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An Investigation of E-shopping for Clothing and Books, with a Focus on Taste Heterogeneity: Evidence from Northern California

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At the end, I would like to dedicate this work to my parents and my husband.

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ABSTRACT

Online shopping is increasing steadily, and could lead to substantial impacts on trip generation, destinations, and timing. Understanding the potential transportation impacts requires us to better understand the adoption of this new shopping alternative (or "channel"). Using data collected from a web-based survey of two university towns in Northern California (N=967) in 2006, we developed models of the intention to purchase one of two different product types: book/CD/DVD/videotape or clothing/shoes. We were especially interested in exploring the nature of taste heterogeneity (differences across people in the importance placed on factors affecting the decision), including the best way to identify and model it. The model types we used include logistic regression (LR), latent class models (LCM) and LR with interaction terms.

Preliminary results showed that product type matters; variables such as trustingness and store brand independence are only significant for book purchases, while others such as efficiency/inertia and being female are only significant for clothing purchases. Accordingly, later models are product-type-specific.

The main findings are as follows. With respect to the e-shopping application context, we found, first, that product type, and general and channel-specific shopping attitudes, in addition to previously-identified effects (such as sociodemographics) clearly contribute to the purchase intention. Second, channel-specific perceptions substantially differ, on average, by product type. Therefore, it is dangerous to elicit general channel perceptions (or, comparative judgments not distinguished by individual channel) without regard to

product type. With respect to the methodological approach, we found that empirically, LCM is not always superior to a conventional LR model with interaction terms. Instead, it can function as a useful diagnostic tool for dealing with taste heterogeneity, by leading us to more intelligently specify a conventional model with interaction terms. The latter often yields a more parsimonious and better-fitting model.

This study constitutes an early application of taste heterogeneity analysis to an e-shopping context. The models developed here improve our understanding of people's shopping behavior, which will ultimately improve our ability to predict its impacts on transportation demand. Accordingly, our methodological approach and our specific results are of value to both marketing researchers and transportation planners.

Key words: internet/online shopping, store shopping, product type, logistic regression model, market segmentation, latent class model, taste heterogeneity, attitudinal factors

1. INTRODUCTION

E-commerce can be simply defined as buying and selling goods or services via the internet. It basically consists of three components: business-to-business (B2B), business-to-consumer (B2C) and consumer to consumer (C2C) (such as eBay) (http://www.answers.com/e-commerce&r=67, accessed Oct. 10, 2009). Since e-commerce refers explicitly to purchase-related activities whereas e-business might be used to denote a total presence on the web, it is natural to think of e-commerce as a sub-concept of the umbrella term "e-business". In this dissertation we focus on B2C e-commerce. More specifically, we focus on the activities that are undertaken by the consumer (rather than the retailer), which we refer to as e-shopping or internet shopping, indicating that goods and services can be purchased online. E-shopping continues to grow in recent years. For example, internet-based retail sales in the US constituted about 1.1% of total retail sales in 2001 and 2.0% of total retail sales in 2004. By 2007, online retail, at $126.7 billion, accounted for 3.2% of total retail sales[1]. Online purchases of the product types of particular interest to the present study are also increasing. Specifically, the percentage of retail spending on *books, music, and videos* that takes place online has nearly doubled in five years, from 7.7% in 2001 to 16.3% in 2007. And the online sales percentage of retail spending on *apparel, accessories, footwear, and jewelry* jumped from 1.6% in 2001 to 6.3% in 2007[2]. It is predicted that online retail sales (excluding travel) will reach $235.4 billion in 2009, rising to $334.7 billion in 2012[3]. Among the three components of e-commerce, the potential effects of the B2C segment could be substantial

[1] Source: http://www.census.gov/compendia/statab/cats/wholesale_retail_trade/online_retail_sales.html (Table 1021), accessed January 2, 2010.
[2] Table 1016, http://www.census.gov/compendia/statab/tables/09s1016.pdf, accessed July 13, 2009.
[3] Table 1015, http://www.census.gov/compendia/statab/tables/09s1015.pdf, accessed July 13, 2009.

although “the B2B segment dominates e-commerce in terms of the dollar value of transactions made” (Cao and Mokhtarian, 2005, p. 1).

By now B2C e-commerce permeates the daily lives of many Americans. It influences the style and location of our working, shopping, traveling and living (Cao and Mokhtarian, 2005). The rapid growth of e-commerce is inducing impacts on society in areas such as transportation (particularly with respect to urban travel in terms of mode and frequency), land use patterns (retail store and warehouse location and relocation, including new construction as well as closures), and people’s shopping behavior. Specifically, it potentially results in reductions of consumers’ shopping travel and increases of package delivery trips (Mokhtarian et al., 2009). However, a number of previous studies (Mokhtarian, 2004; Farag et al., 2006; Cao, 2010) have pointed out that the evidence does not support a reduction in travel; on the contrary, the net effect may well lie in the direction of increasing travel. Furthermore, future air quality and fuel consumption will possibly be affected if the change in transportation demand is substantial. Compared to store shopping, e-shopping offers the advantages of flexible “opening hours” and unrestricted product storage space. Its attractive characteristics also include the ease of spreading product information, by which means consumers can find the best prices for their desired products by comparing the voluminous information the online channel provides. Taking other advantages (in Table 1) into account, we confidently predict that e-shopping will be adopted more intensively over time. We also expect that (because of the relative ease of reaching and developing global markets) the development of e-shopping will contribute to the increasing internationalization of product manufacturing and distribution, which has major transportation implications (Mokhtarian et al., 2009).

As for the transportation impact of B2C e-commerce, Mokhtarian (2004) pointed out that the future shopping-related changes in transportation are the net outcome of four fundamental causes: changes in (1) shopping mode (or channel) share, (2) volume of goods purchased, (3) per capita consumption spending, and (4) demographics. Among those potential effects, some of them will decrease travel while others will increase it. The combined effects do not clearly support either direction of impact in particular. This illustrates the complex nature of the effects of e-commerce on transportation.

There are two main components of an analysis of the transportation impacts of B2C e-commerce: assessing the transportation impacts for a given level or pattern of B2C e-commerce adoption, and assessing the level/pattern of adoption, including details such as who, how frequently, for what products, under what circumstances, and in what form (Mokhtarian, 2006). While the transportation planners' ultimate goal is to forecast transportation impacts by predicting changes in future traffic demand, to do so, they need to accurately understand adoption processes and trends. Thus, similarly to previous studies (Mokhtarian, 2006; Mokhtarian et al., 2009) which took the consumer perspective, this study focuses on the latter issue, that is, it addresses modeling a shopper's adoption of B2C e-commerce (i.e. e-shopping or internet shopping), among other shopping channels (specifically store). In this study, we consider e-shopping to be a subset of teleshopping – a broader term which also includes catalog shopping and TV shopping. To set up a feasible and manageable project, we exclude TV shopping in this study for two reasons: (1) TV shopping appears to be largely impulse buying – most buyers using a TV channel treat it more as an entertainment form than as a "real" alternative form of shopping; (2) purchases made from TV shopping channels have the smallest share among the four modes of in-store, online, catalog and TV (Handy and Yantis, 1997). In addition, because the catalog channel was not well-represented in our sample, in this study we focused on the two most popular shopping channels: store and internet.

From the standpoint of better understanding and predicting the effects of e-commerce on transportation, it is important to assess the characteristics of the internet channel comprehensively and precisely. And we should better understand consumers' behaviors, preferences, and attitudes toward different means of shopping: how much do they prefer to shop online? How frequently do they choose to buy items via the internet? What kind of product is more preferred to be purchased by one channel over the other options? Which shopping channel is more likely to be adopted by individuals with specific characteristics, compared to other people? These are all interest-triggers for fully exploring the issue. The development of e-commerce is still at an early stage, and why consumers choose (or do not choose) online purchasing is far from being completely understood. Therefore, in order to better anticipate and evaluate the impacts of e-commerce, "it is important to further refine our understanding of consumers' e-shopping behavior" (Cao and Mokhtarian, 2005, p. iii).

Considerable research has investigated e-shopping behavior (as will be discussed in the following chapter), but has left several important questions for deeper and more systematic exploration. The main research questions to be addressed by this exploratory research build on two questions mentioned in a prior study (Ory and Mokhtarian, 2007): ***(1) "[W]hat are the advantages (motivators and facilitators for choosing) and disadvantages of (constraints on choosing) each shopping mode" (Ory and Mokhtarian, 2007, p. 2) for various product types?*** A number of scholars (e.g. Tauber, 1972; Salomon and Koppelman, 1988; Alba, et al., 1997; Childers, et al., 2001; Bhatnagar and Ghose, 2004; Mokhtarian, 2004) have identified the potential advantages and disadvantages of online shopping and store shopping. As indicated by them, store shopping and e-shopping are quite different in many aspects such as product information provision, search speed, and transaction process, as well as the ability to compare prices. Besides those attributes that help to complete purchasing per se, store shopping also provides many other experiences that are relatively difficult to obtain and/or satisfy via internet platforms (Ory and Mokhtarian, 2007). These include social experiences outside of home, communication with others having common interests, the pleasure of bargaining, some physical exercise, and so on. Thus Ory and Mokhtarian (2007, p. 2) summarized that "[s]hopping, under many circumstances, is a combined maintenance – leisure activity". The choice between store shopping and e-shopping has not pointed to a specific preferred direction in that both channels have pros and cons. As a result, the final decision of whether (out-of-home) store shopping or (often in-home) online shopping is chosen really depends on the nature of the shopping channel and the individual's characteristics, as well as product type (Salomon and Koppelman, 1988; Handy and Yantis, 1997).

Although many studies of e-shopping adoption have been conducted in which channel perceptions have been measured, most of those studies have at least one of two limitations: (a) they tend to focus only on the perceptions of the internet (e.g. Ahn et al., 2004), or at best a directly comparative judgment of the internet relative to stores (e.g. Farag et al., 2006); and (b) the perceptions are typically gathered without regard to product type (e.g. Belanger et al., 2002). With respect to the first issue, we believe it is important to view shopping behavior not just as a choice of e-shopping or not, but as a choice among multiple shopping channels, where traits of each channel can be separately perceived, and perhaps only indirectly compared, by the consumer in making the choice. Further, the various channels (online, store, and catalog shopping) are possibly complementary to each other. A consumer can shop through any or all of them over time, so the “chosen” alternatives are not mutually exclusive. Because of that, it is quite important for the analyst to explicitly compare advantages and disadvantages between shopping channels and understand the circumstances under which one channel is likely to be more preferred or chosen over the other. Accordingly, in the present study we ask for separate but parallel judgments on the channels of interest.

With respect to the second limitation of previous studies, it seems clear that at least some channel perceptions are likely to differ for different types of products. For example, where an item (such as a book) is essentially uniform regardless of its retail source, and where its basic nature can be assumed, the perceived risk of purchasing over the internet may be much lower than when a generic item (such as a blouse) can vary widely on quality of fabric, workmanship, and fit. On the other hand, perhaps other perceptions, such as the ability to save money, will be similar across product type. In any case, it seems important to determine whether perceptions differ by product type rather than to act as though they do not. In the present study, each survey respondent provides channel-specific perceptions in the context of purchasing one of two product types: clothing/shoes (henceforth "clothing"), or book/DVD/videotape/CD (henceforth "book").

The second key question addressed by this research is:

(2) Is taking taste heterogeneity into account logical and necessary in this context? Or, in other words, can different importance weights on the various factors affecting channel choice be identified for different members of the population? There are basically two different types of approaches to analyzing the taste heterogeneity of a population: the *constant-coefficient-within-class* approach and the *continuously-varying coefficient* approach. The former approach is often referred to as "market segmentation", which includes deterministic segmentation and stochastic segmentation (see Section 5.2 for details), and focuses on identifying specific groups of people whose importance weights differ *across* groups but are constant *within* group. The latter method includes the mixed logit model (MLM) and interaction terms approaches (see Section 6.2 for details), where each individual is allowed to have a unique set of coefficients. We elaborate on those approaches below.

Taking a market segmentation approach, a number of studies (Tacken, 1990; Cairns, 1996; Gould and Golob, 1997; Ren and Kwan, 2005) have identified four segments of the population that are more likely to be e-shopping adopters: the “mobility-limited”, “time-starved”, “technophilic”, and “shopping-phobic” (Ory and Mokhtarian, 2007). These four segments suggest some basic characteristics of e-shopping adopters and are very possibly extendable to many e-shopping contexts (Ory and Mokhtarian, 2007). However, they are not necessarily mutually exclusive nor collectively exhaustive. In reality, individuals may possess all, some or none of those four characteristics to varying degrees. In this study, we try to broaden those dimensions and aim at identifying more attributes that help in better segmenting the population and explaining shopping behavior.

Given the selection of a discrete segmentation approach, an important choice is whether to define the segments deterministically or stochastically. There are at least three approaches to deterministic segmentation: (1) using a single variable (e.g. gender, education level or employment status); (2) using cross-tabs of multiple variables; or (3) conventional cluster analysis. Using a single variable to segment the population is quite simple (and common) but it is likely that a single variable will not be an adequate basis for defining groups with similar and different tastes. The second method (cross-tabs of multiple variables) offers a lot of flexibility – but in fact too much so: there are numerous possible combinations of the variables of interest, and it is cumbersome to set up cluster definitions, estimate choice models for each cluster, test whether the segmented model improves on the pooled one, and then (if so) interpret the segmented model – all on a trial-and-error basis. Similarly, conventional cluster analysis can also involve multiple variables, and further, can produce clusters that are not limited by the rigid cell demarcations of cross-tabulations, but again requires a cumbersome procedure, with numerous possible combinations, and a largely ad hoc process.

In the stochastic (latent class modeling, or LCM, where the “M” can refer to “model” or “modeling”, depending on the context) approach, by contrast, once a pool of prospective cluster variables has been identified, the model estimation process finds the combinations of those variables that best delineate the clusters (latent classes). Although cluster membership for a given individual is unknown (hence the term “latent”), we model the probability that a given individual belongs to a certain cluster, as a function of those cluster variables. Further, the channel choice model is estimated simultaneously with the cluster membership model, and the clusters are defined *on the basis of their ability to best discriminate between different market segments with respect to channel choice*. It is this ability to (loosely speaking) automatically find the optimum set of clusters *for a given choice context* that is the strength of the LCM method, and our reason for choosing it in this study. In short, the LCM (see Section 5.3.2) we create is a two-level model (i.e. an LC choice model, or LCCM), with a latent class membership model as the first level and segmented choice models (for each segment) as the second level.

The market segmentation approach falls between the two extremes of (a) no segmentation – estimating a single model on the pooled sample, such that everyone is assumed to have the same coefficients, or weights, for a given explanatory variable, and (b) “atomistic” segmentation, in which each individual may have a different weight for a given explanatory variable (i.e. the continuously-varying coefficient approach). The latter approach is now commonly implemented (in a discrete choice context) using a MLM, in which the coefficients are taken to be random variables – unknown for a given individual, but having a population distribution whose parameters (means, standard deviations, covariances) are estimated and interpreted. Although it might be argued that such an approach is conceptually superior for dealing with the presumed uniqueness of each individual (and our inability to know precisely each individual's personal weights), it is not straightforward to operationalize it. As we will see in Section 5.2, MLM needs prior assumptions about the distributions of the parameters. Based on the literature review and informed judgment, there is no clearly best distribution to adopt, and a bad assumption with respect to the distribution may lead to poor results. Accordingly, in implementing the continuously-varying coefficient approach, we chose an alternative in which coefficients – rather than viewed as unknown random variables – are modeled as deterministic functions of other observed variables. This is accomplished by incorporating interaction terms into a conventional choice model (Scarpa et al., 2003) (see Section 6.2),

To summarize, in this study, we apply and compare three selected approaches to analyze taste heterogeneity: the two constant-coefficient-within-class approaches of deterministic market segmentation and latent class modeling, and the continuously-varying coefficient approach involving a choice model with interaction terms. We use interpretability and goodness-of-fit (GOF) considerations to identify "best" models for each dependent variable analyzed.

Our examination of taste heterogeneity occurs in the context of e-shopping behavior modeling. In the literature, that behavior includes three main dimensions: adoption, spending and frequency (Cao and Mokhtarian, 2005). In this study, we only consider the adoption dimension, specifically measuring purchase channel intention (see the dependent variable in Section 3.2.1). We will use data collected from an internet-based survey (conducted in the spring of 2006) of northern California residents (see Chapter 3 for detailed data information). The survey consists of seven parts asking questions related to general shopping-related attitudes, purchasing experiences, a recent purchase, channel-specific shopping attitudes, shopping frequency, respondents' usage of the internet, and sociodemographic information. This study makes the following main contributions:

(1) Most other studies have tended to focus only on the perceptions of the internet, or at best a directly comparative judgment of the internet relative to stores. In this study, we separately captured people's perceptions of internet and store. Although only the difference in the utility of each channel matters to a discrete choice or intention, understanding individual channel perceptions is also of interest in its own right, and we have further found that the same explanatory variable can be weighted differently in the utility function depending on the channel with which it is associated.

(2) Most studies have disregarded product type, and pooled all kinds of products together. This can yield vague or inconsistent results: it may overstate or understate consumers' e-shopping intention, because one or a few products they considered will be more or less suitable for e-shopping, and it may fail to identify explanatory variables that are important to some product types but not others. Our study explicitly considered two

product categories: book (as a "search" good) and clothing (as an "experience" good) (see Nelson 1970 for detailed explanations of these two types of goods).

(3) We examined a rich set of explanatory variables, including general shopping attitudes, channel-specific attitudes, shopping experience, internet usage and sociodemographics. Although subsets of most of these variables have been used in one or another study, the combined availability of all of them is virtually unique.

(4) We especially focused on addressing the issue of taste heterogeneity, or importance weights that vary across the population, in the context of shopping channel intention. We mainly focused on two approaches: a conventional logistic regression (LR) model with interaction terms, and a LCM. We also selectively compared LCM to a deterministic segmentation approach. Our approaches and results offer useful experience that can improve future analyses of taste heterogeneity in other contexts as well as this one.

(5) The study has provided potential insights to help transportation planners forecast future transportation demand and optimize system operation (see Section 7.2 for details). By addressing the potentially substantial social and transportation impacts of e-shopping, it may also increase urban planners' awareness of these impacts and help them develop effective strategies for using land wisely. It has also provided useful insights to market researchers and retailers, with respect to the roles of various factors in shopping channel choice, and the nature of population heterogeneity with respect to those roles. For example, we found that the perception that one channel is more enjoyable than the other is only relevant to purchase intention for those who fundamentally enjoy shopping. Although this result may seem logical in retrospect, it would be completely missed by a model requiring the same coefficient of channel enjoyment for everyone in the population.

Knowing these taste differences is helpful for retailers to (1) better understand people's behavior; and thereby (2) more effectively market their channels and (3) make substantive changes to their channels to broaden or deepen their appeal.

The organization of this dissertation is as follows. The following chapter reviews (1) three determinants of shopping channel adoption (characteristics of products, shopping channels and individuals), (2) previous shopping channel choice modeling, and (3) generic use of the LCM in other studies. Chapter 3 describes the data collection process and variables available to this research. Chapter 4 develops models of intended shopping channel for a future purchase of clothing or books. It presents three simple LR models, for the pooled data and the two product type specific subsamples, which then collectively yield an "optimized" hybrid model with product type specific interaction terms added to the base pooled model, as appropriate. Chapter 5 develops a LCM of book purchase intention and compares it with a counterpart deterministic segmentation approach. It then also presents a conventional LR model with interaction terms, which gives better model GOF and parsimony. Chapter 6 presents shopping channel intention modeling for a clothing purchase, with a focus on accounting for taste heterogeneity similar to that in Chapter 5. Finally, Chapter 7 recapitulates the main findings. In addition, policy implications, the limitations of the study, and directions for future analyses are also discussed.

2. LITERATURE REVIEW

This chapter consists of three sections. The first section reviews three determinants influencing shopping behavior: characteristics related to the product, the consumer, and the shopping channel. The second section reviews the previous research on e-shopping intention modeling. And the last section reviews the generic use of LCM in other studies and provides example studies involving taste heterogeneity.

2.1 Variables Influencing Shopping Behavior

Shopping is a process comprising a number of potential components such as product information search, brand choice, channel choice, transaction and delivery. The components involved are linked together in a sequence that varies with the situation (Peterson et al. 1997; Mokhtarian, 2004). As one of the shopping channels, accordingly, e-shopping also consists of several components. To accurately understand the consumer's e-shopping adoption behavior and its potential transportation impacts, it is helpful to know the detailed components of the shopping process (Mokhtarian, 2004). Salomon and Koppelman (1988) divide the shopping process into five distinct but possibly overlapping phases: (1) entry into the market; (2) shopping mode choices; (3) information gathering; (4) information evaluation; (5) choice of consequent actions such as purchase, continue shopping or exit the market. Some shopping cases involve all five phases but others may just involve some of them. They further commented that "Shopping for and purchasing goods and services are complex, interdependent activities" (p. 248). It is also possible that some phases may be repeated in a given shopping activity (Mokhtarian, 2004). As for the variables influencing consumers' e-shopping behavior, previous studies have identified numerous determinants. Salomon and Koppelman (1988) summarize that three essential groups of factors affecting shopping behavior are (1) characteristics of the vendor and the product; (2) characteristics of the shopping channel; and (3) characteristics of the individual shopper. The remainder of this section will provide a brief review of those three important determinants.

2.1.1 Characteristics of the Product and Product Market

The likelihood of a shopping channel being chosen depends a great deal on the characteristics of the vendors and products in question. The internet, as a shopping medium, shows diverse suitability for different products. It is reasonable to deduce that "mixing product categories in e-shopping behavior research tends to yield vague or inconsistent results" (Cao and Mokhtarian, 2005, p. 19). Therefore, "it is useful to classify product attributes along dimensions that relate to communicability by different modes" when exploring consumers' e-shopping behavior (Salomon and Koppelman, 1988, p. 252). However, characteristics of the product and its market have not been examined extensively by previous studies in the context of e-shopping. To classify product characteristics, "the number of attributes necessary to distinguish between product types" (p. 252) is one dimension that comes readily to mind. Some goods can be uniquely identified by one or a few attributes while others require more. A second dimension is the degree to which the information is "differentially interpreted by consumers". And a third is the "multisensual nature of the stimuli generated by the product". For example, some products can be fully described by looking at them while others need further “tests” such as taste, smell or touch (Salomon and Koppelman, 1988, p. 252).

As early as the 1920’s, Copeland classified products into three categories: convenience goods (e.g. newspapers and grocery products), shopping goods (e.g. furniture and apparel) and specialty goods (specific brands of computers and wedding dresses) (cited by Cao and Mokhtarian, 2005). Customers’ satisfaction with delivery and post-delivery of online purchases could differ by product type. Thirumalai and Sinha (2005) used sample data collected from 256 firms engaged in B2C e-commerce to test the hypothesis stating “customer satisfaction with the order fulfillment process will decrease [as we move] from convenience goods to specialty goods along a product continuum” (p. 296). The data were collected on dimensions of customer satisfaction with order fulfillment and the results suggested that statistically significant differences exist between satisfaction with specialty goods and the other two types, but not between satisfaction with shopping goods and convenience goods. Consumers who are looking for convenience goods and shopping goods are more easily satisfied with respect to their order fulfillment than those who are looking for specialty goods. However, this classification mechanism does not relate to shopping channel characteristics (one of the major factors affecting the suitability of a shopping channel) such as the easy search function provided by the internet channel and experiencing the product provided by store shopping. It mostly focuses on the pure product dimension, thus it is not sufficient “to evaluate the online-purchasing suitability of products” (Cao and Mokhtarian, 2005, p. 16).

Nelson (1970) classified products using a dichotomous designation system – search good or experience good. The features of a search good can be fully ascertained and evaluated from externally provided information prior to use, whereas an experience good needs to be personally tried before the consumer judges the product quality and makes a final decision. “If a good is a search good and its features can be objectively assessed using readily available information” (Peterson, et al., 1997, p. 334), the internet can serve as the channel of transaction and communication. If a good is an experience good, its features as demonstrated by the internet may not be sufficient for consumers to engage in internet-based e-shopping because this medium cannot fully satisfy those who want to experience the good before buying. Actually a particular product may possess both search and experience traits. Normally it is defined as a search good if its search qualities dominate its attributes (such as software). Conversely, it is grouped as an experience good if its experience qualities outweigh those of search (Cao and Mokhtarian, 2005). “For any good, the consumer has a choice between searching or experiencing to obtain information about the good’s qualities. The cost of experimenting [intuitively] sets an upper limit to the cost of search that a person is willing to undergo” (Nelson, 1970, p. 317). Obviously, neither the attributes of the product nor the choices open to consumers are absolutely binary: a variety of mixed processes are possible, such as using the internet to search for basic information about the product and in-store trials to narrow down the choice set, and then making the final purchase based on the best price obtained over the internet (Cao and Mokhtarian, 2005). Bhatnagar and Ghose (2004) point out that in the context of the internet, search and experience traits are not fixed but changeable: for example, some products that are generally search goods can sometimes be experience goods (such as flowers – “sending flowers” by phone is often done sight unseen, whereas on the internet the arrangement can at least be visually experienced), and conversely (such as software and music).

