theta_m, \psi_{hm}, \tau_m) \propto \prod_{h:\psi_{hm}=0} \frac{\phi(\mu_{hm} - q_h^T \theta_m)}{\Phi(\tau_m - q_h^T \theta_m)} \prod_{h:\psi_{hm}=1} \frac{\phi(\mu_{hm} - q_h^T \theta_m)}{1 - \Phi(\tau_m - q_h^T \theta_m)}$$

their joint distribution is

$$p(\tau_m, \mu_{hm} | \theta_m, \psi_{hm}) \propto \prod_h \phi(\mu_{hm} - q_h^T \theta_m).$$

We can therefore use the proposal density

$$\begin{aligned}
g(\tau_m^{new}, \mu_{hm}^{new} | \tau_m^{old}, \mu_{hm}^{old}, \theta, \psi_{hm}) &= g(\tau_m^{new} | \tau_m^{old}, \mu_{hm}^{old}, \theta, \psi_{hm}) g(\mu_{hm}^{new} | \tau_m^{new}, \tau_m^{old}, \mu_{hm}^{old}, \theta, \psi_{hm}) \\
&= \phi\left(\frac{\tau_m^{new} - \tau_m^{old}}{\sigma_\tau}\right) \times \\
&\quad \prod_{h:\psi_{hm}=0} \frac{\phi(\mu_{hm}^{new} - q_h^T \theta_m)}{\Phi(\tau_m^{new} - q_h^T \theta_m)} \prod_{h:\psi_{hm}=1} \frac{\phi(\mu_{hm}^{new} - q_h^T \theta_m)}{1 - \Phi(\tau_m^{new} - q_h^T \theta_m)},
\end{aligned}$$

which leads to the acceptance rate  $\min(1, R)$ , with  $R$  given by

$$R = \prod_{h:\psi_{hm}=0} \frac{\Phi(\tau_m^{new} - q_h^T \theta_m)}{\Phi(\tau_m^{old} - q_h^T \theta_m)} \prod_{h:\psi_{hm}=1} \frac{1 - \Phi(\tau_m^{new} - q_h^T \theta_m)}{1 - \Phi(\tau_m^{old} - q_h^T \theta_m)}.$$

Thus, to draw  $\tau_m$  and  $\mu_{hm}$  we do as follows.

**5.A** For each  $m = 1, \dots, M$ , we generate a candidate  $\tau_m^{new}$  from  $N(\tau_m^{old}, \sigma_\tau^2)$

**5.B** With probability  $R$  as given above, we accept each candidate and generate  $\mu_{hm}$  drawing from the posterior  $p(\mu_{hm} | \theta_m, \psi_{hm}, \tau_m) \propto N(\theta_m^T q_h, 1) \times I(c_L < \mu_{hm}) < c_H)$  where  $c_L = g_{\psi_{hm}}$ ,  $c_H = g_{\psi_{hm}+1}$ ,  $g_0 = -\infty$ ,  $g_1 = \tau_m$ ,  $g_2 = \infty$ , and  $I(\cdot)$  is an indicator function that equals 1 when its argument is true, zero otherwise. To draw from this truncated normal, we draw from  $\nu_{hm} \sim UNIF(\Phi[c_L - \theta_m^T q_h], \Phi[c_H - \theta_m^T q_h])$  and let  $\mu_{hm} = \theta_m^T q_h + \Phi^{-1}(\nu_{hm})$ .

**STEP 6** We draw  $\theta_m$  conditional on  $\boldsymbol{\mu}_h = [\mu_{h1}, \dots, \mu_{hM}]^T$  by adapting Smith and Kohn's (2002) algorithm for the estimation of covariance matrices. To this end, we first need to define the estimates  $\hat{\boldsymbol{\kappa}}_h = \boldsymbol{\mu}_h - q_h^T \Theta$ , where  $\Theta = [\theta_1, \dots, \theta_M]$ . The likelihood of these estimates is given by

$$p(\hat{\boldsymbol{\kappa}}_h | B, C) = (2\pi)^{-\frac{HM}{2}} \prod_{m=1}^M c_m^{\frac{H}{2}} \exp\left(-\frac{c_m}{2} \{S_m + (\mathbf{b}_m^u + A_m^{-1} a_m)^T A_m (\mathbf{b}_m^u + A_m^{-1} a_m)\}\right),$$

where  $a_m = \{a_{i,m} | i > m\}$ ,  $A_m = \{a_{i,j} | i > m, j > m\}$ ,  $\mathbf{b}_m^u = \{b_{i,m} | i > m\}$  is the  $m$  vector of the unconstrained elements of the  $m$  column of matrix  $B$ ,  $c_m$  is the  $m$  diagonal element of matrix  $C$ , and  $S_m = a_{m,m} - a_m^T A_m^{-1} a_m$ .

We let the priors of  $c_m$  be gamma with shape  $\varphi/\iota$  and scale  $\iota$ , such that

$$p(c_1, \dots, c_M | \varphi, \iota) = \prod_{m=1}^M \frac{c_m^{\varphi/\iota-1} \exp(-c_m/\iota)}{\Gamma(\varphi/\iota) \iota^{\varphi/\iota}}.$$

We use conditional priors for  $\mathbf{b}_m^u$  of the form

$$p(\mathbf{b}_1^u, \dots, \mathbf{b}_M^u | C) = \prod_{m=1}^{M-1} p(\mathbf{b}_m^u | C)$$

where  $\mathbf{b}_m^u | C \sim MVN(-A_m^{-1}a_m, HA_m^{-1}/c_m)$ .

From this likelihood and these priors we derive the conditional distributions

$$\begin{aligned} p(B | C, \boldsymbol{\mu}_h) &\propto p(\hat{\boldsymbol{\kappa}}_h | B, C) p(B | C) \\ &\propto p(\hat{\boldsymbol{\kappa}}_h | B, C)^{1 + \frac{1}{H}} \\ p(C | B, \boldsymbol{\mu}_h) &\propto p(\hat{\boldsymbol{\kappa}}_h | C, B) p(B | C) p(C) \\ &\propto p(\hat{\boldsymbol{\kappa}}_h | C, B) \prod_{m=1}^{M-1} p(\mathbf{b}_m^u | C) \prod_{m=1}^M p(c_m), \end{aligned}$$

that will be used in the steps described next.

**6.A** We draw the unconstrained elements of the  $m$  column of  $B$ ,  $\mathbf{b}_m^u$ , from the distribution

$$p(\mathbf{b}_m^u | C, \boldsymbol{\mu}_h) = MVN \left( -A_m^{-1}a_m, \frac{H}{c_m(H+1)} A_m^{-1} \right).$$

**6.B** We draw the elements of the matrix  $C$  from the conditional

$$p(C | \mathbf{b}_m^u, \boldsymbol{\mu}_h) \propto \prod_{m=1}^m \exp \left( -c_m \left\{ \frac{h_m}{2} + \frac{1}{\iota} \right\} \right) c_m^{\frac{H+n_m}{2} + \frac{\varphi}{\iota} - 1},$$

where  $n_m$  is the number of elements of  $\mathbf{b}_m^u$  and

$$h_m = \begin{cases} S_m + \left(1 + \frac{1}{H}\right) (\mathbf{b}_m^u + A_m^{-1}a_m)^T A_k (\mathbf{b}_m^u + A_m^{-1}a_m) & \text{if } m < M \text{ and } n_m > 0, \\ a_{m,m} & \text{otherwise.} \end{cases}$$

**STEP 7** We draw the  $\rho_k$  parameters using an additional MH step. We use the semi-flat prior proposed by (Lahiri and Gao, 2002), such that the density of  $\rho_k$  is

$$f(\rho_k) \propto \begin{cases} 0 & \text{if } \rho_k \leq 0, \\ \phi & \text{if } 0 < \rho_k < 1, \\ \phi \exp \frac{\phi}{1-\phi}(1 - \rho_k) & \text{if } \rho_k \geq 1. \end{cases}$$

Because the condition  $\rho_k \geq 0$  prevents us from using a standard random walk, we developed a non-negative random walk that generates only positive values of the chain candidate values by drawing the innovation term from a gamma distribution with scale parameter equal to  $t_\rho/\rho$  and shape parameter equal to  $\rho^2/t_\rho$ . This random walk satisfies the detailed balance condition, ensuring that the target posterior distribution is invariant.

