Three Essays on Consumer Behavior under Uncertainty

by

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ABSTRACT

It is well understood that decisions made under uncertainty differ from those made without risk in important and significant ways. Yet, there is very little research into how uncertainty manifests itself in the most ubiquitous of decision-making environments: Consumers' day-to-day decisions over where to shop, and what to buy for their daily grocery needs. Facing a choice between stores that either offer relatively stable "everyday low prices" (EDLP) or variable prices that reflect aggressive promotion strategies (HILO), consumers have to choose stores under price-uncertainty. I find that consumers' attitudes toward risk are critically important in determining store-choice, and that heterogeneity in risk attitudes explains the co-existence of EDLP and HILO stores —an equilibrium that was previously explained in somewhat unsatisfying ways. After choosing a store, consumers face another source of risk. While knowing the quality or taste of established brands, consumers have very little information about new products. Consequently, consumers tend to choose smaller package sizes for new products, which limits their exposure to the risk that the product does not meet their prior expectations. While the observation that consumers purchase small amounts of new products is not new, I show how this practice is fully consistent with optimal purchase decision-making by utility-maximizing consumers. I then use this insight to explain how manufacturers of consumer packaged goods (CPGs) respond to higher production costs. Because consumers base their purchase decisions in part on package size, manufacturers can use package size as a competitive tool in order to raise margins in the face of higher production costs. While others have argued that manufacturers reduce package sizes as a means of raising unit-prices (prices per unit

of volume) in a hidden way, I show that the more important effect is a competitive one: Changes in package size can soften price competition, so manufacturers need not rely on fooling consumers in order to pass-through cost increases through changes in package size. The broader implications of consumer behavior under risk are dramatic. First, risk perceptions affect consumers' store choice and product choice patterns in ways that can be exploited by both retailers and manufacturers. Second, strategic considerations prevent manufacturers from manipulating package size in ways that seem designed to trick consumers. Third, many services are also offered as packages, and also involve uncertainty, so the effects identified here are likely to be pervasive throughout the consumer economy.

To my wife Ai Tee Koo

for my son Ryo Yonezawa

with thanks to my mom Kimiko Yonezawa

and in memory of my dad Akihiro Yonezawa

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PREFACE

This dissertation is written in a three-essay style. However, each essay deals with the subject related to consumer behavior under uncertainty and firm optimal response. Chapters 1 and 5 provide an introduction and conclusion applicable to all three essays. Chapters 2, 3, and 4 are self-contained and independent from one another in terms of notations and equations.

CHAPTER 1.

INTRODUCTION

In 2013, US consumers spent over $579 billion on groceries, or consumer packaged goods (CPG) (U.S. Census Bureau 2014). Despite the industry's fundamental economic importance to consumer welfare, some practices, whether in retailing or manufacturing, appear to be far from efficient, or at least consistent with what we understand as competitive behavior. First, some retail stores offer prices that vary considerably from week to week (the HILO model used by Kroger, for example), while others offer prices that are relatively constant (the everyday-low-price, or EDLP model used by Walmart). According to standard economic theory, two store formats should not be able to coexist in an efficient, competitive market. Second, most new products ultimately fail. Every year, more than 1,500 new brands are launched in the CPG market, but nearly 80 percent of them failed to achieve more than $7.5 million in year-one sales (SymphonyIRI 2012a). Third, when costs increase, manufacturers appear to reduce package sizes, raising unit-prices in a way that is not readily apparent to consumers. In 2011, Heinz reduced the size of its ketchup products by an average of 11%, but maintained package prices (McIntyre 2011). These observations appear disparate, but may have a common cause. Namely, if suppliers – manufacturers and retailers – are rational, and consumers make decisions in an environment of chronic uncertainty, then pricing and product design decisions are fundamentally shaped by considerations of risk. In this dissertation, I examine these two examples and show that they are not market failures, but rather rational responses to pervasive sources of uncertainty.

There are two sources of uncertainty: (1) unfamiliarity with the product, or attribute uncertainty, implying a lack of information about how the product fits an individual's preferred attribute set, and (2) price variability over time and source, implying a lack of information about price. Attribute uncertainty largely derives from the fact that when consumers purchase an unfamiliar product, they cannot know whether it will meet their prior expectations. While product information such as nutritional and caloric content is observable on package labels, taste and aroma are inherently indeterminable until the product is purchased and used (or experience goods in the terminology of Nelson (1970)). Price uncertainty, on the other hand, cannot be perfectly resolved through experience. Even through substantial purchase or usage experience, consumers cannot have complete price information because prices vary from day to day and from place to place due to price discounting. Attribute uncertainty reduces expected utility and, hence, purchase probability (Meyer and Sathi 1985; Roberts and Urban 1987), while price uncertainty raises search cost and, again, reduces purchase probability (Mehta, Rajiv, and Srinivasan 2003). While these insights are not new, there is little empirical research that formally examines how these sources of risk affect brand and store choice, and how product suppliers optimally respond. Manufacturers and retailers recognize that consumers are inherently risk averse, and, at least implicitly, adopt pricing, promotion, and product design strategies in response.

Consumers are generally risk-averse (Kahneman and Tversky 1979) and prefer certainty in the prices they pay, and the products they buy. One of the reasons for Walmart's growth lies in the fact that they offer consumers relatively stable, everyday-low-prices. Consumers can expect the same price whenever they visit a store, so the level of certainty offered by Walmart often overcomes any other reservations shoppers may have. Consider also new product introductions. Consumers are likely to be excited about trying a new product because it may offer a new function, taste, or experience that they have not found in existing products. However, purchasing a new product means losing an opportunity to benefit from the product that they usually purchase, and a potential waste of money. If a new product does not meet their prior expectations, a loss in utility arises. Bacon-flavored soda is one of many examples. One of the ways consumers can limit their exposure to risk in purchasing new products is simply to buy a smaller, trial amount. Manufacturers understand this behavior, so have an incentive to offer a small package in response to consumers' risk-averse behavior. In general, risk has a significant impact both on consumer and supplier behavior, yet few have studied exactly how risk is manifest in CPG market performance. Therefore, the purpose of this dissertation is to examine how consumers behave under uncertainty, how suppliers optimally react, and how this joint recognition changes how we think about intermediation in the CPG market.

Attribute and price uncertainty affects how consumers choose stores, brands, and specific variants of each brand. In this dissertation, I consider each of these problems in turn. Because consumer goods are generally purchased through retail intermediaries, store-choice is of primary concern. When consumers choose a store, they consider not only one item but also a collection of items they plan to buy – their "shopping basket" (Bell and Lattin 1998). The basket price is a source of risk because consumers are usually not aware of price movements for every item in their basket. In the first essay, I show that risk preferences are an important determinant of store choice. Bell and Lattin (1998) and Ho, Tang, and Bell (1998) explain how consumers choose a store by using household demographic attributes and basket size, but do not consider risk preferences. Because consumers are exposed to price uncertainty, and prices are fundamental drivers of any choice decision, my research provides a more fundamental explanation of store-choice behavior. Price uncertainty, however, reflects only part of the problem.

In the second essay, I consider the question of why most new products fail. While new brands may meet consumers' needs in new and often favorable ways, new brands also represent a source of risk for consumers. When a new brand is launched, consumers cannot know the specific "quality" or "fit" of that brand relative to their preferences. In this essay, I examine consumers' risk behavior associated with new brand purchases and explain how their reaction to the uncertainty of new products is manifest in the amounts they purchase. Perceived quality is one of the common risk measures in CPG market analyses, but is not observable (Erdem and Keane 1996; Erdem 1998; Erdem, Keane, and Sun 2008). My study proposes a new risk measure that is tangible and relevant to manufacturers and retailers alike. In these first two essays, I establish a set of core findings regarding the consumer-side of the uncertainty problem.

On the supply-side, the decisions that drive price and attribute uncertainty are commonly assumed to be exogenous. Rather, if suppliers are assumed to be rational, they are likely to respond to consumer uncertainty in predictable ways. Indeed, interactions among consumers, retailers, and manufacturers is commonly understood to be critical to understanding CPG market performance (Villas-Boas and Zhao 2005; Villas-Boas 2007). Therefore, in the final essay, I consider how CPG companies optimally respond to the types of consumer behavior observed in the first two. When consumers purchase a new or unfamiliar product, they tend to choose a smaller package because it allows them to reduce the risk that the product does not meet their prior expectation. Manufacturers adopt product design strategies in response. In the carbonated soft drink category, for example, Coca-Cola launched Coke Zero with both large and small package options. Based on the Nielsen household panel scanner data used in this essay, households tend to choose a small package on their trial purchase while they choose a large package on repeat purchases. Package size may thus play an important role in inducing consumers to try new products. In order to understand how manufacturers choose package sizes, I investigate manufactures' decisions regarding package size and reveal how they vary in response to consumer preferences, the cost of producing packages of different sizes, and competition among manufacturers. While others argue that changes in package size represent a rational response to consumers' preferences for price and convenience (Çakıra and Balagtas 2014), they do not consider the cost nor strategic implications reflected in manufacturers' package-size decisions. I show that these considerations are, in fact, fundamental to understanding why changes in package size occur, and how they represent an important example of supplier response to risk-averse consumers.

1.1 Essay 1: Price Uncertainty and Store Format Choice

In the first essay, I investigate store-choice under uncertainty. Although retailing involves a number of decisions on merchandising strategy, assortment, location, and services, I focus on pricing strategy, or the "store-price format." The choice of format implies a particular pattern of price variation, which frames the degree and nature of uncertainty faced by consumers in choosing a store. Understanding how consumers respond to store price formant is critical to describing how uncertainty affects the retailing function. When consumers decide where to buy, they generally face two alternatives: (1) EDLP stores that offer lower average prices, that tend to vary less over time, or (2) promotion-based (HILO) stores that offer higher average prices, but more variation over time. Formally, each format is characterized by a specific price distribution, or a combination of the mean and the variance of basket price. Walmart and Food Lion are typical examples of EDLP stores while Kroger and Safeway are HILO stores (Ellickson and Misra 2008; Shankar and Bolton 2004). While it would seem that one type of format should be preferred from a management perspective, we observe different types of store price format in the same market. If retail food markets are competitive, then how can they coexist? That is, if one format is preferred, we would expect it to dominate the market. In this essay, I show that there is a systematic relationship between consumers' risk preference and their choice of store price format. Consequently, I demonstrate how consumer heterogeneity in risk behavior explains why EDLP and HILO stores coexist in the same market.

Consumers choose stores for many reasons (Bell and Lattin 1998; Smith 2004), but prices are both an important and transparent competitive tool (Arnold, Oum, and Tigert 1983). While consumers may find the best deal at HILO stores, there is also a chance they may pay a higher price for the same product due to price dispersion among stores. EDLP stores offer lower mean prices and less variability, but HILO stores offer a chance to pay lower prices on some items, at the risk of paying more for other items. Under price uncertainty, consumers' risk preferences may, therefore, play a key role in explaining their store choice behavior.

Prior empirical studies find that prices, store location, assortment size, basket size, and consumer demographic attributes are all important determinants of store choice (Arnold, Oum, and Tigert 1983; Lal and Rao 1997; Bell, Ho, and Tang 1998; Bell and Latin 1998; Ho, Tang, and Bell 1998; Briesch, Chintagunta, and Fox 2009).

However, they do not consider consumers' attitudes toward uncertainty with respect to any store attribute. In the first essay, I conduct an experiment that incorporates consumer heterogeneity in risk preference in order to investigate the impact of consumers' risk attitudes on their store choice decisions. I find that risk-averse consumers tend to choose EDLP stores and risk-loving consumers choose HILO stores because consumers perceive shopping at HILO stores as more risky due to the greater variation in prices. Bell and Lattin (1998) find that consumers who shop for many items on each trip prefer EDLP stores, and those with smaller baskets prefer HILO stores, so I conduct my experiment on both types of shoppers. Controlling for basket size, I still find that price variability dominates the store-choice decision. This study is the first to demonstrate how consumers with different risk preferences respond to retailers' pricing strategies. More generally, this study explains how EDLP and HILO stores can coexist in the same retail market.

On a fundamental level, I show that what was once considered a behavioral anomaly, or market failure, can easily be explained by natural heterogeneity in risk preferences. Properly understood, risk can explain other features of the CPG industry that are otherwise considered to be inefficiencies or competitive failures.

1.2 Essay 2: Attribute Uncertainty and New Product Choice

After choosing a store, risk and uncertainty are also likely to be important determinants of brand-choice. While there is little uncertainty regarding the quality or taste of established brands, new products present a fundamentally different problem. In the second essay, I consider the risk associated with consumers' purchases of new products – products that different from existing, familiar products in important, salient ways. When consumers purchase a new or unfamiliar product, they do not know how that product with their preferred attribute set. If consumers are risk averse, they seek to avoid uncertainty, which is likely to be reflected in the products they buy. In the CPG market, most new products do not succeed. In 2011, nearly 80 percent of the new products that were introduced failed to achieve more than $7.5 million in year-one sales, and less than 3% of the new products achieve over $50 million in year-one sales (SymphonyIRI 2012a). Because the purchase of a new or unfamiliar product involves a higher degree of uncertainty, poor sales performance may be due to the risk that new products fail to meet consumers' prior expectations. In an expected-utility maximization framework, this risk affects purchase behavior.

Consumers respond to the risk that a new product proves to be unacceptable in two ways. One of the ways consumer may reduce risk is to use quality signals such as brand, price, and advertising (Erdem 1998; Erdem, Katz, and Sun 2010; Erdem, Keane, and Sun 2008; Ackerberg 2003; Anand and Shachar 2011; Byzalov and Shachar 2004; Erdem and Keane 1996; Erdem and Sun 2002; Mehta, Chen, and Narasimhan 2008). Another is to purchase a smaller amount than usual. Shoemaker and Shoal (1975) find that consumers tend to choose a smaller than usual package or quantity on their trial purchase of a new product, but do not explain why. While the role of quality signals has been studied extensively, consumers' tendency to reduce purchase quantity has not.

In order to understand why consumers choose smaller quantities of new products, I estimate a model of household-level demand for newly-introduced products that includes a consideration of package-size choice. One empirical issue with household-level demand models, however, is that consumers tend to purchase multiple, discrete items, and in continuous quantities (Dube 2004; Richards, Gomez, and Pofahl 2012).

Therefore, I specify and estimate a multiple-discrete continuous extreme value (MDCEV) model (Bhat 2005, 2008) in household panel scanner data from the yogurt category. The MDCEV model identifies household-level satiation points while controlling for demographic attributes and other, unobserved sources of heterogeneity. This model shows that when consumers purchase a new brand for the first time, their utility function is more concave and satiation occurs at a smaller quantity, suggesting that consumers reduce the risk associated with the trial purchase of a new brand by choosing a smaller quantity.

This study is unique in that it measures consumers' risk attitudes toward trial purchases of new products, and, as such, provides an explanation for the reduced purchased quantities observed by Shoemaker and Shoal (1975). More generally, it again reveals the importance of risk in explaining what would otherwise be considered a market anomaly. From a managerial perspective, my findings highlight the importance of a practice some marketers understand intuitively – offering samples of a new product is an effective tool to build consumer interest.

1.3 Essay 3: Consumer Risk Behavior and Firm Response

In the first two essays, I consider consumer behavior under uncertainty. The primary implication of the second essay is that consumers choose package sizes, at least in part, due to the perceived risk of a mismatch between product attributes, and their own preferences. In the second study, I followed the existing literature by assuming package size is exogenous, or determined in a prior stage of a multi-stage game played between consumers and product manufacturers. If firms are rational, they ought to be able to capitalize on how they expect consumers to react to the uncertainty inherent in trying any new product. In fact, when manufacturers launch a new brand, they typically offer at least one small package to give consumers the incentive to try that brand. So, in the third essay, I relax the assumption that package sizes are exogenous and examine how CPG companies optimally react to consumers' quantity choice behaviors. Because purchase quantities are constrained by package sizes in the CPG market, I focus on manufacturers' optimal package-size decisions.

Package size is an important element of the marketing mix, because a specific combination of package size and price determines price per unit, and therefore has a significant impact on manufacturers' profitability. Manufacturers simultaneously choose the package size and price in response to consumer preferences for package size and the cost associated with producing package of a particular size. According to McIntyre (2011), for example, Heinz reduced some of its ketchup products by an average of 11% and kept its package price the same. Kraft changed the amount of crackers contained in its Nabisco Premium saltines and Honey Maid graham crackers boxes by 15% while keeping box prices the same. PepsiCo reduced the size of its half-gallon cartons of Tropicana by 8% and, in doing so, increased the carton price by 5 to 8%. In these examples, unit prices rose with a change in package size. However, it is not clear whether these changes are driven by demand, cost considerations, or recognition of the strategic nature of package sizes.

It seems reasonable that package size is a strategic variable among manufacturers, but has not been regarded as such in the literature. Prior studies focus on how manufacturers and retailers set prices for different package sizes (Khan and Jain 2005; Cohen 2008; Gu and Yang 2010), but they do not consider that price and package size are jointly determined. If consumers prefer smaller package sizes, as my previous essay shows, then package size can be a point of competition. By competing in package sizes, firms may be able to soften the degree of price competition in the downstream market, and raise margins accordingly.

Testing this hypothesis requires an equilibrium model of the interaction between consumers with heterogeneous preference for package size, and profit-maximizing retailers and manufacturers. An equilibrium model is necessary to endogenize manufacturers' simultaneous decisions regarding package size and price. On the demand side, consumers are assumed to make a discrete choice among differentiated products. On the supply side, manufacturers set package sizes and wholesale prices simultaneously taking into account manufacturer costs, retailers' response, and competition among manufacturers, and retailers set retail prices taking into account retailer costs and demand.

I apply a structural model of vertical equilibrium to store-level scanner data for the ready-to-eat breakfast cereal category in the Chicago market. I find that package size decisions reflect consumer preferences, costs, and manufacturers' price competition in the consumer market. Consumers prefer a small package, in part due to the perceived risk, and have heterogeneous responses to package size. At the same time, the cost of producing packages of different sizes rises in a nonlinear way. CPG manufacturers make package-size and pricing decisions in response to consumer preferences, the structure of costs, and strategic considerations in the downstream market.

Others find that change in package size, especially package downsizing, is a more effective tool than a change in price because consumers are less responsive to the former than the latter (Çakıra and Balagtas 2014). However, my results suggest that package size and price are strategic complements – downsizing causes competitors to lower their prices, which leads to further downsizing, and more price competition until a particularly undesirable (from the manufacturers' perspective) equilibrium is reached. Therefore, package downsizing is not necessarily the best way to extract surplus from consumers as the existing literature would lead us to believe. Rather, if manufacturers offer larger packages in response to a cost increase, for example, price competition would soften as competitors raise their prices in response. Margins rise as a result, and the cost increase is covered more effectively than if downsizing would have been used. More generally, this study provides new insight into manufacturer package-size decisions as I show that they are not driven by consumer response alone, but also by market competition, and cost factors.