Although Nelson’s classification method is simple yet useful enough to have market behavior implications, a more detailed three-dimension classification system (cost and frequency of purchase, value proposition, and degree of differentiation) was proposed by Peterson et al. in 1997, which is more relevant in the context of internet shopping. The first dimension ranges from low-cost, frequently purchased goods (such as milk) to high-cost, infrequently purchased goods (such as home stereo systems). Generally, “when purchase fulfillment requires physical delivery, the more frequent the purchase and the smaller the cost” (p. 335), the less likely for e-shopping to be chosen as a shopping channel. “Goods vary along the second dimension according to their value proposition, [i.e.] whether they are tangible and physical or intangible and service related” (p. 335). Because the internet is well suited for certain types of products such as digital ones, the greater the frequency of purchasing or using a good, the more obvious the advantage of e-shopping as a transaction medium if the product is intangible. The third dimension reflects the extent to which a vendor can “create a sustainable competitive advantage through product and service differentiation” (p. 336). When products or services are significantly differentiable (i.e. the distinctive qualities of products or services can be easily perceived), the internet can serve as an effective mechanism to guide consumers to their ideal product or service. On the other hand, when a product or service is incapable of significant differentiation (such as insurance and stock market quotes), the internet can result in extreme price competition (Peterson, et al., 1997). After deciding the product or service type (and therefore category), the successive steps for the consumer are which brand to choose, and which shopping channel(s) (internet or traditional in-store shopping) to use for information acquisition and final transaction (see Peterson, et al, 1997 for detailed conceptual consumer decision sequences). Phau and Poon (2000) applied this classification system in an empirical study and confirmed that the product or service type has a significant influence on the consumer choice between store shopping and internet shopping.

Based on the first two dimensions of the classification system of Peterson et al., Vijayasarathy (2002) divided products into four types: low cost and tangible, low cost and intangible, high cost and tangible, and high cost and intangible. He found that a product's tangibility had a significant influence on consumers' intentions toward e-shopping. Specifically, consumers intend to choose e-shopping for intangible products more than for tangible products, whereas cost and the interaction of cost and tangibility were not significant in the study.

To conclude, product type matters a great deal in e-shopping behavior research. Different product categories have different extents of suitability to the various shopping channels. For example, a consumer may be likely to purchase software online but may seldom buy clothes via e-shopping. If we pool different products together, it will overstate or understate consumers' e-shopping intention because one or a few products they considered will be more or less suitable for e-shopping. Many studies (e.g., Belanger, et al., 2002; Huang, 2000; Ranganathan and Ganapathy, 2002) neglected product classification and measured intention without specifying the category of a product. However, on the other hand, choosing particular product categories will necessarily limit the generalizability of the study (Cao and Mokhtarian, 2005). Thus, the decision of whether or not to focus on some specific product categories when we model e-shopping behavior involves some tradeoffs. Nevertheless, as summarized by Cao and Mokhtarian (2005) (p. 20), confounding different types of products in e-shopping surveys “hinders our understanding of consumers’ e-shopping behavior”.

2.1.2 Attributes of Different Shopping Channels

As mentioned in Section 2.1.1, once a product category is specified, the consumer needs to choose the shopping channel. Salomon and Koppelman (1988) comment that the decision on shopping channel is assumed to depend on four elements: “individual’s characteristics”, “systems’ characteristics”, “individual’s perceptions of and feeling toward the alternatives”, and “situational constraints” (p. 251). They also mention that shopping channels differ in their information transmission ability, the manner of product storage and how information is organized, the capability of fulfilling consumers’ other needs (e.g. satisfying their eagerness to use technology or desire for social interaction with others), and the way of delivering products. There is no absolute basis for concluding that one channel is apparently superior to the others because each channel has its pros and cons. For example, although online shopping allows people to compare prices more extensively and quickly than traditional in-store shopping, it cannot offer instant possession of a tangible product while in-store shopping can. On the other hand, even though a store can provide physical trial or usage of the product, the rigid opening-hours of retail stores can be a constraint to some customers.

Considerable research (Tauber, 1972; Salomon and Koppelman, 1988; Hoffman, et al., 1995; Alba, et al., 1997; Peterson, et al., 1997; Childers, et al., 2001; Mokhtarian, 2004; Bhatnagar and Ghose, 2004) has discussed the extensive advantages and disadvantages of traditional retail store shopping and internet-based e-shopping, as those two are the most popular shopping channels and dominate the transaction market (Handy and Yantis, 1997). Table 1 briefly summarizes their advantages and disadvantages from the perspective of the consumer. Because each channel has several advantages and disadvantages, either channel choice is reasonable and the different decisions are conditional on the consumer's characteristics and purchase situation. Therefore, it is not surprising for shoppers with different characteristics to prefer or choose different channels. For different individuals, how they weight the positive and negative features of a shopping channel with respect to the merchandise of interest drives their final decisions to a large extent.

Table 1. Comparison of E-shopping and Store Shopping from the Consumer Perspective

	Advantages	Disadvantages
e-shopping	Unlimited selection (Alba, et al., 1997) Lower prices/ search costs (Hoffman, et al., 1995; Alba, et al., 1997) Voluminous information (Salomon and Koppelman, 1988; Hoffman, et al., 1995; Alba, et al., 1997) Convenience and flexible schedule with respect to making purchase (Salomon and Koppelman, 1988; Childers, et al., 2001) Rapid assembly of information (Hoffman, et al., 1995) Does not require travel (Salomon and Koppelman, 1988) Low entry and establishment costs for e-sellers may lower costs to consumers (Alba, et al., 1997; Peterson, et al., 1997) Can provide perceptual experiences for particular types of products such as music and magazine (Peterson, et al., 1997)	The wealth of product information stimulates more shopping opportunities and induces people to spend more money. In addition, some deals provided by the internet (if stating in-store only) can actually cause more personal trips (Salomon and Koppelman, 1988) Does not satisfy the social-recreational functions associated with store shopping (Salomon and Koppelman, 1988) Increased time spent at home may reduce physical activity and outdoor exposure (Salomon and Koppelman, 1988) Cannot possess the product instantly Inadequacy of searchable experimental information (Alba, et al., 1997; Childers, et al., 2001) Absence of the actual experience (Childers, et al., 2001; Bhatnagar and Ghose, 2004) Security risk (Bhatnagar and Ghose, 2004)
Store shopping	Sensory information (Tauber, 1972) Tangibility of the product (Alba, et al., 1997) Immediate possession (Alba, et al., 1997) Social interaction outside of home (Tauber, 1972) Entertainment (Mokhtarian, 2004) Movement and physical exercise (Tauber, 1972) Many shopping trips linked to trips for other purposes makes the marginal cost of store shopping negligible (Mokhtarian, 2004) Peer group attraction (e.g. record stores provide a meeting place for teenagers to gather) (Tauber, 1972) The general concepts of serving the public can make a customer command status and authority (Tauber, 1972) Pleasure of bargaining (Tauber, 1972)	Limited merchandise availability (Alba, et al., 1997) Increased cost in time and travel to buy the merchandise Less flexible schedule (Salomon and Koppelman, 1988; Childers, et al., 2001; Mokhtarian, 2004) Potentially longer transaction time (Hoffman, et al., 1995; Mokhtarian, 2004)

2.1.3 Characteristics of the Individual Shopper

Individual characteristics constitute the third important factor affecting shopping behavior. Many such variables will influence a consumer's choice of shopping channel. We can distinguish shoppers based on two types of characteristics: the characteristics that directly help explain choice (e.g. sociodemographic traits such as income), and those that are associated with having different tastes (such as "Pro-technology" and "Time-conscious"), which may include some of the same variables as the first group. Therefore, even for a given product, consumers are likely to make different channel choices because of their differences on attitudinal traits (such as trustingness, self-confidence and risk aversion) and sociodemographics (Salomon and Koppelman, 1988). Those differences may be associated not only with having different tastes for a certain explanatory variable, but also reflect differences in the explanatory variables per se. Either kind of difference could yield different final decisions because it would cause a difference in the utilities of the available alternatives.

Relevant consumer characteristics can be classified into several groups (Chang et al., 2005): shopping orientation, social-psychological variables, channel knowledge (computer skill and internet experience), in-home shopping experience and sociodemographics. Specifically, shopping orientation is "a general predisposition toward acts of shopping" (p. 10). A variety of shopping behaviors have been identified such as economic, price-oriented, brand conscious and so on. Psychological variables include attitudes such as pro-technology, shopping-lover, pro-exercise and so on; together with other aspects of the consumer, they are all presumed to be factors affecting shopping decision-making (Chang, et al., 2005). As a result, consumers with different characteristics may have different tastes (reflected by different importance weights they put on attributes associated with a given channel), and a good understanding of their characteristics can help us better classify them and model their shopping behavior.

2.2 Previous Shopping Channel Choice Modeling

A number of studies have analyzed e-shopping intention in the past decade (Van den Poel and Leunis 1999, Bellman, et al., 2000, Bhatnagar, et al., 2000, Phau and Poon 2000, Liao and Cheung 2001, Shim et al. 2001, Belanger et al. 2002, Lee 2002, McKnight et al. 2002, Ahn et al. 2004, Chen and Tan 2004, Choi and Geistfeld 2004, Gefen and Straub 2004, Teo and Yu 2005, Van den Poel and Buckinx 2005). A summary of some previous research is presented in Table 2. The table shows that many different methodologies have been used to conduct e-shopping intention research, such as discriminant analysis (Phau and Poon 2000), ANOVA and t-test (Van den Poel and Leunis 1999), regression (Liao and Cheung 2001, Belanger et al. 2002), structural equation modeling (SEM) (Shim et al. 2001, Chen and Tan 2004), and binary logit modeling (Bellman, et al., 2000; Bhatnagar, et al., 2000, Van den Poel and Buckinx 2005).

As early as 1999, Van den Poel and Leunis used 93 responses to an electronic questionnaire, to explore the e-shopping propensity for 10 specified product categories (concert tickets, hotel reservations, car rental, software and newspapers, etc.). They conducted ANOVA and t-tests, focusing on the interaction effects of shopping channel with three “risk relievers” (i.e. price reduction, well-known brand and money-back

Table 2. Overview of Previous Research on E-shopping Modeling

Study	Methodology	Dependent variables	Explanatory variables (“0”: insignificant; “+/-”: positive/negative relationship)
Van den Poel and Leunis (1999)	ANOVA and t-test	Likelihood of e-shopping	Heavy internet users (+) Price reduction (+) Well-known brand (+) Money-back guarantee (+)
Bellman et al. (2000)	Logistic regression and regression	E-shopping adoption and annual online spending	**Consumer characteristics:** Looking at product information (+, +); Months online (+, 0); Number of daily emails (+, +); Working online at work every week (+, 0); Reading news online at home every week (+, 0); Total household working hours (+, 0); Clicking on banners (+, 0); Ordering from catalogs (0, +); Agreeing internet improves productivity (+, +); Ordering from catalogs using the internet (0, +); Using internet at office regularly for work (0, +); Like being first to use new technologies (0, +); Number of years online (0, +); Hours per week online (0, +); Not ordering by mail (0, +).
Bhatnagar et al. (2000)	Binary logit model	E-shopping adoption for 17 product categories	**Shopping channel characteristics:** Convenience (+ or -); Financial risk (- or 0); Access point * financial risk (+, -, or 0). **Consumer characteristics:** Age (+ or -); Years using internet (+ or 0); Male (+, -, or 0); Married (+ or 0); Age * financial risk (+ or 0); Years using internet * financial risk (+ or 0); Male * financial risk (+ or 0); Married * financial risk (- or 0).
Phau and Poon (2000)	Discriminant analysis	E-shopping intention for 20 product and service categories	Products and services having low outlay (+) Having intangible value (+) Having high differentiation (+)

Liao and Cheung (2001)	Regression	Willingness to e-shop	Perceived risks on transaction security (-) Education and IT training (+); Price (-) Perceived relative life content of e-shopping (-) Perceived quality of e-vendors (+) Level of internet usage (+)
Shim et al. (2001)	SEM	E-shopping intention	Intention to use web for information search (+) Attitudes (+); Internet purchase experience (+) Perceived behavioral control (+, indirect)
Belanger et al. (2002)	Regression	E-shopping intention	Importance of privacy and security features (-) Site quality (+)
Chen and Tan (2004)	SEM	E-shopping intention	Perceived usefulness (+); Perceived trust (+, indirect) Compatibility (+, indirect); Perceived ease of use (+, indirect) Perceived service quality (+, indirect) Product offerings (+, indirect); Usability of storefront (+, indirect) Attitude toward using e-shopping (+)
Choi and Geistfeld (2004)	SEM	E-shopping intention	Perceived risk (-, -); Perceived self-efficacy (+, +) Subjective norm (+, +)
Teo and Yu (2005)	SEM	Willingness to buy online	Transaction cost (-); Performance uncertainty (-, indirect) Behavioral uncertainty (-, indirect) Environmental uncertainty (-, indirect) Dependability (+, indirect) Online buying frequency (+, indirect)
Van den Poel and Buckinx (2005)	Binary logit model	E-shopping adoption during the next visit	Number of days since last visit (+) Squared number of days since last visit (-) The average time per click in the session is lower than the average (-) Number of personal pages viewed during the last visit (-) Total number of products viewed (-) Male (+); Trust (+) Total number of purchases ever made at the site (+) Number of days between the visit and the last purchase (-)

guarantee); they found all “risk relievers” have positive effects on the propensity to choose e-shopping. This study made a pioneering contribution, but was limited by a small sample, a simple methodology, and having few explanatory variables.

In 2001, Liao and Cheung developed regression models of the willingness to e-shop, based on information obtained from 312 internet users in Singapore. The variables they considered (“transaction security”, “price”, “shopping experience” and “network speed”) are quite similar to some of ours. However, our study includes more attitudinal factors and channel-specific ones. Choosing a different model (logistic regression) and analyzing data from a different country also distinguishes our study from theirs.

The work done by Van den Poel and Buckinx (2005) brought us a new approach to modeling e-shopping intention. They mainly focused on “clickstream” variables, that is, data obtained purely by analyzing the stream of mouse clicks an individual makes while browsing the internet. They created clickstream variables at both the general level (such as “number of days since last visit”) and the detailed level (such as “total number of products viewed”), obtained from 1382 observations. Binary logit modeling was applied and substantial effects of clickstream variables on people’s e-shopping intention during the next visit were found.

Not surprisingly, factors related to e-shopping advantages such as speedy information-searching, perceived quality of e-vendors, ease of use, perceived trust and product offerings all show significantly positive impacts on e-shopping intention; variables reflecting computer knowledge, internet experience and e-shopping experience also show significantly positive influences. Other variables (e.g. transaction security risk, e-shopping transaction cost, performance uncertainty and behavioral uncertainty) have negative effects. Finally, as we expected, sociodemographic characteristics (e.g. income, education, gender) have strong influences on e-shopping behavior as well. However, none of those studies involve all of the elements that we incorporate here (specifying product type, comparing different shopping channels and including channel-specific perceptions). Most of them considered shopping channel characteristics and consumer characteristics, but the product dimension was not considered by all of them. In addition, they modeled people's behavior based on either their attitudes with respect to e-shopping or the pros and cons of the e-shopping channel, without doing a cross-channel comparison and modeling the behavior as a choice among multiple available alternatives. Our study seeks to address these limitations.

2.3 Generic Use of LCM in Other Studies

As early as 1968, Haley pointed out that "the benefits which people are seeking in consuming a given product are the basic reasons for the existence of true market segments" (i.e., diversity in desired benefits would lead to different people placing different weights on a given variable important to choice[4]). Three years later, Darden and Reynolds (1971) found significant differences with respect to consumers' shopping orientations, supporting Stone's (1954) classification of shoppers as economic,

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[4] Although there is a difference between a revealed choice and a stated intention, in this dissertation we will often use the word "choice" interchangeably with "intention", in view of the fact that the choice of interest to this study is the choice of intended purchase channel.

personalizing, ethical or apathetic. These studies suggested the necessity of considering shopper segments "by their preferences for the alternative benefits they obtain from shopping" (Tauber, 1972, p. 49). Mokhtarian (2004) also advocated that when modeling e-shopping adoption behavior, we should "seek to identify segments of the population that have distinct [tastes] among those [explanatory] factors" (p. 263). As a tool for market segmentation, the latent class model has been used extensively in the marketing research literature (Greene, 2003; Louviere et al, 2005), and to a lesser extent in the transportation field out of which this study arose (Walker and Li, 2007). In the remainder of this section, we briefly review selected studies from each field in turn.

In the context of seeking latent predisposition segments with respect to retail store format (e.g. hypermarket, supermarket, and local discount store) selection, Gonzalez-Benito (2004) found that various segments exist. He assumed a discrete probability distribution for response parameters (just as the semi-parametric LCM approach does), based on the conclusion from the study of Chintagunta et al. (1991) stating that segmenting the population by a family of response parameters (corresponding to the coefficients of the segmentation variables of our study) is more suitable than relying on a prior distribution assumption (as MLM does). Bhatnagar and Ghose (2004) segmented a sample of national survey data collected online, based on respondents' perceptions of the benefits and risks of internet shopping. The LCM approach was used to identify the latent segments and the results largely supported their hypotheses that the importance placed on the two dimensions of risk (product risk vs. security risk) vary across segments (specifically, they hypothesized that the importance of product risk would decrease with age and internet experience and that of security risk would decrease with education).

With respect to travel/activity-oriented studies, Bhat (1997) applied an endogenous segmentation approach to model mode choice on a Canadian intercity travel dataset (N=3593); the multinomial-logit based Expectation-Maximization algorithm was used in his study. The results show that the endogenous segmentation model fits the data best and yields more reasonable and interpretable results compared to other approaches (i.e. refined utility function specification models and limited-dimensional exogenous segmentation models). Greene and Hensher (2003) proposed a semi-parametric extension of the multinomial logit (MNL) model (based on the latent class formulation), and then compared it with the fully parametric mixed logit model. The comparison was performed in an application to the choice of long distance car travel by three road types in New Zealand, and the results revealed both merits and limitations of both models. The LCM frees the researcher from the necessity of making possibly unwarranted distributional assumptions about the population heterogeneity, but can only accommodate a finite (small) number of segments, while the MLM allows infinite variability in individuals' unobserved heterogeneity. Thus to some degree the flexibility of the MLM specification offsets the distributional assumptions required, and the study did not certify either approach as unambiguously preferred.

Kemperman and Timmermans (2006) used diary data from 803 residents living in the Eindhoven region in the Netherlands to identify their leisure activity patterns and in turn to analyze the relationship between leisure activity participation and characteristics of the built environment, controlling for sociodemographic characteristics. Four segments were identified: low frequency recreational users, traditionalists, urban cultural participants and club recreationers. Besides sociodemographic characteristics (gender and education level), the degree of urbanization and green space accessibility were also found significant to leisure activity participation.

Walker and Li (2007) conducted latent class choice modeling on stated preference data obtained from a household activity and travel behavior survey (conducted in Portland, Oregon in 1994), to represent the effect of heterogeneous lifestyles on residential location choice. Their final model segmented the population into three latent classes, which they referred to as suburban dwellers, urban dwellers and transit-riders (in terms of their attitudinal orientations). Their research provided a behavioral model for understanding the relationship of lifestyle and residential location selection, and also demonstrated the potential of LCM in “uncovering discrete heterogeneity of lifestyle preferences” (p. 21).

From the above studies, we can see that the LCM approach has been used in many applications. Those studies provide basic knowledge and help us to understand the fundamental model structure and application, as well as in which contexts it is suitable to be used. Our approach is similar to the studies of Bhat (1997) and Walker & Li (2007), but we use a totally different dataset to model different variables of interest in the e-shopping behavior context. Some examples of how taste varies between members in different latent classes, drawn from the studies just described, are provided in Table 3.

Table 3. Examples of How Taste Varies Between Members of Different Latent Classes

Study (Dependent variable)	**Segmentation variables**	**Choice model variables**	**Taste variation**
Bhat (1997) (Intercity mode choice)	Income; gender; traveling alone; weekend travel; trip distance.	Mode constraints; travel time/cost; frequency of service; large city indicator.	The segment including more females and people who have more weekend travel put a heavier weight on frequency of service.
Bhatnagar and Ghose (2004) (Product category)	Education; income; gender; marriage status; age; number of years on internet.	Product risk; internet benefit; security risks; fractional segment size.	The segment including people who have lowest mean age and least internet experience put the heaviest weight on both product risk and security risk.
Kemperman and Timmermans (2006) (Leisure activity patterns)	Gender; education level; degree of urbanization; green space accessibility.	Frequency & duration of in-home social activities; in-home time-out activities; out-of-home social activities; out-of-home cultural activities and out-of-home touring etc.	Traditionalists put a heavier weight on in-home social activities and club recreationers put a heavier weight on out-of-home social activities; low frequency recreational users put a lower weight on visiting restaurant/café/disco and recreational activities outside.
Walker and Li (2007) (Residential location choice)	Household structure; employment; age of the head of household etc.	Housing attributes; neighborhood attributes; transportation/access attributes etc.	People in the segment with a suburban- and auto-oriented lifestyle weight home size and travel time more heavily while urban- and high density-oriented people are more concerned about safety.

Note that sociodemographic traits are significant segmentation variables for all the presented studies (in Table 3), indicating their deep influence on (or at least associations with) people's tastes. These findings provide us with insightful potential variables for our own model specifications.

3. DATA COLLECTION AND VARIABLES

In this chapter, we first explain the sampling and data collection process. Next, the dependent variables and explanatory variables of interest will be described.

3.1 Sampling and Data Collection

The data analyzed in this study were collected from an internet-based survey of Northern California residents (see Ory and Mokhtarian, 2007 for more details). The purpose of our study is to investigate e-shopping behavior as a function of other measured variables, rather than to estimate population characteristics using descriptive statistics of the sample distributions of those characteristics. Accordingly, the representativeness of the sample is not our primary concern because the relationships of interest can be reliably measured even if the sample is not strictly representative (Brownstone, 1998; Babbie, 1998, cited by Ory and Mokhtarian, 2007). It is more important to have adequate variability on the dimensions of interest and "to have a substantial number of e-shopping occasions in the sample" (Ory and Mokhtarian, 2007, p. 3).

To maximize the computer literacy and knowledge of e-shopping in the sample, two university communities were selected as study sites: Santa Clara and Davis. Both cities contain a large number of internet-literate residents, which helps to enrich the sample with a sizable portion of e-shopping adopters. One difference between the two neighborhoods is their regional locations: Santa Clara lies in the heavily urbanized Silicon Valley, while Davis is a smaller college town in the Sacramento metropolitan region.

The sampling plan segmented the study population by city (Santa Clara vs. Davis) and neighborhood type (suburb vs. traditional), selecting two or three census tracts within each combination. Recruitment letters were mailed to 2000 randomly-selected residents in each combination (Santa Clara suburb, Santa Clara traditional, Davis suburb and Davis traditional), 8000 in all (Ory and Mokhtarian, 2007). Approximately 6,500 letters apparently reached their intended addressee and around 1,000 respondents went to the website to complete the survey. In addition, 72 respondents requested and returned a paper version of the survey that was offered as an option. Overall, the response rate was 16%, which we considered quite good for an internet survey of this length (117 web pages; the paper version has 19 pages) and complexity. Typical response rates for mail-out/mail-back surveys of the general population are 10-40% (Babbie, 1998). We presume the higher end of that range to be unlikely for a survey as long as ours, with the additional barrier of being administered over the internet. Screening out cases with too much missing data resulted in a working sample size of 967 cases. For Chapters 4, 5 and 6, because our target groups of people are different, the specific samples and their selected characteristics for each study will be discussed in the corresponding chapters.

3.2 Variables

The survey started with a simple welcome question: “If you HAD to spend an hour or two shopping, where would you prefer to be?”, with seven available choices (downtown shopping district, bookstore, electronics store, hardware/home improvement store, shopping mall, grocery store and “other (please specify)”). This question was followed by seven parts asking questions related to general and channel-specific shopping attitudes, previous general purchasing experience by channel and a specific recent purchase, shopping frequency for specific product types, respondents' usage of the internet, and sociodemographics. A more detailed description is presented below.

As mentioned earlier, some portions of the survey focus on two product types – book or clothing – based "on the assumption (supported by other research) that relevant variables could be weighted differently depending on the nature of the product" (Ory and Mokhtarian, 2007, p. 18). We chose these two relatively low-cost and frequently-purchased product categories to ensure the presence of sufficient recent purchase occasions in the sample. Each respondent answered detailed questions with respect to a recent purchase of one of the two product types (the selected item was referred to as the "key item" or "key purchase").

Several different versions of the internet survey were employed. The Welcome, Part A and Part B portions of the survey were completed by all respondents. The branching starts in Part C, in which questions about a recent purchase (i.e. key item/purchase) and how was it made (with respect to shopping channel, referred to as "key mode") were asked first. The results directed respondents to one of six Part C tracks representing the item-mode combination of their key purchase, that is, book-internet, clothing-internet, book-store, clothing-store, book-catalog and clothing-catalog. Part D of the survey asked questions related to two of the three shopping channels (internet, store and catalog) (to reduce the fatigue of respondents). The first set of statements related to store shopping, with which it was presumed all respondents would be familiar. The second set of parallel statements related to internet shopping unless catalog was the chosen channel for the key item (because catalog was only a secondary interest of the study). Thus, four versions of the internet-based survey were completed: book-store + book-internet, clothing-store + clothing-internet, book-store + book-catalog, clothing-store + clothing-catalog. For those who preferred a paper survey or could not complete the internet survey, paper counterparts to those versions (except the third one) were available (full options of the internet survey were not available to them because of the limiting nature of a paper survey) (Ory and Mokhtarian, 2007). In general, paper-survey respondents were given the clothing-store + clothing-catalog version, unless they indicated computer usage when they called to request the survey (e.g. their computer was malfunctioning, or they had trouble accessing the survey website), in which case one of the first two versions was assigned more or less at random.