**STEP 8** We finally draw the parameters  $\gamma$  and  $\sigma_\xi$  conditional on the draws of  $\delta$  using a standard Gibbs sampler for the univariate regression. We let the priors be given by

$$p(\sigma_\xi^2) \propto (\sigma_\xi^2)^{-\frac{t_\sigma}{2}+1} \exp\left(-\frac{t_\sigma s_0^2}{2\sigma_\xi^2}\right)$$

$$p(\gamma|\sigma_\xi^2) \propto (\sigma_\xi^2)^{-\frac{n_z}{2}} \exp\left(-\frac{1}{2\sigma_\xi^2}(\gamma - \gamma_0)^T A_\gamma (\gamma - \gamma_0)\right)$$

and draw from the posteriors

$$\gamma|\sigma_\xi^2, \delta, Z \sim MVN((\hat{Z}^T \hat{Z} + A_\gamma)^{-1}(\hat{Z}^T \delta + A_\gamma \gamma_0), \sigma_\xi^2(\hat{Z}^T \hat{Z} + A_\gamma)^{-1})$$

$$\sigma_\xi^2|\delta, \hat{Z} \sim \frac{t_\sigma s_0^2 + \delta^T (I - \hat{Z}(\hat{Z}^T \hat{Z})^{-1} \hat{Z}^T)^T (I - \hat{Z}(\hat{Z}^T \hat{Z})^{-1} \hat{Z}^T) \delta}{\chi_{t_\sigma + H}^2}.$$

## Appendix 3.B Computation of DIC

The proposed model extends the baseline model by introducing the  $\psi$  “random effects”. Because of this additional level in the hierarchy, the models are not directly comparable in terms of fit at the group level (see, for instance, Millar, 2009). One must then marginalize

over the random coefficients to write the likelihood of an observation as

$$\begin{aligned} p(\bar{r}_{hj}) &= \sum_{\psi_{h1}=0}^1 \dots \sum_{\psi_{hA}=0}^1 p(\bar{r}_{hj}|\psi_{h1}, \dots, \psi_{hA}, \alpha, \lambda, \delta) p(\psi_{h1}, \dots, \psi_{hA}|\alpha, \lambda, \delta) \\ &= \sum_{\psi_{h1}=0}^1 \dots \sum_{\psi_{hA}=0}^1 p(\bar{r}_{hj}|\psi_{h1}, \dots, \psi_{hA}, \alpha, \lambda, \delta) p(\psi_{h1}, \dots, \psi_{hA}), \end{aligned}$$

where  $p(\bar{r}_{hj}|\psi_{h1}, \dots, \psi_{hA}, \alpha, \lambda, \delta)$  is the conditional likelihood described in (3.12). Since  $\boldsymbol{\kappa}_h$  follows a multivariate normal distribution, we can write

$$p(\psi_{h1}, \dots, \psi_{hA}) = \Phi_{\Sigma} \left( \{\tau_1 - q_h \theta_1\} \{-1\}^{\psi_{h1}}, \dots, \{\tau_A - q_h \theta_A\} \{-1\}^{\psi_{hA}} \right),$$

where  $\Phi_{\Sigma}$  is the c.d.f. of a multivariate normal distribution with covariance matrix  $\Sigma$  and zero mean. The log-likelihood of the observed choice of a household that chooses alternative  $k$  is then given by

$$\begin{aligned} \log\{p(\bar{\mathbf{r}}_h)\} &= \sum_{j=1}^J \bar{r}_{hj} \log\{p(\bar{r}_{hj}|\alpha, \lambda, \delta)\} \\ &= \log\{p(\bar{r}_{hk}|\alpha, \lambda, \delta)\} \\ &= \log \left\{ \sum_{\psi_{h1}=0}^1 \dots \sum_{\psi_{hA}=0}^1 p(\bar{r}_{hj}|\psi_{h1}, \dots, \psi_{hA}, \alpha, \lambda, \delta) p(\psi_{h1}, \dots, \psi_{hA}) \right\}, \end{aligned}$$

and must be computed through a computationally demanding procedure that numerically solves the multidimensional integrals associated with the evaluation of  $\Phi_{\Sigma}$ . This procedure was used to compute the DIC reported in the main text.

## CHAPTER 4

# The effects of economic inequality on the demand for status-signaling brands

### 4.1 Introduction

The distribution of income has lately become an important topic in the popular press, the academic literature, and managerial studies because of the sustained rise of its inequality over the last few decades (Levy and Murnane, 1992; Burkhauser, Feng, Jenkins and Larrimore, 2009; Kim, 2012). Some firms have already redesigned their product lines to better suit the evolving distribution of consumer income. For instance, Procter & Gamble is reducing the number of mid-range products and increasing the number of low-end and high-end items (Byron, 2011). This trend is in fact not limited to individual firms. Entire industries (Knudsen, Randel and Rugholm, 2005), such as the automobile industry, are witnessing a polarization of the quality of their offerings (Figure 4.1 illustrates the changes in the distribution of prices for low-end and high-end car makes from 2001 to 2010). Given the magnitude of this trend, some firms targeting the low-end market face important challenges. Walmart, for instance, is now losing many of its impoverished customers to dollar stores (Ousley, 2011). On the other hand, the demand for some high-end products is on the rise (Clifford, 2011) and high-end firms need to redesign their offerings to meet the evolving expectations of wealthy consumers.

The growth of income inequality may drive these important market changes by pushing consumers with shrinking income to choose low-end products (a behavior hereafter referred to as trade down) while enabling consumers with growing income to choose high-end alternatives (that is, to trade up.) Income inequality may however not be the only cause of increased trade

down and trade up. Consumer assets also affect consumption decisions (see, for example, Paiella, 2009) and therefore the inequality in the distribution of wealth could also help explain the observed patterns of substitution between low-end and high-end products. We accordingly rely on a model of consumer choice that accounts for the effect of income on budget constraints and the role of wealth on consumer motivation.

We use the motivation-based model to investigate the effects of increasing income and wealth inequality on consumer demand for low-end and high-end products. In particular, we predict consumer preferences and choices under simulated scenarios in which income and wealth are redistributed. We find that wealth disparities intensify the consequences of income disparities on consumer expenditures. While income inequality harms the sales of mid-range products and favors those of entry-level luxury products, wealth inequality harms the sales of both segments. This results from preferences for status signaling becoming more disperse. Preferences for more functional product attributes such as seating capacity are, in contrast, not affected.

The paper is organized as follows. We start by reviewing the literature on the effects of income inequality on market outcomes in Section 4.2. An exploratory analysis of car expenditure and choice is presented in Section 4.3 to motivate the study of wealth on consumer choice. The simulation study that analyzes the effects of income and wealth inequality is described in Section 4.4. The results, implications, and contribution are discussed in Section 4.5 and conclusions are offered in Section 4.6.

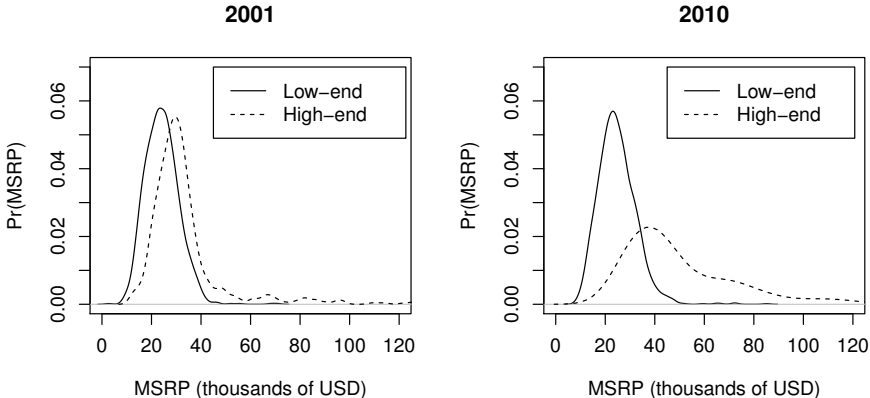


Figure 4.1: Distributions of low-end and high-end car prices (MSRP) at two points in time.



## 4.2 Relevant literature

Most work on the effects of inequality on consumption has focused on the distribution of income. For instance, within the macroeconomics literature, Frank, Levine and Dijk (2010) found positive effects of income inequality on non-business bankruptcy rates, divorce rates, and commuting times. Their analysis attributes these effects to the increased spending by the wealthy, which raises the consumption standards of the the poor. In a similar vein, Drennan (2011) found that income inequality has a positive effect on consumer liabilities and that raising inequality may have a stronger effect on borrowing than on consumption. The results by Christen and Morgan (2005) supported these findings as they suggest that the increasing income inequality observed in the U.S. has led to significantly larger consumer debt.