In competitive markets, pricing is the primary concern. But, this essay shows that interdependence between price and package size determines manufacturer decisions. Package size affects consumer choice, market share, and competition, which in turn influences pricing decisions and vice versa. Such interdependence applies to markets beyond the CPG industry, and describes a more general pattern of competition in price and product, or service, attributes. In the internet services providers' market, for example, firms offer multiple service packages that differ in price and download speed. Consumers choose their services from among providers such as Comcast, AT&T, CenturyLink, or any one of a number of local firms according to not only price but also download speed. Those who watch the video online may prefer a higher download speed while those who use only e-mail and social media may choose a lower download speed. It is highly likely that firms compete in both price and download speed, and the interdependence between them plays an important role in explaining how firms set price and download speed of each package. In healthcare insurance, package size refers to coverage levels, the number of procedures included, and the extent of the service network. Ultimately, firms compete in more than just price.

1.4 Conclusion

This dissertation reveals that uncertainty plays a crucial role in explaining consumers' store and product choices, and how their behavior conditions the products offered for sale. I find that suppliers in the CPG market recognize that consumers are exposed to a significant risk, so use marketing strategies that limit consumers' exposure to risk in order to increase their own profits. From a practical perspective, my findings allow retailers and manufacturers to better understand the role of consumer risk in choosing stores, and products, and how to respond appropriately.

The concepts advanced in this dissertation are fundamental, general characteristics of consumer behavior that are manifest in nearly every purchase environment. For example, in the first essay, I explain the coexistence of EDLP and HILO stores by consumer heterogeneity in risk preferences. This mechanism is likely common in many other fields. In insurance markets, for example, risk-averse consumers may prefer a higher-deductible health plan while risk-loving consumers are satisfied with a lower-deductible. Insurance products not only offer the ability to diversify risk, but also screen consumers with different risk attitudes. The methodological framework used in the first essay may be applied to better understand the role of risk in not only insurance-product choice, but many other types of financial products that involve risk, consumer durables, or even educational choices. Moreover, the risk behavior considered in the second essay is typical not only of the CPG market, but also of the service industries. Consumers usually make decisions about which services they choose and how much they use these services, while they are exposed to the risk that expectations about these qualities will not be met. My insights may help understand consumer behaviors in service industries such as why consumers choose a small usage level of a chosen service when they are uncertain about its quality. Once they become familiar with the quality of the service, they will then be willing to commit to longer-term, more lucrative contracts, often with additional service components.

Finally, the framework used in the third essay is not limited to the CPG market. Package choices are often made in other markets such as wireless, cable, and internet services providers, or healthcare and auto insurance. In the market for wireless services, for example, carriers offer multiple service packages in which a monthly line access fee is same, but a number of megabytes of data per month that consumers can access is different across packages. For example, Verizon has a Verizon JetPack 4G LTE in which consumers pay \$20 for a monthly line access fee, and \$40 if they choose a data package up to 1GB, \$50 if they choose up to 2GB, and so on. Some users may frequently access the Internet through their mobile devices, but others do not, which implies data allowance may be an important determinant of choice, and a point of competition among firms. My findings suggest that price and data allowance are strategic variables, and, like the price and size of a box of cereal, they arise through a strategic market equilibrium, and not a simple response to consumer demand. Carriers consider consumer demand, costs, and competitors' responses when they set data-allowance package prices and sizes. The insights provided by my third essay help us understand competition in price and non-price attributes more generally, and apply to many industries beyond consumer goods.

The reminder of this dissertation is organized as follows. In the first essay, I study the relationship between price uncertainty, and consumers' choice of store format. The second essay follows in which I explain consumers' choice of package size for new products as a function of their aversion to attribute uncertainty. Next, the third essay applies these insights to equilibrium firm behavior, using firms' choice of package size and price as an example. I reserve my concluding remarks, and offer more general implications of my findings, for a final chapter.

CHAPTER 2.

ESSAY 1: PRICE UNCERTAINTY AND STORE FORMAT CHOICE

2.1 Introduction

Retail pricing strategies tend to follow patterns that are repeated over thousands of products offered throughout each store. These patterns are referred to generically as the "pricing format," of the store, which can be either everyday low price (EDLP) or promotion-based (HILO). Whereas EDLP stores set prices that are relatively constant over time, HILO stores set prices that are higher than EDLP stores on average, but use frequent sales featuring deeply-discounted prices on a smaller set of products. More formally, store price format can be defined by the mean and variance of prices. In reality, there are no pure examples of either as pricing strategies tend to be located on a continuum between pure EDLP and pure HILO depending observed degrees of price variability. Walmart and Food Lion are the closest examples to pure EDLP stores, while Kroger and Safeway are the closest to pure HILO (Shankar and Bolton 2004; Ellickson and Misra 2008). However, it is not obvious how different types of store format can coexist in the same market. Consumer heterogeneity is one explanation. While others find that consumer heterogeneity in shopping frequency and basket size may explain how both formats can survive together (Bell and Lattin 1998; Ho, Tang, and Bell 1998), the observation that the fundamental difference between store formats lies in the riskiness of the value proposition offered to consumers suggests that heterogeneity in risk preferences may be equally important. Therefore, in order to explain the coexistence of HILO and EDLP store formats, I examine the relationship between heterogeneity in consumer risk preferences and the preference for store price format.

Retail stores are largely differentiated on the basis of a variety of non-price attributes. Market shares differ, in part, due to heterogeneity in consumer preferences for these attributes. A number of studies find that consumers base their store selection decisions not only on prices, but also on non-price attributes such as store location, service quality, and product variety (Arnold, Oum, and Tigert 1983; Bell, Ho, and Tang 1998; Bawa and Ghosh 1999; Briesch, Chintagunta, and Fox 2009). These findings lead to the conclusion that retailers have a significant degree of market power, and tend to act as local monopolists once consumers are in the store (Walters and McKenzie 1988; Slade 1995; Besanko, Gupta, and Jain 1998). Retailers may use consumers' preferences for non-price attributes to differentiate themselves into local monopoly markets. Somewhat paradoxically, Lal and Rao (1997) find that store price format can be regarded as a non-price attribute, and can therefore serve as a key element of a positioning strategy. In an equilibrium framework, they show that different store price formats may exist if consumers differ in terms of the opportunity cost of their time spent traveling. In a series of experimental studies, I identify consumer heterogeneity regarding risk preferences and explain how EDLP and HILO stores can coexist in the same market via systematic relationship between store price format and consumers it attracts in terms of risk preferences.

Consumers are uncertain about retail prices that vary from day to day and place to place, even for frequently-purchased items, so their attitudes toward risk likely influence their store choice. Consumers typically purchase many products across many categories on a single purchase occasion, yet do not make a detailed purchase plan, nor do they have complete price information before their trip. SymphonyIRI Group (2012b) reports that motivations for a "quick trip" account for 56% of all purchase occasions and that the rest (44%) involve more complete "stocking up" purchase behaviors. When making a quick trip, consumers need few items immediately and may not have enough time to search for these prices. When consumers stock up on many items, on the other hand, they may find it costly to search for every price of item included in their basket. Also, Point of Purchase Advertising International (2012) reports that 76% of consumer's purchases result from unplanned and in-store decisions. These shopping behaviors do not allow consumers to search for every price in their basket, so consumers ultimately decide where to shop under a veil of uncertainty as to what the total shopping basket price will be. In the consumer packaged good (CPG) market, consumers' risk attitudes affect their product choice (e.g. Erdem and Keane 1996; Erdem 1998; Erdem, Zhao, and Valenzuela 2004; Erdem, Keane, and Sun 2008), so the same is logically true of their store choice. Because consumers tend to choose a store before choosing a specific product (Bell and Lattin 1998), their attitudes toward risk may influence store choice as well. Therefore, I hypothesize that price variation forms a key source of uncertainty that drives consumers' store-choice decisions.

How shopping basket size and shopping frequency influence preferences for store-price format is relatively well understood. Bell and Lattin (1998) and Ho, Tang, and Bell (1998) show that large basket shoppers (i.e. those who buy more and shop less) prefer EDLP stores because they do not have the flexibility to take advantage of occasional price deals on each product in their basket. On the other hand, small basket shoppers (i.e. those who buy less and shop more) prefer HILO stores because they can take advantage of price variations for each product. Small basket shoppers can lower their basket price by buying each product on sale, despite the higher average store-price. Such heterogeneity in consumer shopping behavior allows EDLP and HILO stores to coexist in the same market. Both studies, however, assume consumers are risk neutral. That is, they are silent on how consumers' risk attitudes under basket price uncertainty influence their choice of store price format. In this paper, I analyze the role of consumers' risk attitudes in their store-choice decisions. Further, I explain the coexistence of EDLP and HILO stores in terms of heterogeneity in consumers' attitudes toward risk.

My model of store choice assumes consumers choose from among several stores in order to purchase their typical shopping basket, or choose not to shop at all. Utility implicitly depends on store price format in that it is a function of the variability of prices within the shopping basket, and other non-price attributes such as store location and product variety. A unique aspect of my demand model is that I explicitly incorporate consumers' risk attitudes into the marginal utility from choosing a particular store price format.

I test this model using data from a two-stage experimental design. In the first stage, I elicit consumers' risk attitudes using an incentive-compatible lottery-choice experiment (Holt and Laury 2002). The primary advantage of using the Holt and Laury (2002) framework is that it is more likely to capture actual individual behavior under uncertainty, because real money is at stake. Further, it is context free so it is widely used in experimental economics to measure risk preferences (Lusk and Coble 2005; Anderson and Mellor 2008; Nguyen and Leung 2009; Dohmen and Falk 2011; Anderson, Freeborn, and Hulbert 2012).[1] However, there is no evidence as yet that

[1]There are several alternatives to the Holt and Laury (2002) method of eliciting risk preferences, differing in the trade-off between simplicity and richness of elicited risk preferences. Eckel and Grossman (2002, 2008) design a simple way to elicit risk

links risk attitudes to store choice. Conditional on consumers' revealed attitudes toward risk, I then implement an incentive-compatible choice-based conjoint study that provides data on subjects' store-price format preferences. Price variation in the context of store choice is fundamentally different from that observed for typical financial assets in that financial assets tend to reflect either high risk and high return or low risk and low return. The risk-return reward for store choice is more subtle, and yet more pervasive in consumers' daily consumption decisions. Muthukrishnan, Wathieu, and Xu (2009) use a similar approach to test for a relationship between ambiguity aversion in a lottery choice experiment and a preference for established brands. Although the context of my experiment differs from theirs, these authors demonstrate the validity of a two-stage approach to estimate the effect of attitudes on choice. My goal is similar in nature to theirs, namely to seek evidence that links consumers' attitudes toward risk to their store-choice decisions.

My results show strong support for the hypothesis that consumers self-select store-price format based on their risk attitudes. Specifically, more risk-averse con-

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preferences in which subjects are asked to make a single choice among five lotteries with constant probabilities, but changing payoffs. However, their approach does not allow me to differentiate between degrees of risk loving behavior, and I require consumer heterogeneity in both the risk-averse and risk-loving domains. Gneezy and Potters (1997) and Charness and Gneezy (2012) propose a risk elicit method in which subjects are asked to allocate their endowment between safe and risky investments. However, this method cannot reveal subjects' heterogeneity in risk loving behavior. Lejuez, Read, Kahler, Richards, Ramsey, Stuart, Strong, and Brown (2002) and Crosetto and Filippin (2013) develop a pictorial method of eliciting risk preferences without explicitly using the probability distribution of the realization of risky outcomes. In my empirical model, though, I require quantitative information on subjects' risk preferences, so their approach is not suitable. Finally, Dohmen, Falk, Huffman, Sunde, Schupp, and Wagner (2011) use self-reported questions to elicit risk attitudes that are relatively easy to understand. Similar to the previous approach, this method does not enable me to calibrate expected utility functions, nor are subjects incentivized to respond accurately. In sum, while other methods are superior in some aspects, the Holt and Laury (2002) method is the most suitable for the problem at hand.

sumers are likely to choose EDLP stores rather than HILO stores. They perceive that shopping at HILO stores is risky due to the higher price variability for the goods that comprise their typical shopping basket and, therefore, have an incentive to choose EDLP stores. On the other hand, more risk-loving consumers prefer HILO stores because they have a positive probability of finding a product with lower price. Also, I find that the risk-attitude effect becomes less important with smaller basket sizes, a finding that suggests risk preferences are the mechanism underlying the findings of Bell and Lattin (1998) and Ho, Tang, and Bell (1998). My findings also provide evidence that the coexistence of EDLP and HILO stores in the same market is at least in part due to heterogeneity in risk preferences. Choosing a store price format is not only a form of strategic pricing, but also screening device to sort consumers with differing attitudes toward risk.

My research contributes to the empirical marketing literature in two ways. First, I am the first to combine experimental evidence on risk aversion and store choice in a consistent way. To the best of my knowledge, experimental risk preferences have not been used in store-choice experiments. Second, this is the first store-choice study to incorporate consumers' risk attitudes. I provide both an analytical model of store choice that recognizes the importance of risk attitudes, and experimental evidence that supports the hypotheses that follow. I make a significant contribution to the literature by offering a new explanation regarding how EDLP and HILO stores can coexist in the same market, and offer a new interpretation of prior findings. On a more practical level, I recognize that each retail chains tend not to choose pure EDLP or HILO strategies, but typically arrive at something in-between. My results suggest that retail managers would be well-advised to better understand the risk preferences of their market in order to tailor a strategy that maximizes market share.

The reminder of this paper is organized as follows. In the second section, I describe the experimental design used to generate the data and test my hypothesis. In the third section, I describe my econometric model, and how it is used to examine the relationship between consumers' risk attitudes and store choice. I present and interpret the data and estimation results in the fourth section. Conclusions, implications, and potential extensions are described in the final section.

2.2 Experimental Design

2.2.1 Overview

In this essay, I offer evidence from a two-stage, incentive-compatible experiment that shows how consumers' risk attitudes affect their choice of store price format. Household-panel data can also be used for this purpose, but has significant drawbacks. First, it is difficult to define a shopping basket over time as consumers do not always purchase the same item on every purchase occasion. Second, because there are no pure examples of EDLP or HILO stores, identifying and classifying stores into different pricing formats is difficult with household panel scanner data. In fact, Ellickson and Misra (2008) point out that most stores do not announce their pricing strategies and, moreover, individual stores within the same chain often adopt different pricing strategies depending on their location and competition. Third, it is impossible to obtain a precise measure of the distance between store locations, and between stores and individual households. Further, there are many variables that are important to store choice, but are inherently unobservable: Assortment depth, availability, and product quality, for example. My experimental approach overcomes each of these problems.

Experimental data allows me to design a very specific set of pricing strategies using the mean and the variance of a basket price, to control for store location, assortment depth, and product quality, and to precisely estimate the effect of consumers' risk attitudes on store preference.

The experiment consists of two stages. I identify subjects' risk attitudes in the first stage, and preference for store price format in the second stage. Each stage is implemented using the Qualtrics online research panel (http://www.qualtrics.com). To participate in the experiment, subjects had to be 18 years old or above, live in the United States, purchase grocery items for their household at supermarket at least once a month, and usually drive to their chosen supermarket. A total of 275 subjects participated in the experiment. The experiment is incentive compatible in that subjects are paid depending on their performance during each stage. Compensation was recorded during the experiment in monetary units called "experimental units (EU)," and one EU was converted into 0.25 dollars for payment at the end of the experiment.

2.2.2 First-Stage Experiment

In the first stage, I conduct an incentive-compatible lottery experiment (Holt and Laury 2002) in order to identify subjects' risk preferences. Subjects were presented with ten choice tasks, each task consisting of two lotteries (called option A and option B), and were asked to choose between the options in each task. Table 2.1 shows the specific choice tasks the subjects faced. In any choice task, option A is referred to as the "safe" choice and option B as the "risky" choice because the payoffs from option A are less variable than option B. As subjects proceed through the choice tasks, the expected value of both options increase, but the expected value of option B becomes greater than that of option A. In my lottery choice experiment (as in others), subjects typically begin by choosing option A and switch to option B, and continue to choose option B until the end. Risk-neutral subjects are expected to choose option A in the first four choice tasks and option B in the last six choice tasks, because the expected payoff from option A exceeds that from option B in the first four choice tasks. Risk-loving subjects are expected to start by choosing option B prior to the fourth choice task, and risk-averse subjects are expected to continue to choose option A even after the fifth choice task, switching to option B somewhere between the sixth and tenth choice task. One lottery is randomly chosen for payment, and subjects are paid the amount indicated by their selection. It is through this mechanism that the Holt-Laury experiment is incentive compatible.

Table 2.1
Incentive-Compatible Lottery Choice Experiment

Choice task	Option A	Option B
1	10% chance of 20.00 EUs, 90% chance of 16.00 EUs	10% chance of 38.00 EUs, 90% chance of 2.00 EUs
2	20% chance of 20.00 EUs, 80% chance of 16.00 EUs	20% chance of 38.00 EUs, 80% chance of 2.00 EUs
3	30% chance of 20.00 EUs, 70% chance of 16.00 EUs	30% chance of 38.00 EUs, 70% chance of 2.00 EUs
4	40% chance of 20.00 EUs, 60% chance of 16.00 EUs	40% chance of 38.00 EUs, 60% chance of 2.00 EUs
5	50% chance of 20.00 EUs, 50% chance of 16.00 EUs	50% chance of 38.00 EUs, 50% chance of 2.00 EUs
6	60% chance of 20.00 EUs, 40% chance of 16.00 EUs	60% chance of 38.00 EUs, 40% chance of 2.00 EUs
7	70% chance of 20.00 EUs, 30% chance of 16.00 EUs	70% chance of 38.00 EUs, 30% chance of 2.00 EUs
8	80% chance of 20.00 EUs, 20% chance of 16.00 EUs	80% chance of 38.00 EUs, 20% chance of 2.00 EUs
9	90% chance of 20.00 EUs, 10% chance of 16.00 EUs	90% chance of 38.00 EUs, 10% chance of 2.00 EUs
10	100% chance of 20.00 EUs, 0% chance of 16.00 EUs	100% chance of 38.00 EUs, 0% chance of 2.00 EUs

With certain assumptions about the functional form of utility, lottery choices are used to identify either the coefficient of absolute risk aversion or the coefficient of relative risk aversion. I assume utility takes a constant absolute risk aversion (CARA) form:

$$U(Y) = -\exp\left(-\rho_i Y\right), \tag{2.1}$$

where ρ_i is the coefficient of absolute risk aversion for subject i and Y is the payoff in the lottery. Consider a subject who chooses option A in the first three tasks and then chooses option B in the subsequent tasks. The lower bound of ρ_i for this subject is determined such that she or he is indifferent between option A and option B in the third choice task. That is, ρ_i must satisfy the following equation:

$$-0.3\exp\left(-20\rho_i\right) - 0.7\exp\left(-16\rho_i\right) = -0.3\exp\left(-38\rho_i\right) - 0.7\exp\left(-2\rho_i\right) \Leftrightarrow \rho_i = -0.030. \tag{2.2}$$

For the same subject, the upper bound of ρ_i can be obtained by:

$$-0.4\exp\left(-20\rho_i\right) - 0.6\exp\left(-16\rho_i\right) = -0.4\exp\left(-38\rho_i\right) - 0.6\exp\left(-2\rho_i\right) \Leftrightarrow \rho_i = -0.008. \tag{2.3}$$

Because this process identifies only a range for the constant absolute risk aversion coefficient, I use the midpoint of the upper bound and lower bound of ρ_i and use this as the coefficient of risk aversion in the subsequent analysis (Lusk and Coble 2005; Anderson and Mellor 2008; Nguyen and Leung 2009; Dohmen and Falk 2011; Anderson, Freeborn, and Hulbert 2012). In the above example, ρ_i is set to -0.019, and ρ_i for other lottery choices can be similarly obtained as reported at table 2.2. A value of $\rho_i < 0$ indicates a risk-loving subject, while $\rho_i = 0$ indicates risk neutrality, and $\rho_i > 0$ risk aversion.