3.2.1 Dependent Variables

The purpose of this study is to explore and model e-shopping behavior. As mentioned earlier, such behavior can be characterized by at least three dimensions: adoption, frequency and spending (Cao and Mokhtarian, 2005). Although the survey obtains information for a number of potential dependent variables of interest, this study analyzes people's intended shopping channel for a future purchase similar to the recent one for which the detailed information had just been obtained. As such, this variable belongs to the adoption dimension. Usually, as a revealed preference, actual choice is arguably the most reliable indicator of adoption, at least in this studied context. However, there is a temporal mismatch between the explanatory variables and dependent variables, in that the choice took place in the past (although not too far in the past), whereas the explanatory variables – most problematically, the attitudes – are measured in the present. So the measured attitudes (reflected by survey responses) may not accurately represent the individual's attitudes at the time when the purchase is being made. Especially, if the recent choice in question had a negative outcome, or if some other events happened between the recent choice and the time when the survey was being performed, these factors could possibly change one's attitudes. Therefore, we are likely to be measuring the *updated* attitudes, which are more relevant to the *next* choice (i.e. shopping channel choice for a future similar purchase), rather than the previous attitudes related to the last choice. If attitudes actually changed *as a consequence* of the recent purchase, a model of (past) purchase choice having the updated (present) attitude variables as explanatory would reverse the proper roles of cause and effect. Accordingly, we elected to model intention rather than adoption per se. Intention for the next choice is an informative indicator, which can help us predict actual behavior even though it may or may not be acted upon as reported.

The dependent variable is created from the survey question which asks "If you were going to make a similar purchase today, how would you do so?", with four possible response options: "In a store", "Over the internet", "Through a catalog" and "Other (please specify)". As indicated in the introduction chapter, in the current study we concentrate on the first two channels: store and internet. As a result, our dependent variable is binary.

3.2.2 Explanatory Variables

Developed from an extensive literature review (Cao and Mokhtarian, 2005), the explanatory variables measured by the survey fall into five main categories, each described below.

General shopping-related attitudes: In Part A, the survey presented a series of 42 general shopping-related statements, with responses ordered on a 5-point scale from "strongly disagree" (1) to "strongly agree" (5). Common factor analysis was used to extract 13 (obliquely-rotated) factors (see Mokhtarian et al., 2009 for the detailed results), and standardized scores on these 13 factors were included as potential explanatory variables. Table 4 presents the strongly-loading statements for each factor. While some of these factors (e.g. impulse-buying, materialism, shopping enjoyment) could apply about equally well to either shopping channel (and were developed primarily for models of shopping frequency), many of them (e.g. pro-technology, pro-environmental, caution, time consciousness, trustingness, pro-exercise and store enjoyment) could differentially affect individuals' shopping channel intentions.

Purchase experiences: In Part B, respondents were asked whether they had purchased each of 15 kinds of products in the past year, separately by internet, store and catalog. In survey Part C, several questions related to the recent purchase were asked, such as how much money was spent, how the item was obtained, the purchase location, and the availability of alternative channels for that specific purchase. All these are possibly

Table 4. General Attitudes/Personality Traits/Values Factors [a]

Factor	Survey Statement	Loading [b]
Pro-credit card	Credit cards encourage unnecessary spending.	-0.573
	I prefer to pay for things by cash rather than credit card.	-0.514
Pro-environ-mental	We should raise the price of gasoline to reduce congestion and air pollution.	0.605
	To improve air quality, I am willing to pay a little more to use a hybrid or other clean-fuel vehicle.	0.556
	Shopping travel creates only a negligible amount of pollution.	-0.447
	A lot of product packaging is wasteful.	0.388
	Whenever possible, I prefer to walk or bike rather than drive.	0.354
Pro-exercise	I follow a regular physical exercise routine.	0.562
	Whenever possible, I prefer to walk or bike rather than drive.	0.540
Impulse buying	I generally stick to my shopping lists.	-0.586
	When it comes to buying things, I'm pretty spontaneous.	0.565
	I like a routine.	-0.289
	If I got a lot of money unexpectedly, I would probably spend more of it than I saved.	0.273
Caution	"Better safe than sorry" describes my decision-making style.	0.634
	Taking risks fits my personality.	-0.509
	I like a routine.	0.319
	I am generally cautious about accepting new ideas.	0.316
	I prefer to see other people using new products before I consider getting them myself.	0.265
Materialism	For me, a lot of the fun of having something nice is showing it off.	0.604
	I would/do enjoy having a lot of expensive things.	0.495
	Buying things cheers me up.	0.363
	My lifestyle is relatively simple, in terms of material goods.	-0.302
Price consciousness	It's too much trouble to find or take advantage of sales and special offers.	-0.648
	It's important to me to get the lowest prices when I buy things.	0.604
Time consciousness	I'm often in a hurry to be somewhere else when I'm shopping.	0.580
	I'm too busy to shop as often or as long as I'd like.	0.425
Trend-setting	I often introduce new trends to my friends.	0.604
	I like to track the development of new technology.	0.392

Trusting-ness	People are generally trustworthy.	0.469
	I tend to be cautious with strangers.	-0.408
	I enjoy the social interactions shopping provides.	0.343
Store enjoyment	Even if I don't end up buying anything, I still enjoy going to stores and browsing.	0.769
	I like to stroll through shopping areas.	0.752
	Shopping helps me relax.	0.586
	Shopping is fun.	0.529
	For me, shopping is sometimes an excuse to get out of the house or workplace.	0.427
	Shopping is usually a chore for me.	-0.389
	Buying things cheers me up.	0.293
	Shopping is too physically tiring to be enjoyable.	-0.285
Shopping enjoyment	Shopping is too physically tiring to be enjoyable.	-0.440
	Shopping is usually a chore for me.	-0.408
	My lifestyle is relatively simple, in terms of material goods.	-0.309
	"Variety is the spice of life".	-0.267
Pro-technology	Computers are more frustrating than they are fun.	-0.735
	The internet makes my life more interesting.	0.582
	I like to track the development of new technology.	0.478
	Technology brings at least as many problems as it does solutions.	-0.444

[a] Adapted from Mokhtarian et al. (2009). Based on oblique rotation of the common factor analysis solution (Rummel, 1970).
[b] Pattern matrix loadings, reflecting the contribution each factor makes to the variance of each observed variable (higher-magnitude loadings reflecting a greater association between variable and factor). Only loadings greater than 0.25 in magnitude displayed.

relevant explanatory variables giving important information on why the particular channel was adopted. Obviously, whether the experience is satisfying or not could play a very important role with respect to the next purchase intention.

Channel-specific attitudes: In survey Part D, respondents were asked to agree or disagree (on a five-point scale) with 28 channel-specific statements, assuming they were to make a purchase similar to the one discussed in Part C. To reduce the burden on the respondents, they were asked to complete such a set of statements for two of the three main shopping channels (store, internet, and catalog) – the channel chosen for the key purchase, and one alternative. Store was always assumed to be an alternative, so most (927) respondents completed the store-internet pair, with the remainder (40) reporting for store and catalog (38 for clothing and 2 for book). As mentioned earlier, these 40 cases, together with 24 whose future intended purchase channel was either catalog or missing, were excluded from the present analysis, leaving 903 cases.

Common factor analysis was also conducted for this set of statements (the analysis will be described in detail in the next section, i.e. Section 3.2.3). The statements were pooled across channel and factor-analyzed to find eight underlying dimensions, as shown in Table 5. Standardized scores on the final extracted factors will help us examine how attitudes differ by channel and product type. And they can serve as a useful complement to the general (Part A) shopping attitudes, allowing us to model e-shopping behavior from a more specific and concrete perspective. Channel-specific attitudes such as "post-purchase satisfaction", "cost savings", "convenience" and "enjoyment" are all likely to affect people's intention for a future similar purchase. Since, in a utility-maximizing discrete choice model such as ours, only differences in utility matter (Train, 2009), these variables are represented in the model as differences between the store and internet scores on each factor.

Table 5. Channel-specific Perceptual Factors

Factor	Survey statement (book – store version)	Loading
Conven-ience	When it comes to buying books/CDs/DVDs/videotapes, I can find anything I want in stores.	0.640
	A lot of times, products I want are unavailable in stores.	-0.636
	The product information I need is easy to find in stores.	0.615
	Stores are open whenever I want to shop.	0.518
	When shopping in stores, it is easy to check the availability of products.	0.475
	The stores I want/need to shop at are conveniently located.	0.447
	All things considered, buying in stores saves me time.	0.413
	I often find shopping in stores to be frustrating.	-0.345
Product risk	I'm concerned that a product I purchase in a store will not perform as expected (e.g. quality, etc.).	0.469
	When shopping in stores, I am able to experience products before buying, to the extent that I want to.	-0.374
	I am concerned that unfamiliar stores will fail to meet my expectations.	0.334
Enjoy-ment	Shopping in stores is boring.	-0.768
	I enjoy shopping in stores.	0.760
	I often find shopping in stores to be frustrating.	-0.407
	With respect to buying books/CDs/DVDs/videotapes, I am always on the lookout for a new store to check out.	0.323
Financial/ identity risk	It is risky to release credit card information to stores.	0.838
	I am uncomfortable about providing personal information to stores.	0.627
Efficiency /inertia	I value stores that allow me to fulfill many of my shopping needs in just one location.	0.449
	When it comes to books/CDs/DVDs/videotapes, I have a strong preference for shopping at one or a few particular stores.	0.414
	When shopping in stores, I am able to experience products before buying, to the extent that I want to.	0.322
Cost-saving	All things considered, buying in stores saves me money.	0.760
	Considering taxes and other costs, books/CDs/DVDs/videotapes are usually more expensive when purchased in stores.	-0.753
Store brand indepen-dence	I prefer to shop at independent stores rather than national chains.	0.561
	With respect to buying books/CDs/DVDs/videotapes, I am always on the lookout for a new store to check out.	0.389
Post-purchase satis-faction	I often have to wait too long for a store to obtain the product I want to purchase.	-0.594
	Stores typically provide poor after-purchase customer service.	-0.559
	If necessary, it is easy to return a product purchased at a store.	0.486
	When shopping in stores, I am able to immediately obtain the products I purchase.	0.412
	It is difficult to compare products at stores.	-0.316

Notes: Based on oblique rotation of the common factor analysis solution. Pattern matrix loadings greater than 0.30 in magnitude are displayed.

Use of internet and communication technology: In Part F, the survey asked some general questions about the respondents' usage of the internet, as well as other communication technologies. The information captured in this part reflects the individual's overall computer-use pattern, which can help to explain the propensity to choose the internet shopping channel in particular.

Sociodemographic characteristics: Part G of the survey captured an extensive list of sociodemographic variables such as gender, age, employment status (part time or full time), available work arrangements, and educational background, as well as household information such as household income, household size, number of clothing and book stores near home and work, and so on.

3.2.3 Factor Analysis of Channel Perceptions

The 28 channel-specific items were chosen to reflect 13 potential perceptual dimensions identified through a review of the literature and the research team's judgment. The items, sorted by the construct to which they were associated, are shown in Table 6 for the store channel and book product type. To condense these numerous interrelated items into a smaller set of more distinct constructs suitable for inclusion in later models, an exploratory factor analysis was performed on 27 [5] of the 28 items, using the SPSS statistical software package. To ensure that the resulting factors reflected the same

[5] The statements referring to getting dressed and going out were dropped, partly because they confounded affective (enjoyment) and cognitive (having to get dressed) beliefs. The item had to be worded oppositely for store versus internet/catalog in order to make sense, which raised the issue of whether one of the two statements in the pair should be reversed before conducting the factor analysis. Reversing one of the statements led to the item not loading on any factor, while dropping the item resulted in factor solutions that were essentially the same as those including both statements in their original forms. Thus, the cleanest course was to drop the item; in future analyses each statement can still be used as a channel-specific variable in its own right.

Table 6. Channel-Specific Perceptions (Book – Store Version [a])

Conceptual construct	*	Statement
Availability/ selection	+	When it comes to buying books/CDs/DVDs/ videotapes, I can find anything I want in stores.
	–	A lot of times, products I want are unavailable in stores.
Convenience	+	The stores I want/need to shop at are conveniently located.[b]
	+	Getting dressed and going out is an enjoyable aspect of store shopping for me.[c]
	+	Stores are open whenever I want to shop.[d]
Customer service	–	Stores typically provide poor after-purchase customer service.
	+	If necessary, it is easy to return a product purchased at a store.
Ease of use	+	The product information I need is easy to find in stores.
	–	I often find shopping in stores to be frustrating.
Financial/ identity risk	+	It is risky to release credit card information to stores.
	+	I am uncomfortable about providing personal information to stores.
General enjoyment	–	Shopping in stores is boring.
	+	I enjoy shopping in stores.
Gratification delay	+	I often have to wait too long for a store to obtain the product I want to purchase.[e]
	–	When shopping in stores, I am able to immediately obtain the products I purchase.[f]
Cost savings	–	Considering taxes and other costs, books/CDs/ DVDs/videotapes are usually more expensive when purchased in stores.[g]
	+	All things considered, buying in stores saves me money.
Product risk	+	I'm concerned that a product I purchase in a store will not perform as expected (e.g. quality, etc.).
	–	When shopping in stores, I am able to experience products before buying, to the extent that I want to.
Search costs (effort savings)	–	It is difficult to compare products at stores.
	+	When shopping in stores, it is easy to check the availability of products.
Store-brand attachment	–	With respect to buying books/CDs/DVDs/ videotapes, I am always on the lookout for a new store to check out.
	+	When it comes to books/CDs/DVDs/ videotapes, I have a strong preference for shopping at one or a few particular stores.
Time savings	+	I value stores that allow me to fulfill many of my shopping needs in just one location.
	+	All things considered, buying in stores saves me time.
Trust	+	I prefer to shop at independent stores rather than national chains.
	–	I value the anonymity (e.g. paying with cash) that shopping in stores provides.
	–	I am concerned that unfamiliar stores will fail to meet my expectations.

* Directionality with respect to construct label.
[a] Footnotes provide the internet version when it differs more than trivially from the store version.
[b] Internet shopping is available to me anywhere I would like it to be.
[c] I enjoy being able to shop from home without having to get dressed and go out.
[d] Internet shopping is available any time I want it.
[e] I often have to wait too long to receive a product purchased over the internet.
[f] When shopping over the internet, I am confident of getting a desired item within an acceptable amount of time.
[g] Considering shipping costs, books/CDs/DVDs/ videotapes are usually more expensive when purchased over the internet.

construct across all channels, we treated the data as if there were (967 x 2 =) 1934 observations on 27 variables, rather than treating each item-channel combination as a separate variable. (For the same reason, we included the relatively small number of catalog observations in with the store and internet ones). Of course, this (conventional) practice assumes that perceptual spaces are constructed similarly (have the same axes, or factors) regardless of channel – an assumption that is subject to testing in future confirmatory analyses.

In keeping with the admonition (Widaman, 1993) that common factor analysis (called principal axis factoring in SPSS) is more appropriate than principal components analysis (PCA) when the purpose of the procedure is to identify latent constructs, we used common factor analysis (CFA). (Note that factor loadings, and thence percent variance explained by the factor solution, are generally lower with CFA than with PCA, but Widaman indicates that the apparent superiority of PCA on these grounds is spurious, since the PCA loadings are more biased estimators of the true population values than are the CFA loadings). Oblique rather than orthogonal rotation was used to more faithfully reflect the conceptual relationships among even the smaller set of factor dimensions.

Several criteria were used in selecting the preferred 8-factor solution. Application of the conventional eigenvalue-one rule (to initial eigenvalues, per Fabrigar et al., 1999) identified six factors with eigenvalues greater than one; the 7th was 0.96. The “elbow” or “scree rule” (finding the elbow in a plot of number of factors against percent of variance explained) pointed to five or possibly seven factors. In view of these considerations and the fact that 13 constructs were originally identified, we then undertook a detailed examination of the obliquely rotated solutions for number of factors ranging between 5 and 13, to enable the final choice to be made on conceptual interpretability grounds. The 8-factor solution was preferred over the 7-factor solution because it separated the post-purchase satisfaction and product risk factors, while the solutions involving fewer than 7 or more than 8 factors were clearly inferior conceptually. The literature (e.g. Fabrigar et al., 1999) also advises that all else equal, too many factors is preferred over too few, and we believe that if our 8-factor solution errs, it errs on the side of overfactoring rather than underfactoring.

The important pattern matrix loadings for the obliquely-rotated 8-factor solution are presented in Table 5. The solution explained 45% of the total variance in the statements, on the high side of the typical range of 30-50% for common factor analysis reported by Widaman (1993).

The first factor is labeled *convenience*; it combines the items relating to availability/selection, convenience, and ease of use in Table 6, together with two logical items ("easy to check availability" and "saves time") from other categories (search costs and time savings, respectively). The *product risk* factor contains the two items hypothesized for that construct, logically joined by a third, drawn from the trust construct: "concern that unfamiliar [retailers] will fail to meet expectations".

The *enjoyment* factor also contains the two items expected for it, plus two others that fit as well, albeit with double loadings elsewhere: "often frustrating" (from the ease of use construct, and loading less strongly on convenience), and "always on the lookout for a new [retailer]" (loading more strongly on store brand independence). The latter was (correctly) hypothesized to be negatively associated with a store brand attachment construct, but it is also natural that one who enjoys the act of shopping would tend to be on the alert for new ways to achieve that enjoyment.

The *financial/identity risk* and *cost savings* factors exactly reproduce their hypothesized constructs. The *efficiency/inertia* factor, on the other hand, draws its three items from three different constructs. Especially the first two items can refer either to a desire to be efficient by limiting the retail outlets one patronizes, or to a desire for the familiar, i.e. an inertia against experimentation. While the third item ("can experience products to the extent I want to") has only a moderate loading, it also relates to a sense of satisfaction with the status quo.

The *store brand independence* factor took one item ("always on the lookout for a new [retailer]" from the expected store-brand attachment construct; its second item ("prefer independent [retailers] rather than national chains") had been associated with the trust construct (lack of trust being a common reason for shoppers to stick to well-known store brands; Jarvenpaa et al., 2000) but fits quite naturally here. Finally, the *post-purchase satisfaction* factor combines the items from the customer service and gratification delay constructs, together with (having a relatively small loading) the "difficult to compare products" item from the search costs construct, which may point to a fear that the purchased product will be unsatisfactory because it couldn't be researched easily in advance.

In general then, although the factors do not always reproduce the hypothesized constructs exactly, the deviations are logical and the resulting factors are quite interpretable.

Prompted by recent empirical experience, we computed factor scores by multiple methods for the purposes of comparison – specifically, we compared the default regression factor scores to the Bartlett scores (Beauducel, 2007; Grice, 2001; McDonald & Burr, 1967). Counterpart scores from each method have very high correlations with each other (ranging from 0.94 to 0.99), indicating that the two methods do not produce dramatically different solutions. However, the regression solution has substantially larger "highest correlations" of scores within method (0.68 and 0.70 between the cost savings and convenience factor scores for the store and internet channels respectively) than does the Bartlett solution (0.42 between the convenience and post-purchase satisfaction scores for store, and 0.50 between the convenience and enjoyment scores for internet). Accordingly, we decided to use Bartlett factor scores to reduce potential collinearity problems in future modeling where these factors would be explanatory variables. Although the Bartlett highest correlations of 0.42 and 0.50 are moderately high and an issue to monitor in future models containing both factors as explanatory variables, given our reasonably large sample size we are not overly concerned about a collinearity problem. Other factor pairs that are moderately correlated are convenience with cost savings for store/internet (0.34/0.39) and cost savings with enjoyment for internet (0.38). No other pair has a correlation above 0.3 in magnitude.

4. IMPACT OF PRODUCT TYPE ON PURCHASE INTENTIONS

As explained in Chapters 1 and 2, in theory, product type does matter in the context of modeling people's shopping behavior; different types should not be pooled together. Empirically, to explore and demonstrate the impact of product type on purchase intentions, we used the conventional logistic regression (LR) model (equivalent to binary logit, BL) to model people's intended shopping channel for a future purchase of clothing or books.

Although considerable research has been done on purchase intention modeling, including the choice of LR modeling in some studies (see Section 2.2), our study is still distinct from those previous ones in four respects: (1) we used a completely different data set collected in different target areas; (2) our data measured not only the relative difference in perceptions between shopping channel alternatives but also the separate channel-specific perceptions; (3) we included a much richer set of variables than those identified in previous studies; and (4) most importantly, we distinguished product type, picking book and clothing as representing "search" and "experience" goods, respectively. In this chapter, we will explain the methodologies we used in detail and present the modeling results, to demonstrate the importance of product type in shopping intention modeling.

4.1 Selected Characteristics of the Samples

Since we only focus on store and internet channels, we excluded 64 catalog-related cases (from the 967-case working sample) and used the remaining 903 cases as our final working sample. The sample includes individuals who are retired (12.7%), homemakers

(3.8%), and not currently working (3.5%), as well as those who work full time (60.5%) and part time (16.1%).

Table 7 presents sample statistics for the variables significant in the final model, together with a few additional characteristics. By design, the sample is fairly evenly distributed between the two product types studied here (where people are assigned to a category based on a recent purchase). People recently purchasing clothing were more likely to be female, while those purchasing in the book category were more likely to be male. The clothing subsample has more people in the relatively high annual household income categories than the book subsample does. Average age, average educational level, and home and work internet access are very similar between the book and clothing subsamples.

4.2 Discrete Choice Modeling

In this study, we mainly used the logistic regression model. Since it is a special case (when the choice is binary) of discrete choice modeling, it is useful to provide a basic introduction to discrete choice models here.

Discrete choice models have played a critical role in transportation demand forecasting, as well as market research, for the last four decades. The first transportation application of discrete choice models can be traced back to 1962; Warner used the idea to model the binary behavior of choosing travel mode (car or transit) for a given trip (Ben-Akiva and Lerman, 1985). Many other applications, and extensions such as modeling multiple

Table 7. Selected Characteristics of the Sample, by Product Type Subgroup

Characteristic (sample sizes)	**Pooled data N (%)**	**Book N (%)**	**Clothing N (%)**
Number of cases	903	450	453
Number of females	486 (54.1)	214 (48.0)	272 (60.2)
Average age (years) (881, 440, 441)	46.1	45.4	46.8
Average educational level [a] (903, 450, 453)	5.61	5.81	5.42
Annual household income (859, 433, 426)			
Less than $15,000	39 (4.3)	22 (4.9)	17 (3.8)
$15,000 to $29,999	59 (6.5)	29 (6.4)	30 (6.6)
$30,000 to $49,999	114 (12.6)	61 (13.6)	53 (11.7)
$50,000 to $74,999	189 (20.9)	100 (22.2)	89 (19.6)
$75,000 to $124,999	274 (30.3)	129 (28.7)	145 (32.0)
$125,000 or more	184 (20.4)	92 (20.4)	92 (20.3)
Home internet access [b] (902, 450, 452)			
Low speed	185 (20.5)	92 (20.4)	93 (20.5)
Broadband	730 (80.8)	366 (81.3)	364 (80.4)
Work internet access [b] (889, 446, 443)			
Low speed	41 (4.6)	20 (4.5)	21 (4.7)
Broadband	700 (78.7)	366 (82.1)	334 (75.4)
	Mean (s.d.)	**Mean (s.d.)**	**Mean (s.d.)**
Shopping attitudinal factors			
Trustingness	-0.014 (0.751)	-0.034 (0.778)	0.005 (0.722)
Post-purchase satisfaction [c]	0.921 (1.688)	0.825 (1.745)	1.016 (1.626)
Efficiency and inertia [c]	0.716 (1.607)	0.263 (1.564)	1.166 (1.523)
Cost savings [c]	-0.378 (2.085)	-1.153 (1.921)	0.393 (1.953)
Store brand independence [c]	0.587 (1.570)	0.801 (1.557)	0.374 (1.556)
Convenience [c]	-1.118 (1.602)	-1.589 (1.582)	-0.651 (1.481)
Purchase experiences			
Activeness of searching [d]	2.576 (0.699)	2.660 (0.670)	2.500 (0.718)
Context-specific cost difference [e]	-0.072 (0.739)	0.130 (0.731)	-0.320 (0.672)

[a] 1=Some grade school or high school; 2=High school diploma or equivalent; 3=Some college or technical school; 4=Two year college associates degree; 5=Four year college/technical school degree; 6=Some graduate school; 7=Completed graduate degree(s).
[b] Categories are not mutually exclusive.
[c] Difference between channel-specific perceptions: store factor score minus internet factor score.
[d] 1=I had not previously thought about buying such an item – I just came across it; 2=I had previously thought about buying such an item if I found it, but I was not actively looking for it on this occasion; 3=I was actively looking for such an item on this occasion.
[e] A qualitative measure of the perceived cost difference between store and internet with respect to the recent purchase; a higher value means the store channel costs more (-1=store is cheaper; 0=about the same price; 1=store is more expensive).

choices, were developed afterwards. Briefly, a discrete choice model is used to represent the selection of a decision-maker among a finite set of categorical alternatives (namely, the choice set); such models are usually based on random utility theory, reasonably assuming that the alternative with the highest utility is the one chosen (which is also referred to as utility maximization theory, UMT) (Ben-Akiva and Lerman, 1985). Analysts can observe an individual's behavior, and individuals make their decisions by comparing the utilities of each alternative they consider feasible, but in reality the utilities are not known with certainty to the modeler. Thus the utility is modeled as a random variable in order to reflect the analyst's uncertainty. Specifically, it consists of a deterministic part and a stochastic part (also called the random term). The former part is usually assumed to be a linear function of attributes of the individual and the alternative, with weights of each attribute that are unknown and to be estimated by analyzing the choices made and the values of the attributes assumed to influence those choices. The latter part captures uncertainty from four main sources: unobserved alternative attributes, unobserved individual attributes (or unobserved taste variations), measurement errors and proxy (or instrumental) variables (Manski, 1973, cited by Ben-Akiva and Lerman, 1985 and Bierlaire, 1997). The first three kinds of unobserved variables are very familiar. The last one – proxy (or instrumental) variable – refers to situations where the "true" explanatory variable is not available, but another one is which is related to, and serves as a proxy or substitute for the true one, is used instead.