The literature on new product diffusion has also discussed the role of income heterogeneity. For instance, Foellmi and Zweimüller (2006) relied on analytical modeling to study a case of a market in which consumers can be classified as either poor or rich. The authors found that increasing inequality leads to a higher willingness to pay among a shrinking population of rich consumers. Therefore, the firm is better off by increasing prices and selling less. This strategy is found to slow down diffusion into mass markets but also to favor the firm by shifting profits to earlier stages of the life cycle. For a scenario in which income follows an extreme value distribution, Horsky (1990) also concluded that higher income dispersion results in lower penetration of new products. Regarding the speed of diffusion, Van den Bulte and Stremersch (2004) found that income heterogeneity positively correlates with the  $q/p$  ratio. This implies that, the higher the income heterogeneity is, the more important consumer imitation is relative to consumer innovation. Thus, the diffusion curve is more pronounced when income inequality is higher.

Another body of literature has addressed the effect of inequality on conspicuous consumption (the consumption of status-conferring goods.) Relying on auction theory, Hopkins and Kornienko (2004) concluded that income equality increases the conspicuous consumption of those with middle incomes or low and middle incomes, while decreasing the conspicu-

ous consumption by the rich. Similarly, the laboratory experiments by Ordabayeva and Chandon (2011) found that lower inequality motivates individuals to increase conspicuous consumption when social competition is salient. It is however difficult to infer how these individual-level findings shape overall demand. One would need to aggregate these results on individual behaviors across heterogeneous consumers and conditioning on the distribution of income to make predictions of how inequality affects aggregate demand.

Income inequality has also been studied in the industrial organization literature as a factor that influences the structure of vertically differentiated markets. For example, Gabszewicz and Thisse (1979) theoretically modeled a scenario in which two firms compete for consumers with heterogeneous income but homogeneous taste. They analyze the model to conclude that “income differentiation plays a central role to sustain product differentiation”. Benassi, Chirco and Colombo (2006) built a similar theoretical model assuming a duopolistic setting and a trapezoidal distribution of taste for quality (which they assume to be proportional to income). This model led the authors to conclude that income (taste) inequality mitigates price competition and thus reduces product differentiation. This conclusion was later found to hold only under particular cost structures (Yurko, 2011). For other conditions, greater income inequality results in more intense quality competition among more firms that compete for the shrinking high-income segment.

Our work differs from the extant literature cited above in at least the following ways. With respect to the macroeconomics literature, our work differs in that we focus on the inequality of not only income but also wealth. We attempt to explain brand choice and not debt, bankruptcy, or spending. Methodologically, the main difference is that we rely on cross-sectional data and simulations rather than on longitudinal data. We are able to do so by imposing theory-driven structure on our model of consumer choice.

With respect to the literature on new product diffusion (for example, Horsky, 1990; Van den Bulte and Stremersch, 2004), our work differs in terms of the consumer decision being considered. The new product diffusion literature studies the decision to adopt a new product. The framework proposed here, in contrast, focuses on the choice of a product given that a purchase takes place and thus does not consider purchase incidence. Our work is thus more

relevant to mature markets with competing products.

The consideration of competing products and brands also differentiates our work from that on the effects of inequality on conspicuous consumption (such as Hopkins and Kornienko, 2004; Ordabayeva and Chandon, 2011; Krueger and Perri, 2006), which has typically studied consumer expenditures rather than product or brand choices. Furthermore, we do not only consider status-seeking behavior; instead, we allow for any consumption motive that can be associated to a measurable product attribute.

With respect to the aforementioned work in the Industrial Organization literature (e.g., Gabszewicz and Thisse, 1979; Benassi et al., 2006), our work differs in terms of scope. The Industrial Organization literature has investigated how income inequality affects the structure of vertically differentiated markets. To holistically model markets, this stream of research has resorted to highly stylized abstractions of consumer behavior that limit their generality (for example, Gabszewicz and Thisse, 1979; Yurko, 2011, assumed that consumers have identical preferences and a analytically-tractable distribution of income.) We, in contrast, prioritize realism over completeness and empirical testability over analytical tractability. We propose a more realistic model of consumer demand that controls for the endogeneity of firm behavior. We then use this new model to investigate how consumer demand is affected by inequality.

### **4.3 Exploratory analysis**

To offer some intuition on how the distributions of income and wealth affect consumer behavior, we offer an exploratory analysis of trends in consumer behavior and demographics. We use data from the new car market because for this product category budget constraints play a clear and important role and because cars cater a broad range of consumption motives. By empirically identifying the role of budget constraints, we can focus on additional effects of income and wealth on consumer behavior. By considering multiple consumption motives, we can more clearly identify the effects of wealth on different dimensions of quality.

The plots displayed in Figure 4.1 suggest that, between 2001 and 2010, car manufacturers

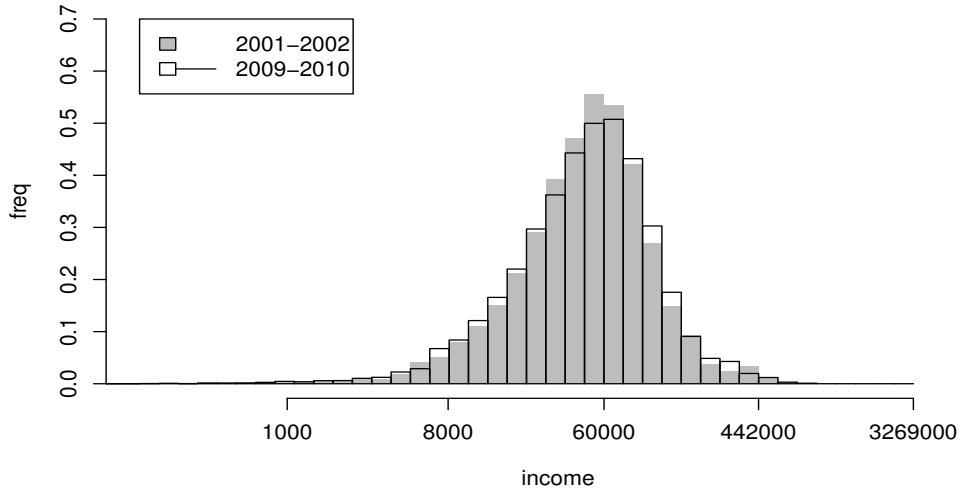


Figure 4.2: Distributions of U.S. household income at two periods of time. Data source: U.S. Census Bureau.

attempted to satisfy what they expected to be a growing demand for high-end vehicles. These expectations on demand appear reasonable if we examine the trends in the distribution of income as reported by the U.S. Census Bureau. Figure 4.2 displays the distributions of (inflation-adjusted) household income in the U.S. during the 2001-2002 and 2009-2010 periods. The plots make evident that, by the end of the decade, some households earned less income than at the beginning of the decade. However, we also observe that the opposite was true for a large number of households who saw their incomes increase. It thus seems that manufacturers may have used the trends in income distribution to forecasts demand and thus to design and price their product lines.

The trend in the distribution of income was however not very predictive of the trend in the demand for high-end cars. To the disappointment of car makers, actual demand for high-end cars declined instead of growing. Figure 4.3 presents the distributions of household expenditures on new cars and indicates that the demand for high-end vehicles declined instead of increasing. Only the demand for very economic cars expanded. It thus appears that, even some households saw their income grow, their additional income was not used to purchase expensive new cars.