Table 2.2
Coefficient of Absolute Risk Aversion

Choice task in which subject switches to option B	Lower bound	Upper bound	Midpoint
First choice task	-0.095	-0.095	-0.095
Second choice task	-0.095	-0.056	-0.075
Third choice task	-0.056	-0.030	-0.043
Fourth choice task	-0.030	-0.008	-0.019
Fifth choice task	-0.008	0.013	0.002
Sixth choice task	0.013	0.033	0.023
Seventh choice task	0.033	0.056	0.044
Eighth choice task	0.056	0.084	0.070
Ninth choice task	0.084	0.126	0.105
Tenth choice task	0.126	0.126	0.126

2.2.3 Second-Stage Experiment

In the second stage, I administer an incentive-compatible choice-based conjoint (Louviere and Woodworth 1983; Louviere 1988; Louviere, Hensher, and Swait 2000) experiment designed to elicit data on subjects' store-choice behavior. The "stores" are defined as generic supermarkets that differ in terms of the variability of shopping-basket prices, the number of brands available in each product category, and distance from the shopper. Basket-price variation is the key attribute as it defines the pricing format for each store. In addition to prices, selection and convenience are important choice criterion (Arnold, Oum, and Tigert 1983; Bell, Ho, and Tang 1998; Bawa and Ghosh 1999; Briesch, Chintagunta, and Fox 2009). In my experiment, I use the number of brands as a measure of selection and distance (driving time) as a measure of shopping convenience. Arnold, Oum, and Tigert (1983) also find that the quality of fresh produce is also an important determinant of store choice. I control for this effect by instructing subjects that they are only shopping for CPGs. When shopping for CPGs, quality does not vary from store to store. Shopping basket size is an important chooser-attribute in determining store choice (Bell and Lattin 1998; Ho, Tang, and Bell 1998), so I hold shopping-basket size constant on each choice occasion.

Basket-price variation is represented by presenting subjects with a set of "usual" and "sale" prices for products in a typical shopping basket. By presenting each subject with two prices (usual and sale), they do not know the exact price charged for each product in the basket before shopping and, therefore, are forced to make their store-choice decision under a condition of price uncertainty. The degree of uncertainty assumes three levels, indicating either an EDLP store, HILO store, or something in-between that I refer to as a Hybrid store. In this way, basket-price variation reflects the revealed pricing pattern of each store price format in a general way. That is, subjects are not told that a particular store is EDLP, HILO, or Hybrid, but only observe the variation in prices I reveal to them (Ellickson and Misra 2008). In order to maintain consistency with prior store-choice research, I define the shopping basket as consisting of 12 CPGs (bacon, butter, margarine, ice cream, soda crackers, liquid detergent, ground coffee, hot dogs, soft drinks, granulated sugar, tissue, and paper towels), and generate price variability using the mean and variance of the basket price calculated by Bell and Lattin (1998). Specifically, I use their mean price as my usual price and their mean price minus two standard deviations as my sales price, assuming the basket price follows a normal distribution.

The number of brands available in each category has three levels: One brand, three brands, and six brands. This assumption is based on the observation that, on average, consumers consider approximately three alternatives and choose one when purchasing CPGs (Hauser and Wernerfelt 1990; Mehta, Rajiv, and Srinivasan 2003). One-brand represents no selection at all, three-brands an average selection, and six-brands an extensive selection. Finally, driving time has three levels: 5 minutes, 10 minutes, and 20 minutes. I choose these levels based on Fox, Montgomery, and Lodish (2004), who report the average shopping-trip time of around 10 minutes. All attributes and levels are summarized at table 2.3.

Table 2.3

Attributes and Attribute Levels (12 CPGs in the Shopping Basket)

Attribute	Attribute level
Basket-price variation	The usual price is 23.00 EUs but, there is a chance it could be 21.00 EUs if items are on sale.
	The usual price is 24.00 EUs but, there is a chance it could be 20.00 EUs if items are on sale.
	The usual price is 25.00 EUs but, there is a chance it could be 19.00 EUs if items are on sale.
The number of brands available in each category	1 brand
	3 brands
	6 brands
Driving time to the supermarket	5 minutes
	10 minutes
	20 minutes

Note: The 12-CPG includes bacon, butter, margarine, ice cream, soda crackers, liquid detergent, ground coffee, hot dogs, soft drinks, granulated sugar, tissue, and paper towels.

I use SAS experimental design macros (Kuhfeld 2010) to create full-factorial choice design with three three-level attributes. I first set the number of alternatives to three and create possible combinations of the attributes and the attribute levels for one alternative at a time. Then, I search for an efficient design for a main-effects model, i.e. a design in which the variances of the parameter estimates are minimized under the assumption that the parameter vector of the design matrix is equal to zero. My design, therefore, consists of three alternatives plus a "no shopping" option and nine choice sets. In this design, all parameters for a main-effects model are estimable and the variances are similar and close to the minimum which is the inverse of the number of choice sets.[2]

I use a Becker-DeGroot-Marschak (BDM 1964) procedure to ensure that it is in a subject's best interest to reveal his or her true preferences. The BDM mechanism works as follows. I assign a specific value to each shopping option that reflects the price of the 12 products the subject purchases, the cost of travel, and the value of having access to a larger selection. My assigned value thus reflects a reasonable estimate of the total value of each option to the subject. Subjects start with a budget equal to 26 EUs to spend on each choice set. They can either choose one shopping option, or to not shop at all. Subjects know that the assigned value depends on all the attributes that comprise each alternative, but do not know the actual assigned value until the end of the experiment. I then choose one choice set at random. For the option chosen out of that choice set, I choose a price at random from a uniform distribution between 0 EU and the total budget. If the value of the shopping option is above the random price, subjects receive the value of their choice, but pay an amount

[2]The SAS code and output are available upon request.

equal to the random price. If the value of their choice is below the random price, subjects keep their entire budget and pay nothing. If subjects select the "no shopping" option in the chosen choice set, they receive the value of the bundle (0 EU) as they do not shop, and keep their entire budget. This mechanism is well-understood to be incentive compatible under a wide variety of auction scenarios.[3] The instructions carefully explain how the BDM mechanism works using an example and why it is in subjects' best interest to make the choice that best reflects the importance they place on each attribute (see Instructions in Appendix A).

In my experiment, the size of each shopping basket is fixed at 12 items. However, Bell and Lattin (1998) and Ho, Tang, and Bell (1998) find that consumers' basket size plays a crucial role in their choice of store. I account for the importance of basket size by conducting the same experiment again with a smaller basket size. Specifically, I define a smaller shopping basket to consist of 6 items (bacon, butter, margarine, ice cream, soda crackers, and liquid detergent), and reduce both basket prices and the total budget in half. The resulting attribute levels for this "small basket" experiment are summarized in table 2.4.

[3]Karni and Safra (1987) point out that the BDM mechanism is not incentive compatible when the good being evaluated is a lottery. Horowitz (2006) further shows that BDM is not incentive compatible even when the value of the good is certain. This is because subjects are still uncertain about whether the bit is accepted and how much they are asked to pay, so their willingness to pay typically depends on the distribution of an unknown price. Because these observations are common in most experiments, I assume that the arguments do not have a substantial impact on my findings.

Table 2.4
Attributes and Attribute Levels (6 CPGs in the Shopping Basket)

Attribute	Attribute level
Basket-price variation	The usual price is 11.50 EUs but, there is a chance it could be 10.50 EUs if items are on sale.
	The usual price is 12.00 EUs but, there is a chance it could be 10.00 EUs if items are on sale.
	The usual price is 12.50 EUs but, there is a chance it could be 9.50 EUs if items are on sale.
The number of brands available in each category	1 brand
	3 brands
	6 brands
Driving time to the supermarket	5 minutes
	10 minutes
	20 minutes

Note: The 6-CPG includes bacon, butter, margarine, ice cream, soda crackers, and liquid detergent.

After the experiment has been conducted, I gather demographic and behavioral information on each subject, including income, household size, age, education, employment status, and shopping frequency. Each of these covariates is used in the econometric model described in the next section. In general, my sample appears to be broadly representative of the U.S. population (table 2.5). An average subject in my sample is 46 years old, and belongs to a household earning $59,220 per year, consisting of 2.5 people. Fully 43 percent of the subjects hold a bachelor's degree and are full-time workers. On average, subjects shop approximately 7.9 times per month, which is more than once per week.

Table 2.5
Demographic Variables

Variable	Symbol	Obs.	Mean	Std. dev.
Annual income	Inc_i	218	59219.720	40104.063
Household size	Hsz_i	218	2.514	1.307
Age	Age_i	218	45.826	15.577
Education	Edu_i	218	0.431	0.495
Employment	Emp_i	218	0.431	0.495
Shopping frequency (times per month)	$Sfrq_i$	218	7.931	6.044

Note: Education takes one if subject is a college graduate and zero otherwise.
Employment takes one if subject is a full time worker and zero otherwise.

2.3 Model

I estimate a structural model of store choice and risk preference. Shopping utility depends on both the purchase of a shopping basket, and other non-price attributes of the chosen store (convenience and assortment depth). A unique feature of my model is that basket price is stochastic, and there is a one-to-one correspondence between a particular combination of the mean and the variance of the price and store price format. That is, format choice is completely identified by the empirical price distribution used in the experiment. The objective of my empirical model is to test how consumers' attitudes toward the risk affect their choice of store.

Consider consumer i, $i = 1, 2, ..., I$ who visits store j, $j = 1, 2..., J$ with k non-price attributes, $k = 1, 2, ..., K$ and purchases product l, $l = 1, 2, ..., L$ at time t, $t = 1, 2, ..., T$. I assume that each consumer has well-defined preferences regarding the purchase of a focal product, Q_{ijlt}, a composite commodity of all other goods, Z_{ijt}, and a non-price store attribute, X_{jk}, and that the utility level of consumer i from choosing store j at time t is given by:

$$U_{ijt} = u\left(\alpha \sum_{l=1}^{L} Q_{ijlt} + \beta Z_{ijt} + \sum_{k=1}^{K} \gamma_k X_{jk}\right), \tag{2.4}$$

where $u(\cdot)$ is an increasing, concave, and continuously differentiable function, α and β are the marginal benefits from the purchase of the shopping basket $(\sum\limits_{l=1}^{L} Q_{ijlt})$ and the composite commodity (Z_{ijt}), respectively, and γ_k is the marginal utility of the non-price store attribute, X_{jk}. Each consumer faces the following budget constraint:

$$\sum_{l=1}^{L} p_{jlt} Q_{ijlt} + Z_{ijt} \leq m_{it}, \tag{2.5}$$

where p_{jlt} is the price of product l offered by store j at time t, and m_{it} is the total budget available to consumer i at time t. Notice that I normalize the price of the composite commodity to one. Basket-price uncertainty is introduced by assuming that p_{jlt} is normally distributed with mean $\mu_{p_{jlt}}$ and the variance $\sigma^2_{p_{jlt}}$. The behavioral implication of this assumption is that consumers do not know the actual price for each product in their shopping basket, but know the price distribution. This is a reasonable assumption as consumers are exposed to price information through supermarket flyers, websites, or their own shopping experience.

My cross-sectional (over shopping baskets) manifestation of risk is not the only way of modeling uncertainty in a retail context. Forward-looking consumers make optimal purchase timing, brand choice, and quantity decisions depending on not only the current price but also their expectation of future prices (Erdem, Imai, and Keane 2003; Sun 2005; Hendel and Nevo 2006). In the context of store-choices, however, such dynamic decision making imposes very strong assumptions on the sophistication of consumers' shopping behavior. Because a typical shopping basket is composed of many products, across many product categories, it may be infeasible for consumers to look at every product in their basket or form expectations regarding future prices before they visit a store (SymphonyIRI 2012b). In fact, Point of Purchase Advertising International (2012) reports that consumers generally make decisions on which product to purchase only after they have entered the store. Moreover, experiments such as the one I use are designed specifically to abstract from the types of complexities involved in dynamic decision making in order to focus subjects' decisions on my operationalization of risk. My maintained hypothesis is that consumers face uncertainty regarding current prices. Every day, consumers make store-choice decisions facing cross-sectional uncertainty in current basket prices. Although future expectations about prices may help explain consumers' brand choice decisions, they are irrelevant to the store-choice context of my experiment. For that reason, my model is inherently static, so I drop the time subscript t hereafter.

Assuming the budget constraint is binding, I rewrite equation (2.4) as:

$$U_{ij} = u\left(\alpha \sum_{l=1}^{L} Q_{ijl} - \beta \sum_{l=1}^{L} p_{jl} Q_{ijl} + \beta m_i + \sum_{k=1}^{K} \gamma_k X_{jk}\right). \tag{2.6}$$

Define the argument of $u(\cdot)$ in equation (2.6) as Π_{ij}. Notice that Π_{ij} is normally distributed due to the distributional assumption regarding p_{ij}. With the assumption that the utility function has the CARA property, the expected utility of consumer i from choosing store j is written as:

$$
\begin{aligned}
E[U_{ij}] &= E[\Pi_{ij}] - \frac{\rho_i}{2} V[\Pi_{ij}] \qquad (2.7) \\
&= \underbrace{-\beta E\left[\sum_{l=1}^{L} p_{jl} Q_{ijl}\right] - \frac{\beta^2 \rho_i}{2} V\left[\sum_{l=1}^{L} p_{jl} Q_{ijl}\right]}_{\text{Store price format}} + \sum_{k=1}^{K} \gamma_k X_{jk} \\
&\quad + \alpha \sum_{l=1}^{L} Q_{ijl} + \beta m_i,
\end{aligned}
$$

where ρ_i is the coefficient of absolute risk aversion for consumer i, $E[\cdot]$ is the expected value and $V[\cdot]$ is the variance. As explained above, I assume that store format is defined by a specific combination of the mean and variance of basket price in that a store close to EDLP offers prices that are less volatile and lower on average, while a store close to HILO offers relatively higher mean prices that exhibit much volatility than EDLP. This observation implies that $-\beta E\left[\sum_{l=1}^{L} p_{jl} Q_{ijl}\right] - \frac{\beta^2 \rho_i}{2} V\left[\sum_{l=1}^{L} p_{jl} Q_{ijl}\right]$ in equation (2.7) can be converted into a single measure of store price format: $\sum_{s=1}^{S} \delta_s(\rho_i) W_{js}$ where $\delta_s(\rho_i)$ is the marginal benefit from choosing a store price format s and W_{js} is an indicator variable that takes a value of one if store j adopts store price format s and zero otherwise. Following Bell and Lattin (1998), I further allow $\delta_s(\rho_i)$ to depend on N demographic attributes of consumer i, d_{in}, $n = 1, \ldots, N$, so δ_s becomes $\delta_s(\rho_i, d_{i1}, \ldots, d_{iN})$. Because there is likely to be considerable heterogeneity in risk preferences, this approach allows me to control for differences among consumers while testing my core hypothesis that ρ_i helps explain store choice.

When consumers choose the outside option, shopping utility is zero and they keep their entire budget. That is, the expected utility of consumer i from choosing not to shop at any store can be written as: $E\left[U_{i0}\right] = \beta m_i$. Thus, the expected utility for consumer i is:

$$\begin{aligned}
E\left[U_{ij}\right] &= \sum_{s=1}^{S} \delta_s\left(\rho_i, d_{i1}, \ldots, d_{iN}\right) W_{is} + \sum_{k=1}^{K} \gamma_k X_{jk} + \alpha \sum_{l=1}^{L} Q_{ijl} + \beta m_i,\ j \neq 0 \\
E\left[U_{i0}\right] &= \beta m_i. \qquad (2.8)
\end{aligned}$$

In my empirical application, there are three store price formats, EDLP, Hybrid and HILO, which is written $s = 1$ if the store employs EDLP, $s = 2$ if Hybrid, and $s = 3$ if HILO. For each store price format, I specify $\delta_s\left(\rho_i, d_{i1}, \ldots, d_{iN}\right)$ by the following linear equation:

$$\begin{aligned}
\delta_s &= \phi_{si} + \psi_s \rho_i + \omega_{s1} Inc_i + \omega_{s2} Hsz_i + \omega_{s3} Age_i + \omega_{s4} Edu_i + \omega_{s5} Emp_i + \omega_{s6} Sfrq_i, \\
\phi_{si} &= \overline{\phi_s} + \Theta_{si},\ \Theta_{si} \sim N(0, \sigma_s^2), \qquad (2.9)
\end{aligned}$$

where $\overline{\phi_s}$, σ_s, ψ_s, and ω_{sl}, $l = 1, \ldots 6$ are parameters to be estimated, Inc_i is household income, Hsz_i is household size, Age_i is consumer i's age, Edu_i is consumer i's educational attainment, Emp_i is consumer i's employment status, and $Sfrq_i$ is consumer i's usual shopping frequency. Equation (2.9) incorporates both observable and unobservable sources of heterogeneity as Θ_{si} is an iid normal error term designed to account for any unobserved heterogeneity in $\delta_s\left(\rho_i, d_{i1}, \ldots, d_{iN}\right)$.