The random term of each alternative's utility function is composed of two parts: the mean and the error term. The mean of the random term is captured by the alternative specific constant (ASC). The ASC captures the mean effect of unobserved variables on the utility of each alternative compared to the base alternative; the actual effect of unobserved variables is the sum of the ASC coefficient and the error term. Because the random term partially influences the utility of an alternative, different assumptions on the distribution of the error term will result in different models. In practice, the most widely used model is the MNL model, which assumes that the error term is independent and identically Gumbel distributed (i.i.d. Gumbel; see Ben-Akiva and Lerman, 1985, pp. 104-105 for details). Because the difference of i.i.d. Gumbel random variables is logistically-distributed, the logistic distribution is used to derive the probability of choosing one particular alternative (Ben-Akiva and Lerman, 1985; Bierlaire, 1997), specifically the probability that the utility of the selected alternative exceeds the utilities of the other alternatives in the choice set. That is, the probability for an individual *n* to choose alternative *i* among the choice set C_n is

$$P_n(i) = \Pr[V_{in} + \varepsilon_{in} \geq \max_{\substack{j \in C_n \\ j \neq i}} (V_{jn} + \varepsilon_{jn})], \tag{1}$$

where V_{in} denotes the deterministic part and ε_{in} denotes the stochastic part of the utility of alternative *i* for individual *n*. For the MNL model, we have

$$P_n(i) = \frac{\exp[V_{in}]}{\Sigma_{j \in C_n} \exp[V_{jn}]}. \tag{2}$$

Under the standard assumption that V_{in} is linear-in-parameters, $V_{in} = \beta' x_{in}$, we have

$$P_n(i) = \frac{\exp[\beta' x_{in}]}{\Sigma_{j \in C_n} \exp[\beta' x_{jn}]}, \tag{3}$$

where x_{in} is the vector describing the attributes relevant to alternative *i* for individual *n*, and β is the vector of coefficients expressing the weight that each attribute is given in the utility function. Note that the conventional assumption is that the weight for attribute k, β_k, is constant across alternatives and across individuals. In our study, discrete choice models are binary logit (when consumers are confronted with a binary choice, i. e. "internet" or "store", which can be considered a special case of MNL).

To evaluate model results, the informal rho-square ρ^2 and adjusted rho-square $\bar{\rho}^2$ goodness-of-fit measures are usually used. They can be computed by

$$\rho^2 = 1 - \frac{LL(\hat{\beta})}{LL(0)}, \tag{4}$$

$$\bar{\rho}^2 = 1 - \frac{LL(\hat{\beta}) - K}{LL(0)}, \tag{5}$$

where $LL(\hat{\beta})$ and $LL(0)$ are the log likelihoods for the "full" model (model to be tested) and equally-likely model, respectively (the latter of which can be obtained from the number of cases selecting a given alternative and the total sample size; see Chapter 7 of Ben-Akiva and Lerman, 1985 for details); and K is the number of estimated parameters in the "full" model.

4.3 Methodologies and Model Results

We hypothesized that variables might be weighted differently for different product types, so we first divided the data by product type, and then developed three separate LR models on the pooled data, the book subsample and the clothing subsample. Using the collective information indicated by those three models, we finally found a "best" hybrid model in which coefficients were either pooled or product-type-specific, as appropriate.

4.3.1 The Three Separate LR Models

Table 8 summarizes the three separate LR models, which are individually described below.

Pooled Model

In this model, 405 respondents intended to choose store shopping for their next similar purchase and 285 favored internet shopping. The ρ^2 value (Ben-Akiva and Lerman, 1985) is 0.357, which is considered quite acceptable in the context of disaggregate discrete choice models. The 0.357 value is based on the equally-likely model, and since the market shares are not too unbalanced[6] (58.7% and 41.3% for store and internet respectively), the market-share model (the model containing just the constant term) has a ρ^2 of just 0.022. That means the main contribution to the model is from "true" variables (i.e. those other than the constant term), which is confirmed by the ρ^2 of 0.336 of the model re-estimated without the constant for illustrative purposes.

From the table, we see that shopping attitudinal factors and purchase experience variables play a key role in explaining the next purchase intention. They all show the expected signs. Four channel-specific perceptions (post-purchase satisfaction, efficiency/inertia, cost savings and convenience) are relevant to one's purchase channel intention. Not

[6] The focus of the survey on a recent internet purchase versus recent store purchase was manipulated somewhat to ensure the presence of a sizable number of internet purchases in the sample (Ory and Mokhtarian, 2007], and intention is highly correlated with choice. Thus, we effectively have a "choice-based sample", and although, in such a case, all coefficients except the constant term are consistently estimated (Ben-Akiva and Lerman, 1985), the raw intention (and choice) market shares are by no means representative.

Table 8. Logistic Regression Model of Intended Next-Purchase Channel for Pooled, Book and Clothing Data (1 = Store, 0 = Internet)

Variable Name	**Model 1: pooled**		**Model 2: book**		**Model 3: clothing**	
	Coeff.	P-value	Coeff.	P-value	Coeff.	P-value
Constant	1.956	.000	.702	.260	1.188	.000
Shopping attitudinal factors						
Trustingness			-.359	.051		
Post-purchase satisfaction [a]	.399	.000	.342	.000	.446	.000
Efficiency and inertia [a]	.191	.008			.305	.008
Cost savings [a]	.172	.012	.259	.005		
Store brand independence [a]			.335	.001		
Convenience [a]	.379	.000	.511	.000	.340	.010
Purchase experiences						
Activeness of searching [b]	-.273	.069	-.425	.037		
Context-specific cost difference [c]	-1.127	.000	-1.258	.000	-1.209	.000
Internet usage						
Broadband internet accessibility at work			.770	.049		
Sociodemographics						
Female	-.482	.023			-.675	.048
Product type						
Dummy variable for book	-.884	.000				
Valid number of cases, N	690 (S: 405; I: 285) [d]		382 (S: 166; I: 216) [d]		310 (S: 239; I: 71) [d]	
Final log-likelihood, LL(β)		-307.520		-168.712		-126.433
LL for market share (MS) model		-467.784		-261.501		-166.812
LLfor equally-likely (EL) model, LL(0)		-478.272		-264.782		-214.876
No. of explanatory variables, K (including constant)		9		9		6
$\rho^2_{ELbase} = 1 - \frac{LL(\beta)}{LL(0)}$		0.357		0.363		0.412
Adjusted $\rho^2_{ELbase} = 1 - \frac{LL(\beta) - K}{LL(0)}$		0.338		0.329		0.384
χ^2 (between final model and the EL model)		341.503		192.141		176.886
χ^2 (between final model and the MS model)		320.526		185.577		80.759

[a] Difference between the store-specific and internet-specific factor scores.
[b] See Table 7 for definition.
[c] See Table 7 for definition.
[d] S and I represent store and internet respectively.

surprisingly, the more positively store is perceived relative to the internet on these characteristics, the more likely store is to be the intended channel for the next purchase. However, it is interesting to note that four channel-specific perceptions are *not* significant in this model: product risk, financial/identity risk, enjoyment, and store brand independence. Although those perceptions are conceptually expected to be significant too, it is possible that their influence is partly reflected by the four perceptions that *do* appear. Each of the four perceptions not in the model has multiple significant (even if generally only around 0.1) correlations with the perceptions that *are* in the model. In particular, the enjoyment difference variable has correlations of 0.4 – 0.5 with three of the four significant channel-specific perceptions.

Two purchase experience variables (activeness of searching and context-specific cost difference) are significant in this pooled model. A higher value of the former variable means a respondent was more actively looking for the item on the purchase occasion. It has a negative sign (and is significant at the 7% level), meaning that the person who searched more actively for the previous purchase is more likely to intend to make the next similar purchase over the internet. Our interpretation is that such a person either learned or already knew the value of the internet for aiding a specific product search, and once using the internet to search, it is convenient to use it to purchase if the sought item is found there. Similarly, the context-specific cost difference variable also has a negative sign. A higher value of this variable indicates that store was perceived to be more expensive than internet for the specific purchase made recently. As a result, people with higher values are more likely to intend to use the more economical channel – internet –

for their next purchase. In addition, a dummy variable for the book product type entered the model. As expected, it is more natural to purchase (and accordingly to intend to purchase) a book, as a "search" good, online compared to clothing, an "experience" good.

Finally, a sociodemographic trait – the binary variable for being female – is also significant in the model. Although its negative sign defies our expectation, it is also saying something meaningful. Originally, we expected women to be more likely than men to intend a store purchase, consistent with the image of men being more pro-technology, and enjoying store shopping less, than women. But in our sample, just looking at gender and intention, there is no significant difference in the distribution of intended channel between genders. So the fact that gender is significant in the model means that controlling for other variables is revealing a relationship that was hidden (suppressed) when only the two (i.e. gender and intention) were examined together. Specifically, gender explains an important component of the "residual" information in the intention variable after controlling for the other variables in the model.

It may be that we are trying to represent an essentially non-linear relationship as a linear one, and that some of the other variables (cost savings and convenience) are overemphasizing the influence of being female on store intentions (given that women have a significantly larger difference favoring store on those two variables than men do, with p-values of 0.000 and 0.028 for cost savings and convenience respectively). The dummy variable of being female seems to be partly correcting for that overemphasis. It may also be partly indicating a time pressure or impulse-buying effect (women are significantly more time conscious and impulse-buying than men in our sample): women, who tend to experience more time pressure than men (e.g. Sayer, 2007), may be more inclined to shop over the internet to save time and/or to more readily indulge their impulsiveness. We tested whether the effect was stronger for women with young children; the interaction term did have a negative sign, but also a higher p-value (0.097) and the model had a somewhat lower goodness of fit. In addition, combined with the high correlation (0.76) between intention and adoption in our sample, our result is consistent with that of Bhatnagar et al. (2000): they found women to be more likely than men to adopt internet shopping, particularly for product categories such as books, music and CDs, and apparel and clothing. Finally, when we excluded the gender variable entirely, the ρ^2 dropped from 0.357 to 0.351. Although that is not a large drop, we decided to retain the gender variable because we believe that it is trying to tell us something useful. The sign is also quite robust: whenever the female binary variable appears in a model, it is with a negative sign.

Book model

In this model, 166 respondents intended to choose store for their next book purchase and 216 favored internet. The ρ^2 value is 0.363 and the market-share model has a ρ^2 of 0.012. The model re-estimated without the constant has a ρ^2 of 0.360. There are a total of eight significant explanatory variables in the book model: five shopping attitudinal factors (trustingness, post-purchase satisfaction, cost savings, store brand independence and convenience), two purchase experience variables (activeness of searching and context-specific cost difference) and one internet usage variable (broadband internet accessibility at work).

Similarly to the pooled model, three channel-specific perceptions – post-purchase satisfaction, cost savings and convenience – have positive signs; the two purchase experience variables both have negative signs. The explanations are essentially the same as above.

Two other attitudinal factors are also significant in the book model: trustingness and store brand independence. The negative coefficient for trustingness means that those who are less trusting are more likely to intend to purchase in a store. This is the expected sign, since a tangible store can be more reassuring than a seemingly intangible internet retailer.

As shown in Table 5, high scores on the channel-specific store brand independence factors reflect people who are "always on the lookout for a new [store/internet site] to check out" (i.e. seek variety in their shopping locations), and/or who "prefer to shop at independent [stores/internet sites] rather than [those of] national chains" (perhaps to support small local businesses, or internet retailers with specialized goods or a particularly endearing character). The stronger this brand independence is for bricks-and-mortar stores compared to internet sites (i.e., the more positive the difference between store and internet scores on this factor), the more likely the individual is to intend to purchase in a store next time. This is an interesting finding, in view of the conventional wisdom that fostering retailer loyalty is desirable (e.g. Srinivasan et al., 2002). The implication is that people “locked in” to a certain internet site may (it stands to reason, though not directly shown by our results) be more likely to purchase from that site *if they purchase via the internet at all*, but may (our results suggest) be even more likely to purchase from stores, if they have a greater desire for independence there. Of course, the opposite can be true as well, for the shopper who is loyal (or captive) to a bricks-and-mortar store but brand-independent in cyberspace.

Finally, one variable in the internet usage category – broadband internet accessibility at work – appears in the model. The positive sign (indicating a higher intention to purchase in a store) seems counterintuitive because (particularly for book) we would expect ease of access to the internet to support intentions to buy online. However, we believe it may be a marker for individuals holding a largely sedentary desk job, who, to the extent they associate shopping with the work environment, would prefer store shopping (e.g. during the lunch hour) for exercise and a change of scenery.

Clothing model

Among the 310 cases included in this model, 239 respondents intended to choose store for their next clothing purchase and 71 favored internet. The ρ^2 value is 0.412. Since the market shares are unbalanced (77.1% and 22.9% intended store and internet respectively), the market-share model alone has a ρ^2 of 0.224. Re-estimating the final model without a constant term, however, yields a ρ^2 of 0.379, indicating that most of the explanatory power of the model lies in the “true” variables (i.e. they are helping to explain *why* the shares are unbalanced), not just the constant term. Five variables besides the constant are significant in the model: three channel-specific attitudinal factors (post-purchase satisfaction, efficiency/inertia and convenience), one purchase experience variable (context-specific cost difference) and the female indicator variable. These five variables all appear in the pooled model with the same signs, and have been discussed there.

Considering the dearth of clothing stores in Davis, we thought that people in Davis might be more likely to intend buying clothes online than those in Santa Clara, our other study neighborhood. So we included a city dummy variable in the clothing model, however, it turned out to be insignificant. This is not necessarily surprising, because city-related effects are probably being captured by some other variables in the model, especially general attitudes and channel-specific perceptions. For example, the mean factor scores for store convenience are -0.431 for Davis and -0.074 for Santa Clara, indicating that residents of the latter city perceive shopping for clothes in stores to be significantly more convenient ($p = 0.000$) than do residents of Davis (although in view of the negative sign of both means, residents of both areas see stores as less convenient than the internet for this purpose, on average).

4.3.2 The Hybrid Model Including Product-type-specific Variables

The three models of Table 8 show that some variables appear important for both book and clothing product types, while others are product-type specific. Even among the former group, the weight given to a particular variable could differ by product type. At the same time, where variables are relevant to both product types, with similar weights, greater efficiency (smaller standard errors, meaning more precise estimates) can be attained by using the entire sample rather than smaller subsets to estimate the coefficients. Accordingly, it is worthwhile to develop a hybrid model in which coefficients are allowed to be product-type-specific or constant across product types, as appropriate. Using the collective information indicated by the previous three models, the "best" hybrid model we could find is presented in Table 9.

There are 690 cases included in the model, with 405 intending store and 285 intending internet. The ρ^2 value is 0.370 and the market-share model has a ρ^2 of 0.022. The 10 significant explanatory variables (excluding the constant) are: six shopping attitudinal factors (including one clothing-specific variable and two book-specific variables), two purchase experience variables, a binary variable for book product type and a clothing-specific binary variable for being female. All coefficients show the same signs as in the three separate models. The book-specific trustingness coefficient is of borderline significance (p=0.083), but we retain it for its conceptual contribution to the model. Based on a comparison of the separate book and clothing models we tested making some coefficients, such as the one for convenience, product-type-specific, but the outcomes were not statistically superior. Thus, all coefficients in the final model are either equal for both product types, or specific to only one of them.

The model displays some robustness with respect to the influence of product type, as well as some distinctions. Exactly half of the 10 significant variables are weighted equally across product: three channel-specific perception differences (post-purchase satisfaction, cost savings, and convenience), and the two experience variables (activeness of searching

Table 9. Logistic Regression Hybrid Model Result (1 = Store, 0 = Internet)

Variable Name	**Hybrid model**	
	Coefficient	P-value
Constant	2.149	.000
Shopping attitudinal factors		
Trustingness (book-specific)	-.305	.083
Post-purchase satisfaction [a]	.381	.000
Efficiency and inertia (clothing-specific) [a]	.301	.009
Cost savings [a]	.183	.008
Store brand independence (book-specific) [a]	.292	.002
Convenience [a]	.378	.000
Purchase experiences		
Activeness of searching [b]	-.293	.054
Context-specific cost difference [c]	-1.176	.000
Sociodemographics		
Female (clothing-specific)	-.851	.013
Dummy variables or interaction terms		
Dummy variable for book	-1.419	.000
Valid number of cases, N		690 (S: 405; I: 285) [d]
Final log-likelihood, LL(β)		-301.330
Log-likelihood for market share model, LL(MS)		-467.784
Log–likelihood for equally-likely (EL) model, LL(0)		-478.272
No. of explanatory variables, K (including constant)		11
$\rho^2_{ELbase} = 1 - LL(\beta) / LL(0)$		0.370
Adjusted $\rho^2_{ELbase} = 1 - [LL(\beta) - K] / LL(0)$		0.347
χ^2 (between final model and the EL model)		353.883
χ^2 (between the final model and the MS model)		332.907

[a] Difference between the store-specific and internet-specific factor scores.
[b] See Table 7 for definition.
[c] See Table 7 for definition.
[d] S and I represent store and internet respectively.

and context-specific cost difference). It is natural to expect these variables to have a similar impact on intention regardless of product type (of course, between the two types studied here). On the other hand, half of the variables are product-type-specific.

Thus, having a higher level of trustingness, or more strongly preferring independent retailers in cyberspace than on the ground, leads to a stronger intention to purchase books online, but has no apparent effect on clothing purchase intentions. Conversely, having a stronger preference to concentrate one's activity at a few locations when it comes to online shopping compared to store shopping (i.e. having a more negative efficiency/inertia difference) leads to a stronger intention to purchase clothes online, but has no evident effect on book purchase intentions. Although these are not necessarily distinctions we would have predicted, and although their collective improvement to the model's goodness of fit is modest (informally judging by the difference in final log-likelihood functions of the pooled and hybrid models), they nonetheless justify our assumption that the same variables could weight differently for different products, and confirm the value of dividing products into different types for properly understanding online purchase behavior. One distinction that *is* unsurprising is that, all else equal, the book category has a stronger intention of being purchased online than does the clothing category.

4.4 Conclusions

This study modeled shopping channel intention with respect to a future purchase of a book/CD/ DVD/videotape or clothing/shoes, for more than 900 residents of two university towns in northern California, with particular attention to the influences of product type and shopping attitudinal factors. In addition to previously-identified influences of internet usage, transaction cost and sociodemographics, we found that product type and comparative channel-specific perceptions play important roles in these models.

Both in the separate book and clothing models and in the final hybrid model, there is a certain degree of commonality of important variables. Post-purchase satisfaction, cost savings, convenience, activeness of searching, and context-specific cost difference have essentially equal coefficients for both product types, with the expected signs. The first three variables are differences in channel-specific perceptions between store and internet, so the greater that difference (in favor of store), the more strongly store is intended. The greater the activeness of searching for the most recent purchase, the more strongly internet is intended for a future similar purchase. And for the context-specific cost difference variable, a higher value indicates that store was perceived to be more expensive than internet for the specific purchase made recently, and is thus associated with a stronger intention to use the more economical internet channel on the next purchase.

Despite that commonality, there are also some differences between product types. The remaining five of the 10 variables significant in the final hybrid model are product-specific: three for book (dummy variable for book product type, trustingness and store brand independence) and two for clothing (efficiency/inertia and being female). These effects indicate the importance of distinguishing product type.

Half or more of the variables in each of the four models presented here are (store minus internet differences in) channel-specific perceptions. Although our binary dependent variable required only the differences between the store and internet channels as explanatory variables, many online shopping models have not even measured differences, but rather characteristics for online shopping alone. A few studies (e.g. Farag, et al., 2006) measured characteristics of the internet relative to those of the store, but we are not aware of any others that measured characteristics of each channel separately, as we have done. Doing so is not only critical to any multinomial context seeking to model choice or intention among more than two alternatives, but there is another issue as well. Some exploratory research in progress on this data set suggests that individuals may weight a characteristic differently depending on the channel. For example, the perceived product risk of a channel may be more important to choice (weighted more heavily in the utility function) for internet than for store. In that case, while it is still only the differences in (channel-weighted) perceptions that determine choice, obtaining only a comparative judgment ("internet much worse than store … store much worse than internet") would not allow channel-specific judgments to be differentially-weighted in computing that difference. Accordingly, for maximum flexibility in specifying the channel-specific utility functions, it is imperative to collect channel-specific perception data.

Only one of the 13 general shopping attitude factors shown in Table 4 (namely, trustingness) is significant in any of our models. Many of them were not expected to favor one channel over another, and most of those that *were* expected to impact channel intentions show significant (if generally modest) correlations with the channel-specific correlations that *do* appear in the models. In the strongest instance, the pro-technology factor has correlations of -0.14, -0.27, and -0.36 with post-purchase satisfaction, cost savings, and convenience, respectively. So it is reasonable to conclude that the influences of those variables are reflected in the channel-specific perception variables.

In summary, our findings indicate: (1) product type matters; we should not ignore it or blindly combine product type in choice or intention models; and (2) the perceived differences between store and internet shopping channels have significant impacts on people's purchase intention; changing the features of one channel will have crossover effects on the tendency to choose another channel. Therefore, to better understand people's intention or adoption, we should include multiple shopping channels considered to be salient by consumers, not just the one of main interest to the study, and measure variables specific to each channel, not just comparative judgments between two (or more) channels.

5. TASTE HETEROGENEITY FOR BOOK PURCHASES

From the previous chapter, we know that the product type matters and thus that different product types should not be considered together. Therefore, in this and the next chapters, we further analyzed people's online shopping behavior only for a specific product type. In this chapter, book purchases are analyzed; Chapter 6 treats clothing purchases.

To accommodate taste heterogeneity, LCM is one increasingly popular method. Theoretically, as a stochastic approach to market segmentation, LCM is superior to the conventional deterministic approach for reasons explained in the introduction. However, to confirm its superiority in practice, in this study we conducted analyses using both approaches. We first use LCM to explore the effects of channel-specific perceptions, along with other variables, on purchase channel intention. We then compare it to the unsegmented model and to models deterministically segmented. In the end, we turn to another approach and identify the "best" model, that is, a conventional (technically unsegmented) model that accounts for taste heterogeneity by including interactions of the segmentation variable (identified from the LCM) with the other explanatory variables.

5.1 Selected Characteristics of the Sample

Among the 903 cases in our final working sample, 450 cases involved a recent book purchase and 453 involved a clothing purchase. In this chapter, we only analyzed the 450 book cases (although the final model has only 373 cases due to missing data on variables included in the model).

Table 10 presents a few major characteristics of the sample, including sample statistics for the variables significant in the final model. Average traits include being middle-aged (45), slightly more likely to be male (52%) than female (48%), and having education beyond a four-year college or technical school degree. About 70 percent of the households have annual incomes higher than $50,000. The majority of the respondents (more than 80 percent) have broadband internet access either at work or at home. The attitudinal factor scores were discussed when those variables were introduced in Section 3.2.2.

5.2 Taste Heterogeneity

As indicated in Chapter 1, in reality, each individual has a unique set of tastes, i.e. a distinct set of preference weights. In terms of equation (3) in Section 4.2, the implication is that in reality, the β weights differ by individual. MLM, in which the βs are taken to be random variables following an assumed distribution, is one conceptually appropriate approach, but it is not unequivocally superior. For one thing, MLM permits the estimation of the parameters characterizing the assumed distribution of the βs, but gives no hint regarding the specific tastes a given individual might have. For another thing, it is far from clear what distribution should be assumed for a given coefficient – the ubiquitous normal distribution, for example, allows the coefficient to take either sign, which may not always be appropriate. And according to at least some studies (Greene and Hensher, 2003; Magidson et al., 2003; Hess et al., 2005), assuming an inappropriate continuous distribution for each β_k can be worse than a model with one or a finite number of values for the coefficient – i.e. the assumption of population homogeneity or the presence of a

Table 10. Selected Characteristics of the Sample (book cases)

Characteristic (sample sizes)	**N (%)**
Total number of cases	450
Number of females (446)	214 (48.0)
Average age (years) (440)	45.4
Average educational level [a] (450)	5.81
Annual household income (433)	
Less than $15,000	22 (4.9)
$15,000 to $29,999	29 (6.4)
$30,000 to $49,999	61 (13.6)
$50,000 to $74,999	100 (22.2)
$75,000 to $124,999	129 (28.7)
$125,000 or more	92 (20.4)
Home internet access [b] (450)	
Low speed	92 (20.4)
Broadband	366 (81.3)
Work internet access [b] (446)	
Low speed	20 (4.5)
Broadband	366 (82.1)
	Mean (s.d.)
Shopping attitudinal factors	
Post-purchase satisfaction [c]	0.825 (1.745)
Convenience [c]	-1.589 (1.582)
Purchase experiences	
Activeness of searching [d]	2.660 (0.670)
Context-specific cost difference [e]	0.130 (0.731)

[a] 1=Some grade school or high school; 2=High school diploma or equivalent; 3=Some college or technical school; 4=Two year college associates degree; 5=Four year college/technical school degree; 6=Some graduate school; 7=Completed graduate degree(s).
[b] Categories are not mutually exclusive.
[c] Difference between channel-specific perceptions: store factor score minus internet factor score.
[d] 1=I had not previously thought about buying such an item – I just came across it; 2=I had previously thought about buying such an item if I found it, but I was not actively looking for it on this occasion; 3=I was actively looking for such an item on this occasion.
[e] A qualitative measure of the perceived cost difference between store and internet with respect to the recent purchase; a higher value means the store channel costs more (-1=store is cheaper; 0=about the same price; 1=store is more expensive).

finite number of market segments. Thus, in this study we initially chose to take a market segmentation approach to addressing taste heterogeneity.