Several hypotheses can be advance to explain the apparent disconnect between the dis-

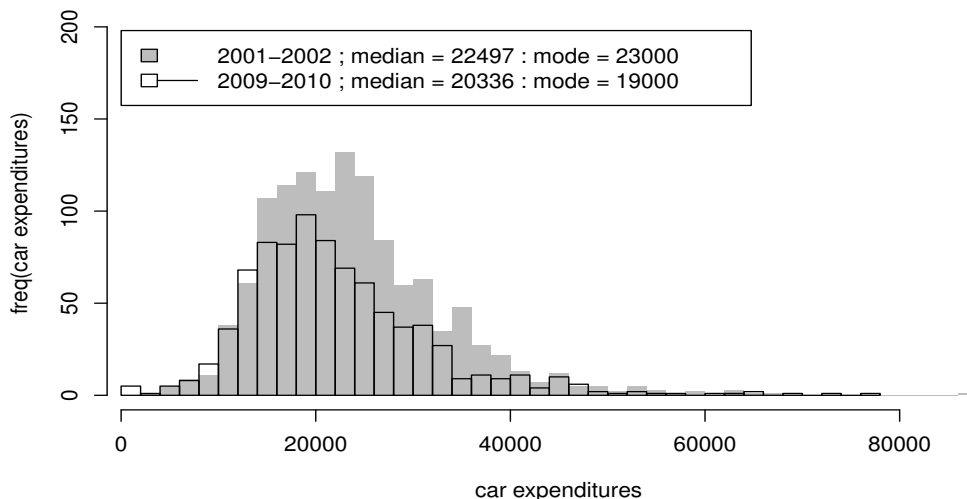


Figure 4.3: Distributions of inflation-adjusted household expenditures on new cars at two periods of time in the U.S. Data source: Consumer Expenditure Survey, Bureau of Labor Statistics.

tribution of income and the distribution of expenditures. For instance, one could argue that the additional income could instead have been allocated to fuel expenses because fuel prices significantly increased during that period of time. However, the households that saw their income increase could be better off by replacing their vehicles by more fuel-efficient though expensive hybrid cars. The price premium that some hybrid vehicles command can be very well offset by the savings in fuel expenses.

A second explanation to the apparent discrepancy between the distribution of income and the distribution of expenditures is that consumers choosing high-end cars could have favored leasing over purchasing. A large proportion of leased cars are in fact luxury cars. However, as depicted by Figure 4.4, the percentage of leases did not increase over the 2001-2010 decade. In addition, leases account for about 20% of all new-car acquisitions. It is therefore unlikely that the large contraction of the sales of high-end cars could be explained by a surge in number of leases of luxury vehicles.

While increasing fuel prices and the availability of leases may explain why some households decided to purchase inexpensive rather than premium vehicles by the end of the last decade, we offer one additional explanation. We propose that the observed changes in con-

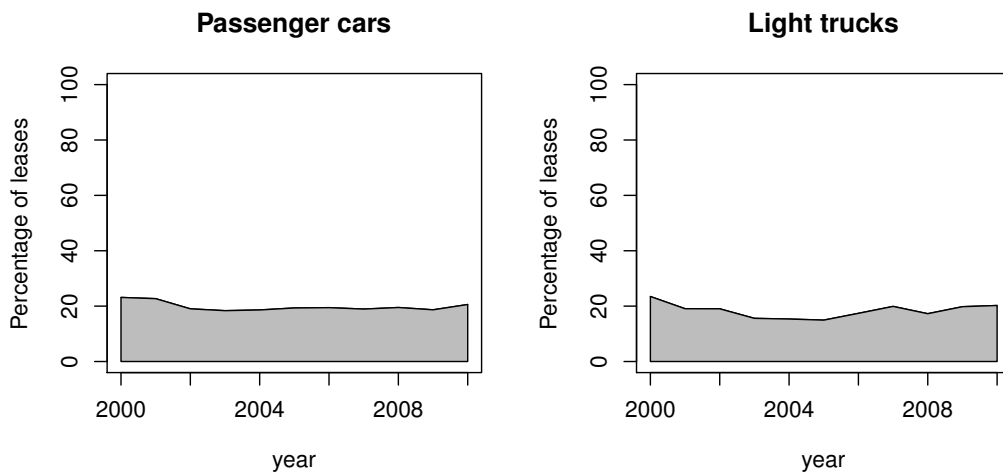


Figure 4.4: Number of leases as a percentage of the combined number of leases and sales for passenger cars and light trucks. Data source: Bureau of Transportation Statistics.

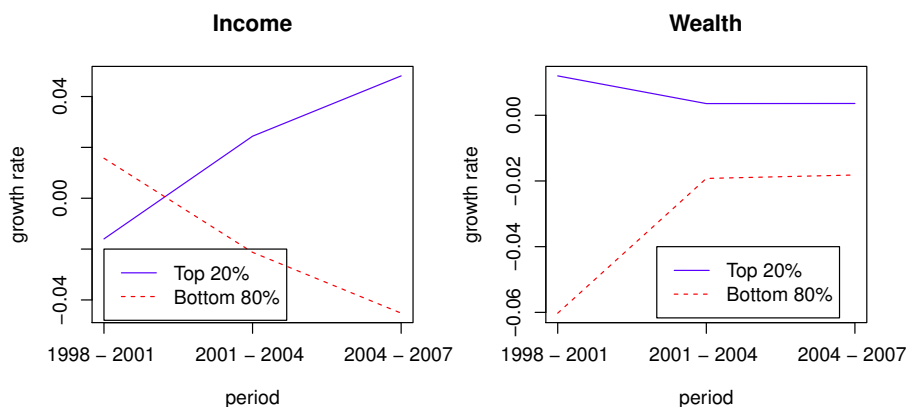


Figure 4.5: Income and wealth growth rates. Data sources: Congressional Budget Office and U.S. Federal Reserve Board, Survey of Consumer Finances and Federal Reserve Flow of Funds.

sumer behavior are partly due to changes in the revealed preferences of households. In addition, we propose that revealed preferences are affected by consumer wealth and not only by income. Wealth could better explain the observed patterns of consumer behavior because the distribution of wealth changed over the last decade in a less symmetric way than the distribution of income. In particular, the number of households that lost wealth was larger than the number of households that gained wealth.

To provide some preliminary support for this proposition, we use income statistics re-

ported by the U.S. Congressional Budget Office and wealth statistics reported by Allegretto (2011). Using these statistics, we present a) recent income growth rates for the top 20% and the bottom 80% income earners; and b) recent wealth growth rates for the 20% wealthier and the 80% lesser wealthy households in the U.S. These growth rates are plotted in Figure 4.5. The plots indicate that income growth rates are quite symmetrical for the top and bottom income earners. This is consistent with the plot presented in Figure 4.2 and, again, may suggest that top earners would have more income to purchase expensive cars. In contrast, the plot of the wealth growth rates shows that the wealth growth rates for the two groups of households are not very symmetrical. While the bottom 80% lesser wealthy households appear to suffer significant losses of assets, the top 20% wealthier households experience modest gains. The trend of the distribution of expenditures on new cars thus appears to be more consistent with the distribution of household wealth than with the distribution of household income.

#### 4.4 Simulation study

If income and wealth affect how consumers prioritize different product attributes, then different income and wealth distributions should result in different patterns of consumer behavior. Rising income inequality increases the resources of a group of consumers while reducing the resources of the rest. Therefore, rising income inequality may lead a group of consumers to trade up and another group to trade down. The aggregate demand for low-end and high-end vehicles should rise, while the demand for mid-range cars should decline. We use the model and the data introduced in Chapter 3 to test this prediction and, in general, to investigate how the demand for automobiles is affected by increasing wealth inequality.

We use the model of consumer behavior introduced in Chapter 3 because it accounts for a) the effect of income on budget constraints and b) the effect of wealth on the exercise of preferences. This model proposes that consumers choose products according to how these products fulfill different consumption motives. Consumption motives can be pursued or repressed depending on whether there is sufficient motivation. Motivation, in turn, depends

on a number of consumer characteristics and circumstances, among which we find wealth. Wealthier individuals are less likely to suppress their consumption motives, independently of their ability to fulfill them.

We also rely on the data described in Chapter 3, which were collected from several sources. The main source is the 2009 National Highway Transportation Survey (NHTS). Additional data on car attributes, home values, costs of living, etc. were collected as well. The demographic variables collected by the NHTS and geography-specific home values were used to compute metrics of household wealth. Metrics of brand status (Chapter 2) and assortment variety (Chapter 3) were computed to assess the importance of product line composition and prices on the performance of brands when consumer inequality increases.

In what follows, we use the model and the parameter estimates presented in Chapter 3 to predict consumer choices and brand sales under the actually observed and the increased levels of inequality. We attempt to separately predict: a) the effects that different levels of income inequality have on consumer choice through budget constraints; and b) the effects that different levels of wealth inequality have on choices through the saliency of different consumption motives. We accordingly study two simulated scenarios. In the first one, we redistribute the income of the households in the NHTS dataset. In the second simulated scenario, we also redistribute household wealth.