There are three stores (i.e. $J = 3$) and one non-shopping option. Each store has a different value for the format variable, the two non-price attributes, the number of brands available in each product category, and driving time. I specify the non-price attributes in equation (2.8) as: $\sum\limits_{k=1}^{K} \gamma_k X_{jk} = \gamma_1 Nb_j + \gamma_2 Time_j$ where γ_k, $k = 1, 2$ are parameters to be estimated, Nb_j is the number of brands available in each product category at store j, $Time_j$ is driving time to store j. In the experiment, I hold shopping-basket size and total budget constant across subjects, so $\sum_{l=1}^{L} Q_{ijl}$ and m_i in equation (2.8) are normalized to zero for estimation purposes. Finally, I add a random component to the expected utility as it is possible that expected utility includes factors that are unobservable to the econometrician. Thus, equation (2.8) is written as:

$$\begin{aligned}
E\left[U_{ij}\right] &= \begin{pmatrix} \phi_{1i} + \psi_1 \rho_i + \omega_{11} Inc_i + \omega_{12} Hsz_i \\ +\omega_{13} Age_i + \omega_{14} Edu_i + \omega_{15} Emp_i + \omega_{16} Sfrq_i \end{pmatrix} W_{j,EDLP} \\
&\quad + \begin{pmatrix} \phi_{2i} + \psi_2 \rho_i + \omega_{21} Inc_i + \omega_{22} Hsz_i \\ +\omega_{23} Age_i + \omega_{24} Edu_i + \omega_{25} Emp_i + \omega_{26} Sfrq_i \end{pmatrix} W_{j,Hybrid} \\
&\quad + \begin{pmatrix} \phi_{3i} + \psi_3 \rho_i + \omega_{31} Inc_i + \omega_{32} Hsz_i \\ +\omega_{33} Age_i + \omega_{34} Edu_i + \omega_{35} Emp_i + \omega_{36} Sfrq_i \end{pmatrix} W_{j,HILO} \\
&\quad + \gamma_1 Nb_j + \gamma_2 Time_j + \epsilon_{ij},\ j \neq 0, \\
\phi_{1i} &= \overline{\phi_1} + \Theta_{1i},\ \Theta_{1i} \sim N(0, \sigma_1^2), \\
\phi_{2i} &= \overline{\phi_2} + \Theta_{2i},\ \Theta_{2i} \sim N(0, \sigma_2^2), \\
\phi_{3i} &= \overline{\phi_3} + \Theta_{3i},\ \Theta_{3i} \sim N(0, \sigma_3^2), \\
E\left[U_{i0}\right] &= \epsilon_{i0}.
\end{aligned} \tag{2.10}$$

Comparing the relative magnitudes of ψ_1, ψ_2, and ψ_3 allows me to test the relationship between consumers' risk attitudes and preferences for a particular store price format. More risk-averse consumers, who are characterized by a higher coefficient of absolute risk aversion, may perceive that shopping at HILO stores is risky due to higher price variability and, therefore, have an incentive to choose EDLP stores.

On the other hand, more risk-loving consumers, who are characterized by a lower coefficient of absolute risk aversion, may prefer HILO stores because they have a positive probability of finding a product with lower price. Thus, my hypothesis is that: $\psi_3 < \psi_2 < \psi_1$.

For estimation purposes, I assume that ϵ_{ij} are distributed iid extreme value, so the probability that alternative j is chosen is given by:

$$P_j = \int\int\int \frac{\exp(V_j)}{1 + \sum_{j=1}^{3} \exp(V_j)} dF(\Theta_{1i}) \times dF(\Theta_{2i}) \times dF(\Theta_{3i}), \tag{2.11}$$

where V_j is the deterministic component of expected utility and $F(\cdot)$ is the cumulative standard normal distribution. I use the simulated maximum likelihood to approximate the integrals in equation (2.11), and maximize the logarithm of the resulting simulated likelihood function with respect to the parameters (Train 2009). This method provides consistent parameter estimates under rather weak regularity conditions. To aid in the computational speed and efficiency of estimation, I use 100 Halton draws for realizations of Θ_{1i}, Θ_{2i} and Θ_{3i} (Bhat 2003).

2.4 Results and Discussion

I estimate a number of alternative specifications for (2.10) in order to examine the robustness of my model. Therefore, I begin by describing my experimental data, report specification tests that compare the goodness of fit across models, and then present and interpret the results obtained by estimating the preferred store-choice model. I then draw a number of implications regarding the practical importance of my findings.

A total of 275 subjects completed all parts of the experiment. However, in order to ensure that all subjects fully understood the rules of the lottery experiment, I embedded a control question. If subjects responded to this question in a way that suggested they were not making rational decisions, I excluded them from further analysis. Of the total sample, 57 subjects chose option A in the tenth choice task of the lottery experiment. Because this means that the subject prefers a certain 20 EUs to a certain 38 EUs, I interpreted this as an indication that the subject did not understand the rules of the lottery. That such subjects exist is perhaps not surprising, because I draw my sample from the general public rather than from a population of students who may be more familiar with this type of experiment, or at least the calculation required. Because it is impossible to calculate the coefficient of absolute risk aversion from data that includes responses such as this, I exclude these subjects and use the responses from the remaining 218 subjects for the subsequent analysis. The exclusion of these responses is not likely to have any adverse effects because those who make irrational lottery choices appear randomly in my sample. In other words, I retain the random nature of my sample by randomly excluding part of the observations. Following this procedure is well accepted in the literature (Harrison, List, and Towe 2007; Anderson and Mellor 2008).

Among the remaining responses, 138 subjects start with option A and then switched to option B and continue to select option B thereafter while 80 subjects switch back to option A even after having chosen option B. This type of behavior is also reported in other lottery choice experiments (Holt and Laury 2002; Lusk and Coble 2005; Harrison, List and Towe 2007; Anderson and Mellor 2008). In these cases, I employ the method of calculating the coefficient of absolute risk aversion used by these authors. Namely, for subjects who made multiple switches, I use the midpoint between the lower bound and the upper bound of the coefficient of absolute risk aversion, where the lower bound is determined by the first switch from option A to option B, and the upper bound is determined by the last time a subject chose option B. For example, suppose a subject chose option A for the first three choice tasks, switches to option B in the fourth task, switches back to option A in the fifth task, chose option B in the eighth task, and then continues to choose option B for all remaining tasks. In this case, the lower bound is -0.030 and the upper bound is 0.084, so the midpoint that is used for the estimation is 0.027.

I find considerable heterogeneity in subjects' attitudes toward risk. Table 2.6 reports the distribution of subjects' coefficient of absolute risk aversion, while tables 2.7 and 2.8 provide some descriptive data on the relationship between risk aversion and store choice. Specifically, these tables compare the choice share of each store price format, and the "non-shopping" option, for a range of coefficient of absolute risk aversion values. Table 2.7 reports the choice share based on a shopping basket that is comparable to Bell and Lattin (1998), while table 2.8 is based on a smaller basket. The summary statistics in these tables reveal some preliminary support for my hypothesis as there appears to be a positive relationship between the coefficient of constant risk aversion and the EDLP and Hybrid shares: More risk-averse subjects appear to choose EDLP or Hybrid stores more often. Moreover, these summary statistics show a negative relationship between the coefficient of constant risk aversion and the share of the HILO store. This result implies that risk-averse subjects prefer EDLP stores to HILO stores. However, this trend could be due to any one of a number of factors such as assortment depth, store location, and subjects' demographic attributes, so more conclusive evidence will need to found from the econometric estimates.

Table 2.6
Coefficient of Absolute Risk Aversion

Range of coefficient of absolute risk aversion	Obs.
$\rho_i \leq -0.095$	13
$-0.095 < \rho_i \leq -0.056$	0
$-0.056 < \rho_i \leq -0.030$	11
$-0.030 < \rho_i \leq -0.008$	19
$-0.008 < \rho_i \leq 0.013$	36
$0.013 < \rho_i \leq 0.033$	59
$0.033 < \rho_i \leq 0.056$	30
$0.056 < \rho_i \leq 0.084$	20
$0.084 < \rho_i \leq 0.126$	12
$0.126 \leq \rho_i$	18
Total	218

Table 2.7
Coefficient of Absolute Risk Aversion and Choice Share

Range of coefficient of absolute risk aversion	Obs.	EDLP (%)	Hybrid (%)	HILO (%)	Non-shopping (%)	Total (%)
$\rho_i \leq -0.056$	117	23.077	26.496	50.427	0.000	100
$-0.056 < \rho_i \leq -0.008$	270	27.778	30.741	36.296	5.185	100
$-0.008 < \rho_i \leq 0.033$	855	27.018	31.696	36.608	4.678	100
$0.033 < \rho_i \leq 0.084$	450	29.111	29.778	34.889	6.222	100
$0.084 \leq \rho_i$	270	24.815	33.333	36.667	5.185	100
Total	$1,962$	27.064	31.040	37.003	4.893	100

Note: Obs. = number of subjects $\times$ number of choice occasions.

Table 2.8
Coefficient of Absolute Risk Aversion and Choice Share (Small Shopping Basket)

Range of coefficient of absolute risk aversion	Obs.	EDLP (%)	Hybrid (%)	HILO (%)	Non-shopping (%)	Total (%)
$\rho_i \leq -0.056$	117	23.932	28.205	47.863	0.000	100
$-0.056 < \rho_i \leq -0.008$	270	24.815	31.111	36.296	7.778	100
$-0.008 < \rho_i \leq 0.033$	855	28.889	29.591	34.854	6.667	100
$0.033 < \rho_i \leq 0.084$	450	28.444	27.556	36.889	7.111	100
$0.084 \leq \rho_i$	270	24.815	36.296	32.222	6.667	100
Total	$1,962$	27.370	30.173	35.933	6.524	100

Note: Obs. = number of subjects $\times$ number of choice occasions.

My choice-based conjoint experiment is designed so that store choice depends on the variability of shopping-basket price, the number of brands available in each product category, and driving time to the store. I also include subjects' demographic attributes and risk attitudes, which are collected in the first-stage experiment. In order to evaluate the validity of the model specification, I conduct specification tests using the Akaike information criterion (AIC), Bayesian information criterion (BIC), and likelihood ratio (LR) test statistics. In table 2.9, I report the AIC and BIC for my proposed model, and an alternative model that does not include demographic attributes or risk attitudes. These results show that the proposed model achieves the lower value for AIC but, not for BIC. Despite the negative result from the BIC criterion, the LR test supports the proposed model. For the LR test, I define the proposed model as the alternative specification, and the model without demographic attributes and risk attitudes as the null specification. As shown in table 2.10, I reject the null in favor of the alternative according to the LR test. Thus, I conclude that the preferred specification must include both demographic attributes and risk attitudes, so I present and interpret the estimation results from this model.[4]

Table 2.9
AIC and BIC

Model	Log likelihood	Number of parameters	AIC	BIC
Proposed model	$-1,942$	29	$3,943$	$4,105$
Without demographic and risk variables	$-1,980$	8	$3,975$	$4,020$

[4] To investigate the influence of the assumption about utility form, I also estimate the proposed model using different risk measures such as coefficient of constant relative risk aversion, the number of safe choices, and choice task corresponding to the first risky choice. I obtain similar results regardless of which risk measure I use. Nevertheless, the proposed model achieves the highest log likelihood value and smallest standard errors for some important variables. These estimation results are available upon request.

Table 2.10
LR Statistic When the Alternative Model Is the Proposed Model

Null model	Degree of freedom	Critical value for 95%	LR statistic
Without demographic and risk variables	21	32.671	74.786

Estimates from the preferred specification again support my primary hypotheses. These results are shown in table 2.11. In order to examine the nature of the relationship between risk aversion and store choice, I interact each subject's coefficient of absolute risk aversion with a set of store-format indicator variables. In each case, these coefficients are all significant, suggesting that consumers' risk attitudes are important in explaining the marginal utility from choosing each store price format. Notice that all of these coefficients are negative. This is because subjects can receive a certain budget amount by choosing the "no shopping" option in each choice set. In the econometric model, the utility from choosing a "no shopping" option is normalized, so all estimates are measured relative to this option. Because the "no shopping" option is regarded as the safest choice available in each choice set in terms of price variation, it is natural that the coefficients of the interactions between subjects' coefficient of absolute risk aversion and each store price format are all negative.

Table 2.11
Estimation Result of the Proposed Model

Variable	Parameter	Symbol	Estimate	Std. error
Coef. of absolute risk aversion × EDLP	Mean coef.	ψ_1	-4.109^{*}	2.202
Coef. of absolute risk aversion × Hybrid	Mean coef.	ψ_2	-3.979^{*}	2.187
Coef. of absolute risk aversion × HILO	Mean coef.	ψ_3	-6.661^{**}	2.213
EDLP	Mean coef.	$\overline{\phi_1}$	2.721^{**}	0.554
	Std. dev. coef.	σ_1	-0.321	0.437
Hybrid	Mean coef.	$\overline{\phi_2}$	3.012^{**}	0.550
	Std. dev. coef.	σ_2	0.089	0.322
HILO	Mean coef.	$\overline{\phi_3}$	2.330^{**}	0.566
	Std. dev. coef.	σ_3	0.843^{**}	0.328
The number of brands	Mean coef.	γ_1	0.245^{**}	0.019
Driving time	Mean coef.	γ_2	-0.098^{**}	0.007
Income × EDLP	Mean coef.	ω_{11}	-0.693^{**}	0.292
Income × Hybrid	Mean coef.	ω_{21}	-0.469	0.286
Income × HILO	Mean coef.	ω_{31}	-0.470	0.287
Household size × EDLP	Mean coef.	ω_{12}	0.603	0.927
Household size × Hybrid	Mean coef.	ω_{22}	0.129	0.922
Household size × HILO	Mean coef.	ω_{32}	0.841	0.930
Age × EDLP	Mean coef.	ω_{13}	-1.554^{*}	0.823
Age × Hybrid	Mean coef.	ω_{23}	-1.695^{**}	0.817
Age × HILO	Mean coef.	ω_{33}	0.235	0.830
Education × EDLP	Mean coef.	ω_{14}	0.739^{**}	0.257
Education × Hybrid	Mean coef.	ω_{24}	0.500^{**}	0.255
Education × HILO	Mean coef.	ω_{34}	0.152	0.258
Employment × EDLP	Mean coef.	ω_{15}	-0.974^{**}	0.261
Employment × Hybrid	Mean coef.	ω_{25}	-0.872^{**}	0.258
Employment × HILO	Mean coef.	ω_{35}	-0.925^{**}	0.260
Shopping frequency × EDLP	Mean coef.	ω_{16}	0.335	0.224
Shopping frequency × Hybrid	Mean coef.	ω_{26}	0.300	0.223
Shopping frequency × HILO	Mean coef.	ω_{36}	0.439^{*}	0.225
Simulated log likelihood at convergence			$-1,942$	
AIC			$3,943$	
BIC			$4,105$	

Note: A single-asterisk indicates significance at a 10% level.
A double-asterisk indicates significance at a 5% level.

My main interest lies in examining the relative values of ψ_1, ψ_2, and ψ_3 in order to test whether there is any systematic relationship between consumers' risk attitudes and preference for store price format. The values of these coefficients in table 2.11 imply that the more risk-averse the subject, the more he or she prefers EDLP to HILO stores. However, it is not clear whether this relationship is statistically significant. The 90 percent confidence interval for ψ_1 is $[-7.731, -0.486]$ and ψ_3 is $[-10.301, -3.022]$. Because there is some overlap in the region between them, it is possible that $\psi_1 < \psi_3$ rather than $\psi_3 < \psi_1$ depending on the sample. To address this issue, I have to formally test the relative values of each parameter. I first test the relationship between ψ_1 and ψ_3. Following Kane and Rouse (1995), I consider the following specification of the expected utility:

$$\begin{aligned}
E\left[U_{ij}\right] &= \begin{pmatrix} \phi_{1i} + \psi_1 \rho_i + \omega_{11} Inc_i + \omega_{12} Hsz_i \\ +\omega_{13} Age_i + \omega_{14} Edu_i + \omega_{15} Emp_i + \omega_{16} Sfrq_i \end{pmatrix} W_{j,EDLP} \\
&+ \begin{pmatrix} \phi_{2i} + \psi_2 \rho_i + \omega_{21} Inc_i + \omega_{22} Hsz_i \\ +\omega_{23} Age_i + \omega_{24} Edu_i + \omega_{25} Emp_i + \omega_{26} Sfrq_i \end{pmatrix} W_{j,Hybrid} \\
&+ \begin{pmatrix} \phi_{3i} + \omega_{31} Inc_i + \omega_{32} Hsz_i \\ +\omega_{33} Age_i + \omega_{34} Edu_i + \omega_{35} Emp_i + \omega_{36} Sfrq_i \end{pmatrix} W_{j,HILO} \\
&+\psi_3 \times (\rho_i \times W_{j,EDLP} + \rho_i \times W_{j,HILO}) \\
&+\gamma_1 Nb_j + \gamma_2 Time_j + \epsilon_{ij},\ j \neq 0, \\
\phi_{1i} &= \overline{\phi_1} + \Theta_{1i},\ \Theta_{1i} \sim N(0, \sigma_1^2), \\
\phi_{2i} &= \overline{\phi_2} + \Theta_{2i},\ \Theta_{2i} \sim N(0, \sigma_2^2), \\
\phi_{3i} &= \overline{\phi_3} + \Theta_{3i},\ \Theta_{3i} \sim N(0, \sigma_3^2), \\
E\left[U_{i0}\right] &= \epsilon_{i0}.
\end{aligned} \tag{2.12}$$

The term, $\psi_3 \times \rho_i \times W_{j,EDLP}$ is added to the expected utility specification in (2.10) to establish (2.12). The coefficient on $\rho_i \times W_{j,EDLP}$ is key to testing the statistical difference between the coefficients for $\rho_i \times W_{j,EDLP}$ and $\rho_i \times W_{j,HILO}$. If I reject the hypothesis, $H_0 : \psi_1 = 0$ in (2.12), then the coefficient for $\rho_i \times W_{j,EDLP}$ is $\psi_1 + \psi_3$, which is different from the coefficient for $\rho_i \times W_{j,HILO}$. If I fail to reject the hypothesis, on the other hand, it is possible that ψ_1 is zero and the coefficients for $\rho_i \times W_{j,EDLP}$ and $\rho_i \times W_{j,HILO}$ are same and ψ_3. In this case, I cannot conclude that there is a statistically significant difference between the coefficients for $\rho_i \times W_{j,EDLP}$ and $\rho_i \times W_{j,HILO}$.

Table 2.12 reports the results obtained from estimating the expected utility specification in (2.12). I find that the coefficient on $\rho_i \times W_{j,EDLP}$ is positive and significant, which means that the coefficient on $\rho_i \times W_{j,EDLP}$ is greater than the coefficient on $\rho_i \times W_{j,HILO}$, and that this difference is statistically significant. Based on this test, my results show that consumers' risk attitudes have a different impact on the marginal utility from choosing EDLP and HILO stores in the context of the utility model in equation (2.10). Namely, more risk-averse consumers gain more from choosing EDLP than HILO, because they perceive shopping at a HILO store is risky due to greater price variation. Next, I conduct a similar test for investigating the relationship between ψ_2 and ψ_3. Table 2.13 shows that the coefficient for $\rho_i \times W_{j,Hybrid}$ is positive and significant, implying that the coefficient for $\rho_i \times W_{j,Hybrid}$ is greater than $\rho_i \times W_{j,HILO}$. This relationship is also statistically significant. Finally, I compare ψ_1 with ψ_2 in the same way. The results in table 2.14 show that the coefficient for $\rho_i \times W_{j,EDLP}$ is not significant, suggesting that there is no statistical difference between the coefficients for $\rho_i \times W_{j,EDLP}$ and $\rho_i \times W_{j,Hybrid}$ in equation (2.10). In total, these tests reveal that more risk-averse consumers tend to prefer EDLP to HILO stores and Hybrid to HILO stores.