Market segmentation divides a population into several distinct groups based on certain characteristics or attributes (e.g. sociodemographic traits, and/or general shopping attitudes). Within a group, people are assumed to be homogeneous and share similar tastes (i.e. importance weights or β coefficients) with respect to attributes relevant to choice, and on the other hand, people in different groups are assumed to be heterogeneous and have substantially different tastes. For example, those who more readily trust others are likely to put less weight on the risk associated with a given shopping channel. That is, a segment membership variable (trustingness) affects the weight (β) a person gives to an attribute (risk) of a shopping channel. Thus, two people who perceive the same risk of internet shopping, and have all other channel attributes the same as well (i.e. have identical values on the x variables), could still make different choices because of the different weights placed on those attributes. Of course, people in the *same* segment may also choose different alternatives, because of their different individual-specific characteristics (including income, education level, and gender) and perceptions of the alternatives (personal cognition of their pros and cons) – i.e. different values of the x variables.

Figure 1 illustrates a typology of ways for dealing with population heterogeneity in disaggregate discrete choice models, from ignoring it (i.e. assuming constant βs) to assuming it to be infinitely variable (i.e. continuously varying βs). In between those two extremes is the approach we had initially planned to take, that of assuming discrete market segments, with segment-specific βs. In addition to the market segmentation approach, we also chose an alternative approach to MLM – incorporating interaction

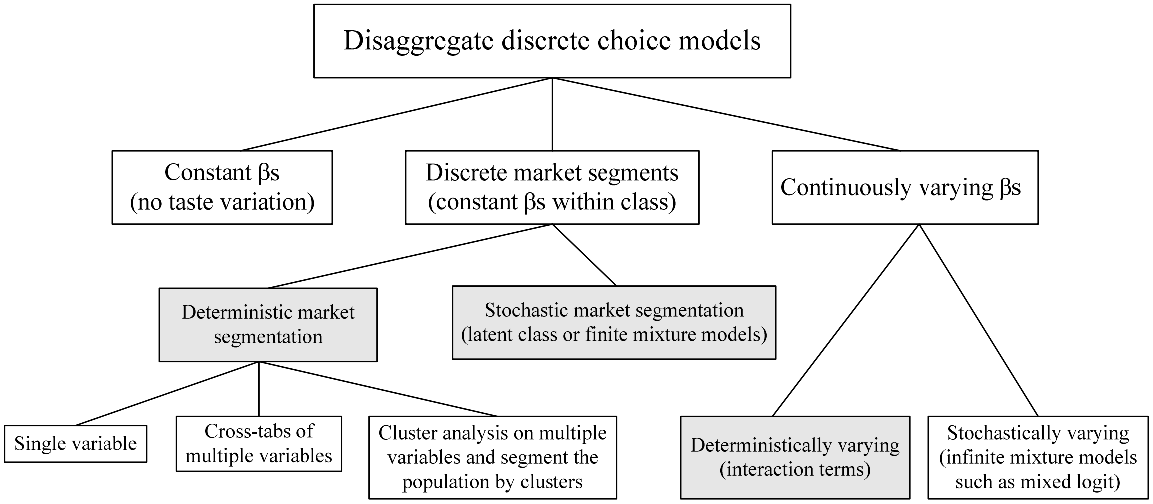

Figure 1. Overview of Ways to Account for Taste Heterogeneity in Discrete Choice Models

terms into a conventional choice model – to implement the continuously-varying coefficient approach. The gray-shaded blocks identify the main interests of our study. Given a decision to use discrete segmentation, there are two key approaches to segmenting the population: deterministically and stochastically (i.e. via latent classes). We introduce the deterministic approach in this section, and the stochastic approach in the next section.

There are several possible ways to segment the population deterministically. The most straightforward (and probably most common) ways are to segment on a single discrete (or discretized) variable, or (less often) on cross-tabulated combinations of a small number of such variables, e.g. an income*gender segment: high-income females, high-income males, low-income females and low-income males. But segmentation on a single variable is quite restrictive, and may not be a realistic representation of the basis for population heterogeneity, whereas segmenting on cross-tabs of multiple variables rapidly generates an unwieldy number of possible combinations. The cluster analysis approach, by contrast, is first to perform a cluster analysis and then to estimate different choice models by cluster. Any number of variables can be used as a basis for creating the clusters, but the actual number of clusters can be kept relatively small.

To summarize, the deterministic market segmentation approach consists of two steps: (1) deterministically dividing cases into several clusters (using any of the above three ways); (2) using the appropriate discrete choice models to model shopping behavior for each cluster. To evaluate the goodness of fit of those discrete models, we use the segmented-model counterparts of the ρ^2 and $\bar{\rho}^2$ statistics presented earlier (equations 4 and 5 in Section 4.2) for the pooled model. Assuming the models for each segment have identical specifications (where some estimated coefficients may be statistically zero for some segments but not others), these statistics can be calculated by

$$\rho^2_{segmented} = 1 - \frac{\Sigma_g LL(\hat{\beta}^g)}{\Sigma_g LL(0^g)}, \text{ and} \tag{6}$$

$$\bar{\rho}^2_{segmented} = 1 - \frac{\Sigma_g LL(\hat{\beta}^g) - GK}{\Sigma_g LL(0^g)}, \tag{7}$$

where G is the number of market segments; $\hat{\beta}^g$ is the vector of estimated coefficients for market segment g; $LL(\hat{\beta}^g)$ and $LL(0^g)$ are maximum log likelihoods of the gth segments (g=1, 2, … , G) for the "full" model (model to be tested) and equally-likely model respectively; and K is the number of estimated parameters for each segment in the "full" model (lecture notes on "Taste Variations", UC Davis course ECI 254, instructor Patricia Mokhtarian, Spring 2006). Various versions of the chi-squared (χ^2) test (Ben-

Akiva and Lerman, 1985) can be conducted to test nested models, with a null hypothesis stating that the more complex of the two models to be tested is not different from the simpler one. The tests are based on the approximate chi-squared distribution of a linear expression of the models' log likelihoods, which can be written as

$$-2\ln(L^R / L^U) = -2(LL^R - LL^U) \sim_{asympt.} \chi^2 \qquad (8)$$

with r degrees of freedom (r is the number of linearly independent restrictions), where LL^R and LL^U represent the log likelihoods for the restricted (simpler) model (such as the equally-likely model or the market share model) and unrestricted (i.e. "full") model, respectively (and where both models must be estimated on the identical sample). If the test result is significant, then we can say that the "full" model has better explanatory power than the "restricted" model, otherwise, an insignificant result tells us that the two models are not statistically different. Specifically, to test taste variations (or in other words, to test the existence of segments) in the population, equation (8) becomes:

$$-2[LL(\hat{\beta}) - \sum_{g=1}^{G} LL(\hat{\beta}^g)] \sim_{asympt.} \chi^2 \qquad (9)$$

with $(G-1)K$ degrees of freedom.

5.3 Latent Class Modeling (LCM)

5.3.1 Introduction to LCM

Because the literature does not provide clear definitions for LCM and latent class analysis (LCA), these terms have been used in different contexts to represent different concepts. It is thus necessary for us to first define them for our study. Here LCM includes three major applications: latent class (LC) cluster models, LC factor models and LCCM (Magidson and Vermunt, n.d.). By LCA, we mean a general "multivariate technique" that can be applied to all three types of LCM[7], even though the term has been used to denote a specific analytical approach in some previous studies such as Goodman (1974a), McCutcheon (1987), and Magidson and Vermunt (2003). As indicated by Magidson and Vermunt (n.d.), LCA can be used to replace traditional factor analysis and cluster analysis, and as a tool for estimating choice models for each segment. Therefore, in our study, LCA also means a general reference to any methods using latent class constructs. To our knowledge, LCA and LCM are interchangeable in most circumstances.

LCM was introduced by Lazarsfeld and Henry (1968). Their initial concern was simply to identify latent classes of survey response patterns, without the second stage of modeling choice given latent class with which we are concerned (their approach belongs to the first of the above-mentioned three applications of LCM, i.e. LC cluster models). They use accounting equations, which relate the latent parameters to the manifest discrete response data and observed frequencies, to identify latent classes and find the nature of them, and then use Bayes' theorem to classify respondents to one of the latent classes, given their patterns of manifest responses. In further development, LCM was extended to finding latent classes from continuous manifest variables (e.g. the application of latent profile analysis). LCM uses the LCA method – a statistical method for finding categorical latent classes of related cases from various types of data. For example, it can be used to find distinct attitude structures from survey responses, or consumer segments from sociodemographic and attitude variables (e.g. shopping channel perceptions in our study)

[7] Source: http://www2.chass.ncsu.edu/garson/PA765/latclass.htm, accessed Jan. 10, 2010.

(http://ourworld.compuserve.com/homepages/jsuebersax/faq.htm, accessed Feb. 10, 2007).

Among the three above-mentioned major applications of LCM, LCCM serves as a clustering method with respect to unobserved heterogeneity on parameters of an equation with a continuous or discrete dependent variable, and is the technique we are going to use in this study (Magidson and Vermunt, 2003). LCCMs are also known as finite mixture models, assuming that each respondent belongs to one and only one of a finite set of latent classes, each of which represents unique tastes (Magidson et al., 2003). So the unique preference profile (set of β weights) is segment-based, not individual-based, which is consistent with our assumption of the same set of βs for cases within a class and different βs across classes. To be consistent with many other studies, in our exposition we also use LCM to refer to the LCCM, as appropriate.

Goodman (1974a, 1974b) introduced the "maximum likelihood (ML) algorithm that serves as the basis for many of today's LC software programs" (Magidson and Vermunt, 2003, p. 2). We can obtain the ML estimates of the model parameters, and then calculate the adjusted ρ^2 to assess whether or not the model fits the observed data well.

LCM posits that an individual's behavior (e.g. choice or preference) with respect to discrete alternatives is a function, in part, of unobserved (by the analyst) latent heterogeneity that varies with (observed) factors (Greene and Hensher, 2003). It involves two levels: (1) Classifying the population into several latent groups (it is called "latent" because class membership is unobserved, i.e. the class to which any particular individual belongs is unknown to the analyst) based on segmentation variables. Specifically, segmentation variables are explanatory variables in the class membership model, that is, variables considered likely to impact the importance given to variables affecting discrete responses, as described by Bhat (1997). (2) Modeling behavior for each latent class (market segment) separately (though simultaneously) using UMT as the basis for the individual's response. Considering the different characteristics of members in different latent classes (i.e. the heterogeneity across latent classes), it is believed that they will tend to have different sensitivity to the manifest variables, which will result in different sets of parameters across segments. In other words, the latent heterogeneity can be reflected by different sets of parameter vectors, i.e. βs (Greene and Hensher, 2003). As mentioned, which individual belongs in which class is unknown to the analyst. She does, however, know the expected segment sizes through the predicted probabilities of individuals belonging to each class. Furthermore, she can explore the nature of each segment through analyzing (1) the segment membership model, (2) the segment-specific coefficients of the discrete response model, and (3) the expected characteristics of each segment (based on the average value of certain variables across the estimation sample, weighted by the probability of segment membership for each case). See the next subsection for further details.

5.3.2 Latent Class Model Structure and Estimation

A LCM can be expressed as the product of the (unconditional) probability of belonging to a given latent class and the corresponding conditional response probability for choosing an alternative given that the individual belongs to that class, summed over classes (Magidson and Vermunt, 2003). That is, the probability that a person *n* chooses alternative *i* can be written as:

$$P_n(i) = \Sigma_g P_n(i|n \in g)\Pr(n \in g), \tag{10}$$

where g denotes segment or group. The individual-level probabilities of class membership, $\Pr(n \in g)$, should sum to one for each n. To be consistent with the previous assumption mentioned in Section 5.3.1, UMT will be used as the central behavioral model for a discrete choice among alternatives; we assume that the random components in an alternative's utility function follow the extreme value (EV) distribution and are independent and identically distributed (IID). Then the probability that individual *n* chooses alternative *i* conditional on the individual belonging to segment $g, P_n(i|n \in g)$, would typically be a MNL probability with segment-specific coefficients. Taking the familiar MNL form (McFadden, 1974), we have

$$P_n(i|n \in g) = \frac{\exp[\beta^g x_{in}]}{\Sigma_{j \in C_n} \exp[\beta^g x_{jn}]}, \tag{11}$$

where C_n is the choice set of alternatives available to person *n*; x_{in} is a vector comprising variables associated with individual *n* and alternative *i*; and β^g is a segment-specific parameter vector to be estimated.

The probability of class membership, $\Pr(n \in g)$, is typically modeled as a function of other explanatory variables. In this study, we use the MNL formulation for this model as well; thus we have

$$P_{ng} = \Pr(n \in g) = \frac{\exp[\gamma^g z_n]}{\Sigma_g \exp[\gamma^g z_n]}, \tag{12}$$

where the vector z_n contains the variables expected to influence segment membership (i.e. expected to distinguish groups with different β weights in equation (11)), such as sociodemographic and general personality traits and attitudes, and the γ^g s are parameter vectors to be estimated for the class membership model. The assignment of individuals to segments in our proposed model is probabilistic, and is based on equation (12) after replacing the γ^g s with their estimated counterparts (as in Bhat, 1997). Obviously, the expected number of individuals in segment g is given by $\Sigma_n P_{ng}$, and the share of each segment, R_g, may be obtained as

$$R_g = \frac{\Sigma_n P_{ng}}{N}, \tag{13}$$

where N is the total number of individuals in the estimation sample.

Some attributes of each segment can be inferred from the signs and relative magnitudes of the coefficients of the segmentation variables in equation (12). For instance, if a segment membership function has positive coefficients for “education level” and “trendsetting”, and a negative coefficient for “caution”, (meaning that more heavily educated trendsetters and less cautious people have a higher probability of belonging to that group), then it is reasonable for us to deduce that “risk-seeking” is one trait describing a general tendency of the group. In addition, we can estimate the means of those (and other) variables for each segment by taking its probability-weighted average across the sample, i.e. by

$$\overline{v}_g = \frac{\Sigma_n P_{ng} v_n}{\Sigma_n P_{ng}}, \tag{14}$$

where v_n refers to the measure of person *n* on any particular attribute of interest.

Using a maximization routine, the log likelihood function to be maximized for a given G can be written as (Bhat, 1997, Greene and Hensher, 2003):

$$\ln L = \sum_{n=1}^{N} \ln \left\{ \sum_{g=1}^{G} \left(P_{ng} \times \prod_{i \in C_n} [P_n(i | n \in g)]^{\delta_{ni}} \right) \right\}, \tag{15}$$

where δ_{ni} is defined as follows:

$$\delta_{ni} = \begin{cases} 1 & \textit{if the nth individual chooses alternative i} \\ & \qquad (n = 1, 2, ..., N;\ i \in C_n) \\ 0 & \textit{else.} \end{cases}$$

The estimation used by the routine is applicable for a given number of segments G. It is an important step to identify the most appropriate value for G. The basic idea is to estimate a single-segment model first, and then keep adding one more segment until a statistical test fails to reject the null hypothesis that the two models are equivalent. Details about how to choose the most appropriate number of segments G will be presented in the next section.

5.3.3 Model Fit Assessment and Hypothesis Testing

Model fit (or GOF) measures how adequately the model accounts for the data, that is, how closely the model-predicted values reproduce the observed values (real data). The value of the likelihood ratio index (ρ^2) and the adjusted likelihood ratio index ($\overline{\rho}^2$) are usually used as GOF measures (in a fashion similar to the R^2 and adjusted R^2 in regression analysis). There are no general criteria for deciding if a value is sufficiently high (Ben-Akiva and Lerman, 1985), but at least with ρ^2, there is a clear maximum value of 1 (and minimum of 0), and the ρ^2 of a given model can be evaluated against that ideal target.

For a number of other so-called GOF measures, however, an upper bound either does not exist or is not known. These measures are used as comparative means of assessing model fit – that is, two or more models are compared on these measures to identify the best model among the set, with little or no information about how good the model is in any absolute sense (i.e. even the "best" model may not explain the data very well). In recent years, the use of information statistics to create "parsimony indices" is attracting more and more interest as such a means of assessing model fit. "These statistics are based mainly on the value of -2 times the log likelihood of the model, adjusted for the number of parameters in the model, the sample size, and, potentially, other factors" (http://ourworld.compuserve.com/homepages/jsuebersax/faq.htm, accessed Jan. 13, 2007). The basic idea is a parsimony criterion, meaning that all other things (including log likelihoods) being equal, the model with fewer parameters is the better one. Common parsimony indices include the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), and the Consistent Akaike Information Criterion (CAIC). They are computed by the following expressions respectively (Akaike, 1974; Kamakura and Russell, 1989; Bhatnagar and Ghose, 2004):

$$\begin{aligned} AIC &= -2LL + 2p, \\ BIC &= -2LL + p\ln(N), \textit{ and} \\ CAIC &= -2LL + p[1 + \ln(N)], \end{aligned} \tag{16}$$

where p is the number of estimated model parameters and N is the sample size. To decide the "best" number of latent classes G, as mentioned earlier, we basically start from a single-segment model and then keep adding one more segment at each stage. The log-likelihood (LL) of the model will improve (get less negative) as segments are added, so -2LL will get smaller (less positive), while the penalty for loss of parsimony (the increase in the number of parameters p) increases the information criterion. If the loss-of-parsimony penalty outweighs the improvement in the model, the information criterion will increase with the additional segment. Thus, from a statistical standpoint alone, the "best" model, i.e. the one with the most appropriate number of segments G, is considered to be the one with the lowest information criterion[8]. However, conceptual considerations should also be an important basis for determining G, and the size of each segment may be a further relevant consideration. Numerous empirical studies (Bockenholt and Bockenholt, 1991; Bhat, 1997; Greene and Hensher, 2003; Magidson and Vermunt, 2003; Bhatnagar and Ghose, 2004; Gonzalez-Benito, 2004; Chung, et al., 2006; Walker and Li, 2007; Lee and Timmermans, 2007) have applied one or more of these criteria, but the multiple criteria can point to different "best" values of G, and none of the studies give a strong reason for choosing one of the three indices over the others. In practice, we can compute all of them, and then find an optimal solution from the perspectives of both interpretability and statistics, as has been done by Walker and Li (2007).

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[8] Source: http://www2.chass.ncsu.edu/garson/PA765/latclass.htm, accessed Feb. 13, 2007.

Another way of making a comparative assessment of model fit is to conduct a hypothesis test. There are several different types of hypothesis tests, but all of them essentially compare one model to another, to see which fits the data better – again without saying anything about whether the better model is any good in an absolute sense. One such test already discussed (see Eq. 9 in Section 5.2) is the chi-squared test (for nested models), which compares the log likelihoods of the "full" model and restricted models (Bhat, 1997; Greene and Hensher, 2003; Kemperman and Timmermans, 2006). For non-nested models, there is another way to compare two models, using the adjusted rho-square ($\bar{\rho}^2$) to test the null hypothesis that the model with the lower $\bar{\rho}^2$ (model 1) is true compared with a model having additional classes or different variables and a higher $\bar{\rho}^2$ (model 2). From the log-likelihood values of each model, the adjusted rho-squares can be computed (see Section 4.2), and then the test-statistic

$$\Pr[\bar{\rho}_2^2 - \bar{\rho}_1^2 > z] \leq \Phi\left\{-[2Nz\ln J + (K_2 - K_1)]^{1/2}\right\},\ z > 0\,, \tag{17}$$

where z is the difference seen between adjusted rho-squares for the two models; Φ is the cumulative distribution function of the standard normal distribution; N is the number of observations; J is the number of alternatives and K_i is the number of parameters estimated for model i (Ben-Akiva and Lerman, 1985). This inequality holds, under the null hypothesis that model 1 is the true model. So if the probability of observing a $\bar{\rho}_2^2$ larger than $\bar{\rho}_1^2$ by z is too small to be credible, we should reject the null hypothesis and conclude that model 1 is not true.

To conclude, there are three types of approaches that can be used to evaluate whether a model is good or not: absolute GOF measures, comparative GOF measures applied informally, and hypothesis tests. Absolute GOF measures include rho-square (ρ^2) and adjusted rho-square ($\bar{\rho}^2$). Parsimony indices (AIC, BIC, CAIC) are GOF-related but not absolute measures because we cannot judge whether a model is good or not given specific values of those statistics. However, applying them on a comparative basis helps us choose the best among a set of models. Hypothesis tests consist of the chi-squared test and the non-nested model $\bar{\rho}^2$ test (by equation 17); they can test the significance of estimated parameters and help us choose the better model between a "full" model and a restrictive one.

5.3.4 Model Specification Considerations

In this section, we will discuss model specification issues, meaning the research hypotheses expressed in constructing a latent class model. First, the dependent variable in this study is the binary stated preference for a future similar purchase, and we have an interest in the relationships between predictors and the e-shopping behavior. To investigate those relationships, the literature review and intuition may suggest that a variety of variables have potential influences on these relationships. However, it is not practical to include all of them in the model due to data limitations and estimation difficulties. Therefore, it is necessary to judge which variables are most essential and have priority to be included in the model. After those variables are preliminarily chosen, another important issue arises: which variables should be the market segmentation variables and which should be the variables belonging to the choice model for each segment? Although (at least some of) the same variables can appear in both models, it is important to give careful consideration to the question of which variables most appropriately belong to each model. In this study, the initial model specification is mainly based on published work and our intuition. One variable might be insignificant in market segmentation but show its significance for the segmented choice models. We may also find that a variable is more conceptually interpretable in one model than in another. Keeping conceptual considerations as our main principle, any important variables filtered from the initial specification may be tested again in a later round of the modeling process. In addition, variables in the membership model and choice model can switch their positions in different trials in order to get better model fit and interpretability. Based on these approaches and *ad hoc* trial and error, combined with model fit consideration and diagnostics, it is expected that a near-optimal model specification can be developed.

Conceptually, segmentation variables should be those that influence an individual's sensitivity to a given variable that affects channel choice – that is, those that influence a β coefficient in the choice model. Thus we expect the general shopping attitudinal factors extracted from survey Part A to be more likely to be significant in the cluster membership model (because they reflect general attitudes, such as "Store enjoyment" and "Pro-technology", that may affect the weights (βs) the customer places on variables affecting choice), while the channel-specific shopping attitudes (such as the advantages and disadvantages) extracted from the survey Part D are more likely to enter the segmented choice models. According to the literature review, intuition, and shopping perception factors provided in Chapter 3, we summarize plausible segmentation variables and choice model variables in Table 11. Example hypothesized impacts of segmentation variables on weights put on attributes associated with a shopping channel (β_x) are provided in Table 12.

5.4 LCM Results

Theoretically, we should start from a single-segment model (that is, a conventional pooled discrete choice model) and then keep adding one more segment at a time. To obtain the optimal number of segments, we need to compare model statistics such as the AIC, the BIC, and the CAIC. In this exploratory study, we were unable to find an appropriate model with more than two segments. All of the three- and four-segment models we attempted resulted in either too many segments (based on the p-values of 1 for all the choice model variables of one or more segments), or computation failures due to a singular variance-covariance matrix.

Table 13 summarizes our two-class LCM results for purchase channel intention, with the same results obtained from both the software packages of Limdep 9.0/Nlogit 4.0 (Greene, 2007) and Mplus 5.1 (Muthén and Muthén, 1998-2007). A number of different specifications were tested, drawing from the variety of possible explanatory variables available in the data. However, insignificant variables were excluded from the final model, and only the remaining, significant, variables are shown in the table and discussed below. Due to missing data on significant variables, the final sample size is 373 cases; the expected segment shares are 48% (180) and 52% (193). The ρ^2 value (Ben-Akiva and Lerman, 1985) of the LCM is 0.365 (with the equally-likely pooled model as base),

Table 11. Potential Model Specifications

Cluster membership variables (z)	*General shopping-related attitudes:* "Store enjoyment", "Caution", "Trendsetting", "Pro-technology", "Trust", "Time-conscious", and "Pro-environment" etc.
	Sociodemographic variables: income, age, education level, work arrangement, and gender etc.
	Purchase experience variables: "Was the purchase a gift [or not]", purchase frequency etc.
	Use of internet and communication technology
Choice model variables (x)	*Channel-specific attitudes:* "Post-purchase satisfaction", "Convenience", "Product risk", "Financial/identity risk", "Enjoyment" and "Cost savings" etc.
	Other potential choice model variables: product type/cost, purchase experience, product & service quality (on delivery and return etc.), total cost difference on different channels.

Table 12. Example Hypothesized Impacts of Segmentation Variables on Weights

Hypothesized segmentation variable category	**Example hypothesized impacts of z on β_x**
General shopping-related attitudes	People who more readily trust others (z) will put less weight (β_x) on the risk (x) associated with a given shopping channel. People who are more "Time-conscious" (z) will put heavier weight on the "Time savings" (x) associated with a given shopping channel.
Sociodemographic variables	People who have high income and are more educated will put heavier weight on the "Time savings" / "Convenience" / "Ease of use" (x) associated with a given shopping channel. Females will put heavier weight on the "General enjoyment" associated with a given shopping channel.
Purchase experience variables	People who frequently purchase an item via a channel will put less weight on the risk (x) associated with that channel.
Use of internet and communication technology	People who use the internet a lot may put lower weight on the "Ease of use" (x) associated with the e-shopping channel.

Table 13. Latent Class Model of Purchase Channel Intention (sample size: 373)

Model	Variables	Segment 1		Segment 2	
		Coefficient	P-value	Coefficient	P-value
Unstandardized coefficients					
Segmentation model	Constant	-3.633*	0.064	Base Segment	
	Respondent's age	0.079**	0.013		
Segment-specific choice model	Constant	-1.698	0.225	1.032	0.448
	Post-purchase satisfaction perception difference [a]	1.556**	0.048	0.067	0.829
	Convenience perception difference [a]	1.431***	0.005	0.354	0.161
	Broadband internet accessibility at work	2.707*	0.078	-0.796	0.468
	Context-specific cost difference [b]	-1.009	0.146	-2.328***	0.001
Standardized coefficients					
Segmentation model	Constant [c]	-0.034	0.970	Base Segment	
	Respondent's age	1.198**	0.013		
Segment-specific choice model	Constant	-0.594	0.213	-0.425	0.215
	Post-purchase satisfaction perception difference [a]	2.712**	0.048	0.116	0.829
	Convenience perception difference [a]	2.260***	0.005	0.559	0.161
	Broadband internet accessibility at work	1.039*	0.078	-0.305	0.468
	Context-specific cost difference [b]	-0.736	0.146	-1.700***	0.001

[a] Difference between channel-specific perceptions: store factor score minus internet factor score.
[b] See Table 7 for definition.
[c] Ordinarily a constant would not be included in a standardized model, but one is automatically supplied by the software; not surprisingly, its estimate is essentially zero.