#### **4.4.1 Data and procedure**

To redistribute household income, we use data from the 2001-2009 waves of the Panel Study of Income Dynamics (PSID) to model as a first order Markov process the dynamics of the income of households that purchased cars during that period of time. That is, we model the probability of a household belonging to each income bracket given its income bracket membership in the previous time period. For each pair of subsequent waves in which a household reports income, the household is assigned to one of the income brackets defined by the NHTS. Pairs of subsequent observations are pooled across the five waves so as to increase the reliability of the model. This is desirable as each year only a couple hundred households



in the PSID reported buying new vehicles. Having computed the transition matrix of the Markov process, we use it to redistribute the income of the NHTS households that reported car purchases by probabilistically assigning them to an income bracket. In addition, the probability of transitions to more extreme income brackets was favored by weighting the probabilities of the transition matrix. This was done to the end of obtaining clearer results and is not inconsistent with actual trends in the distribution of income (redistributing income without weighting the transition probabilities generates changes that are qualitatively equivalent but less drastic.) As a result, this redistribution of income led the Gini coefficient of the income distribution to increase 48% from from 0.26 to 0.38.

To redistribute the wealth of the households, we first redistribute their income and then use the simulated income brackets to redistribute their home and car ownership status. Current income has been shown to be, among a set of common demographics, the most important determinant of home ownership (Struyk and Marshall, 1973). This relationship has been shown to be very stable (probabilistically) and generalizable (see, for example, Struyk and Marshall, 1975). We accordingly use the data from the 2001-2009 waves of the PSID to compute the probability of owning a home given the household’s income bracket and its home ownership status in the previous time period. We then use these probabilities to randomly assign new home ownership status to the NHTS households that owned a 2008 vehicle. This random assignment could represent the purchase of new homes and the foreclosure of the homes owned by households who lost current income.

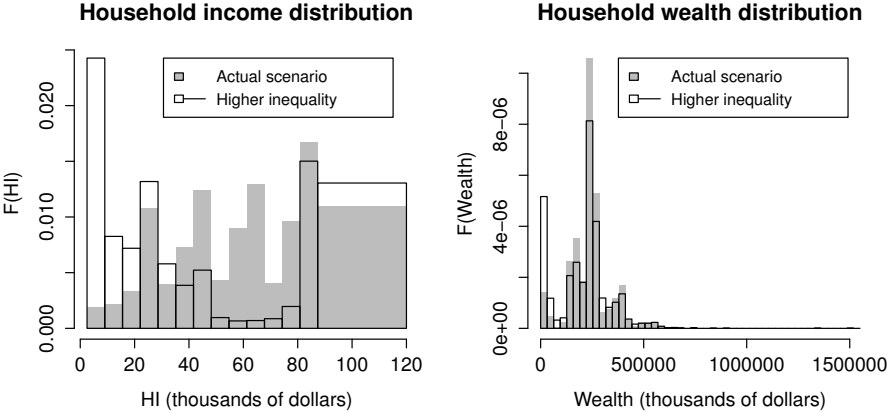


Figure 4.6: Actual and simulated distributions of income and wealth.

We likewise use the PSID sample of households that purchased cars to compute the probabilities of owning each possible number of vehicles given the household's reported income-bracket. We used these probabilities and the simulated income brackets to probabilistically assign car-ownership levels to each household in the sample of households in the NHTS that owned 2008 models. The simulated income brackets and home and car ownership indicators were finally used to recompute the wealth proxy for each household purchasing a car. The redistribution of income and home ownership caused the Gini coefficient of the distribution of wealth to increase 60% from 0.21 to 0.37.

The thus redistributed income and wealth levels appear in Figure 4.6. The plots show that many households see their income reduced, which is consistent with actual events because the very wealthy are underrepresented in this dataset. In fact, during the 2001-2010 decade, only the top 1% income earners saw their real incomes grow. The remaining 99% of the population experienced income losses or no change (Stone, Shaw, Trisi and Sherman, 2012). At the same time, our redistribution algorithm causes wealth to be redistributed mostly towards both the lower tail of its distribution. This shift of probability mass towards the lower tail is driven by a steadily growing number of defaults and foreclosures (Wood, 2007).

In what follows, these simulated distributions of income and wealth are used to predict consumer preferences and choices, as well as product and brand sales, under different levels of income and wealth inequality.

## **4.4.2 Results**

### **4.4.2.1 Consumer preferences**

We expect the distribution of wealth to be an important determinant of the distribution of preferences for different product attributes because wealth affects the saliency of different consumption motives. We accordingly use the proposed model to estimate consumer preferences under two of the scenarios described above. Because a redistribution of income does not affect the saliency of consumption motives nor preferences directly, we only discuss the actual scenario (given by the original data from the survey) and the scenario in which both

income and wealth are redistributed. For each of these two scenarios, we compute the  $\beta$  weights (preferences) and plot their distributions. These plots appear in Figure 4.7.

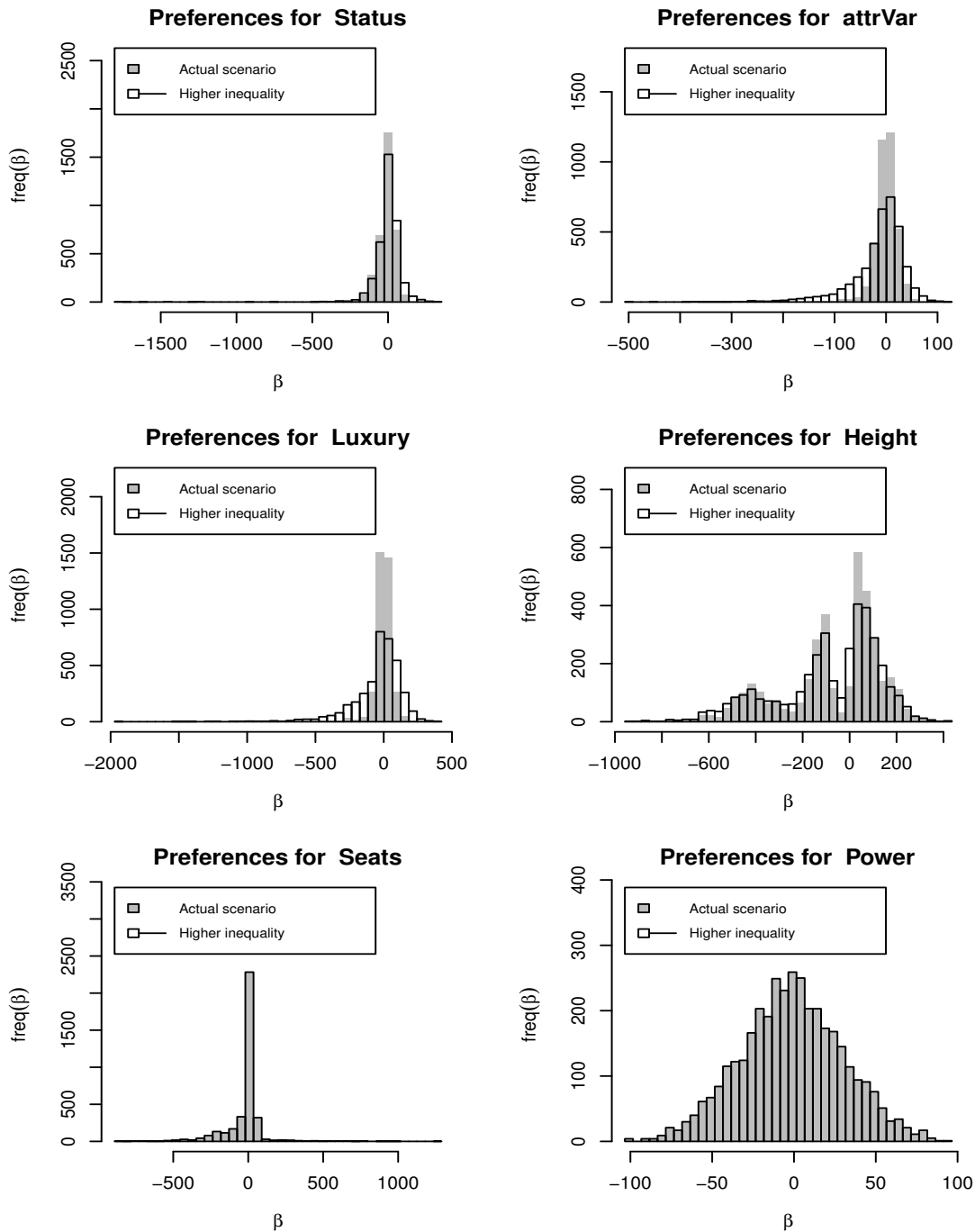


Figure 4.7: Consumer preferences for different product attributes under for actual and increased levels of economic inequality.