Table 2.12
Testing of the Magnitude Relationship 1

Variable	Parameter	Symbol	Estimate	Std. error
Coef. of absolute risk aversion $\times$ EDLP	Mean coef.	ψ_1	2.553^{*}	1.363
Coef. of absolute risk aversion $\times$ Hybrid	Mean coef.	ψ_2	-3.978^{*}	2.187
$\rho_i \times W_{j,EDLP} + \rho_i \times W_{j,HILO}$	Mean coef.	ψ_3	-6.660^{**}	2.212
EDLP	Mean coef.	$\overline{\phi_1}$	2.721^{**}	0.554
	Std. dev. coef.	σ_1	-0.321	0.437
Hybrid	Mean coef.	$\overline{\phi_2}$	3.012^{**}	0.550
	Std. dev. coef.	σ_2	0.089	0.322
HILO	Mean coef.	$\overline{\phi_3}$	2.331^{**}	0.566
	Std. dev. coef.	σ_3	0.843^{**}	0.328
The number of brands	Mean coef.	γ_1	0.245^{**}	0.019
Driving time	Mean coef.	γ_2	-0.098^{**}	0.007
Income $\times$ EDLP	Mean coef.	ω_{11}	-0.693^{**}	0.292
Income $\times$ Hybrid	Mean coef.	ω_{21}	-0.469	0.286
Income $\times$ HILO	Mean coef.	ω_{31}	-0.470	0.287
Household size $\times$ EDLP	Mean coef.	ω_{12}	0.603	0.927
Household size $\times$ Hybrid	Mean coef.	ω_{22}	0.129	0.922
Household size $\times$ HILO	Mean coef.	ω_{32}	0.841	0.930
Age $\times$ EDLP	Mean coef.	ω_{13}	-1.555^{*}	0.823
Age $\times$ Hybrid	Mean coef.	ω_{23}	-1.696^{**}	0.817
Age $\times$ HILO	Mean coef.	ω_{33}	0.234	0.830
Education $\times$ EDLP	Mean coef.	ω_{14}	0.739^{**}	0.257
Education $\times$ Hybrid	Mean coef.	ω_{24}	0.500^{**}	0.255
Education $\times$ HILO	Mean coef.	ω_{34}	0.152	0.258
Employment $\times$ EDLP	Mean coef.	ω_{15}	-0.974^{**}	0.261
Employment $\times$ Hybrid	Mean coef.	ω_{25}	-0.872^{**}	0.258
Employment $\times$ HILO	Mean coef.	ω_{35}	-0.925^{**}	0.260
Shopping frequency $\times$ EDLP	Mean coef.	ω_{16}	0.335	0.224
Shopping frequency $\times$ Hybrid	Mean coef.	ω_{26}	0.300	0.223
Shopping frequency $\times$ HILO	Mean coef.	ω_{36}	0.439^{*}	0.225
Simulated log likelihood at convergence			$-1,942$	
AIC			$3,943$	
BIC			$4,105$	

Note: A single-asterisk indicates significance at a 10% level.
A double-asterisk indicates significance at a 5% level.

Table 2.13
Testing of the Magnitude Relationship 2

Variable	Parameter	Symbol	Estimate	Std. error
Coef. of absolute risk aversion × EDLP	Mean coef.	ψ_1	-4.107^{*}	2.202
Coef. of absolute risk aversion × Hybrid	Mean coef.	ψ_2	2.683^{*}	1.376
$\rho_i \times W_{j,Hybrid} + \rho_i \times W_{j,HILO}$	Mean coef.	ψ_3	-6.661^{**}	2.212
EDLP	Mean coef.	$\overline{\phi_1}$	2.722^{**}	0.554
	Std. dev. coef.	σ_1	-0.321	0.437
Hybrid	Mean coef.	$\overline{\phi_2}$	3.012^{**}	0.550
	Std. dev. coef.	σ_2	0.089	0.322
HILO	Mean coef.	$\overline{\phi_3}$	2.331^{**}	0.566
	Std. dev. coef.	σ_3	0.843^{**}	0.328
The number of brands	Mean coef.	γ_1	0.245^{**}	0.019
Driving time	Mean coef.	γ_2	-0.098^{**}	0.007
Income × EDLP	Mean coef.	ω_{11}	-0.693^{**}	0.292
Income × Hybrid	Mean coef.	ω_{21}	-0.469	0.286
Income × HILO	Mean coef.	ω_{31}	-0.470	0.287
Household size × EDLP	Mean coef.	ω_{12}	0.603	0.927
Household size × Hybrid	Mean coef.	ω_{22}	0.129	0.922
Household size × HILO	Mean coef.	ω_{32}	0.841	0.930
Age × EDLP	Mean coef.	ω_{13}	-1.555^{*}	0.823
Age × Hybrid	Mean coef.	ω_{23}	-1.696^{**}	0.817
Age × HILO	Mean coef.	ω_{33}	0.234	0.830
Education × EDLP	Mean coef.	ω_{14}	0.739^{**}	0.257
Education × Hybrid	Mean coef.	ω_{24}	0.500^{**}	0.255
Education × HILO	Mean coef.	ω_{34}	0.152	0.258
Employment × EDLP	Mean coef.	ω_{15}	-0.974^{**}	0.261
Employment × Hybrid	Mean coef.	ω_{25}	-0.872^{**}	0.258
Employment × HILO	Mean coef.	ω_{35}	-0.925^{**}	0.260
Shopping frequency × EDLP	Mean coef.	ω_{16}	0.335	0.224
Shopping frequency × Hybrid	Mean coef.	ω_{26}	0.300	0.223
Shopping frequency × HILO	Mean coef.	ω_{36}	0.439^{*}	0.225
Simulated log likelihood at convergence			$-1,942$	
AIC			$3,943$	
BIC			$4,105$	

Note: A single-asterisk indicates significance at a 10% level.
A double-asterisk indicates significance at a 5% level.

Table 2.14
Testing of the Magnitude Relationship 3

Variable	Parameter	Symbol	Estimate	Std. error
Coef. of absolute risk aversion × EDLP	Mean coef.	ψ_1	-0.130	1.396
$\rho_i \times W_{j,EDLP} + \rho_i \times W_{j,Hybrid}$	Mean coef.	ψ_2	-3.979^{*}	2.187
Coef. of absolute risk aversion × HILO	Mean coef.	ψ_3	-6.661^{**}	2.212
EDLP	Mean coef.	$\overline{\phi_1}$	2.722^{**}	0.554
	Std. dev. coef.	σ_1	-0.321	0.437
Hybrid	Mean coef.	$\overline{\phi_2}$	3.012^{**}	0.550
	Std. dev. coef.	σ_2	0.089	0.322
HILO	Mean coef.	$\overline{\phi_3}$	2.331^{**}	0.566
	Std. dev. coef.	σ_3	0.843^{**}	0.328
The number of brands	Mean coef.	γ_1	0.245^{**}	0.019
Driving time	Mean coef.	γ_2	-0.098^{**}	0.007
Income × EDLP	Mean coef.	ω_{11}	-0.693^{**}	0.292
Income × Hybrid	Mean coef.	ω_{21}	-0.469	0.286
Income × HILO	Mean coef.	ω_{31}	-0.470	0.287
Household size × EDLP	Mean coef.	ω_{12}	0.603	0.927
Household size × Hybrid	Mean coef.	ω_{22}	0.129	0.922
Household size × HILO	Mean coef.	ω_{32}	0.841	0.930
Age × EDLP	Mean coef.	ω_{13}	-1.555^{*}	0.823
Age × Hybrid	Mean coef.	ω_{23}	-1.696^{**}	0.817
Age × HILO	Mean coef.	ω_{33}	0.234	0.830
Education × EDLP	Mean coef.	ω_{14}	0.739^{**}	0.257
Education × Hybrid	Mean coef.	ω_{24}	0.500^{**}	0.255
Education × HILO	Mean coef.	ω_{34}	0.152	0.258
Employment × EDLP	Mean coef.	ω_{15}	-0.974^{**}	0.261
Employment × Hybrid	Mean coef.	ω_{25}	-0.872^{**}	0.258
Employment × HILO	Mean coef.	ω_{35}	-0.925^{**}	0.260
Shopping frequency × EDLP	Mean coef.	ω_{16}	0.335	0.224
Shopping frequency × Hybrid	Mean coef.	ω_{26}	0.300	0.223
Shopping frequency × HILO	Mean coef.	ω_{36}	0.439^{*}	0.225
Simulated log likelihood at convergence			$-1,942$	
AIC			$3,943$	
BIC			$4,105$	

Note: A single-asterisk indicates significance at a 10% level.
A double-asterisk indicates significance at a 5% level.

Among the other estimates reported in table 2.11 are a number of results that also may be of interest to practitioners. First, each store price format, EDLP, Hybrid, and HILO, has a positive and significant impact on expected utility. The magnitude of this format-effect is slightly larger for Hybrid than the others, suggesting that consumers may prefer moderate price variation. Further, the standard deviation of the coefficient of HILO store is significant, indicating that there is considerable variation in preferences for the HILO format. Second, the number of brands available in each product category has positive and statistically significant impact on expected utility. Consumers prefer stores with deeper assortments, which is consistent with Oppewal and Koelemeijer (2005), Borle, Boatwright, Nunes, and Shmueli (2005), and Briesch, Chintagunta, and Fox (2009). As expected, the distance to the store, as measured by driving time, has a negative and statistically significant effect on expected utility. This finding both makes sense as consumers tend to shop at stores that are nearer to them, and is consistent with the literature (Arnold, Oum, and Tigert 1983; Bell, Ho, and Tang 1998; Bawa and Ghosh 1999).

Demographic heterogeneity appears to be important in explaining store choice. Specifically, I find that income has statistically significant negative effect on marginal utility from choosing an EDLP store, while its effect on other store price formats is not significant. This implies that low-income households prefer certain low prices and tend to shop more often at EDLP stores. Age has statistically significant impact on the marginal utility from choosing EDLP and Hybrid stores, but not from HILO, indicating that younger people have a stronger preference for EDLP and Hybrid stores. I find that education has a positive effect on the marginal utility from choosing EDLP and Hybrid stores. It may be the case that higher-educated consumers tend to be more conscious about price fluctuations, do not prefer variation in the prices they face, and choose to shop at EDLP and Hybrid stores as a result. For all formats, employment status has negative and significant impact. Because employment status is defined so that a one indicates full-time employment, this result may be simply because busy full-time workers are reluctant to shop at all. Shopping frequency plays an important role in explaining the marginal benefit from shopping at a HILO store. The positive and significant effect of shopping frequency on subjects' preference for

HILO stores suggests that frequent shoppers prefer the ability to find a good deal. Frequent shoppers are able to take advantage of price variation because they tend to have greater knowledge about shelf prices in general through their deeper shopping experience (Bell and Lattin 1998).

Finally, I investigate how the results of my proposed model change when I reduce the size of the shopping basket (table 2.15). One notable difference between the results reported in tables 2.11 and 2.15 is that the coefficients of the interactions between subjects' coefficient of absolute risk aversion and the EDLP and Hybrid indicators become insignificant in table 2.15.[5] This result implies that consumers' risk attitudes become less important when their basket size is small. When the total amount at risk is reduced, consumers logically become less sensitive about price variation, so this result is intuitive.

[5] I find a similar tendency even when I use different risk measures such as the coefficient of constant relative risk aversion, the number of safe choices, and choice task corresponding to the first risky choice. This implies that my finding is not due to my assumption regarding the nature of the utility function. These estimation results are available upon request.

Table 2.15
Estimation Result of the Proposed Model with Small Shopping Basket

Variable	Parameter	Symbol	Estimate	Std. error
Coef. of absolute risk aversion × EDLP	Mean coef.	ψ_1	-2.146	1.928
Coef. of absolute risk aversion × Hybrid	Mean coef.	ψ_2	-1.051	1.923
Coef. of absolute risk aversion × HILO	Mean coef.	ψ_3	-4.058^{**}	1.914
EDLP	Mean coef.	$\overline{\phi_1}$	2.088^{**}	0.477
	Std. dev. coef.	σ_1	-0.237	0.467
Hybrid	Mean coef.	$\overline{\phi_2}$	1.791^{**}	0.478
	Std. dev. coef.	σ_2	-0.059	0.367
HILO	Mean coef.	$\overline{\phi_3}$	2.004^{**}	0.477
	Std. dev. coef.	σ_3	-0.551	0.369
The number of brands	Mean coef.	γ_1	0.242^{**}	0.017
Driving time	Mean coef.	γ_2	-0.096^{**}	0.006
Income × EDLP	Mean coef.	ω_{11}	-0.170	0.268
Income × Hybrid	Mean coef.	ω_{21}	-0.219	0.268
Income × HILO	Mean coef.	ω_{31}	-0.282	0.266
Household size × EDLP	Mean coef.	ω_{12}	0.232	0.834
Household size × Hybrid	Mean coef.	ω_{22}	1.182	0.829
Household size × HILO	Mean coef.	ω_{32}	0.588	0.823
Age × EDLP	Mean coef.	ω_{13}	-1.305^{*}	0.698
Age × Hybrid	Mean coef.	ω_{23}	-1.039	0.698
Age × HILO	Mean coef.	ω_{33}	-0.322	0.691
Education × EDLP	Mean coef.	ω_{14}	0.150	0.223
Education × Hybrid	Mean coef.	ω_{24}	0.120	0.223
Education × HILO	Mean coef.	ω_{34}	-0.093	0.221
Employment × EDLP	Mean coef.	ω_{15}	-0.544^{**}	0.228
Employment × Hybrid	Mean coef.	ω_{25}	-0.360	0.227
Employment × HILO	Mean coef.	ω_{35}	-0.228	0.225
Shopping frequency × EDLP	Mean coef.	ω_{16}	0.265	0.195
Shopping frequency × Hybrid	Mean coef.	ω_{26}	0.222	0.195
Shopping frequency × HILO	Mean coef.	ω_{36}	0.271	0.194
Simulated log likelihood at convergence			$-2,016$	
AIC			$4,089$	
BIC			$4,251$	

Note: A single-asterisk indicates significance at a 10% level.
A double-asterisk indicates significance at a 5% level.

Retail managers may be interested in my findings, primarily because of the importance and prominence of format choice. Because the format of individual stores differs even within the same chain, managers must carefully consider the implications for market share, and for profitability. My finding with respect to consumers' store choice behavior provides some information that may be useful in this regard. I find that there is a systematic relationship between consumers' risk attitudes and their preference for store-price format, so managers would be well-advised to obtain data on the risk-profile of their particular market. Because consumers perceive the risk associated with basket-price variation, and because stores differ in terms of their format, consumers with different risk attitudes will self-select stores that are consistent with their risk preferences. Given that risk attitudes differ among consumers, any store price format has a potential for success in a particular market. For example, if a chain is contemplating opening in a relatively low-income area in a market, it would benefit from adopting a format more toward the EDLP end of the format continuum as I find that low income consumers tend to prefer less variable prices. My results also explain the coexistence of different store price formats within each market. Because risk attitudes differ and consumers self-select, each market needs a variety of stores to cater to the revealed risk preferences of its clientele.

This study implies that coexistence of EDLP and HILO stores in the same market is attributed to heterogeneity in risk preferences. Such a mechanism is common in many other fields. In insurance markets, for example, a certain type of insurance may screen a certain type of consumer e.g. a risk-averse consumer may have an incentive to choose a higher-deductible health plan. In job markets, a certain payment scheme may elicit a certain type of employees e.g. risk-loving employees may prefer incentive or variable payment which varies based on their performance. Consumers' or employees' self-selection based on different risk attitudes may play an important role in explaining coexistence of different alternatives in the same market.

2.5 Conclusions and Implications

In this chapter, I investigate retailer motivations for offering different store-price formats. In general, retailers choose a pricing format that is characterized by either more variable prices (HILO), or less variable, lower-mean prices (EDLP), or somewhere in-between. As prices vary over time and each format is defined by the mean and the variance of prices, consumers perceive different formats as offering either a low-risk or high-risk proposition. In any uncertain choice context, attitudes toward risk are important for observed behavior, so I expect the same to be true for consumers' store choice decisions. I examine how consumers respond to price uncertainty when choosing where to shop.

In order to understand the relationship between consumers' risk attitudes and retailers' pricing strategies, I develop a discrete choice model of store choice. I test this model using data generated by a two-stage, incentive-compatible experiment in which I elicit subjects' risk attitudes through a lottery choice experiment, and then, in a second stage, use a choice-based conjoint experiment to determine how consumers' attitudes toward risk influence their choice of store format.

I show that consumers perceive considerable risk in choosing between stores, and that this risk ultimately influences the choices they make. My estimates reveal a systematic relationship between consumers' risk attitudes and preferences for particular store price formats. More risk-averse consumers are more likely to choose an EDLP store that is characterized by less price variability and lower average price. My findings suggest that pricing strategies allow consumers with different risk attitudes to self-select a particular store format, which explains the evident coexistence of stores with different pricing formats in the same market. Moreover, I find that this effect is less important when basket size is small.

Some consumers may search for a better price for every product in their shopping basket across time and space, and purchase only those items that sell for the lowest possible price. As discussed above, however, such complete-price search is usually impossible due to the high search cost. As a result, average consumers buy higher at HILO stores than EDLP stores. Under this circumstance, risk-averse consumers may demand "insurance" to cover against basket price variation. As EDLP stores guarantee relatively a constant basket price, risk-averse consumers are likely to perceive that shopping at EDLP stores provides the insurance they seek. This may be another reason why risk-averse consumers tend to prefer EDLP stores to HILO stores. Namely, by shopping at EDLP stores, risk-averse consumers purchase an insurance to manage price variation. The difference between the basket price that achieves the expected utility from shopping at HILO stores and a certain basket price realized by shopping at EDLP stores can be interpreted as a risk premium. This risk premium represents disutility for risk-averse consumers from facing the price variation in the retail market and their willingness-to-pay for reducing the risk.

My study provides information that may be useful to managers charged with designing retail pricing strategies. Most importantly, any type of store price format has the potential to succeed if consumers differ in terms of their attitudes toward risk. My results show that store price format is not merely a strategic choice of prices, but also a screening device that effectively separates consumers with different risk attitudes. Consumers' self-selection among stores is one of the reasons why there is no single, dominant store format in most markets.