Note: *10% significance level, ** 5% significance level, *** 1% significance level. The log-likelihood value at zero is -258.544; the log-likelihood value for the unsegmented model with only a constant term is -254.766 (the intention shares are 42.9% store, the “1” alternative, and 57.1% internet, the “0” alternative); the log-likelihood value for the unsegmented model with only choice model variables (including the constant) is -176.149; the log-likelihood value at convergence for the two-segment solution is -164.261.

which is considered quite acceptable in the context of disaggregate discrete choice models. The BL model on the unsegmented (pooled) sample with the same choice model explanatory variables yields a ρ^2 of 0.319. For comparison, the ρ^2 of the market-share (constant-term-only) model on the pooled sample is only 0.015, since the intention shares are relatively balanced (store 43%; internet 57%). The relevant chi-squared test shows that the latent segmentation model is significantly better than the model on the pooled data ($p = 0.001$).

In lieu of reporting elasticities (which were not available as an option in the LCM modules of Limdep/Nlogit nor Mplus), we (as endorsed by Miller, 2005 for logistic regression models) report the coefficients obtained when all explanatory variables are standardized (as well as the conventional unstandardized coefficients), which, similar to elasticities (and analogous to the standardized coefficients in regression), serves the purpose of making the coefficients independent of the scale of the explanatory variables.

Turning to the model interpretation, only one segmentation variable (besides the constant term) is significant for the membership model, that is, the respondent's age. Its positive coefficient indicates that older respondents are more likely to belong to Segment 1. Candidly, we expected a more "interesting" class membership model. Specifically, we expected some general shopping-related attitudes to be significant, in keeping with the recognition that class membership variables constitute moderators of the coefficients of the choice model, and that moderators are likely to be fairly stable individual traits (Wu and Zumbo, 2008). It is quite possible, however, that age is serving as a single marker for a complex bundle of traits associated with age in a non-straightforward way. For example, age is significantly correlated with employment status (0.49), with internet usage diversity (-0.52), with the time consciousness factor (-0.18), with income (0.17), and with some other variables. Thus, although none of those variables was individually significant in the class membership model, it could be that age is representing a non-linear combination of them (and others) that *is* significant. And from a practical standpoint, it is certainly convenient for age to be the only segmentation variable, not only because having only one variable keeps the model relatively simple, but also because that particular variable is easy to forecast, and constitutes a clear-cut basis on which to target marketing messages. Accordingly, what in this case is a necessity, is also a virtue.

At the suggestion of a reviewer, to further explore the effects of the segmentation variable (i.e. age) on class membership, we tried creating three dummy variables for different age groups (i.e. for age “younger than 40”, “between 40 and 60, including 40” and “60 or older”), and then interacted age with two of those three dummy variables in the class membership model. This, in effect, created a piecewise-linear function for the coefficient, reflecting that the marginal impact on the probability of class membership of being another year older might differ depending on one's age group. However, this approach did not improve the model.

With respect to the choice model component of the LCM, four variables (besides the constant term) were significant: two channel-specific perceptions (post-purchase satisfaction and convenience), one purchase experience variable (context-specific cost difference) and one internet usage variable (broadband internet accessibility at work). Each of these variables is significant to only one of the two segments, indicating that the LCM has identified two classes that have almost completely distinct tastes – at least as far as the variables observed in this study are concerned.

As mentioned in Section 3.2.2, channel-specific perceptions are represented in the model by differences between store and internet factor scores. Not surprisingly, the more positively store is perceived relative to the internet on post-purchase satisfaction and convenience, the more likely store is to be the intended channel for the next purchase. However, while these variables are strongly significant for Segment 1, the older group (respectively the first- and second-most important variables in the model for that segment, based on the standardized coefficients), they are quite insignificant for the younger segment. Similarly, the dummy variable representing broadband internet accessibility at work is also significant for the older segment but not the younger one. The positive sign (indicating that those who have broadband internet access at work are more likely to intend to purchase in a store) seems counterintuitive because (particularly for the book product type) we would expect ease of access to the internet to support intentions to buy online. However, we believe that (for the older segment particularly) it may be a marker for individuals holding a largely sedentary desk job, who, to the extent they associate shopping with the work environment, would prefer store shopping (e.g. during the lunch hour) for exercise and a change of scenery. Especially, considering the higher age of Segment 1, they may possibly prefer physical store shopping as a pleasant way to get more exercise.

The context-specific cost difference variable is the only variable significant in the choice model for Segment 2 (and, not surprisingly then, by far the most important variable according to the standardized coefficients). A higher value of this variable indicates that store was perceived to be more expensive than internet for the specific purchase made recently. As a result, it is natural that people with higher values of this variable are more likely to intend the more economical channel – internet – for their next purchase.

The picture that emerges from the distinctive variables significant to each segment is that Segment 1 places a higher value on convenience (including concerns about the potential hassle of customer service and/or returns if the item purchased is not satisfactory), whereas Segment 2 is mainly concerned about cost. It is not surprising that these heterogeneous tastes are closely associated with age – older people will tend to have higher incomes and more time pressure, whereas younger people may tend to have more time than money.

5.5 Additional Interpretation of the Segments

To better understand the respective natures of the two segments, it is useful to compute their (estimated) expected values on a number of attributes of interest. For a given attribute *x*, this is done using the formula $\overline{x}_g = \frac{\Sigma_n P_{ng} x_n}{\Sigma_n P_{ng}}$. That is, we compute the weighted average value of attribute *x* for segment *g*, where the weights are the probabilities that each case in the sample belongs to segment *g*.

Table 14 lists the expected values of the significant variables in the final LCM model, together with several other important variables. We see, for example, that the mean age of people in Segment 1 is 52.6 years, while that of Segment 2 is 38.3 years. Both segments perceive store to be superior to the internet on post-purchase satisfaction; interestingly, Segment 2's perception of that difference is even more positive than that of Segment 1, but that variable is not significant to Segment 2's intention. Conversely, both segments perceive the internet to be superior to stores on convenience; Segment 2 favors the internet on that dimension even more strongly than Segment 1, but again, that variable is not significant to Segment 2. These results illustrate the obvious (but occasionally neglected) point that finding one alternative to be superior to another on a given characteristic is only relevant if that characteristic is important to choice. This is all the more critical when a given characteristic is important to some market segments but not others.

Several variables support our interpretation of Segment 1 as being more time-pressured and less money-sensitive than Segment 2, and also less internet-savvy. For example, people in Segment 1 tend to be less price conscious (-0.170) than those in Segment 2 (-0.024). Segment 1 has somewhat higher education and income than Segment 2 (consistent with their age differences). People in Segment 1 on average use the internet for fewer types of functions (5.48 vs. 7.09), which also makes sense in view of the age difference between the segments, and further, less often have broadband internet access at work (78% vs. 90%). On the other hand, on average there is little difference between the segments (at least, as measured by the statements shown in Table 3) with respect to their

Table 14. Characteristics of the Segments

Variables		Attribute Means	
		Segment 1 (48.3%)	Segment 2 (51.7%)
Segment-specific choice model variables	Post-purchase satisfaction perception difference [a]	0.817	0.898
	Convenience perception difference [a]	-1.392	-1.757
	Broadband internet accessibility at work (dummy variable)	0.779	0.901
	Context-specific cost difference [b]	0.118	0.144
Segmentation model variable	Respondent's age (years)	52.571	38.313
Dependent variable	Intended channel for future book purchase (1=store; 0=internet)	0.445	0.414
Other important variables	Chosen channel for the recent book purchase	0.558	0.516
	Store enjoyment factor [c]	-0.158	-0.051
	Price consciousness factor [c]	-0.170	-0.024
	Time consciousness factor	-0.058	0.058
	Pro-exercise factor	-0.013	0.028
	Cost saving factor [a, c]	-1.068	-1.362
	Activeness of searching [b]	2.670	2.645
	Internet usage diversity [d]	5.478	7.086
	Education level [b]	5.908	5.759
	Annual household income [e]	4.612	4.316

[a] Difference between channel-specific perceptions: store factor score minus internet factor score.
[b] See Table 10 for definition.
[c] The means for both segments can have the same sign because the factor scores were standardized across the entire sample, including the clothing-purchase segment not analyzed in this study. Thus, for example, both segments of book purchasers analyzed here have lower store enjoyment scores, on average, than do the clothing purchasers in the rest of the sample.
[d] Index variable created by summing the 14 binary variables indicating usage of the internet for “Email”, “Instant messaging”, “Audio conversations”, “Video conversations”, “Chat rooms”, “Viewing blogs/bulletin boards”, “Blogging”, “Making own website”, “Internet radio or television”, “Banking/paying bills”, “Selling goods”, “Personal networking”, “Job search” and “Collaborative professional work”.
[e] Categories numbered 1 through 6 correspond to those in Table 10.

time consciousness and attitudes toward exercise.

However, given the central tendencies of the variables shown in Table 14, the taste differences that do exist between the segments do not overwhelmingly favor one channel over the other. For Segment 1, for example, there is a clear tradeoff: the importance of the post-purchase satisfaction factor tends to favor store, but the importance of the convenience factor tends to favor the internet. For Segment 2, the perceived cost difference between the two channels is the only significant observed variable, but its value does not always favor the internet. Overall, people in Segment 1 are more likely than those in Segment 2 to have chosen store for their recent book purchase (56% vs. 52%), and to intend to make a similar future purchase in a store (45% vs. 41%) – but only marginally so[9].

5.6 Comparison of LCM with Deterministic Approaches to Treating Taste Heterogeneity

5.6.1 Deterministic Market Segmentation

As mentioned in the Introduction, LCM is theoretically superior to the conventional deterministic two-stage market segmentation approach, because in LCM the choice model is estimated simultaneously with the class membership model, and the classes are defined specifically so as to best discriminate between different market segments with respect to choice. As a result, we expect LCM to give us models that have better GOF and interpretability. However, it is relevant to wonder how large the improvement from

[9] Due to the essentially choice-based nature of the sampled channel choices, the specific shares presented here should not be taken as representative of the population shares; it is the comparison between Segments 1 and 2 that is relevant.

using LCM is in practical terms, and in particular whether it is sufficiently large to justify the increased complexity of implementation. Accordingly, in this section we conduct a limited comparison of the two approaches. That is, we restrict the deterministic segmentation to using the same class membership variable identified by the LCM, namely age.

For this initial comparison, we divided the sample into two segments based on age. To reflect the fact that the best cutpoint for the two segments would not be known in advance, we prepared five different segmentations, using different segment shares. Specifically, the second segment (i.e. those who tend to be younger) contains 10 percent, 24 percent, 50 percent, 73 percent and 90 percent of the total number of cases respectively, corresponding to highest ages of 26, 31, 45, 55, and 63. The second and fourth segmentations are slightly irregular (with Segment 2 shares originally planned to be 25 and 75 percent, respectively), to avoid placing people of the same age into different segments. The cutpoint of 45 for the third (50-50) segmentation also corresponds both to the age beyond which the LCM first predicts a higher probability of belonging to Segment 1, and to the weighted average of the two mean ages of the latent segments (38.3 and 52.6), where the weights are the expected segment sizes. Thus, if one took the results of the LCM and subsequently deterministically assigned each case to its highest-probability segment (as seems to be done astonishingly often, despite the practice being "opposed to the meaning of probabilities and the purpose of specifying choice probabilities"; Train, 2009, p. 69), the 50-50 segmentation would result.

The overall comparisons of the LCM, the pooled model, and the five deterministically-segmented (DS) choice models are shown in Table 15. For deterministically segmented choice models, overall log-likelihoods are equal to the sum of the corresponding log-likelihoods of each segment (Ben-Akiva and Lerman, 1985), and thus all models have the same log-likelihood for the equally-likely model (-258.544). As expected, the LCM has the highest log-likelihood at convergence (-164.261), with all the DS model final log-likelihoods falling below -168. Interestingly, among the DS models, DS1 and DS2 (with the smallest shares of younger people) are little better than the pooled model, while at the other extreme, just peeling off the oldest 10% of cases into a separate segment yields the best DS model (DS5) among those tested, one that is almost as good as the LCM (specifically, the LCM final log-likelihood is only 2.4% higher, -164.261 vs. -168.377, and the adjusted ρ^2 is only 2.6% higher, 0.318 vs. 0.310). On the other hand, the fit of the "naïve" 50-50 split model (DS3) is essentially identical to that of DS5, while that of DS4 is worse than either.

Given the foregoing discussion, and especially the similar fits of DS3 and DS5, it is natural to want to compare the (choice model) coefficients estimated from the LCM, pooled, and five DS models. Figures 2 and 3 chart the coefficients for Segments 1 (older people) and 2 (younger people) respectively. The results are interesting. The coefficients of Segment 1 (Figure 2) for the DS models generally get closer to those of the LCM as the size of Segment 1 (the older segment) decreases (i.e. going from DS1 to DS5), suggesting that it is the oldest slice of Segment 1 that dominates the estimation of its coefficients for the LCM. On the other hand, for DS1 – DS4, the context-specific cost

Table 15. Goodness-of-Fit Comparison of the Models

	Segment	Log(beta)	Log(EL)	No. of Parameters	ρ^2	$\bar{\rho}^2$	No. of cases
LCM		-164.261	-258.544	12	0.365	0.318	Seg. 1: expected 180; Seg. 2: expected 193.
Pooled model		-176.149	-258.544	5	0.319	0.299	373
DS Model 1	1	-158.227	-232.897	5	0.325	0.287	336
	2	-16.228	-25.646	5			37
DS Model 2	1	-127.411	-196.161	5	0.329	0.290	283
	2	-46.166	-62.383	5			90
DS Model 3	1	-82.912	-128.925	5	0.348	0.310	186
	2	-85.559	-129.619	5			187
DS Model 4	1	-45.510	-68.622	5	0.343	0.305	99
	2	-124.282	-189.922	5			274
DS Model 5	1	-10.949	-26.340	5	0.349	0.310	38
	2	-157.428	-232.204	5			335

Notes:
(1) The log-likelihood increases of the LCM compared to the pooled and the five DS models are: 6.7%, 5.8%, 5.4%, 2.5%, 3.3% and 2.4%, respectively.
(2) The rho-square and adjusted rho-square for DS models 1 to 5 were computed using formulas for deterministically-segmented choice models (Ben-Akiva and Lerman, 1985).

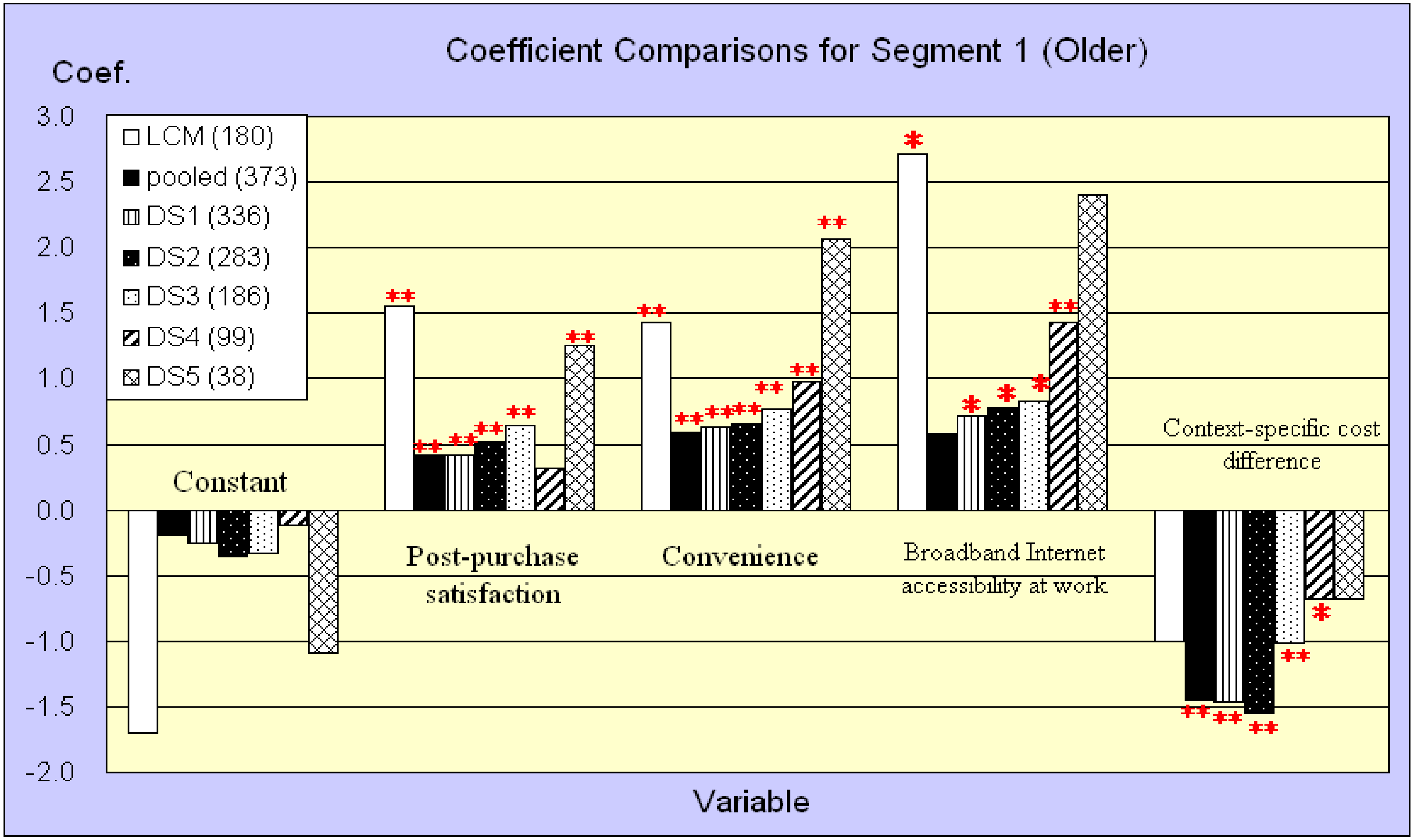

Figure 2. Coefficient Comparisons of the Seven Models[10] for Segment 1

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[10] The numbers in parentheses are the corresponding sample sizes of each model; DS models 1 to 5 are the deterministically segmented choice models containing 90%, 76%, 50%, 27% and 10% of the total cases, respectively, in Segment 1.

Note: * if $0.05 < \text{p-value} \leq 0.1$; ** if $\text{p-value} \leq 0.05$.

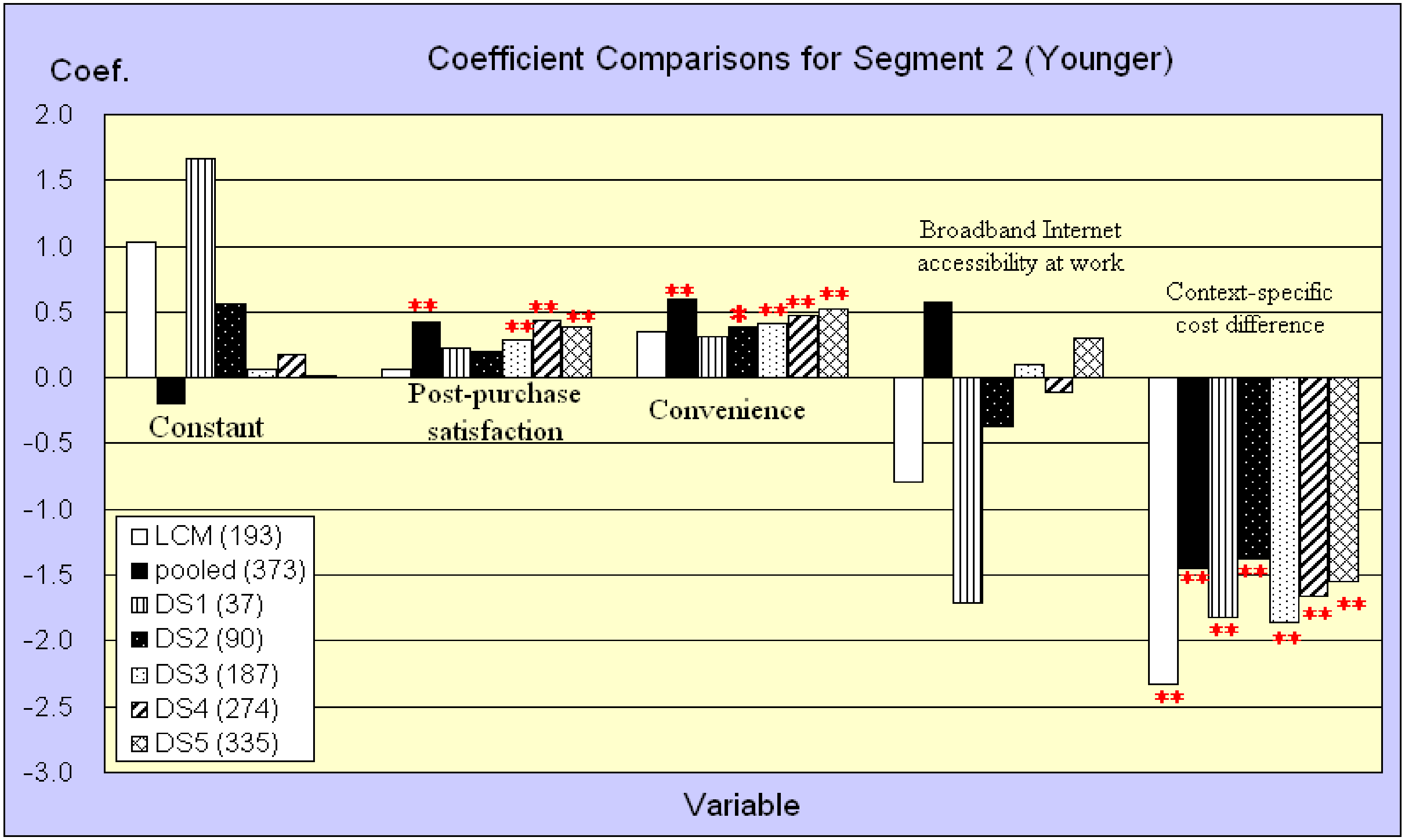

Figure 3. Coefficient Comparisons of the Seven Models[11] for Segment 2

[11] The numbers in parentheses are the corresponding sample sizes of each model; DS models 1 to 5 are the deterministically segmented choice models containing 90%, 76%, 50%, 27% and 10% of the total cases, respectively, in Segment 1.
Note: * if $0.05 < \text{p-value} \leq 0.1$; ** if $\text{p-value} \leq 0.05$.

difference variable is significant for Segment 1, whereas it is not significant in the LCM (nor in DS5). For DS1 – DS3, in fact, all four explanatory variables are significant for Segment 1, so that an analyst might well consider any of those models to be preferable to the LCM (for which one of those four variables, the cost difference, is not significant) on conceptual grounds, if just viewing these results. In any case, however, it is worth noting that although the fits of DS3 and DS5 are essentially equal as mentioned above, their Segment 1 coefficients are not.

The situation for Segment 2 (Figure 3) is somewhat different. The coefficients are generally more stable across the DS models, with the exception of those for broadband internet accessibility, which are never significant. In particular (with that same exception), the coefficients for DS3 and DS5 are quite similar, with those of DS3 being somewhat closer to those of the LCM. Here, the DS coefficients for post-purchase satisfaction (in models DS3-DS5) and convenience (DS2-DS5) are significant for Segment 2 although the LCM coefficients for the same variables are not.

Looking across both segments, then, it appears that the naïve, 50-50, segmentation produces a model which for Segment 2 is rather close to that of the LCM (but with two additional, conceptually relevant, variables achieving statistical significance), and for Segment 1 is arguably better (since one additional conceptually relevant variable is significant). The slight statistical edge gained by the LCM is due to its ability to use all cases in the estimation of the coefficients for both latent class segments, which of course is desirable when class membership is unknown a priori.

Thus, while LCM is the theoretically superior model, at least in this particular application its GOF is not substantially higher than that of models involving deterministic segmentation on the same variable, and its conceptual relevance is arguably somewhat weaker. However, this comparison presupposes that the "right" segmentation variable is known in advance, and also involves just one segmentation variable. For LCMs in which more than one variable is significant in the class membership model, it would be far less clear how to find the best deterministic segmentation using the same variables, even aside from the issue of knowing what variables were best for segmenting in the first place.

5.6.2 Unsegmented Model with Interaction Terms

Given that LCM is not strongly superior to the deterministic market segmentation approach in this instance, a reviewer's comment led us to try using the LCM results to improve the BL model on the pooled data. Specifically, we interacted the age variable (i.e. the only segmentation variable identified by the LCM) with the choice model explanatory variables (allowing both the original variables and the corresponding new interaction variables to enter the model, if both were significant), to create a new BL model on the pooled data. This has the effect of allowing the coefficient of an original variable such as the cost difference ("cost_D") to be a linear function of age, rather than purely a single constant as in the conventional pooled model:

$$\beta_C \; cost\_D + \beta_{A*C} \; (age * cost\_D) = (\beta_C + \beta_{A*C} \; age) \; cost\_D.$$

In this case, it is not clear *a priori* which model will be superior: if the effect of cost_D on choice does change more or less continuously (and linearly) with age, the interaction terms approach could be better; if the effect of cost_D on choice is more or less constant *within* latent segment, the LCM approach could be better. Scarpa et al. (2003) conducted a comparison similar to ours, and found that in their application LCM was not substantially better than the conventional BL representation via interaction variables (final log likelihoods are -1238 vs. -1289).