The plots in Figure 4.7 indicate that, under higher levels of wealth inequality, the distri-

bution of preferences for social status spreads out. The number of households that do not reveal any preferences for social status (the bar at  $\beta = 0$  in the histogram) is smaller under higher inequality, implying that inequality makes the motive to acquire status more salient. Also, the upper tail of the distribution of preferences for social status is thicker under higher inequality. This implies that inequality leads some households to have stronger preferences for high-status products.

High inequality also makes the motive to consume products with more product-line variety (a higher score on the variable `attrVar`) more salient. The spread of the distribution of preferences for this brand attribute is also more significant under higher inequality but, in this case, is the lower tail the one that grows more. When inequality is high, some consumers care more about specific product attribute combinations but many prefer to avoid them. The effects of inequality on preferences for luxury are similar.

Unlike preferences for status, variety, and luxury, preferences for more functional product attributes are not affected by consumer inequality. The distributions of preferences for seating capacity and engine size appear to be the same for different levels of inequality. The distributions of preferences for height are not the same across inequality levels but the differences are not large. Both distributions cover similar ranges though higher inequality does appear to flatten up the histogram.

#### **4.4.2.2 Consumer expenditure**

Figure 4.8 depicts the changes in consumer expenditures that result from the redistributions of income and wealth, as predicted by the proposed model. The histograms show that high income inequality leads consumers to buy more low-end cars as well as more entry-level luxury cars. These gains come at the cost of losses at the mid-range segment. If wealth inequality is increased, the prediction is that an even larger number of low-end vehicles would be sold. However, wealth inequality does not favor but harm the sales of entry-luxury vehicles. Mid-luxury options are somewhat favored by wealth inequality. Overall, we conclude that wealth inequality accentuates the effects of income inequality by spreading its

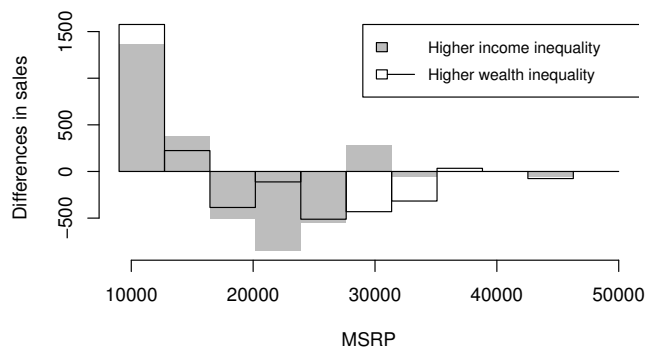


Figure 4.8: Predicted differences in the sales of different price ranges. Differences are taken between the actual scenario and the simulated scenarios.

effects over a wider range of products that encompasses not only the mid-range segment but also the entry-luxury segment.

#### 4.4.2.3 Brand performance

The differences in consumer behavior induced by different distributions of wealth, as described above, affect choice alternatives (nameplates and makes) differently. To show this, we present the predicted sales of the different nameplates considered in the sample under the actual and simulated scenarios (see Table 4.1).

According to the figures in Table 4.1, higher income inequality favors the sales of some vehicles priced around 20,000USD such as the Honda Accord and the Toyota Prius. Luxury cars, such as the BMW 3-Series and the Cadillac CTS, are not strongly affected by the differences in income inequality. An exception is the Infinity G37. The picture is somewhat different when we account for wealth inequality. Wealth inequality appears to reverse the effect of income inequality on the sales of the Buick Lacrosse, the Nissan Altima, the Toyota Camry, the Infinity G37, the Buick Lacrosse, and the Hyundai Sonata. Only in the case of the Chevrolet Malibu, the Ford Mustang, and the Toyota Prius, do the effects of wealth inequality build on the effects of income inequality.

We formalize the assessment of the effects of inequality on product line performance as follows. First, we compute the difference in shares for each make under the observed and the

Table 4.1: Predicted nameplate sales under actual and increased inequality levels.

Make	Nameplate	MSRP	Predicted sales		
			Actual scenario	Higher income inequality	Higher wealth inequality
BMW	3-Series	33,600	8	9	7
Honda	Accord	20,905	508	542	528
Nissan	Altima	19,900	510	500	518
Toyota	Camry	19,145	537	516	581
Cadillac	CTS	36,560	1	1	–
Ford	Fusion	19,035	412	373	354
Infiniti	G37	33,250	16	10	13
Chevrolet	Impala	23,790	408	374	377
Buick	Lacrosse	25,640	285	295	260
Chevrolet	Malibu	21,605	322	317	300
Ford	Mustang	20,430	22	16	10
Toyota	Prius	22,000	372	415	445
Hyundai	Sonata	18,700	288	322	297
Ford	Taurus	25,170	1	–	–

higher-wealth-inequality scenarios. We then compute make attributes as three statistics of the attributes of each make/class within each make. As make/class attributes, we consider a make/class' status scores, its product-line variety, and the coefficient of variation of its prices. We finally regress the differences in shares on the make attributes.

The three make attributes we consider are the mean, variance, and coefficient of variation of the attributes of the make/class combinations belonging to each make. For instance, we compute the mean status of Ford as the mean of the status scores of Ford large cars, Ford compact cars, etc. The mean, variance, and coefficient of variation are not computed directly on the make/class attribute scores. Instead, we use standardized attribute scores

to discriminate between low and high end brands. For example, we measure the status of a make/class  $i$  using the metric

$$\tilde{s}_i = \frac{s_i - \text{mean}(s_j)}{\text{s.d.}(s_j)}, \quad i, j \in \mathbb{J} \quad (4.1)$$

where  $\mathbb{J}$  is the set of all make/class combinations. The subsequent discussion will make evident the motivation to use these standardized scores.

We carry out independent regression analyses for each of the three make statistics. The results appear in Table 4.2 and indicate that the coefficients of variation of the make/class attributes can best explain the differences in make performance, followed by the variances. The means appear to have no explanatory power. Therefore, we discuss the results related to the variance and coefficient of variation regressions.

Table 4.2: Posterior medians of estimates of a regression on make attributes of the differences in sales of makes under actual and higher-inequality scenarios. Numbers in brackets are posterior medians of p-values.

		Make/class attribute				$\bar{R}^2$
		int.	Status	attrVar	CV(Price)	
Statistic	Mean	0.133 (0.765)	-0.340 (0.769)	-0.240 (0.789)	-0.078 (0.913)	-0.175
	Var	-0.112 (0.863)	1.706 (0.100)	-0.197 (0.765)	-0.935 (0.057)	0.18
	CV.	-0.092 (0.753)	-0.348 (0.010)	-0.054 (0.014)	-0.414 (0.002)	0.53

Interesting insights follow from the estimation results of the regression of differences in shares on the variance of make/class attributes. The positive coefficient of the effect of the variance of status implies that the makes that benefit from inequality are those that offer high status in some classes (large cars, for instance) but low status in other classes (compact cars, for example). The negative sign of the effect of the variance of the coefficient of variation of

prices indicates that a high variance leads brands to perform worse under higher inequality. That is, the worst performing makes are those that offer wide price ranges for some classes and narrow price ranges for other classes. To perform better, makes should offer similar price ranges across class-level product lines.

The regression of differences in shares on the coefficient of variation of class/make attributes also offer useful insights. Because the sign of the coefficient of variation depends on the sign of the mean, the coefficient of variation will help us discriminate between high and low status makes. High- (over average) status makes have a positive mean status score and low- (under average) status makes have a negative mean status score. Therefore, the negative coefficient of the coefficient of variation of the make/class status scores (refer to Table 4.2) indicates that the makes that perform best under high inequality are those with a large variance and a small and negative mean. These are makes that offer both low-status products in some classes but also high-status products in other classes such that, in average, all its classes are slightly below the market average status. The makes that perform worst are those that offer low-status class-level product lines and high-status lines but in average their products are slightly above average.