My findings suggest a number of avenues for future research. While my model offers new insight about consumers' store-choice decisions, it does not consider consumers' store-search behavior. In my experiment, the variance of basket price is held constant across subjects. However, it is possible that the variance is endogenous and, in fact, changes depending on subjects' search behavior, exposure to supermarket flyers, or previous shopping experience. It would be worthwhile to incorporate consumers' potential information gain from search into my experiment and analytical model. This research could also be extended to incorporate strategic pricing decisions by retailers. It may be the case that retailers optimally react to the consumers' store price format choice in consideration of rival retailers' strategies. Equilibrium analysis of the interactions between utility-maximizing consumers with different risk attitudes and profit-maximizing retailers may provide insight into retailers' strategies. I leave these ideas for future research.

CHAPTER 3.

ESSAY 2: ATTRIBUTE UNCERTAINTY AND NEW PRODUCT CHOICE

3.1 Introduction

Success in introducing new products is critical for sales growth, yet most new products ultimately fail. SymphonyIRI (2012a) reports that nearly 80 percent of new products introduced in the market fail to achieve more than \$7.5 million in year-one sales and only less than three percent of the new products achieve over \$50 million in year-one sales. Poor acceptance by consumers may be due to the uncertainty about how new or unfamiliar products fit their preferred attribute set. Flavor, aroma, efficacy, usability, and durability are experience attributes that are inherently indeterminable until the product is purchased and used (Nelson 1970). One of the ways a consumer may reduce the risk that a new product proves unacceptable is to use quality signals. For example, a parent brand may signal the quality of an umbrella brand (Erdem 1998), price may signal product quality (Erdem, Keane and Sun 2008; Erdem, Katz and Sun 2010), or a firm may use advertising as a complementary signal to price, or to convey information on product attributes (Erdem and Keane 1996; Erdem and Sun 2002; Ackerberg 2003; Byzalov and Shachar 2004; Chen and Narasimhan 2008; Mehta, Anand and Shachar 2011). Another is to simply purchase a smaller amount than usual on an initial, or trial purchase. Shoemaker and Shoal (1975) find that consumers tend to choose a smaller than usual package or quantity on their trial purchase of a new product, but do not explain why. In this essay, I offer a theoretical explanation and an empirical test of how reducing purchase quantities can serve as a risk reduction strategy.

My explanation is grounded in a model of a utility-maximizing consumer. On the surface, the explanation seems trivial: Reducing the amount purchased limits the financial loss and, hence, the risk of purchase. In product categories such as carbonated soft drinks, ice cream, ready-to-eat cereals, and yogurt, consumers typically shop infrequently relative to their consumption rate, so often purchase either many units of a single product or a bundle of products on a single purchase occasion (Hendel 1999; Kim, Allenby and Rossi 2002; Dubé 2004, 2005). If they purchase their usual quantity and are reluctant to simply throw the new product out, the lost consumption-utility can be substantial. Risk-reduction is therefore a consequence of diminishing marginal utility. If utility must be concave in quantity in order to ensure an interior solution to the utility-maximization problem, and if utility is more concave in quantity under uncertainty, then satiation occurs at a smaller quantity. Because the uncertainty surrounding the trial purchase of a new product is significantly higher than for one that is well-understood, consumers naturally purchase a lower quantity as a result of the lower optimal-satiation level. Therefore, it is important to capture structural changes in utility function as consumers make a trial purchase of a new product.

Consumers are generally regarded as risk averse with respect to their purchases of consumer packaged goods (CPGs) (Kahneman and Tversky 1979). Others account for attitudes toward risk associated with uncertainty in product quality by defining quality as "perceived quality" and find that the risk parameter has a significant impact on utility (Meyer and Sathi 1985; Roberts and Urban 1988; Horsky and Nelson 1992; Erdem and Keane 1996; Erdem 1998; Byzalov and Shachar 2004; Erdem, Zhao, and Valenzuela 2004; Erdem, Keane, and Sun 2008; Mehta, Chen, and Narashimhan 2008; Chen, Sun, and Singh 2009). Perceived quality, however, is an abstract construct that is difficult to model. Therefore, I capture revealed preferences for the risk associated with consumers' purchases of new products by modeling risk-reduction behavior in terms of the concavity of the utility function: If consumers exhibit diminishing marginal returns to purchase-quantity and their utility function is more concave under attribute uncertainty, then they purchase less in response to the risk that a new product does not meet their prior expectation in the subsequent consumption occasions. Erdem, Imai and Keane (2003), Sun (2005), and Hendel and Nevo (2006) model concavity to analyze promotion effects on consumption quantity rather than consumer risk-reduction behaviors. By assuming utility is concave in the quantity of the chosen brand, stockpiling behavior is revealed by estimating satiation points. I use a similar approach, but in the context of consumer risk behavior of new product purchases and uncertainty in product attributes. If structural changes in utility accompany the trial purchase of a new product, then explicitly modeling consumers' attempt to limit their exposure to risk explains observed purchase behavior in a new and novel way.

To investigate satiation with respect to the purchase of CPGs, the model must explicitly account for satiation or concavity of utility. Second, the model should be consistent with the data generating process, namely, it must allow for the purchase of multiple brands within a single category, and continuous amounts of each brand (Hendel 1999; Kim, Allenby, and Rossi 2002; Dubé 2004, 2005). Third, the effect of quality signals, which are often considered as another set of risk-reduction tools, should be taken into account. Fourth, demographic attributes and state-dependence must be included because observed heterogeneity is nearly always an important determinant of purchase-quantity decisions. For example, if the household is large, consumers tend to purchase many units of a single brand or many variants of brands to meet the demands of each person (Dubé 2004). Further, high-income households may not be sensitive to the risk of purchasing a disappointing product and may not see the need to reduce purchase-quantity. Fifth, the effect of any marketing variables must be taken into account. For example, households may change their purchase and purchase-quantity decisions depending on temporary product promotions. For these reasons, I use a demand model that explicitly accounts for the multiple-discrete / continuous nature of packaged-food purchases (Bhat 2005, 2008) to estimate the effect of new product purchase on satiation, while controlling for the effect of both observed and unobserved heterogeneity on demand.

The econometric model is derived from a household-level constrained utility maximization problem, which enables me to estimate structural parameters governing satiation or concavity of utility. By incorporating risk (trial purchases of a new product in my context), the satiation parameters reveal how consumers in the CPG market behave in risky, new product-purchase situations. Perceived quality is modeled explicitly as variation in baseline marginal utility, or the change in utility if consumption moves from zero to a single unit. Finally, the satiation parameter is allowed to depend on demographic, state-dependent, and marketing mix variables to control for observe heterogeneity on demand.

Models of the demand for differentiated products typically assume consumers purchase only one product when faced with a choice of many differentiated products (Guadagni and Little 1983; Besanko, Gupta and Jain 1998). However, because purchases are made in the anticipation of several eating occasions before the next shopping trip, and for many individuals within the household, consumers tend to purchase either multiple variants of one brand or many different brands, and varying quantities of either. Wales and Woodland (1983) describe two alternative approaches for specifying a demand model in which corner solutions are inherent in the problem itself. A researcher can solve a traditional representative-consumer demand system (the Almost Ideal Demand system, for example) and correct for the bias that results from the multiple zeros that follow. However, this approach is somewhat unsatisfying as it leave the reasons for the corner solutions unexplained. Their second approach is a structural one in which the researcher derives the Kuhn-Tucker conditions that solve the consumers' constrained utility-maximization problem while allowing for corner solutions. Phaneuf (1999) and Phaneuf and von Haefen (2005) follow this approach in studying the demand for recreational amenities, while Kim, Allenby and Rossi (2002) use it in a marketing context and Bhat (2005, 2008) and Pinjari and Bhat (2010) to study transportation demand. My approach is most similar to Bhat (2005, 2008) in that I adopt a CES model of sub-utility and assume the distribution of consumer heterogeneity is extreme-value distributed. The resulting multiple-discrete / continuous extreme value (MDCEV) model allows me to parameterize satiation in a framework that is both grounded in a consumer's utility-maximization problem and is empirically tractable.

Identifying household-level satiation points while controlling for demographic attributes requires household-panel purchase data. I frame my test of consumers' risk-reduction behavior using household-panel scanner data for the yogurt category in major U.S. cities. I find that utility is more concave, and satiation occurs, at a smaller quantity on trial purchases of a new brand. This result suggests that consumers reduce the risk of a new brand by purchasing a smaller than usual quantity on their trial purchase. Moreover, I find that risk attitudes toward trial purchases of a new brand are heterogeneous across consumers – 79 percent of those who try a new product are more risk-averse and 21 percent of them are more risk-loving.

My study makes a number of contributions to the empirical marketing literature. First, I am the first to venture and test a theoretical explanation for the reduced purchased quantities observed by Shoemaker and Shoal (1975). Second, I demonstrate how an empirically tractable model of multiple-discrete / continuous purchases can be used to solve a practical problem in marketing. Third, this study is the first attempt to measure consumers' risk attitudes toward trial purchases of a new product. My findings are also of importance to CPG marketers more generally. Most importantly, consumers experience significant risk when contemplating the purchase of an untried-brand. Consumers have a limited number of usage occasions for most products, and do not want to be disappointed on any of them. CPG companies would be well-advised to design appropriate strategies to limit consumers' exposure, either by offering smaller packages, selling single units instead of bundles or merchandising through in-store samples, or offering some type of guarantee.

The reminder of this paper is organized as follows. I provide a theoretical explanation of consumer risk-reduction behavior in the second section. I describe the multiple-discrete / continuous econometric model in the third section, while I summarize and provide more detail on the data in the fourth. I present and interpret the results in a fifth section. Conclusions, implications and potential extensions are described in the final section.

3.2 Economic Model of New Product Choice under Uncertainty

In order to investigate consumer attitudes toward risk associated with trial purchase of a new brand, I consider a consumer who has a preference over qualityadjusted consumption, Q where Q is a stochastic term that is the product of quality, π and consumption, c of a given product. Assuming π is stochastic and c is deterministic, then the value of $Q = \pi c$ is stochastic. Utility of a representative consumer is given by $u(Q)$ where $u(\cdot)$ is assumed to be increasing, concave, and continuously differentiable, and Q is assumed to be normally distributed with mean μ and variance σ^2. Mean utility, μ, represents the consumer's prior expectation of product quality and σ^2 represents his or her level of uncertainty. In other words, large values of σ^2 mean that the consumer has little knowledge about that product. It is well-understood that when Q is normally distributed, the expected utility can be represented by a function of μ and σ^2 alone, increasing in μ, and decreasing in σ^2.

Suppose that the consumer can choose either of two products, product one with $Q_1 \sim N(0, \sigma_1^2)$ or product two with $Q_2 \sim N(0, \sigma_2^2)$ and that $\sigma_1^2 < \sigma_2^2$. These assumptions imply that the consumer has the same prior expectation of Q on products one and two, but is more uncertain about product two than product one. Although risk aversion would imply that the consumer purchases only product one because $E[u(Q_1)] > E[u(Q_2)]$, we often observe consumers purchasing products under greater uncertainty. Why? I reconcile the theory and the observation by hypothesizing that the shape of the utility function changes depending on the nature of the purchase occasion. Because risk aversion implies that the utility from a lottery is less than the utility from the expected value of that lottery, the degree of risk aversion for product one and product two is calculated as $u(0) - E[u(Q_1)]$ and $u(0) - E[u(Q_2)]$, respectively. By normalizing $u(0)$ to zero for any purchase occasion, these terms are written as $-E[u(Q_1)]$ and $-E[u(Q_2)]$. Since $E[u(Q_1)] > E[u(Q_2)]$, the consumer is more risk averse when purchasing product two relative to when he or she purchases product one, which implies larger Arrow-Pratt measure of risk aversion from purchasing product two than product one. Using Pratt's theorem, I can conclude that the utility from purchasing product two is more concave than product one.

In sum, the consumer is more risk averse and his or her utility is more concave when purchasing product two relative to product one. Because consumers usually know less about new products compared to their usual products, it is expected that utility is more concave for trial purchases of a new product relative to those of incumbent products. As a result, consumers become satiated at a lower quantity for trial purchases of a new product. In the following sections, I test this hypothesis using a multiple-discrete / continuous econometric model that explicitly accounts for satiation and concavity of utility.

3.3 Econometric Model

In this section, I derive a demand system that reflects multiple discrete / continuous choices over yogurt brands. In household-panel data, purchase-occasion information is available. Because this type of data reflects purchases made in anticipation of potentially several eating occasions, the data show that households often purchases multiple brands per visit (table 3.2). Therefore, a discrete-choice model is not appropriate. Further, households purchase several units during each trip (table 3.1) so the quantity choice is approximately continuous.[1] Solving the constrained utility maximization problem for each household following the general Kuhn-Tucker (K-T) approach of Wales and Woodland (1983) produces positive demand for a subset of all available yogurt brands, with other food purchases defined as a numeraire or

[1] I describe purchases as "approximately continuous" because consumers are constrained by package-sizes.

outside option. Tastes are assumed to be distributed randomly throughout the population and stochasticity derives directly from consumer heterogeneity. The result is a demand system in which corner solutions are explained and incorporated into the econometric model in a theoretically-consistent way. Estimating corner solutions using a K-T-based model provides a means of estimating a structural model of demand in which postulates regarding the primitives of utility, including satiation and diminishing marginal utility, can be easily tested.

Following Kim, Allenby and Rossi (2002) and Bhat (2005, 2008), I allow utility to be additive over brands, and account for satiation and diminishing marginal utility by introducing curvature in the utility function. The utility function that results from household h purchasing a certain amount of a brand i at occasion j is described as:

$$\begin{aligned} u_j^h(q_{ij}^h, X_{ij}^h, D^h, \theta) &= \frac{1}{\alpha_1}\exp(\varepsilon_{1j}^h)(q_{1j}^h)^{\alpha_1} + \sum_{i=2}^{I}\left(\frac{\gamma_i}{\alpha_i}\right)\varphi_{ij}^h\left\{\left(\frac{q_{ij}^h}{\gamma_i}+1\right)^{\alpha_i} - 1\right\}, \\ & j = 1, 2 \ldots J,\ h = 1, 2 \ldots H, \qquad (3.1) \end{aligned}$$

where q_{ij}^h is an amount of brand i purchased by household h on occasion j, X_{ij}^h is a vector of brand-, occasion-, and household-specific attributes, D^h is a vector of demographic attributes describing household h, θ is a vector of parameters to be estimated, ε_{1j}^h is a brand-, occasion-, and household-specific random term associated with the outside or numeraire good ($i = 1$) that reflects unobservable factors driving demand, φ_{ij}^h is a baseline marginal utility of brand i on occasion j by household h, α_i is a parameter that reflects satiation or curvature of the utility function ($\alpha_i < 1$), and γ_i is a translation parameter. This utility function is nicely behaved namely, it is quasi-concave, increasing, and continuously differentiable with respect to q_{ij}^h.

Bhat (2008) discusses the roles of baseline marginal utility, translation parameter, and satiation as follows. The baseline marginal utility, or quality, parameter represents the marginal utility when none is consumed. The "baseline" interpretation derives from the fact that diminishing marginal utility is assumed, so marginal utility only declines from the value of baseline marginal utility at zero consumption. It can also be interpreted as a measure of embodied quality because higher values of baseline marginal utility mean that the brand confers higher levels of utility from any level of consumption, all else constant. Translation parameter defines both the asymptotic nature and slope of the indifference curve in that each indifference curve is asymptotic to the axes from $(0, 0, \ldots, 0)$ to $(-\gamma_1, -\gamma_2, \ldots, -\gamma_I)$. Therefore, the indifference curve strikes the positive orthant with a finite slope, which allows for corner solutions that depend on the level of the budget constraint. Also, translation parameter governs degree of satiation in that a higher value of translation parameter implies steeper indifference curve slopes and stronger preference for good i. Satiation is also measured by α_i, as it determines how the marginal utility of brand i changes as q_{ij}^h increases. Unlike translation parameter, however, satiation only measures satiation while translation parameter determines both the location of corner solutions and where the consumer becomes satiated. When $\alpha_i = 1$ for all i, there is no satiation and a household purchases a single brand with the highest price-adjusted marginal utility. As α_i falls, on the other hand, satiation increases and the utility function is more concave with respect to brand i, and the satiation occurs at a lower level of q_{ij}^h. In this study, therefore, my primary hypothesis concerns satiation: If utility is more concave, then satiation should be lower for trial purchases of a new brand than for those of existing brands. In other words, if the trial purchase of new brands is inherently risky, then consumers can minimize their utility-loss from a bad choice by reducing purchase quantities because utility is more concave with risk.

Baseline marginal utility is specified as:

$$\begin{aligned} \varphi_{ij}^{h} &= \exp\left(\begin{array}{c} \beta_{1i} + \beta_{2i}Hsz^{h} + \beta_{3i}Inc^{h} + \beta_{4i}Age^{h} + \beta_{5i}Edu^{h} \\ +\beta_{6i}Inv_{j}^{h} + \beta_{7i}Loy_{ij}^{h} + \beta_{8i}Pd_{ij} + \varepsilon_{ij}^{h} \end{array}\right), \\ & i = 2,3\ldots I,\ j = 1,2\ldots J,\ h = 1,2\ldots H, \end{aligned} \tag{3.2}$$

where β_{ki}, $j = 1, 2 \ldots 8$ is a parameter to be estimated, Hsz^h is household size, Inc^h is income, Age^h is age, Edu^h is education, Inv_j^h is inventory, Loy_{ij}^h is loyalty, Pd_{ij} is price discount, and ε_{ij}^h is an iid error term designed to account for any unobserved heterogeneity that may remain in the baseline marginal utility associated with brand i.

While household size and age are continuous variable, income is a categorical variable in my data set. For estimation purposes, it is converted to a continuous variable by assuming each observation lies at the mean of its associated category. Education is an indicator variable that takes one if the household-head is a college graduate or more and zero otherwise. Household size, income, age and education allow me to capture observable heterogeneity in households.

I capture the potential state-dependence in demand in two ways: First, by introducing a variable that measures household inventory at the category-level, and, second, by a measure of brand loyalty. I expect to find the probability of category purchase to fall in the level of inventory, but brand purchase to rise in loyalty. Following Bucklin, Gupta and Siddarth (1998), I define inventory as:

$$Inv_j^h = Inv_{j-1}^h + q_{j-1}^h - Cr^h T_{j,j-1}, \tag{3.3}$$

where q^h_{j-1} is an amount of category products purchased on the previous shopping trip, Cr^h is an average daily category consumption rate calculated from the entire purchase history of household h, and $T_{j,j-1}$ is an interval between successive purchases, measured in days. Equation (3.3) means that inventory accumulates with current purchases of category products and declines according to an average consumption rate. Inventory is also mean-centered by subtracting each household's average level of inventory during the sample period, which makes it a measure of relative category-inventory within a household.