Table 16 summarizes the original BL model (model 1, identical to the pooled model referred to by Table 15) and the new BL-with-interaction-terms model (model 2). Model 1 contains the same four variables (besides the constant term) as the choice model of the LCM, with consistent signs and similar explanations to those described in Section 5.4. However, in model 2, the first three variables are replaced by their corresponding interaction terms, with the positive signs indicating that the marginal effect of each variable on the utility difference (between store and internet) increases linearly with age. For example, the marginal effect on utility of post-purchase satisfaction ranges from 0.180 for the youngest person in our sample (18 years old), to 0.869 for the oldest (87). For the final variable, context-specific cost difference, both the original variable and its interaction term counterpart are significant. The latter two variables have the nice interpretation that the total impact on utility of changing cost_D by one unit is equal to (-2.670 + 0.0269 age). This value remains negative (as expected) for ages up to 99 (i.e., beyond the range of ages found in our sample), but indicates that the sensitivity to cost *steadily diminishes* the older one gets. This is consistent with the LCM result showing that the older segment was less money-sensitive than the younger one, but allows that taste heterogeneity to be expressed in a different way.

Table 16. Comparison of Two Binary Logit Models with and without Interaction Terms

Variable Name	Model 1 (w/o interaction terms)		Variable Name	Model 2 (w/ interaction terms)	
	Coefficient	P-value		Coefficient (value when age = 18, 87)[d]	P-value
Constant	-0.191	0.583	Constant	-0.327	0.292
Post-purchase satisfaction perception difference[a]	0.424	0.000	Age * pps_D[c]	0.0100 (0.180, 0.869)	0.000
Convenience perception difference[a]	0.594	0.000	Age * convenience_D[c]	0.0129 (0.232, 1.123)	0.000
Broadband internet accessibility at work	0.575	0.122	Age * bbw[c]	0.0145 (0.261, 1.262)	0.041
Context-specific cost difference[b]	-1.453	0.000	Age * cost_D[c]	0.0269 (0.485, 2.343)	0.064
			Context-specific cost difference[b]	-2.670	0.000
Valid number of cases, N		373			373
Final log-likelihood, LL(**b**)		-176.149			-168.396
Log–likelihood for equally-likely (EL) model, LL(0)		-258.544			-258.544
Number of estimated parameters		5			6
ρ^2		0.319			0.349
Adjusted ρ^2		0.299			0.325

[a] See Table 10 for definition.
[b] See Table 10 for definition.
[c] We abbreviate the variable names to fit the table size, they correspond to the names which are in the 1st column for the same row.
[d] The lowest and highest ages in the sample.
Note: the adjusted ρ^2 chi-squared test for these two non-nested models shows that model 2 is significantly better than model 1, with a p-value of 0.00007.

Which way is better? The ρ^2 GOF measure is still higher for the LCM (0.365) than for the interaction-terms model (0.349), but requires six more parameters to achieve it. The adjusted ρ^2 measure, which penalizes for lack of parsimony, is actually higher for the interaction-terms model (0.325) than for the LCM (0.318). The adjusted rho-squared test for non-nested models cannot be performed in this case[12], but it can be argued on the grounds of parsimony, simplicity, and the numerically better adjusted ρ^2 that the interaction-terms model is superior in this instance.

5.7 Conclusions

This study modeled shopping channel intention (store versus internet) with respect to a future purchase of a book/CD/DVD/videotape (final N=373), with particular attention to shopping attitudinal factors and the taste heterogeneity of the population. In view of the targeted (and choice-based) nature of the sample, we do not claim that our models per se are necessarily representative of a broader population. However, it is possible that the multivariate relationships between variables, as expressed by the models, are more generalizable than the univariate distributions of those variables are (Babbie, 1998; Brownstone, 1998). In any case, the methodology is generally applicable, and our specific empirical results are of interest in that internet-literate residents of university communities may serve as harbingers of future adoption in the population as a whole.

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[12] Under the null hypothesis that the model with the lower adjusted ρ^2 is the true model (model 1), then the probability of finding a model with an adjusted ρ^2more than z points greater is bounded by the expression $\Pr[\bar{\rho}_2^2 - \bar{\rho}_1^2 > z] \le \Phi\left\{-\left[2Nz \ln J + \left(K_2 - K_1\right)\right]^{1/2}\right\}, z > 0$ (Ben-Akiva and Lerman, 1985). In our case, with z=0.007 (the difference in adjusted ρ^2s between the two models), N = 373, J = 2, K_2 = 6, and K_1 = 12, the argument of the square root function in this expression becomes -2.380. In such cases, the test cannot be performed, as is implicitly remarked in Ben-Akiva and Swait (1984).

Our original expectation was that our best model would be the LCM, and it was only a question of whether it was empirically enough better than more conventional deterministic market segmentation models to justify the added conceptual complexity. Instead, we found the LCM playing a different role: rather than being the apex of the model-building process, it became more of a signpost along the way. Specifically, development of the class membership component of the LCM pointed toward an improvement in the specification of the unsegmented model (i.e., the inclusion of interaction terms) whose outcome turned out to be superior to that of the LCM.

Latent class modeling is still a powerful tool, in that it can help identify the set of variables that best addresses the taste heterogeneity *relevant to the choice at hand*; in that respect it can replace a great deal of ad hoc stumbling around to develop the "best" deterministic segments. But then rather than stopping there, the LCM results can point toward improving an unsegmented (or deterministically-segmented) model. Two reasons to expect results even better than LCM from this process are that (1) an unsegmented model with interaction terms (such as our best model turned out to be) could be considerably more parsimonious than a LCM, which has a full set of choice model coefficients for each segment, plus segment membership model coefficients for each class except the base; and (2) the LCM (in its standard form) assumes constant choice model coefficients within segment, which may or may not be the best reflection of reality in any given application. It is possible to allow the choice model coefficients of the LCM to be randomly-distributed (i.e. constituting a mixed logit model within an LCM) – an extension we leave for future analysis of these data – but even that complex structure may not represent reality better than coefficients of an unsegmented model that are simple functions of variables explaining taste heterogeneity (linear functions of age, in the present case).

Our empirical results can be summarized as follows. The single variable age offers a valuable means of delineating taste heterogeneity in this application context, revealing (in the LCM) two segments with substantively different tastes, or (in the pooled model with interaction terms) coefficients whose magnitudes are intensified or diminished with age. In general, the impacts of post-purchase satisfaction, convenience, and work-based broadband internet accessibility increase with age, while the sensitivity to cost decreases. These are generally logical results, suggesting that money is more critical to the young, while convenience and time are more important to older shoppers. We speculate that age may be an efficient marker for the complex impacts of a bundle of variables with which it is correlated (e.g., employment status (+), internet usage diversity (–), time consciousness (–), and income (+)).

6. TASTE HETEROGENEITY FOR CLOTHING PURCHASES

Following the analysis in Chapter 5, in this chapter, clothing purchases are analyzed. At first, we tried to conduct a parallel analysis to that of Chapter 5 for the book subsample, however the results turned out substantially different. The LCM result was decidedly unsatisfying, which motivated us to mainly focus on the LR-with-interaction-terms approach. Eventually, we developed a conventional logistic regression model with interaction terms as our "best" model, whose result indicated that the functions describing the coefficients take non-linear forms. In view of that finding, the unsatisfying LCM result is not too surprising.

In this chapter, after introducing the selected characteristics of the sample, the general approaches to accommodating taste heterogeneity will be briefly reviewed. Then the methodology and modeling results will be presented, ending with the conclusions.

6.1 Selected Characteristics of the Sample

As we already know, among the 903 cases in our final working sample, 453 cases involved a recent clothing purchase, which is our target sample in this chapter. The final model has only 310 cases due to missing data on variables included in the model.

Table 17 presents a few major characteristics of the sample, including sample statistics for the variables significant in the final model. Average traits include being middle-aged (47), more likely to be female (60%) than male (40%), and having education beyond a four-year college or technical school degree. About 77 percent of the households have

Table 17. Selected Characteristics of the Sample (clothing cases)

Characteristic (sample sizes)	**N (%)**
Total number of cases	453
Number of females (452)	272 (60.2)
Average age (years) (441)	46.8
Average educational level [a] (453)	5.42
Annual household income (426)	
Less than $15,000	17 (4.0)
$15,000 to $29,999	30 (7.0)
$30,000 to $49,999	53 (12.4)
$50,000 to $74,999	89 (20.9)
$75,000 to $124,999	145 (34.0)
$125,000 or more	92 (21.6)
Home internet access [b] (452)	
Low speed	93 (20.6)
Broadband	364 (80.4)
Work internet access [b] (443)	
Low speed	21 (4.7)
Broadband	334 (75.4)
	Mean (s.d.)
Shopping attitudinal factors	
Shopping enjoyment	0.070 (0.807)
Trustingness	0.005 (0.722)
Post-purchase satisfaction [c]	1.016 (1.626)
Efficiency and inertia [c]	1.166 (1.523)
Financial/identity risk [c]	-0.940 (1.154)
Enjoyment [c]	0.276 (1.582)
Purchase experiences	
Context-specific cost difference [d]	-0.320 (0.672)

[a] 1=Some grade school or high school; 2=High school diploma or equivalent; 3=Some college or technical school; 4=Two year college associates degree; 5=Four year college/technical school degree; 6=Some graduate school; 7=Completed graduate degree(s).
[b] Categories are not mutually exclusive.
[c] Difference between channel-specific perceptions: store factor score minus internet factor score.
[d] A qualitative measure of the perceived cost difference between store and internet with respect to the recent purchase; a higher value means the store channel costs more (-1=store is cheaper; 0=about the same price; 1=store is more expensive).

annual incomes higher than $50,000. More than 75 percent of the respondents also have broadband internet access either at work or at home. Again, the attitudinal factor scores were discussed when those variables were introduced in Section 3.2.2.

6.2 Approaches for Accommodating Taste Heterogeneity

The issue of taste heterogeneity, and the basic solution of market segmentation, has, of course, been longstanding in marketing research as well as in transportation (see Section 2.3 for more details). A number of different approaches have been developed to account for taste heterogeneity (Table 18, also see the introduction chapter and Figure 1 in Section 5.2). In this section, we will systematically and briefly review those approaches. For the purposes of discussion, we will assume the context is that of a discrete choice model such as we are developing here, but the discussion applies equally well to a regression or other type of model.

One of the oldest approaches is to segment the sample on the basis of variables expected to be associated with heterogeneity of coefficients (where the segmentation variables are either used singly, crosstabulated, or combined in a cluster analysis), and estimate different choice models for each segment, an approach we call deterministic segmentation. This approach is methodologically straightforward, but can involve a number of somewhat cumbersome steps (developing a segmentation scheme, specifying a "best" choice model for that segmentation, testing whether the segmented model is statistically superior to the pooled model, possibly testing individual coefficients for differences across segments, possibly pooling the sample to estimate some coefficients but retaining segment-specific coefficients for other variables – and repeating the process for a number of different segmentation schemes to see which one is "best"). A typical result is a choice model (some or all of) whose coefficients differ across a small number of deterministically-defined segments, but are constant within segment.

Table 18. Comparison of Approaches to Addressing Taste Heterogeneity

	Nature of segmentation	**Role of segmentation variables**	**Nature of choice model coefficients**
Deterministic segmentation	discrete	deterministically define segments	constant within segment
Latent class models	discrete	influence probability of segment membership	constant within segment
Random coefficient models	(usually) continuous	often implicit, but could be used to parameterize the parameters characterizing the distributions of the random choice model coefficients (e.g., expressing the mean of a random coefficient as a linear function of several other variables)	random variables, defined by the parameters of their assumed distributions (or, by the parameters of an assumed function of segmentation variables)
Interaction terms	continuous	moderate the values of choice model coefficients	deterministically vary as a function of segmentation variables

Latent class models also result in a (generally small) number of segments, where choice model coefficients (may) differ between segments but are constant within segment. The difference is that the segmentation is no longer deterministic but stochastic. There are assumed to be a finite number of segments (or classes) in the population, however class membership for any given individual is not known, but rather is probabilistically modeled as a function of variables expected to be associated with heterogeneity of tastes. Coefficients for both the class membership model and the segmented choice model are estimated simultaneously, and thus the classes are defined specifically so as to best discriminate between different market segments with respect to the choice in question (see Magidson and Vermunt, 2003 for more details). Accordingly, ceteris paribus, the LCM approach would be expected to be superior to the deterministic segmentation approach, in which the segmentation occurs in an ad hoc separate stage from the choice model estimation. LCM has been used extensively in marketing research (Greene, 2003; Louviere et al., 2005), and to a lesser extent in the transportation field out of which this study arose (Bhat, 1997; Walker and Li, 2007). However, to date we are aware of only one other application to modeling shopping channel choice or intention (Bhatnagar and Ghose, 2004).

More recently, random-coefficient models (RCMs) have become quite trendy, exemplified by the mixed logit model (Greene and Hensher, 2003). In this approach, choice model coefficients are assumed to vary randomly across the population according to a given distribution (e.g. normal), and the parameters of that distribution (e.g. means, variances, and covariances) are estimated. Segmentation variables often do not play an explicit role in this approach, but it is possible to parameterize the means (and other parameters) of the coefficient distributions, expressing them as functions of hypothesized segmentation variables (Greene and Hensher, 2007).

The fourth method presented in (the last row of) Table 18 is probably the oldest approach used to address taste heterogeneity, but of late has been somewhat eclipsed by the theoretically more sophisticated LCM and RCM methods. We refer to the practice of incorporating interaction terms into a conventional choice model (Scarpa et al., 2003). This approach, in essence, models the choice model coefficients as functions of segmentation variables. For example, if we hypothesize that a cost advantage of the internet over store is less important the higher an individual's income is, we could model the coefficient of COST, β_{cost}, as

$$\beta_{cost} = \beta_{cost,0} + \beta_{cost\ x\ inc}\ \text{INC}.$$

Rewriting ($\beta_{cost,0} + \beta_{cost\ x\ inc}$ INC) COST as $\beta_{cost,0}$ COST + $\beta_{cost\ x\ inc}$ INC x COST shows that we can reflect this hypothesis through the simple inclusion of the interactive term INC x COST (together with the original COST variable) in an otherwise conventional choice model. The result is a model whose "original" coefficients are allowed to vary continuously (if the interacted variable is continuous), as deterministic functions of segmentation variables. Those functions generally are, but do not need to be, linear.

This approach differs from RCM with parameterized coefficient distributions in that for RCM, an individual's coefficient is still considered to be a random variable – a function of segmentation variables which determine, in effect, the class mean coefficient (across cases falling into the class defined by specific values of those segmentation variables), plus a stochastic term representing the deviation of an individual from the mean of her class. To continue the above example, the RCM approach would model β_{cost} as $\beta_{cost} = \mu_{\beta cost} + \varepsilon_{\beta cost}$, and then parameterize μ as $\mu_{\beta cost} = \beta_{cost,0} + \beta_{cost\ x\ inc}$ INC. Everyone with the same value of INC would have the same $\mu_{\beta cost}$, but would have an individual-specific deviation from $\mu_{\beta cost}$ represented by $\varepsilon_{\beta cost}$.

The interaction terms approach, by contrast, in effect deterministically assigns the class mean coefficient ($\beta_{cost,0} + \beta_{cost\ x\ inc}$ INC) to every member of the class (everyone with the same value of INC) – there is no error term. But this approach, in turn, differs from deterministic market segmentation, by effectively allowing an infinite number of "class" variations to arise, since (in general) each segmentation variable (INC, in our example, but any number of variables could in principle be accommodated in combination) can vary continuously. In principle, each case could have a uniquely-determined coefficient (if no two people had the same combination of values on all the segmentation variables), but modeling it as a continuous function of the segmentation variables allows the information from all the cases to be used simultaneously in estimating the relationships of the segmentation variables to the choice model coefficient. In deterministic market segmentation, by contrast, there are only a finite (usually small) number of segments (e.g. low, medium, and high INCs in our example), and at least initially[13], information from one segment does not influence the estimation of coefficients for a different segment (i.e.

[13] A final, hybrid model may pool the data and allow some coefficients to remain segment-specific while others are pooled. The pooled coefficients use the information in the entire sample, but then they are only constants across the entire sample, not continuously-varying as in the RCM and interaction terms approaches.

segments are independent). Thus, the interaction terms approach allows for complete pooling of the information available in the sample, whereas deterministic market segmentation sequesters the information in one segment away from that of another segment, reducing the precision with which choice model coefficients can be estimated.

It is important to realize that among the interaction-term, LCM, and (constant-parameter) RCM approaches, none of them is theoretically or practically superior to the others. LCM allows the segments to be identified endogenously (in a stochastic manner), but still makes the restrictive assumptions that there are a finite (usually small) number of segments, and that choice-model coefficients are constant within segment. RCMs are theoretically appealing in that they postulate individually-unique choice-model coefficients, but require sometimes arbitrary assumptions on the distributions of those coefficients, and any given parametric distribution may only be an approximation to the true population distribution of a particular coefficient. Further, unlike the other methods, this approach generally does *not* (yet) explicitly associate variations in choice-model coefficients with other observed variables (i.e. segmentation variables), i.e. it most often does *not* parameterize the choice model coefficient parameters. The result is a model that is methodologically sophisticated but may be limited in its behavioral insight. Incorporating interaction terms into a conventional model, on the other hand, is relatively straightforward methodologically, but still requires an assumption on the functional form of choice model coefficients, and the resulting model can sometimes be difficult to interpret, as we experienced while conducting this study. Multicollinearity can also be a concern with this approach, in view of the correlations among original variables and interaction terms.

In this study, we focus on the LCM and interaction-term approaches. Our choice was partly idiosyncratic, but was based on our interest in understanding the sources of taste heterogeneity in this context (which made the RCM approach less appealing, at least as it is currently most-often applied). We are particularly attracted to the explicit role played by the segmentation variables in the interaction-term approach. In the parlance of evaluation and psychometric research, these variables are *moderators* of the impact of the choice model variables on choice. Wu and Zumbo (2008) characterize a moderator using the vivid analogy of a “dimmer switch”, turning the choice coefficient “up” or “down” depending on its (the moderator’s) value. They further speculate that moderators are likely to be fairly stable individual traits (such as gender and general attitudes), as opposed to more temporary conditions (such as, in our context, channel-specific attitudes regarding the recent purchase). This helps simplify our model specification task by suggesting, at the outset, which variables to classify as segmentation variables and which as choice model variables. Note that class membership model variables in an LCM (and segmentation variables in a deterministically-segmented model) can also be viewed as moderators, though in those cases the outcome is not a continuously-varying choice model coefficient, as the dimmer-switch analogy suggests, but rather one of a set of possible discrete values the coefficient can take on (states for the “switch” to be in).

6.3 Methodology and Model Results

6.3.1 Methodology and Model Specification

As mentioned in Section 6.2, in this chapter we focus on the LCM and LR-with-interaction-terms approaches. An important element common to both of those approaches is the need to decide which variables are likely to be associated with the taste heterogeneity of the population, that is, to identify the segmentation variables. Following the suggestion of Wu and Zumbo (2008) that moderators (our segmentation variables) are likely to be fairly stable individual traits, we can group the moderators in our context into three categories: general shopping-related attitudes (such as shopping enjoyment, caution, pro-technology, trust, and time consciousness), sociodemographic characteristics (such as gender, age, education, and income), and usage of ICT (such as an overall internet usage index variable). To further understand how effects on choice may differ by segmentation variable, some example hypothesized relationships (particularly tested in this study) are provided in Table 19.

Using all potential segmentation variables in the above three categories, we started with the LCM approach. The best model we found was a 2-class LCM without any "real" segmentation variables (i.e. in which the class membership model only consists of a constant term). That model is unsatisfying since it indicates that taste heterogeneity exists, without illuminating its source. Then we switched to the interaction-term approach. We first created several interaction terms by multiplying potential choice model variables (mainly the channel-specific perceptions shown in Table 5) with related segmentation variables (especially the general shopping-related attitudes, based on the conceptual

Table 19. Examples of How Effects on Choice May Vary by Segmentation Variable

Hypothesized segmentation variable category (moderators)	**Example hypothesized impacts of segmentation variables on weights**
General shopping-related attitudes	People who more readily trust others will put less weight on the perceived risk associated with a given shopping channel.
	People who are more cautious will put a heavier weight on the perceived risk associated with a given shopping channel.
	People who are more time-conscious will put a heavier weight on the perceived time savings associated with a given shopping channel.
	People who are more price-conscious will put a heavier weight on the perceived cost savings associated with a given shopping channel.
	People who enjoy shopping in general will put a heavier weight on the perceived enjoyment associated with a given channel.
Sociodemographic variables	People who have high income and are more educated will put a heavier weight on the "Time savings" / "Convenience" / "Ease of use" perceptions of a given shopping channel.
	Women will put a heavier weight on the perceived enjoyment associated with a given shopping channel.
Use of ICT	People who use the internet a lot may put a lower weight on the perceived ease of use of the e-shopping channel.

hypothesis that underlying attitudes are a likely source of taste heterogeneity).

Specifically, we created 13 interaction terms[14] (pps_D * AshopEnj, cost_D *Aprice, idrisk_D * Atrust, enjoy_D * AshopEnj, and so on). Testing these 13 interaction terms, together with all other potential choice model variables, led to an LR-with-interaction-terms model containing three interaction terms: pps_D * AshopEnj (where "pps" stands for the post-purchase satisfaction factor defined in Table 5 of Section 3.2.2, and similarly for the others), idrisk_D * Atrust and enjoy_D * AshopEnj. However, the signs of the three interaction terms were difficult to explain and counterintuitive for part of the sample. This result inspired us to speculate that the coefficients of choice model variables were possibly not pure linear functions of the corresponding segmentation variables. We then decided to create more specific interaction terms, defining different groups for people having different general attitudes.

Originating from the three significant interaction terms (pps_D * AshopEnj, idrisk_D * Atrust and enjoy_D * AshopEnj), we then created the following new variables:

1) Dummy variables (DVs) for people who trust more/less than average (DVtrustP/DVtrustN) and dummy variables for people who enjoy shopping more/less than average (DVenjoyP/ DVenjoyN):

   E.g. DVtrustP = 1 if Atrust > 0, and 0 else, with DVtrustN = 1- DVtrustP.

[14] For economy of expression, we use variable abbreviations here. The first part of the interaction term is the potential choice model variable (where "_D" represents the Difference between store and internet measures on that variable), and the second part is the related segmentation variable (where "A" refers to the variable being a factor score based on the attitudinal statements in Part A of the survey).

The enjoyment dummy variables were created similarly.

2) Trustingness and shopping enjoyment attitudes interacted with their respective DVs: AtrustP, AtrustN, AenjoyP and AenjoyN.

   E.g. AtrustP = Atrust * DVtrustP (i.e. AtrustP = Atrust if Atrust > 0 and 0 else) and AtrustN = Atrust x DVtrustN (i.e. AtrustN = Atrust if Atrust < 0 and 0 else);

   AenjoyP and AenjoyN were created similarly.

3) Interactions of choice model variables (pps_D, idrisk_D and enjoy_D) with the above newly-created variables:

   E.g. idrDVtrustP = idrisk_D * DVtrustP; idrDVtrustN = idrisk_D * DVtrustN and idrTrustP = idrisk_D * AtrustP; idrTrustN = idrisk_D * AtrustN.

   Other variables were created accordingly.

The result is a set of functional forms for coefficients of the choice model variables pps_D, idrisk_D and enjoy_D, which allow the impact of trustingness and enjoyment on those coefficients to differ depending on whether the individual is above or below the average on those two traits. We then used the above new variables to refine the LR-with-interaction-terms model. The best model will be presented and interpreted in the next section. Meanwhile, we also tried to improve the LCM by including those newly-created variables in the class membership model, but we were unable to find a satisfactory result. In short, we iteratively explored two approaches to addressing taste heterogeneity in purchase intentions: a LR-with-interaction-terms model and a LCM. The unsatisfactory elements in the one type of model spurred us to consider refinements in the other.

6.3.2 Model Results and Interpretations

Table 20 summarizes our final LR model for purchase channel intention with respect to a future clothing purchase. Among the 310 cases included in this model, 239 respondents intended to choose store for their next clothing purchase and 71 favored internet. The ρ^2 value (Ben-Akiva and Lerman, 1985) is 0.458, which is considered quite acceptable in the context of disaggregate discrete choice models. The 0.458 value is based on the equally-likely model. Since the market shares are unbalanced (77.1% and 22.9% intended store and internet respectively), the market-share model (the model containing just the constant term) alone has a ρ^2 of 0.224. Re-estimating the final model without a constant term, however, yields a ρ^2 of 0.437, indicating that most of the explanatory power of the model lies in the "true" variables (i.e. they are helping to explain *why* the shares are unbalanced), not just the constant term. Seven variables besides the constant are significant in the model: two channel perception factor score differences (post-purchase satisfaction and efficiency/inertia), three interaction terms[15], one purchase experience

[15] They are the post-purchase satisfaction and enjoyment perception differences respectively interacted with the dummy variable representing cases who enjoy shopping more than average, and the financial/identity risk perception difference interacted with more-than-average trustingness. For economy of expression, we use abbreviated variable names – "ppsDVenjoyP", "enjDVenjoyP" and "idrTrustP" – to represent those three interaction terms hereafter (see Section 6.3.1 for how they were created).