To illustrate the implications of this analysis, we consider the particular case of Cadillac. The effects of increased wealth inequality on the sales of this brand are described in Table 4.3 as a difference in shares. (Note that we compute make sales as the sum of the sales of the nameplates included in the sample described in Chapter 3.) Table 4.3 lists the attributes of the members of Cadillac's product lines (premium and SUV) in terms of their social status  $s$ , product variety  $\text{attrVar}$ , and the coefficient of variation of their prices. The table also presents the attributes of the Cadillac make in terms of the coefficients of variation of the status levels, product variety, and price dispersion of the portfolio of product lines. The negative sign of the difference in shares implies that Cadillac's performance in the entry-luxury segment (full-luxury products are not included in the sample) deteriorates under increased inequality and this is due to the relatively unbalanced social status of its products (its  $\text{CV}(\tilde{s})$  score is slightly above average.) The benefits of the unbalanced price dispersion  $\text{CV}(\widetilde{\text{CV}(p)})$  are dominated by the drawbacks of its unbalanced status positioning  $\text{CV}(\tilde{s})$  as



Table 4.3: Attributes of Cadillac’s products and product lines, together with the posterior mean of the percentage difference in market shares between scenarios with observed and increased levels of wealth inequality.

Nameplate	Class	Price (USD)	Make/class attribute			
			$s$	attrVar	$CV(p)$	
XLR	PREMIUM	86,215	1.314	0.536	1724	
DTS	PREMIUM	46,280	1.314	0.536	1724	
CTS	PREMIUM	36,560	1.314	0.536	1724	
CTS-V	PREMIUM	58,575	1.314	0.536	1724	
STS	PREMIUM	46,845	1.314	0.536	1724	
Escalade	SUV	61,130	1.358	0.553	4205	
SRX	SUV	40,460	1.358	0.553	4205	
Make			Make attribute			$E[\Delta\text{shares}]$
			$CV(\tilde{s})$	$CV(\widetilde{\text{attrVar}})$	$CV(\widetilde{CV(p)})$	
Cadillac			0.003	0.001	-1.222	-1.198

a high-status brand.

Cadillac could improve its performance by reducing the dispersion of status or the unbalance in the dispersion of prices of its product lines. This can be achieved by reducing the values of the variables  $CV(\tilde{s})$  and  $CV(\widetilde{CV(p)})$ . If Cadillac were to reduce the price of the Escalade from 61,130USD to 56,130USD, its  $CV(\widetilde{CV(p)})$  score would be significantly reduced. This move would at the same time reduce the status of Cadillac SUV’s to a level closer to the status of Cadillac premium cars. While this price reduction could improve Cadillac’s performance in the entry-luxury segment, it is not its only option. If Cadillac were to increase all of its prices, excepting that of the Escalade, by 5,000USD, similar but stronger results could obtain.

## 4.5 Discussion

### 4.5.1 Contribution to literature

The preceding analysis indicates that high levels of inequality in consumer resources are associated with disperse preferences for status signaling, product variety, and luxury. In particular, high inequality makes social status more salient and desirable to consumers. One could relate this shift in preferences to the literature on power. In particular, the aforementioned shift in preferences can be regarded as a substitution between different forms of power if one is willing to interpret the preferences for specific product attribute combinations (product variety) as the reflection of a desire for self expression. As explained by Lammers et al. (2009), power can be classified as social power (power over others) and personal power (freedom from others). Social power relates to the ability to command respect from others and is attained by successfully signaling social status (Magee and Galinsky, 2008). Personal power is signaled through choices that express individuality (Kim and Drolet, 2003; Levav and Zhu, 2009). Therefore, consumers may substitute between personal and social power by substituting between product variety and status signaling.

Our findings complement the results of Ordabayeva and Chandon (2011) and Hopkins and Kornienko (2004). These authors found that equality can spur status-motivated consumption through social comparisons. We investigated a different process through which inequality affects consumption. We did not focus on how inequality affects the outcomes of social comparisons and thus preferences. We focused on how inequality affects the inequality of consumer motivation to pursue social status through consumption. Thus, we further the work of Ordabayeva and Chandon (2011) and Hopkins and Kornienko (2004) by identifying alternative processes that link inequality and consumption.

By building on an individual level model to make inferences at the aggregate level, we bridge the individual level studies of Hopkins and Kornienko (2004) and Ordabayeva and Chandon (2011) to the aggregate-level study of Cutler and Katz (1992). Paralleling the work of Cutler and Katz (1992), we explain how the inequality of overall consumption seems to increase with the inequality of income. By showing that wealth inequality counters the

effects of income inequality on the sales of mid-range and entry-luxury products, we also provide an alternative explanation to the fact documented by Krueger and Perri (2006) that consumption inequality appears to be lower than income inequality.

#### 4.5.2 Managerial implications

An important implication of our results is that both firms and policy makers should pay attention to both income inequality and wealth inequality. While the consequences of income inequality are of great importance, the effects of wealth inequality seem to be just as consequential. In particular, the effects of wealth inequality may intensify the polarizing effects of income inequality. The accuracy of sales forecast will therefore greatly depend on the whether both income and wealth are considered.

The result that preferences for different product attributes are affected differently by the levels of economic inequality is of great importance to firms. For instance, we find that higher levels of inequality are associated with more positive preferences for the status-signaling value of products but also with less positive preferences for product variety. Preferences for luxury also are less positive and more disperse under higher economic inequality. This suggest that, under increasing inequality, manufacturers may benefit from offering less differentiated product lines that offer little luxury but nonetheless signal high status.

In addition, the results in Table 4.2 imply that makes that profit from higher inequality are those whose product lines are spread out in terms of status (at the class level) but exhibit similar price ranges within each class. That is, their product line covers different status segments but the within-segment sets of offerings are similar in terms of prices. Broad coverage across across status segments can benefit the most those makes that seek a positioning right below the market average in terms of status. At the same time, such large coverage could hurt the most those makes positioned right above the average status. Unbalanced product lines (those with large variance in terms of status across classes) are, in general, beneficial for brands with under-average status. High-status (over-average status) makes are better off offering more balanced product lines when inequality increases. That is, high-status makes

should try to offer only high-status compact cars, high-status large cars, etc.

Finally, we have also shown that changes in the levels of inequality can affect the performance of brands through consumer preferences for the variety of product lines. Previous work by Train and Winston (2007) investigated whether the composition of the product line contributed to the declining market shares of U.S. automakers in the U.S. market. The authors found no effect. In contrast, our results suggest that product line composition could have contributed to these changes in market shares. This follows from the results presented in Table 4.1, which show that increasing inequality can harm the sales of U.S. manufacturers and benefit the sales of Asian brands. The estimates that appear in Table 4.2 indicate that this is partly due to the the variety of the product lines offered by automakers. Thus, in contrast to the results obtained by Train and Winston (2007), our results suggest that product line composition is an important determinant of brand sales. To resolve this apparent disagreement, one could posit that other environmental trends could counter the effects of increasing inequality on preferences for product line variety preventing us from measuring these effects from historical data. A potentially more useful explanation to this apparent discrepancy could be grounded on the nature of measures of product line variety. While Train and Winston (2007) relied on the number of models in the product line, we used the dissociation of the product attributes of the members of the brand. We believe this later metric is more meaningful as some brands offer a very large number of very similar models, making the number of models an inaccurate measure of product line variety. Hence, we propose that effective product line management should focus on product attribute dissociation rather than number of products.

## 4.6 Conclusions

We have investigated how income and wealth inequality affect the demand for the social status, product variety, and luxury of vertically differentiated products. To this end, we have used a model of consumer choice that, by relying on human motivation theory, incorporates consumer wealth to produce more realistic substitution patterns. The model was used

to examine how different levels of income and wealth inequality affect the distributions of consumer preferences and choices. A simulation study indicated that wealth inequality accentuates the effects of income inequality on behavior, explaining why consumption appears to be less unequally distributed than income. The simulation results showed that wealth inequality makes consumer preferences more disperse thus hurting the sales of entry-level luxury products but slightly favoring the sales of higher-end alternatives.

Because the social status of products and the variety of product lines are functions of product line prices and variety, we are able to predict the effect of these marketing actions on the performance of products and brands under different levels of income and wealth inequality. As higher inequality implies stronger preferences for social status and weaker preferences for product variety, firms may benefit from increasing the vertical differentiation of their offerings while reducing the horizontal differentiation within their product lines to better position their brands in terms of the social status they signal. Brand positioning and product line pricing are important determinants of the success or failure of brands in the changing demographic landscape.

# CHAPTER 5

## Conclusions

This doctoral dissertation introduced a framework to quantitatively model the human pursuit for social status in the consumption context. In three chapters, the dissertation introduced the building blocks that allowed us to assess the impact of economic inequality, prices, and product line composition on the sales of status-signaling products and brands. As the components of this project were presented in three separate parts, this last chapter focuses on consolidating and evaluating the contents, findings, and implications of the project.