Loyalty is an indicator variable that takes one if household h purchased the same brand i on the last purchase occasion. Seetharaman (2004) finds that most of the dynamics in households' brand choices can be captured by this lagged choice. Including inventory and loyalty is intended to account for any dynamics in demand.

Elements of the marketing mix may also be important in brand choice. To this end, I include a measure of promotional activity: Price discount is an indicator variable that takes one if brand i is sold at a discount price on occasion j and takes zero otherwise. The price discount variable is included in baseline marginal utility to capture an impact of marketing mix on preference for yogurt purchases.

I test my hypothesis regarding satiation and trial purchases of a new brand by allowing satiation to vary over purchase occasions. Specifically, satiation depends on product and individual attributes as:

$$\alpha_i = 1 - \exp\left[-\left(\lambda_{1i} + \rho_i Tr^h_{ij}\right)\right], \; i = 2, 3 \ldots I, \; j = 1, 2 \ldots J, \; h = 1, 2 \ldots H, \quad (3.4)$$

where λ_{1i} and ρ_i are parameters to be estimated and Tr^h_{ij} is an indicator variable of trial purchase of a new brand that takes one if household h purchase a new brand i

for the first time at occasion j and takes zero otherwise. Because trial purchase of a new brand typically involves a higher degree of uncertainty, I expect that consumers are more risk-averse and their utility function is more concave. If a new brand trial purchase causes the utility function to be more concave, then I expected to find $\rho_i < 0$ for a new brand i. Because using quality signals is also a potential means of reducing the risk associated with new-product adoption, my model controls for variation in evident quality as well. In my econometric model, this effect is modeled explicitly as variation in baseline marginal utility, or the change in utility for the first unit consumed. Baseline marginal utility is an appropriate measure of perceived quality because it is measured from a baseline of zero consumption: Controlling for all other observed sources of variation in baseline marginal utility, the change in utility associated with beginning to consume brand i is captured by the intercept, β_{1i}, or the willingness-to-pay for the mere fact that it is brand i. I label the model with this specification of baseline marginal utility and satiation as model 1.

It is possible that satiation depends on variables other than trial purchase. Demographic variables may be important in determining a household's level of satiation as households of different size, income level, age, educational attainment are likely to vary in the amounts purchased, regardless of whether the brand is new or incumbent. Consumers' quantity decisions may differ depending on state-dependent variables such as category-inventory accumulation and loyalty and marketing mix variable such as price discount. In order to address this issue, I further specify satiation as:

$$\alpha_i = 1 - \exp\left[-\left(\begin{array}{c} \lambda_{1i} + \lambda_{2i}Hsz^h + \lambda_{3i}Inc^h + \lambda_{4i}Age^h + \lambda_{5i}Edu^h \\ +\lambda_{6i}Inv_j^h + \lambda_{7i}Loy_{ij}^h + \lambda_{8i}Pd_{ij} + \rho_i Tr_{ij}^h \end{array}\right)\right], \quad (3.5)$$

$$i = 2, 3 \ldots I,\ j = 1, 2 \ldots J,\ h = 1, 2 \ldots H.$$

This specification is expected to capture the risk attitudes toward new product trial more precisely because effects of demographic, state-dependent, and marketing mix variables on satiation are all controlled for. Notice that the variables explaining baseline marginal utility and satiation are same except for trial purchase, which enables me to examine how each variable have a different impact on baseline marginal utility and satiation respectively. I label the model with this specification of baseline marginal utility and satiation as model 2.

Heterogeneity in consumers' risk attitudes may play a decisive role in explaining trial purchases of a new brand. Some consumers are likely to be risk-averse when they purchase a new brand for the first time. Others may be risk-loving, anticipating that a new brand will offer the benefits that established brands do not. In order to account for unobserved heterogeneity in the hypothesized risk attitudes, I allow ρ_i to consist of a mean and random element. Specifically, equation (3.4) is written as:

$$\begin{aligned} \alpha_i &= 1-\exp\left[-\left(\lambda_{1i}+\rho_i^h Tr_{ij}^h\right)\right],\ \rho_i^h=\overline{\rho_i}+r_i^h,\ r_i^h\sim N\left(0,\sigma_r^2\right), \\ & i=2,3\ldots I,\ j=1,2\ldots J,\ h=1,2\ldots H. \end{aligned} \tag{3.6}$$

I label the model with this specification of baseline marginal utility and satiation as model 3. Finally, unobserved heterogeneity in risk attitudes is also incorporated in equation (3.5) and then satiation is written as:

$$\begin{aligned} \alpha_i &= 1-\exp\left[-\left(\begin{array}{c} \lambda_{1i}+\lambda_{2i}Hsz^h+\lambda_{3i}Inc^h+\lambda_{4i}Age^h+\lambda_{5i}Edu^h \\ +\lambda_{6i}Inv_j^h+\lambda_{7i}Loy_{ij}^h+\lambda_{8i}Pd_{ij}+\rho_i^h Tr_{ij}^h \end{array}\right)\right], \\ \rho_i^h &= \overline{\rho_i}+r_i^h,\ r_i^h\sim N\left(0,\sigma_r^2\right), \\ & i=2,3\ldots I,\ j=1,2\ldots J,\ h=1,2\ldots H. \end{aligned} \tag{3.7}$$

I label the model with this specification of baseline marginal utility and satiation as model 4.

To summarize my specifications: Baseline marginal utility includes same variables in all models while satiation does not. Satiation includes trial purchases of a new brand in models 1 and 3 while in models 2 and 4, satiation includes demographic, state-dependent, and marketing mix variables in addition to trial purchases of a new brand. Heterogeneity in risk attitudes is incorporated in models 3 and 4. I expect that model 4 is the most effective in capturing consumer risk reduction behavior on new brand purchases as it controls possible factors that influence quantity decisions and, moreover, includes heterogeneity among consumers' attitudes toward risk. In the results section below, I compare model 4 with others and show estimation results for all models that were estimated.

With the utility model as discussed above, I derive the K-T conditions to solve the constrained utility maximization problem and, thereby, a demand function that allows either corner or interior solutions. First, the Lagrangian for the MDCEV model is given by:

$$\mathcal{L}_j^h = u_j^h(q_{ij}^h, X_{ij}^h, D^h, \theta) + \Lambda \left(y^h - \sum_{i=1}^{I} p_i q_{ij}^h \right), \tag{3.8}$$

where y^h is the total expenditure made by the household h in the given purchase occasion, p_i is the price paid for brand i, and Λ is the Lagrangian multiplier. With the assumption that among I brands, M brands are purchased and $I-M$ are not, the K-T conditions yield:

$$\varphi_{ij}^h \left(\frac{q_{ij}^h}{\gamma_i} + 1 \right)^{\alpha_i - 1} - \Lambda p_i = 0 \; if \; q_{ij}^h > 0, \; i = 2, 3, ..., I, \tag{3.9a}$$

$$\varphi_{ij}^h \left(\frac{q_{ij}^h}{\gamma_i} + 1 \right)^{\alpha_i - 1} - \Lambda p_i < 0 \; if \; q_{ij}^h = 0, \; i = 2, 3, ..., I, \tag{3.9b}$$

and because the outside option is always consumed, the K-T condition for $i = 1$ is given by:

$$\varphi^h_{1j}(\frac{q^h_{1j}}{\gamma_1}+1)^{\alpha_1-1} - \Lambda p_1 = 0. \tag{3.10}$$

Equations (3.9a) and (3.9b) imply that the marginal utility of all brands are equal if the brand is consumed and is less than the other brands if not consumed. Taking logarithms of equations (3.9a), (3.9b), and (3.10) and eliminating Λ, the K-T conditions are written as:

$$V^h_{ij} + \varepsilon^h_{ij} = V^h_{1j} + \varepsilon^h_{1j} \; if \; q^h_{ij} > 0, \; i = 2, 3, ..., I, \tag{3.11a}$$

$$V^h_{ij} + \varepsilon^h_{ij} < V^h_{1j} + \varepsilon^h_{1j} \; if \; q^h_{ij} = 0, \; i = 2, 3, ..., I, \tag{3.11b}$$

where $V^h_{1j} = (\alpha_1 - 1)\ln(q^h_{1j}/\gamma_1 + 1) - \ln p_1$ for the outside option and $V^h_{ij} = \beta_i + (\alpha_i - 1)\ln(q^h_{ij}/\gamma_i + 1) - \ln p_i$ for $i = 2, ..., I$.

In the MDCEV model, the probability that a particular bundle is chosen is given by the conditions given in equations (3.11a) and (3.11b). Specifically, this is the probability that the marginal utility from M of the brands is equal to the marginal utility available from the outside option and the marginal utility from the others is less than the outside option. Because each bundle potentially consists of several brands, the solution for the choice probability necessarily involves the joint distribution of ε^h_{ij} that captures the distribution of tastes among households. Thus, the probability that any M of the I brands are chosen is given by:

$$\begin{aligned} P(q^h_{1j}, ..., q^h_{Mj}, 0, ..., 0) = {} & |J| \int\limits_{\varepsilon^h_{1j}} \int\limits_{\varepsilon^h_{Mj}} \cdots \int\limits_{\varepsilon^h_{I-Mj}} \int\limits_{\varepsilon^h_{Ij}} \\ & f\left(\varepsilon^h_{1j}, ..., \varepsilon^h_{Mj}, ..., \varepsilon^h_{I-Mj}, ..., \varepsilon^h_{Ij}\right) \\ & \times d\varepsilon^h_{1j}, ..., d\varepsilon^h_{Mj}, ..., d\varepsilon^h_{I-Mj}, ..., d\varepsilon^h_{Ij}, \end{aligned} \tag{3.12}$$

where $|J|$ is the determinant of the Jacobian of the transformation from ε_{ij}^{h} to q_{ij}^{h} with typical element of $J_{lk} = \frac{\partial \varepsilon_{l+1,j}^{h}}{\partial q_{k+1,j}^{h}}$. Bhat (2005) shows that the Jacobian determinant can be simplified to arrive at: $|J| = \prod_{i=1}^{M} g_i \sum_{i=1}^{M} \frac{p_i}{g_i}$ where $g_i = \left(\frac{1-\alpha_i}{q_{ij}^{h}+\gamma_i}\right)$. For estimation purposes, it is further assumed that the error terms are distributed iid extreme value so that equation (3.12) collapses to a relatively simple form:

$$P(q_{1j}^{h}, ..., q_{Mj}^{h}, 0, ..., 0) = \frac{1}{\sigma^{M-1}} \left(\prod_{i=1}^{M} g_i\right) \left(\sum_{i=1}^{M} \frac{p_i}{g_i}\right) \left(\frac{\prod_{i=1}^{M} e^{V_{ij}^{h}/\sigma}}{\left(\sum_{i=1}^{I} e^{V_{ij}^{h}/\sigma}\right)^{M}}\right) (M-1)!, \tag{3.13}$$

where σ is a scale parameter. Equation (3.13) can be interpreted as a general form of the logit choice probability, because when $M = 1$, or only one brand is purchased, the MDCEV model becomes a simple logit model. The MDCEV model is estimated using maximum likelihood method.

Because g_i and V_{ij}^{h} for models 3 and 4 include random element r_i^h, equation (3.13) for these models is expressed as:

$$\widetilde{P}(q_{1j}^{h}, ..., q_{Mj}^{h}, 0, ..., 0) = \int \frac{1}{\sigma^{M-1}} \left(\prod_{i=1}^{M} g_i\right) \left(\sum_{i=1}^{M} \frac{p_i}{g_i}\right) \left(\frac{\prod_{i=1}^{M} e^{V_{ij}^{h}/\sigma}}{\left(\sum_{i=1}^{I} e^{V_{ij}^{h}/\sigma}\right)^{M}}\right) (M-1)! dF\left(r_i^h\right), \tag{3.14}$$

where $F(\cdot)$ is the cumulative standard normal distribution. I use the simulated maximum likelihood method to approximate the integrals in equation (3.14) and maximize the logarithm of the resulting simulated likelihood function with respect to θ (Train 2009). This method provides consistent parameter estimates under rather weak regularity conditions. To aid in the computational speed and efficiency of estimation, I use 100 Halton draws for realizations of r_i^h (Bhat, 2003).

3.4 Data Description

I use household panel scanner data from the yogurt category collected by the Nielsen Company in major U.S. cities. Each alternative is defined by yogurt brand. I use one new brand and five established brands for the analysis, which I label as new brand, brand A, brand B, brand C, brand D, and brand E for confidentiality purposes. The time-period used for estimation includes three years of purchase records, which consist of one year prior to the new-product launch, and two years after. Two years of data post-introduction data are used in order to ensure that households are given sufficient time to try the new brand, but it has not yet become established. Because my specification includes the state-dependent variables, inventory and loyalty, I use one year of data prior to the new product launch to initialize households' purchases of the established brands. To be included in the sample, households must make at least seven purchases of one of these six brands during each year of the three-year period. Furthermore, on each purchase occasion, a household must also purchase either another yogurt brand, or one other food item. Expenditure on these items is used as the outside option, or numeraire that is always purchased on each purchase occasion. Ultimately, I use 256 households and 9,722 purchase occasions for the estimation.

For the MDCEV model to be appropriate for my data, household purchases must be multiple-discrete, or households must purchase multiple brands, and purchase quantities must be approximately continuous. Table 3.1 illustrates the mean and the standard deviation of the purchase volume in ounces and price per ounce, showing that the purchase volume of each brand is widely dispersed and household purchases can be considered to be approximately continuous. Table 3.2 illustrates the purchase-frequency of primary, secondary and tertiary brands by households on single purchase occasion, suggesting households purchase many varieties of brand on a single purchase occasion. Tables 3.1 and 3.2 demonstrate that the MDCEV model is consistent with the data generating process of my data set, namely, households typically purchase multiple brands within a single category and continuous amounts of the chosen brand. A standard discrete choice model ignores this important characteristic of consumer shopping behavior. Also, because my objective is to examine how purchase quantities change when consumers purchase a new brand, the MDCEV model is valuable because it parameterizes curvature in the utility function. Variation in curvature, moreover, identifies structural changes in utility as consumers try new brands for the first time.

Table 3.1
Purchase Volume in Ounces and Price per Ounce

		Purchase volume (oz.)		Price per ounce ($)	
Brand	Obs.	Mean	Std. dev.	Mean	Std. dev.
New brand	527	36.250	28.751	0.148	0.097
Brand A	1,387	33.684	21.722	0.107	0.033
Brand B	3,355	36.531	26.206	0.107	0.028
Brand C	4,161	35.699	26.709	0.103	0.024
Brand D	362	22.591	18.824	0.099	0.029
Brand E	1,076	17.004	13.899	0.158	0.039

Table 3.2
Number of Brands Purchased on a Single Purchase Occasion

Brand purchase	Frequency (%)
1-brand purchase	89.498
2-brand purchase	9.370
3-brand purchase	0.977
4-brand purchase	0.154
5-brand purchase	–
6-brand purchase	–

Formally testing for the effect of trial purchase on satiation requires holding all other potential choice-determinants constant, but the potential validity of my hypothesis is readily apparent from casual observation. Table 3.3 compares the purchase volume in ounces and price per ounce of the new brand on trial purchase occasions to all purchase occasions. The summary statistics reveal some preliminary support for my hypothesis as households in my sample appear to purchase a smaller quantity and pay less money on their trial purchase occasions of the new brand relative to other purchase occasions. I interpret this as revealing risk-reduction behavior associated with a trial purchase of a new brand. This observation is also consistent with Shoemaker and Shoal (1975). However, lower purchase quantities could be due to any one of a number of factors, so I need to control for them econometrically.

Table 3.3
Purchase Volume in Ounces and Price per Ounce of New Brand

		Purchase volume (oz.)		Price per ounce ($)	
Purchase occasion	Obs.	Mean	Std. dev.	Mean	Std. dev.
Trial purchase occasions	71	29.915	22.335	0.148	0.029
All purchase occasions	527	36.250	28.751	0.148	0.097

One limitation of using household-panel purchase data lies in the fact that it contains only price information on items that were actually purchased, and not others in the direct consideration set. However, estimating the MDCEV model requires price information for all brands in the sample at each purchase occasion. To overcome this problem, I estimate unobserved yogurt prices by using observations on other households shopping in the same stores and buying the same brands. Specifically, I use a hedonic model of yogurt prices in which shelf price is a function of yogurt brand, retail store, and week. The parameters from the hedonic model generate fitted prices for all unobserved prices for each brand, retail store and week. Overall, the model explains 48 percent of the total variation of yogurt prices and the parameter estimates exhibit expected signs.[2] All of the data used to estimate the MDCEV model are summarized in table 3.4 below.

Table 3.4
Demographic, State Dependent, and Marketing Mix Variables

Variable	Symbol	Obs.	Mean	Std. dev.
Household size	Hsz^h	256	2.571	1.231
Income ($,000)	Inc^h	256	82.326	41.994
Age	Age^h	256	53.296	9.656
Education	Edu^h	256	0.653	0.470
Inventory (oz., mean-centered)	Inv_j^h	$9,722$	36.026	150.283
Loyalty to new brand	Loy_{2j}^h	$9,722$	0.037	0.188
Loyalty to brand A	Loy_{3j}^h	$9,722$	0.089	0.285
Loyalty to brand B	Loy_{4j}^h	$9,722$	0.274	0.446
Loyalty to brand C	Loy_{5j}^h	$9,722$	0.344	0.475
Loyalty to brand D	Loy_{6j}^h	$9,722$	0.018	0.133
Loyalty to brand E	Loy_{7j}^h	$9,722$	0.069	0.253
Price discount on new brand	Pd_{2j}	$9,722$	0.025	0.157
Price discount on brand A	Pd_{3j}	$9,722$	0.091	0.287
Price discount on brand B	Pd_{4j}	$9,722$	0.197	0.398
Price discount on brand C	Pd_{5j}	$9,722$	0.251	0.434
Price discount on brand D	Pd_{6j}	$9,722$	0.020	0.142
Price discount on brand E	Pd_{7j}	$9,722$	0.070	0.255

3.5 Results and Discussion

In this section, I present the results obtained by estimating the MDCEV models described in the previous section. Before discussing the individual parameter estimates, I present specification tests that compare the goodness of fit across models.

One practical weakness of the MDCEV model is that the satiation and translation parameters are not separately identified (Bhat, 2005, 2008). Recall that satiation determines how the marginal utility of brand i changes as q_{ij}^h rises (pure satiation) and that translation parameter defines the location of corner solutions for brand i

[2] All parameter estimates for the hedonic model are available upon request.

and governs the slope of the indifference curve between the outside option and brand i (satiation and translation). Because my primary interest in this study is to examine how satiation varies with the nature of the transaction, I fix translation parameter at one for all brands in both models. Bhat (2008) refers to this as the "alpha profile" approach. For the same reason, σ is normalized to one as well.