Table 20. Logistic Regression Model of Intended Channel for Next Clothing Purchase (1 = Store, 0 = Internet)

Variable Name	Coefficient	P-value
Constant	.861	.003
Channel perception differences		
Post-purchase satisfaction [a]	.920	.000
Efficiency and inertia [a]	.340	.006
Interaction terms		
pps_D * DVenjoyP (ppsDVenjoyP)	-.638	.011
idrisk_D * AtrustP (idrTrustP)	-1.241	.001
enjoy_D * DVenjoyP (enjDVenjoyP)	.632	.000
Purchase experiences		
Context-specific cost difference [b]	-1.355	.000
Sociodemographics		
Female	-1.262	.001
Valid number of cases, N	310 (S: 239; I: 71) [c]	
Final log-likelihood, LL(β)	-116.382	
Log-likelihood for market share model, LL(MS)	-166.812	
Log–likelihood for equally-likely (EL) model, LL(0)	-214.876	
No. of explanatory variables, K (including constant)	8	
$\rho^2_{ELbase} = 1 - LL(\beta) / LL(0)$	0.458	
Adjusted $\rho^2_{ELbase} = 1 - [LL(\beta) - K] / LL(0)$	0.421	
χ^2 (between final model and the EL model)	196.988	
χ^2 (between the final model and the MS model)	100.860	

[a] Difference between the store-specific and internet-specific factor scores.
[b] See Table 17 for definition.
[c] S and I represent store and internet respectively.

variable (context-specific cost difference), and the female indicator variable. We discuss each in turn.

Not surprisingly, the more positively store is perceived relative to the internet on post-purchase satisfaction and efficiency/inertia, the more likely store is to be the intended channel for the next purchase. Therefore, both these coefficients have positive signs. With respect to post-purchase satisfaction, both the original variable and its interaction term counterpart ("ppsDVenjoyP") are significant. The interaction term has a negative sign (-0.638). These two variables have the nice interpretation that the total impact on utility of changing pps_D by one unit is equal to (0.920 - 0.638 * DVenjoyP). In our case, the "DVenjoyP" variable can only take on two values: 0 (when the general shopping enjoyment factor score is negative) or 1 (when it is positive); therefore, the coefficient of pps_D remains positive for everyone, as expected. It is equal to either 0.282, for those people who enjoy shopping more than average, or 0.920 for those who do not. The interpretation is that the degree to which store is superior to internet on post-purchase satisfaction (or conversely) is considerably more important to those who *don't* enjoy shopping than it is for those who *do*.

Two other interaction terms also enter the model. *Financial/identity risk interacted with more-than-average trustingness* ("idrTrustP"): For 79% of respondents, idrisk_D is negative, indicating that the internet is perceived as being more risky than store in this respect. A negative coefficient on this variable would be expected, meaning that the wider (more negative) this difference, the more likely the respondent is to intend store for the next purchase. The negative coefficient (-1.241) on the interaction of idrisk_D with AtrustP indicates that the expected effect of idrisk_D is magnified linearly for people who trust *more* than average, and insignificant for those who trust *less* than average. This may be in part because those who trust less than average perceive a smaller gap between channels in terms of their risks (with a mean absolute gap of 1.12) compared to those who trust more than average (mean absolute gap of 1.22), since, as is well known, credit card information can be stolen in stores as well as online. Also, perhaps those who trust less are pessimistic that perceived differences in risk are particularly meaningful. In any case the result for the "trusters" means in essence that the more trusting such people are, the more weight they put on whichever channel they perceive to be more trustworthy, i.e. the more likely they are to intend that one to be the channel for their next clothing purchase.

Enjoyment interacted with the dummy variable representing cases that enjoy shopping more than average ("enjDVenjoyP"): This coefficient indicates that the perception that one channel is more enjoyable than the other (measured by enjoy_D) is only relevant to intention for those who fundamentally enjoy shopping. While this is certainly a reasonable result, it is a nuance that could easily have been overlooked.

Figure 4 helps us visualize the estimated coefficient functions for the three variables with moderated effects. For pps_D and enjoy_D, the coefficients appear as step functions because the two moderators are dummy variables. The graph for idrisk_D illustrates that its coefficient is equal to zero for people who trust less than average, while continuously decreasing with trustingness for those who trust more than average.

It is interesting to note that four channel-specific perceptions are *not* significant in this model: product risk, cost savings, convenience and store brand independence. Although those perceptions are conceptually expected to be significant too, it is possible that their influence is partly reflected by the four perceptions that *do* appear. Each of the perceptions not in the model has significant correlations with the perceptions that *are* in the model. In particular, the convenience difference variable has significant correlations of 0.41 with the post-purchase satisfaction difference variable and 0.46 with the enjoyment difference variable.

One purchase experience variable (context-specific cost difference) is significant in the model, with a negative coefficient. A higher value of this variable indicates that store was perceived to be more expensive than internet for the clothing purchase made recently. As a result, people with higher values are more likely to intend to use the more economical channel – internet – for their next similar purchase.

In addition, a sociodemographic trait – the binary variable for being female – is also significant in the model. Although its negative sign may be counterintuitive, the consistency with the result from one of our previous analyses of this sample (Tang and Mokhtarian, 2009a), together with its appearance in a model of clothing shopping frequency on the same sample (Circella and Mokhtarian, 2009) indicates the robustness of the sign. Originally, we expected women to be more likely than men to intend a store purchase, consistent with the image of men being more pro-technology, and enjoying store shopping less, than women. But in our sample, looking at gender and intention in

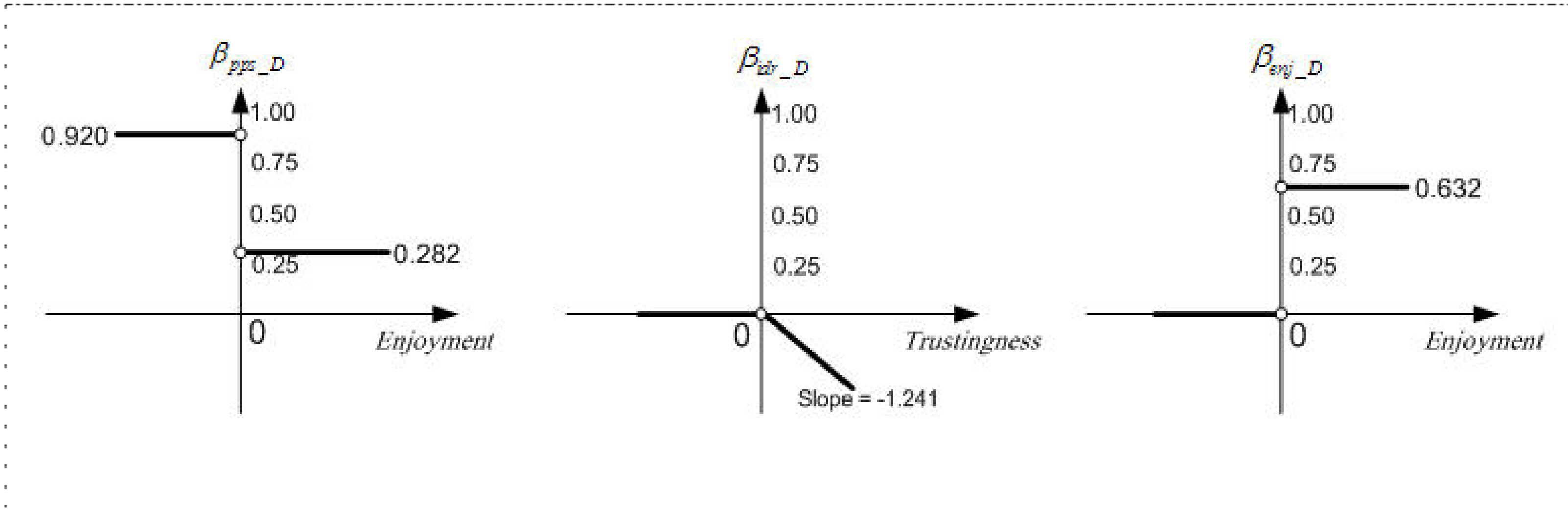

Figure 4. Estimated Coefficients of Intention Model Variables, as a Function of their Moderating Variables

isolation, there is no significant difference in the distribution of intended channel between genders. So the fact that gender is significant in the model means that controlling for other variables is revealing a relationship that was hidden (suppressed) when only the two (i.e. gender and intention) were examined together.

Specifically, it may be partly indicating a time pressure or impulse-buying effect (women are significantly more time conscious and impulse-buying than men in our sample): women, who tend to experience more time pressure than men (e.g. Sayer, 2007), may be more inclined to shop over the internet to save time and/or to more readily indulge their impulsiveness. In addition, combined with the high correlation (0.74) between intention and adoption in our sample, our result is consistent with that of Bhatnagar et al. (2000): they found women to be more likely to adopt internet shopping, particularly for product categories such as books, music and CDs, and apparel and clothing (see Chapter 4 for more details).

6.4 Conclusions

This study modeled shopping channel intention (store versus internet) with respect to a future purchase of clothing/shoes (final N=310), paying particular attention to shopping-related attitudinal factors and the taste heterogeneity of the population. In view of the targeted (and choice-based) nature of the sample, we do not claim that our sample per se is necessarily representative of a broader population. However, it is to be expected that the multivariate relationships between variables, as expressed by the models, are more generalizable than the univariate distributions of those variables are (Babbie, 1998;

Brownstone, 1998). In any case, the methodology is generally applicable, and our specific empirical results are of interest in that internet-literate residents of university communities may serve as harbingers of future adoption in the population as a whole.

Motivated by one of our previous studies (Tang and Mokhtarian, 2009b, i.e. the study in Chapter 5) to address the taste heterogeneity of the population, we focus on two approaches in this chapter: logistic regression modeling with interaction terms, and latent class modeling. Based on a literature review and conceptual considerations, neither approach is clearly superior to the other, so we alternately experimented with the two approaches for several rounds, the unsatisfactory elements in the one type of model spurring us to consider refinements in the other.

In fact, we were unable to find a satisfactory LCM. Given at least one of the non-linear functions of the coefficients (Figure 4) that we ended up with in our final LR model, this may not be too surprising. After all, LCM assumes constant coefficients for a finite (generally small) number of classes. Two of the three moderated coefficients in our final best model are in fact stepwise-constant (as shown in the 1st and 3rd graphs in Figure 4), but the third is "kinked" (i.e. continuously varying over part of the sample, and constant over the remainder; as shown in the 2nd graph in Figure 4). Specifically, the coefficient of the perceived difference (between store and internet) in financial/identity risk is a continuous function of trustingness for the people who are more trusting than average, but stays zero for those who are less trusting than average. The modeling process of this study and our companion analysis (in Chapter 5) of intention for book purchases, together with that of an independent study (Scarpa et al., 2003), supports the contention that no single method of accounting for taste heterogeneity is clearly better than another at the outset – it depends on the actual distribution of the taste heterogeneity in the population.

In this study, our best model is a LR-with-interaction-terms model. The empirical results can be summarized as follows. There are seven variables (excluding the constant term) in our final model: two channel-specific perception factor differences (post-purchase satisfaction and efficiency/ inertia), three interaction terms, one purchase experience variable (context-specific cost difference), and the female indicator variable, all with plausible signs. The interaction terms reflect the taste heterogeneity of the population.

Specifically, with respect to the channel-specific perceptions, both post-purchase satisfaction and efficiency/inertia are constructed as differences between the store and internet, so the greater the differences (in favor of store), the more strongly store is intended. Post-purchase satisfaction ("pps_D"), together with its interaction term counterpart ("ppsDVenjoy"), indicates that the impact on utility of a post-purchase satisfaction comparison is less than one-third as strong for people who enjoy shopping more than average (0.282) as it is for those who enjoy it less than average (0.920). The other two interaction terms ("enjDVenjoyP" and "idrTrustP") have similarly useful interpretations. The purchase experience variable (context-specific cost difference) has a straightforward negative sign: the more expensive store was perceived to be (compared to the internet) for the clothing purchase made recently, the more likely the internet channel is to be intended for the next similar purchase. Finally, we suggest that the negative sign of the female indicator variable means that women, who tend to experience more time pressure and do more impulse-buying than men, may be more inclined to shop over the internet to save time and/or to more readily indulge their impulsiveness.

7. CONCLUSIONS

In this chapter, we will summarize the study and its major results first, followed by the policy implications. In addition, the limitations of the study and directions for future research will be discussed.

7.1 Summary

In this study, our purpose is to answer the two main research questions: (1) "*what are the advantages and disadvantages of each shopping mode?*" and (2) "*can different importance weights on the various factors affecting channel choice be identified for different members of the population?*" so as to better understand people's shopping behavior. Using data collected from an internet-based survey of two university towns in Northern California (N=967) in 2006, we developed several different models to analyze people's intended shopping channel for a future purchase similar to the recent one for which detailed information had just been obtained. We analyzed stated preference (i.e. purchase intention) rather than revealed preference (i.e. purchase choice) because in our context, there is a temporal mismatch between the explanatory variables and shopping channel choice variable, in that the choice took place in the past, whereas the explanatory variables – most problematically, the attitudes – are measured in the present. Ajzen (1991) pointed out that *intentions* represent the motivational components of a behavior, and indicate the degree of effort that people are willing to exert in order to perform the behavior. Therefore, intention for the next choice is very informative, and can help us predict actual behavior even though it may or may not be acted upon as reported.

To better understand e-shopping intention for the next similar purchase, we focus on accounting for taste heterogeneity in this study since (in reality) people are different and each individual has a unique set of tastes, i.e. a distinct set of preference weights (for a given explanatory variable). Generally, there are four approaches to addressing taste heterogeneity (see Section 6.2 for details): (1) Deterministic segmentation: using variables expected to be associated with heterogeneity of coefficients (where the segmentation variables are either used singly, crosstabulated, or combined in a cluster analysis) to segment the population, and estimate different choice models for each segment; (2) Stochastic approach (LCM): simultaneously estimating the membership model and the segmented choice models, where the clusters are defined *on the basis of their ability to best discriminate between different market segments with respect to channel choice*; (3) Random-coefficient models (RCMs), where choice model coefficients are assumed to vary randomly across the population according to a given distribution (e.g. normal), and the parameters of that distribution (e.g. means, variances, and covariances) are estimated; and (4) Conventional choice models with interaction terms, in which the choice model coefficients are essentially modeled as functions of segmentation variables. For the reasons explained in Sections 5.2 and 6.2, in this study we mainly focus on the second and fourth approaches.

In terms of particular modeling methods, we used logistic regression (LR) models, latent class models and LR with interaction terms. Specifically, we first developed three separate LR models for the pooled data, book subsample and clothing subsample, and then found the “best” hybrid LR model by using the collective information indicated by those three models, in which coefficients were either pooled or product-type-specific, as appropriate. The preliminary results showed that there is a certain degree of commonality in the influence of important variables such as post-purchase satisfaction, cost savings, convenience, activeness of searching, and context-specific cost difference. Those variables have essentially equal coefficients for both product types. Despite that commonality, there are also some differences between product types, reflected by the five product-specific variables significant in the final hybrid model (i.e. three for book: dummy variable for book product type, trustingness and store brand independence, and two for clothing: efficiency/inertia and being female). These results indicate that product type matters; we should not ignore it or blindly combine product type in choice or intention models, as many studies have done. With those lessons in mind, we turned to a more in-depth analysis of purchase intentions for each product type separately, with a focus on accounting for taste heterogeneity of the population.

For the reasons described in the Introduction, LCM is theoretically superior to the conventional deterministic two-stage market segmentation approach. As a result, we expect LCM to give us models that have better GOF and interpretability. However, it is relevant to wonder how large the improvement from using LCM is in practical terms, and in particular whether it is sufficiently large to justify the increased complexity of implementation. Accordingly, for the book subsample, we conducted latent class modeling first, then compared its result to the unsegmented model and to models deterministically segmented on the segmentation variable (i.e. age) indicated by the LCM. The outcome surprisingly indicates that the LCM is only slightly better from the statistical perspective, but arguably weaker from the conceptual perspective. However, a model that interacts age with the explanatory variables in the conventional unsegmented model outperforms all the others (though not overwhelmingly so), including the LCM. Thus, the results suggest that using LCM as an initial stage in model exploration allows us to more intelligently specify a model where the taste heterogeneity is (potentially) specified *deterministically* in the end, which often yields a more parsimonious model, and may in fact fit the data better.

For the clothing subsample, we used analytical methods similar to those we employed for the book subsample, but the preliminary results turned out substantially different. We were unable to find an appropriate LCM; the “best” LCM we obtained was a two-class model without any “real” segmentation variable, i.e. whose membership model only contained the constant term. In that case, we have no information about the source of the taste heterogeneity. Thus we turned to the conventional LR model with interactions approach. The results, again, clearly demonstrate the contribution of channel-specific perceptions (post-purchase satisfaction, efficiency/inertia, financial/identity risk, and enjoyment), as well as more conventional variables such as cost and gender. Taste heterogeneity is found to be a function of general shopping enjoyment and trustingness. For example, the impact on utility of post-purchase satisfaction considerations is less than one-third as strong for people who enjoy shopping more than average (coefficient 0.282) as it is for those who enjoy it less than average (0.920).

The detailed modeling results and explanations for each of these three sub-studies can be found in Sections 4.4, 5.6 and 6.4. To conclude, the main findings of the research are: (1) the product type and general and channel-specific shopping attitudes, in addition to previously-identified effects such as sociodemographics, clearly contribute to the purchase intention; (2) it is dangerous (or at least, not appropriate) to analyze e-shopping behavior without regard to product type; (3) empirically, LCM is not always superior to the conventional model with interaction terms. These lessons provide methodological guidance for improving the design of future similar studies and selecting more effective analytical methods. As a result, our understanding of shopping behavior will be improved. Furthermore, the empirical results could provide useful insights to market researchers and retailers, as well as transportation planners. In the next section, we will discuss those in more detail.

7.2 Policy Implications

As described in the Introduction, e-commerce has potential impacts on society in areas such as transportation (particularly with respect to urban travel in terms of mode and frequency), land use patterns (retail store and warehouse location and relocation, including new construction as well as closures), and people's shopping behavior. Furthermore, future air quality and fuel consumption will possibly be affected if the change in transportation demand is substantial. It is obvious that the collective influences on all these aspects could reshape our society if the adoption of e-shopping keeps increasing (as it is doing, indeed) and reaches a certain degree. Thus, the policy[16]

[16] In this study, we include the discussion of suggestions to retailers in the policy category.

implications of the study become important. Those implications have the following aspects:

1) Questions such as "whether or not e-shopping is an effective way to reduce travel" and "is e-shopping a substitute or complement to traditional store shopping" are of interest to transportation planning and forecasting. At first glance, e-shopping seems environmentally beneficial – after all, it evidently replaces a trip to the store – as well as having other advantages such as an extensive selection, rich product information, potentially better prices, flexible schedule, easy access, and so on. However, some previous studies (e.g. Mokhtarian, 2004; Farag et al., 2006; Cao, 2010) have pointed out that the evidence does not support travel reduction while the net effect may well lie in the direction of increasing travel. From a public policy perspective, increasing travel is obviously not a desired direction because it does not help reduce traffic and thereby alleviate traffic congestion, reduce fuel consumption and improve air quality, but deteriorates the situation instead. In addition, several other potential deleterious effects of e-shopping are worth mentioning: (1) e-shopping may involve considerably more packaging (sending one or a few items to each of many homes, in large cardboard boxes) than store shopping does (with bulk packaging and shipping), thereby consuming more resources (Matthews et al., 2001); (2) e-shopping may "suck the retail life" out of small-scale commercial areas (such as mom-and-pop stores in residential neighborhoods, or the central business districts of small towns), and thereby change those areas' economic, social, and physical characteristics (however, the results of Weltevreden and Rietbergen, 2009 are encouraging in this respect); and (3) e-shopping may reduce people's physical activity even more than has already

occurred, thereby contributing further to the obesity epidemic in developed countries (Rajani and Chandio, 2004). However, everything has two sides. Store shopping also has good sides (e.g. tangibility and immediate possession of the product, social interaction outside of home, physical activity benefits, and so on) and bad sides (e.g. the potential congestion and pollution contributions of a physical trip, fixed business hours and limited merchandise availability, and so on). Therefore, we should judge the effects of each shopping channel in a balanced way, by looking at the big picture of its pros and cons. Although our study does not speak directly to these system-level effects such as a change in transportation demand, it helps us better understand e-shopping adoption, which will in turn help in analyzing the transportation and other societal impacts.

2) Our results indicated that the internet is more favorable than the traditional store channel for search goods such as book (see the appearance of the dummy variable for book in the hybrid LR model of Section 4.3.2), which is consistent with the studies of Peterson et al. (1997) and Klein (1998). Therefore, from the perspectives of consumer preference and technological feasibility, it is reasonable to encourage people to purchase more search goods online rather than in stores, to help reduce physical shopping trips, reduce peak hour congestion, and in turn reduce fuel consumption and improve air quality. For example, the book model in Section 4.3.1 indicates that cost savings and convenience have positive impacts on choosing online shopping (for book), thus e-retailers can effectively attract more customers by marking down book prices and improving the convenience of online ordering.

3) Channel-specific perceptions such as post-purchase satisfaction, cost savings, efficiency and inertia, and convenience appeared in most of our final models. The more favorable the channel was with respect to any of those variables, the more likely *that* channel would be intended (as the shopping channel for the next similar purchase). Therefore, to increase the adoption of internet shopping, retailers should try to maintain/improve those favorable characteristics of online shopping and try to minimize people's concerns regarding trust, transaction risk, product risk, and so on. In addition, cost is a robust variable for most of our models as well. So reducing the product cost offered via one channel compared to its cost via others would tend to be an effective way to increase the choice of that channel (although, as some studies have shown, it is not a fully-guaranteed way). In short, with the roles of various factors in shopping channel intention, and the nature of population heterogeneity with respect to those roles, useful insights are provided to market researchers and retailers.
4) Modeling shopping intention for a future similar purchase provides a certain degree of insight to transportation planners. Specifically, the model results indicate the probability of intending to choose each shopping channel, given values on the explanatory variables. Making assumptions about the distributions of the explanatory variables in the population, as well as the correlation of channel intentions and adoptions, we could roughly predict the shares of each channel being adopted for the "next" purchase. Together with assumptions on the extent to which each online shopping transaction replaces a physical trip, that information could be useful input for transportation planners to forecast changes in travel demand. By better understanding people's online shopping behavior, it also increases planners'

awareness of its impacts and helps them develop effective strategies for locating facilities wisely, such as whether or not it is worth relocating the warehouse.

7.3 Limitations and Future Research Directions

Although this study makes a number of contributions from the above-mentioned perspectives, it has several limitations:

1) Because in this study our purpose is identifying relationships among the variables we measure (rather than reporting the descriptive statistics of various measures of interest and then expecting them to reflect the population), we wanted to have a substantial number of e-shopping occasions in the sample, and thus conducted choice-based sampling (Ory and Mokhtarian, 2007). As a result, descriptive statistics will be biased although the multivariate modeling results may be reasonably representative of the highly computer-literate, student-rich, relatively affluent population from which the sample was drawn. However, in view of the targeted (and choice-based) nature of the sample, those models are not necessarily representative of a broader population.
2) Among the two main components of an analysis of the transportation impacts of B2C e-commerce (i.e. assessing the transportation impacts for a given level or pattern of B2C e-commerce adoption and assessing the level/pattern of adoption), this study only focuses on the latter issue. While the transportation planners' ultimate goal is to forecast transportation impacts by predicting changes in future traffic demand, to do so, they need to accurately understand adoption processes and trends. The results of our study will assist that ultimate goal, but falls short of providing quantitative

information on the transportation impacts of the adoption/intentions behavior we analyze.

3) The product types studied in depth are very limited (book/CD/DVD/videotape to represent search goods and clothing/shoes to represent experience goods) and cannot fully represent all types of goods purchased online. In addition, in-depth data on only two shopping channels (usually store and internet, the only two channels analyzed in this study) are obtained in any given version of the survey. These make it uncertain to generalize the results to other product types and possible shopping channels.
4) As mentioned in Section 3.2.1, the survey we used to collect data essentially measured the updated attitudes, which are more relevant to the next choice, rather than the previous attitudes related to the last choice. Although *intentions* represent the motivational components of a behavior and indicate the degree of effort that people are willing to exert in order to perform the behavior, there is still possibility that the planned behavior (i.e. the intended shopping channel for the next purchase) will not be enacted later on. And after all, what really affects transportation is the *actual* shopping channel choice, not the intended choice, so these results can only be considered suggestive, not definitive.

Several directions for future research are indicated. Using the same data set: (1) We could explore people's shopping channel adoption instead of future intention, and then compare the results to those obtained here, to identify variables significant to choice but not intention, and conversely; (2) It would separately be valuable to create a new dependent variable reflecting the change (if any) between channel adoption and the successive intention, using multinomial logit or Markov models to investigate variables associated with changing; (3) We can continue to refine the model specifications, for example by allowing the choice model coefficients of the LCM to be randomly-distributed, but even that complex structure may not represent reality better than coefficients of an unsegmented model that are simple functions of variables explaining taste heterogeneity; (4) It would also be valuable to analyze and model the choice of pre-purchase/purchase channel combinations (such as the use of store to gather information but internet to purchase, or conversely) since: a) pre-purchase choice could possibly involve physical trips and thereby affect future transportation demand; and b) pre-purchase channel choices could be an important indicator for future purchase intentions as well as adoptions.

In addition, it would be valuable to collect new data in light of the results and limitations of this study. When we conducted the latent class modeling, it was difficult to obtain satisfactory models. This might be partially because our data did not include repeated observations for each individual, but only a single intention (and single choice) instead. In addition, the temporal mismatch between the measured channel perceptions and purchase adoption (as mentioned above and in Section 3.2.1) is another drawback of our current data. Therefore, obtaining longitudinal data in which both purchase and attitude measurements are taken across a period of time will help to improve the model specifications and yield more insightful results. Furthermore, considering the limitation that only two product types were included in the current dataset, involving more product types when collecting new data would be highly desirable as well.

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