### 5.1 Objectives accomplished

Through the three chapters of this dissertation, we have accomplished the following goals.

- 1) We integrated theories from cultural studies, sociology, social, evolutionary, and cognitive psychology to propose metrics of the social status signaled by brands and products. These metrics satisfy the following requirements.

- The metrics represent consumer perceptions of the social status associated with brands and products. The correlations between the metrics and consumer perceptions of brand status were high and at least one metric exhibited good discriminant validity as well.
- The metrics predict consumer behavior, as established by an econometric study on secondary data. Through this study, we showed that the metrics do explain consumers' brand choice.
- The metrics are robust, reliable, and objective because they are built using objective data. A robustness test showed that the metrics are good measures of the

perceived status of brands for the majority of consumers.

- The metrics are accessible to marketing practitioners who can compute them using available secondary data. The metrics can be readily computed using product prices and data that describe the population of products in use (which can be approximated using past sales data).
- The metrics provide guidelines for the positioning of brands by establishing a direct link between product line composition, prices and consumer perceptions of the social status of brands.

- 2) We used the proposed metrics of brand status to quantify the economic importance of status-seeking behavior in the consumption context. This was achieved by computing own and cross price elasticities and by showing how these elasticities differ from those computed without accounting for the social status signaled by products.
- 3) We identified conditions that determine the strength of preferences for status-signaling brands. In particular, we related the estimates of consumer preferences for status-signaling products to consumer demographics such as income, education, ethnicity, product usage, etc.
- 4) We also identified conditions that determine whether these preferences are exercised or repressed. To this end, we relied on motivation theory and econometric tools to propose and test a new economic model of consumer choice that allow us to explore the conditions under which preferences for status-signaling products are revealed. We proposed and showed that consumer assets, or wealth, are drivers of consumer motivation and choice.
- 5) We investigated how major demographic shifts affect the market performance of products and brands through changing preferences, motivation, and ability of consumers to signal status through consumption. In particular, we investigate the effects of increasing income and wealth inequality among consumers. We did so by relying on the proposed metrics of brand status and the new model of choice in a simulation study. This simulation study identified product line composition and pricing strategies that favor the sales of brands when consumer inequality increases.

## 5.2 Summary of results

This research has shown that consumer preferences and motivation to signal social status through consumption are important drivers of consumer behavior. In addition, the results have shown that product line composition and prices moderate the effects that increasing consumer inequality has on consumer preferences for status-signaling products. Product line composition and pricing strategies must therefore account for changes in the distribution of consumer assets.

The first essay revealed that, among the proposed metrics of brand status, the best metric is the one defined by the median of the prices of the products in the product line. This metric exhibits better divergent validity and also influences consumer choice. In terms of methodology, the first essay showed that the inclusion of status metrics largely affects the estimated price elasticities. By considering the effects of price on status and the effects of status on purchase probabilities, the proposed model is able to reproduce complex substitution patterns that similar models without status metrics cannot replicate.

The second essay showed that the modeling of the saliency of consumption motives can improve the predictive power of models of consumer demand. The proposed model outperforms standard econometric models in terms of predictive ability in in-sample and out-of-sample tests. This improvement is due to the introduction of wealth into the model but also to the structure imposed on the proposed model. Both wealth and structure allow the model to account for the additional sources of heterogeneity, thus mitigating aggregation bias. The results from this second essay also support the contention that the saliency of motives may depend on the availability of resources and that different levels of resources are required for different motives to be salient. We find that middle levels of wealth make preferences for status-signaling products more likely to be exercised than low or high levels of wealth do.

The results presented in the third essay indicate that high levels of inequality in consumer resources are associated with disperse preferences for status signaling, product variety, and luxury. In particular, high inequality makes social status more salient and desirable to con-



sumers. Because of these changes in the distribution of consumer preferences and motivation, wealth inequality may intensify the polarizing effects of income inequality. Income inequality harms the mid-range segment but favors entry-level luxury products. Wealth inequality harms both mid-range and entry-level luxury segments. The brands that profit from higher inequality are those whose product lines cover different status segments but at the same time exhibit similar levels of price dispersion across product categories. Broad coverage across status segments can benefit the most those brands that seek a positioning right below the market average in terms of status. At the same time, broad coverage could hurt the most those brands positioned right above the average status.

### **5.3 Contribution to literature**

The first essay contributes to the literature on vertical differentiation by demonstrating that product line pricing is important not only because it allows for price discrimination but also because it affects how the entire brand is perceived by consumers (brand equity). In particular, the prices of status-signaling products do have an additional effect on brand choice because they define the social status of brands. By demonstrating this, we highlight the need for incorporating the effect of price on perceived status into current models of vertical differentiation.

The second essay advances a new explanation to observed trade down and trade up behaviors. Because the proposed framework can incorporate multiple consumption motives, the proposed model unifies several of the previously proposed explanations of consumers' choice of low-end and high-end products. Our model can incorporate, for instance, heterogeneous valuations of quality, consumer needs for social status, and any other consumption motive that can be satisfied by a measurable product attribute. In this sense, the proposed theoretical model represents a step towards a richer theory of preferences for quality.

The third essay offers a new perspective on the relationship between consumer inequality and consumption inequality. This new perspective breaks down inequality into income inequality and wealth inequality, identifying the different mechanisms through which each

form of inequality affects consumption. In particular, the theoretical foundations of this study enable us to separate the effects of financial resources on consumer preferences and on the exercise of those preferences. We are thus able to show that inequality in consumer resources drive consumption inequality through its effects on the dispersion of consumer preferences and their saliency.

Overall, these contributions are relevant to different bodies of literature. We bridge the economic and psychological literatures on social status by incorporating both economic and psychological models into our framework (aside from principles and findings developed in other disciplines such as sociology, anthropology, neuroscience, cultural and communication studies, etc.). Because our results have direct marketing implications, this work makes a substantial contribution to the marketing and consumer behavior fields.

## **5.4 Managerial implications**

By revealing the relationships between the different prices of the product line and the perceived attributes of the brand, the results presented in the first essay offer insights as to how to effectively position a brand. In particular, managers can manipulate the median price of a product line to position the brand at a desired level of perceived status because the metric defined in terms of the median price strongly correlates with perceived status and strongly explains consumer behavior. By considering the relationship between prices and the perceived social status of brands, our analysis uncovered rich price elasticity patterns across products of the same brand. For instance, we found that Lexus could improve the sales of its SUV's by increasing the price of its sedans because such a price increase enhances the perceived status of the Lexus brand.

The first essay however also clarified that these pricing strategies must take into account the brand's segmentation goals. As our results show, different consumers interpret and value differently the multiple properties of the distribution of prices within a product line. For instance, we found that a consumer's social class, education, and the size and segregation of the consumer's community affect the consumer's perception of the social status signaled

by brands. Heterogeneity is therefore very important for brands that seek to position their products within specific market segments.

The second essay makes mostly a methodological contribution, but its results are also important for practice. In particular, the results show that consideration of the saliency of consumption motives can improve the predictive power of models of consumer demand. The proposed model is able to: a) identify a stronger effect of the budget constraints; and b) better estimate the magnitude of these preferences. Thus, this essay shows that accounting for the heterogeneity in motivation, can mitigate the effects of aggregation bias. This is relevant to managers as it provides them with ways to better understand customers and to better forecast sales.

The benefits of the better forecasting ability of the model are made evident in the third essay. The results therein presented show that, while the consequences of income inequality are of great importance, the effects of wealth inequality seem to be just as consequential. In particular, the effects of wealth inequality may intensify the polarizing effects of income inequality by harming the sales of not only mid-range products but also of the entry-luxury segment. Increasing wealth inequality furthers the shift of sales towards the low-end of the quality spectrum.

Besides predicting the effects of increasing inequality on sales, the third essay also identified the attributes of the product lines that perform worse and best under higher inequality. For instance, we discussed how the sales of Cadillac can suffer if inequality is high because, as a high-end brand, Cadillac offers product lines with too-dissimilar levels of social status. (Such disparities in the social status of the lines of a brand can, in contrast, favor the sales of low-end brands.) As this example illustrates, our analysis and results can be used to diagnose the readiness of brands to face increasing inequality. Our results can even be used to offer suggestions for brands to better adapt to such demographic trends. Hence, this work can be of great value to a firm's marketing strategy.

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