I first evaluate the models by the Akaike information criterion (AIC) and Bayesian information criterion (BIC). I report these values in table 3.5. Both of the AIC and BIC are the lowest with model 4. I next conduct likelihood ratio (LR) tests to compare my maintained specification (model 4) to plausible alternatives. In table 3.6, I report a set of LR statistics in which the null model is model 1, 2, or 3 and the alternative model is model 4. Based on these tests, I reject models 1, 2, and 3 in favor of model 4. The specification tests consistently recommend model 4 in which possible factors that influence consumers' quantity decisions are all controlled for and heterogeneity in consumers' risk attitudes are taken into account. Therefore, I present the estimation result of model 4 and interpret each of the parameters. As a further robustness check, I present the estimation results obtained for all other models in order to examine whether my primary hypothesis holds under different model specifications.

Table 3.5
AIC and BIC

Model	Log likelihood	Number of parameters	AIC	BIC
Model 1	$-17,175$	56	$34,462$	$34,864$
Model 2	$-16,874$	98	$33,945$	$34,649$
Model 3	$-17,168$	57	$34,451$	$34,860$
Model 4	$-16,866$	99	$33,930$	$34,641$

Table 3.6
LR Statistic When the Alternative Model Is Model 4

Null model	LR statistic	Degree of freedom
Model 1	618.249	43
Model 2	17.022	1
Model 3	605.107	42

Table 3.7 reports the estimation results for model 4. These estimates support my primary hypothesis, namely that utility is more concave on the trial purchases of the new brand, and satiation occurs at a lower purchase quantity. Specifically, my results show that the mean coefficient of trial purchase is negative and statistically significant. In the context of the utility model in equation (3.1), this means that utility is more concave for the trial purchases of the new brand so, lacking an alternate mechanism of limiting their exposure to risk, they purchase a lower quantity. In terms of the structure of the MDCEV model, consumers' risk reduction behavior is manifest in satiation at a lower consumption quantity. If the intent was to simply "taste" the new brand, then the notion of satiation is an intuitive way of understanding how behavior changes with respect to new products. By purchasing a smaller quantity, households avoid the risk of trying a new brand that they may find unsatisfactory when the future consumption occasion, which is anticipated at the time of purchase, actually arises. The other specifications also support the hypothesis, namely the mean coefficient of trial purchase is negative and statistically significant in any models (see tables 3.8, 3.9 and 3.10), and so my finding does not appear to be an artefact of the model itself.

Table 3.7
Estimation Result of Model 4

Variable	Parameter	New brand		Brand A		Brand B		Brand C		Brand D		Brand E	
		Estimate	t value	Estimate	t value	Estimate	t value	Estimate	t value	Estimate	t value	Estimate	t value
Constant	Mean coef. in φ_{ij}^h	3.796*	3.397	2.149*	2.358	4.055*	9.409	5.397*	12.275	5.307*	4.315	6.104*	10.042
	Mean coef. in α_i	−1.223*	−3.420	−1.495*	−6.878	−2.256*	−19.197	−2.723*	−23.652	−4.544*	−10.793	−3.795*	−19.825
Household size (Hsz^h)	Mean coef. in φ_{ij}^h	0.785	0.598	−0.729	−0.833	−1.828*	−4.494	−4.219*	−8.673	−1.084	−0.827	−3.004*	−4.210
	Mean coef. in α_i	−0.446	−1.159	−0.269	−1.208	0.580*	6.174	1.937*	12.918	1.427*	3.596	1.961*	7.465
Income (Inc^h)	Mean coef. in φ_{ij}^h	−0.304	−0.639	1.326*	5.555	−0.472*	−3.501	−0.103	−0.812	−0.713	−1.481	−0.317	−1.249
	Mean coef. in α_i	−0.099	−0.716	−0.464*	−8.509	−0.050	−1.418	−0.249*	−7.092	0.069	0.335	−0.265*	−2.775
Age (Age^h)	Mean coef. in φ_{ij}^h	2.994	1.915	6.597*	5.294	4.062*	6.790	2.250*	3.653	3.499*	2.168	1.827*	2.231
	Mean coef. in α_i	−1.007*	−2.102	−1.764*	−5.956	−0.674*	−4.135	0.030	0.182	1.989*	4.020	0.719*	2.869
Education (Edu^h)	Mean coef. in φ_{ij}^h	0.176	0.500	−0.994*	−4.195	−0.112	−0.892	−0.058	−0.522	−0.651	−1.666	−0.527*	−3.089
	Mean coef. in α_i	−0.140	−1.320	0.251*	4.636	0.121*	3.803	0.091*	3.053	0.393*	3.178	0.029	0.496
Inventory (Inv_j^h)	Mean coef. in φ_{ij}^h	−0.061	−0.692	0.117	1.666	0.082*	2.307	0.115*	3.923	−0.011	−0.107	0.078	1.826
	Mean coef. in α_i	−0.004	−0.199	−0.013	−0.819	0.011	1.446	0.005	0.812	−0.026	−0.857	−0.006	−0.528
Loyalty (Loy_{ij}^h)	Mean coef. in φ_{ij}^h	−0.139	−0.451	−0.143	−0.693	0.492*	4.223	0.115	1.040	0.171	0.605	0.281	1.861
	Mean coef. in α_i	−0.057	−0.618	0.138*	2.844	−0.073*	−2.091	−0.022	−0.703	−0.104	−1.206	0.024	0.434
Price discount (Pd_{ij})	Mean coef. in φ_{ij}^h	1.191*	4.011	0.556*	2.716	0.452*	4.105	0.220*	2.235	−0.146	−0.472	−0.062	−0.356
	Mean coef. in α_i	−0.605*	−7.135	0.089	1.780	0.017	0.550	−0.094*	−3.458	−0.040	−0.433	0.149*	2.359
Trial purchase (Tr_{ij}^h)	Mean coef. in φ_{ij}^h	–	–	–	–	–	–	–	–	–	–	–	–
	Mean coef. in α_i	−0.297*	−3.347	–	–	–	–	–	–	–	–	–	–
	Std. dev. coef. in φ_{ij}^h	–	–	–	–	–	–	–	–	–	–	–	–
	Std. dev. coef. in α_i	0.368*	5.754	–	–	–	–	–	–	–	–	–	–
Simulated log likelihood at convergence		−16,866											
AIC		33,930											
BIC		34,641											

Note: An asterisk indicates significance at a 5% level.

Table 3.8
Estimation Result of Model 1

Variable	Parameter	New brand		Brand A		Brand B		Brand C		Brand D		Brand E	
		Estimate	t value	Estimate	t value	Estimate	t value	Estimate	t value	Estimate	t value	Estimate	t value
Constant	Mean coef. in φ_{ij}^h	5.792^*	8.826	5.929^*	11.317	4.536^*	17.479	4.652^*	18.229	1.057	1.604	4.320^*	10.732
	Mean coef. in α_i	-2.272^*	−56.598	-2.628^*	−113.281	-2.444^*	−167.994	-2.436^*	−184.972	-2.778^*	−66.411	-2.923^*	−117.466
Household size (Hsz^h)	Mean coef. in φ_{ij}^h	0.195	0.231	-1.546^*	−3.160	0.450	1.578	1.223^*	4.725	3.291^*	4.444	1.784^*	3.808
	Mean coef. in α_i	–	–	–	–	–	–	–	–	–	–	–	–
Income (Inc^h)	Mean coef. in φ_{ij}^h	-0.602^*	−2.540	-0.345^*	−2.957	-0.706^*	−8.189	-0.790^*	−10.999	-0.784^*	−3.071	-0.964^*	−6.078
	Mean coef. in α_i	–	–	–	–	–	–	–	–	–	–	–	–
Age (Age^h)	Mean coef. in φ_{ij}^h	1.069	1.239	0.599	0.852	1.929^*	5.622	2.114^*	5.862	7.979^*	7.996	3.030^*	5.594
	Mean coef. in α_i	–	–	–	–	–	–	–	–	–	–	–	–
Education (Edu^h)	Mean coef. in φ_{ij}^h	−0.127	−0.725	−0.110	−0.905	0.312^*	4.272	0.228^*	3.773	0.512^*	2.312	-0.391^*	−3.390
	Mean coef. in α_i	–	–	–	–	–	–	–	–	–	–	–	–
Inventory (Inv_j^h)	Mean coef. in φ_{ij}^h	−0.061	−1.111	0.068^*	1.990	0.116^*	5.256	0.132^*	6.593	−0.092	−1.729	0.073^*	2.343
	Mean coef. in α_i	–	–	–	–	–	–	–	–	–	–	–	–
Loyalty (Loy_{ij}^h)	Mean coef. in φ_{ij}^h	−0.110	−0.568	0.391^*	3.748	0.272^*	3.681	0.047	0.673	−0.071	−0.404	0.286^*	2.821
	Mean coef. in α_i	–	–	–	–	–	–	–	–	–	–	–	–
Price discount (Pd_{ij})	Mean coef. in φ_{ij}^h	-0.431^*	−2.643	0.875^*	8.362	0.483^*	7.521	−0.099	−1.708	−0.301	−1.665	0.192	1.733
	Mean coef. in α_i	–	–	–	–	–	–	–	–	–	–	–	–
Trial purchase (Tr_{ij}^h)	Mean coef. in φ_{ij}^h	–	–	–	–	–	–	–	–	–	–	–	–
	Mean coef. in α_i	-0.234^*	−2.932	–	–	–	–	–	–	–	–	–	–
	Std. dev. coef. in φ_{ij}^h	–	–	–	–	–	–	–	–	–	–	–	–
	Std. dev. coef. in α_i	–	–	–	–	–	–	–	–	–	–	–	–
Log likelihood at convergence		−17,175											
AIC		34,462											
BIC		34,864											

Note: An asterisk indicates significance at a 5% level.

Table 3.9

Estimation Result of Model 2

Variable	Parameter	New brand		Brand A		Brand B		Brand C		Brand D		Brand E	
		Estimate	t value	Estimate	t value	Estimate	t value	Estimate	t value	Estimate	t value	Estimate	t value
Constant	Mean coef. in φ_{ij}^h	3.913*	3.584	2.138*	2.347	4.059*	9.419	5.394*	12.271	5.311*	4.321	6.103*	10.041
	Mean coef. in α_i	−1.324*	−3.705	−1.494*	−6.878	−2.257*	−19.200	−2.723*	−23.647	−4.548*	−10.818	−3.794*	−19.822
Household size (Hsz^h)	Mean coef. in φ_{ij}^h	0.822	0.643	−0.706	−0.806	−1.828*	−4.496	−4.213*	−8.662	−1.085	−0.828	−3.002*	−4.208
	Mean coef. in α_i	−0.396	−1.029	−0.272	−1.225	0.580*	6.173	1.935*	12.908	1.430*	3.601	1.961*	7.463
Income (Inc^h)	Mean coef. in φ_{ij}^h	−0.412	−0.960	1.327*	5.560	−0.472*	−3.496	−0.102	−0.804	−0.715	−1.486	−0.316	−1.246
	Mean coef. in α_i	−0.068	−0.517	−0.464*	−8.510	−0.050	−1.414	−0.249*	−7.089	0.069	0.338	−0.265*	−2.775
Age (Age^h)	Mean coef. in φ_{ij}^h	2.314	1.527	6.599*	5.297	4.054*	6.779	2.247*	3.647	3.494*	2.167	1.823*	2.227
	Mean coef. in α_i	−0.765	−1.609	−1.762*	−5.953	−0.673*	−4.134	0.031	0.187	1.994*	4.036	0.719*	2.868
Education (Edu^h)	Mean coef. in φ_{ij}^h	0.151	0.458	−0.994*	−4.192	−0.113	−0.906	−0.057	−0.512	−0.651	−1.668	−0.528*	−3.095
	Mean coef. in α_i	−0.118	−1.143	0.251*	4.637	0.121*	3.804	0.090*	3.050	0.393*	3.175	0.029	0.499
Inventory (Inv_j^h)	Mean coef. in φ_{ij}^h	−0.021	−0.242	0.117	1.667	0.082*	2.310	0.115*	3.923	−0.011	−0.101	0.078	1.829
	Mean coef. in α_i	−0.016	−0.711	−0.013	−0.817	0.011	1.442	0.005	0.809	−0.026	−0.861	−0.006	−0.531
Loyalty (Loy_{ij}^h)	Mean coef. in φ_{ij}^h	0.246	0.885	−0.145	−0.704	0.492*	4.224	0.115	1.043	0.171	0.606	0.282	1.866
	Mean coef. in α_i	−0.149	−1.657	0.138*	2.847	−0.073*	−2.086	−0.022	−0.701	−0.104	−1.213	0.024	0.432
Price siscount (Pd_{ij})	Mean coef. in φ_{ij}^h	1.008*	3.609	0.558*	2.729	0.452*	4.108	0.219*	2.227	−0.145	−0.471	−0.061	−0.351
	Mean coef. in α_i	−0.565*	−6.830	0.089	1.771	0.017	0.549	−0.095*	−3.462	−0.040	−0.425	0.148*	2.356
Trial purchase (Tr_{ij}^h)	Mean coef. in φ_{ij}^h	–	–	–	–	–	–	–	–	–	–	–	–
	Mean coef. in α_i	−0.254*	−3.029	–	–	–	–	–	–	–	–	–	–
	Std. dev. coef. in φ_{ij}^h	–	–	–	–	–	–	–	–	–	–	–	–
	Std. dev. coef. in α_i	–	–	–	–	–	–	–	–	–	–	–	–
Log likelihood at convergence		−16,874											
AIC		33,945											
BIC		34,649											

Note: An asterisk indicates significance at a 5% level.

Table 3.10
Estimation Result of Model 3

Variable	Parameter	New brand		Brand A		Brand B		Brand C		Brand D		Brand E	
		Estimate	t value	Estimate	t value	Estimate	t value	Estimate	t value	Estimate	t value	Estimate	t value
Constant	Mean coef. in φ_{ij}^h	6.114*	8.904	5.938*	11.328	4.531*	17.449	4.655*	18.239	1.064	1.613	4.319*	10.729
	Mean coef. in α_i	−2.296*	−56.719	−2.628*	−113.295	−2.444*	−167.985	−2.436*	−184.995	−2.778*	−66.415	−2.923*	−117.469
Household size (Hsz^h)	Mean coef. in φ_{ij}^h	0.075	0.087	−1.551*	−3.172	0.452	1.584	1.222*	4.721	3.284*	4.434	1.785*	3.809
	Mean coef. in α_i	–	–	–	–	–	–	–	–	–	–	–	–
Income (Inc^h)	Mean coef. in φ_{ij}^h	−0.592*	−2.405	−0.347*	−2.967	−0.706*	−8.187	−0.791*	−11.018	−0.781*	−3.057	−0.965*	−6.080
	Mean coef. in α_i	–	–	–	–	–	–	–	–	–	–	–	–
Age (Age^h)	Mean coef. in φ_{ij}^h	1.023	1.147	0.591	0.840	1.937*	5.642	2.113*	5.859	7.965*	7.980	3.034*	5.599
	Mean coef. in α_i	–	–	–	–	–	–	–	–	–	–	–	–
Education (Edu^h)	Mean coef. in φ_{ij}^h	−0.182	−0.996	−0.111	−0.910	0.313*	4.287	0.227*	3.766	0.514*	2.319	−0.390*	−3.386
	Mean coef. in α_i	–	–	–	–	–	–	–	–	–	–	–	–
Inventory (Inv_j^h)	Mean coef. in φ_{ij}^h	−0.070	−1.257	0.067*	1.979	0.116*	5.264	0.132*	6.604	−0.092	−1.731	0.074*	2.343
	Mean coef. in α_i	–	–	–	–	–	–	–	–	–	–	–	–
Loyalty (Loy_{ij}^h)	Mean coef. in φ_{ij}^h	−0.291	−1.429	0.392*	3.761	0.273*	3.682	0.046	0.661	−0.067	−0.382	0.285*	2.819
	Mean coef. in α_i	–	–	–	–	–	–	–	–	–	–	–	–
Price discount (Pd_{ij})	Mean coef. in φ_{ij}^h	−0.409*	−2.437	0.874*	8.356	0.483*	7.521	−0.098	−1.698	−0.306	−1.692	0.191	1.731
	Mean coef. in α_i	–	–	–	–	–	–	–	–	–	–	–	–
Trial purchase (Tr_{ij}^h)	Mean coef. in φ_{ij}^h	–	–	–	–	–	–	–	–	–	–	–	–
	Mean coef. in α_i	−0.329*	−3.727	–	–	–	–	–	–	–	–	–	–
	Std. dev. coef. in φ_{ij}^h	–	–	–	–	–	–	–	–	–	–	–	–
	Std. dev. coef. in α_i	−0.359*	−5.105	–	–	–	–	–	–	–	–	–	–
Simulated log likelihood at convergence		−17,168											
AIC		34,451											
BIC		34,860											

Note: An asterisk indicates significance at a 5% level.

I next evaluate the significance of unobserved heterogeneity. The standard deviation of the random coefficient of trial purchase is highly significant, suggesting that the coefficient of trial purchase differs among sample members. This result makes intuitive sense as attitudes toward risk are inherently idiosyncratic. Finding significant heterogeneity also supports my choice of model 4 over models 1 and 2 in which consumer heterogeneity is not considered. Under the assumption of normality, the estimated mean of -0.297 and the estimated standard deviation of 0.368 mean that 79 percent of the distribution is below zero and 21 percent is above. This implies that 79 percent of those who try the new brand tend to be more risk-averse and 21 percent of them be more risk-loving. Comparing the estimated mean and standard deviation of model 4 to those of model 3 also supports the validity of the specification in model 4. Table 3.10 shows that the estimated mean for model 3 is -0.329 and the estimated standard deviation is 0.359, which means that 82 percent of the distribution is below zero and 18 percent is above. Model 3 overestimates the population of those who are risk-averse. Without controlling for demographic, state-dependent, and marketing mix variables, or observed heterogeneity, in model 3, too much of the variation in satiation is attributed to random, personal effects.

Among the other estimates reported in table 3.7 are a number of results also to be of interest to practitioners. The brand-specific parameters in baseline marginal utility can be interpreted as brand equity, or goodwill, because the brand-specific constant is a portion of the baseline marginal utility that is not explained by the demographic, state-dependent, or marketing mix variables. Brand equity is positive and statistically significant for all brands. Brands B, C, D, and E are relatively high-equity brand while the new brand and brand A are low-equity brands. This result makes sense as the new brand may not accumulate sufficient equity as it is just launched at the beginning of the sample period. The reason why the new brand has higher brand equity than brand A may be because manufacturers are likely to advertise a new brand intensively at the time of its launch in order to try to get enough shelf space in retail stores. These activities may contribute to an early accumulation of equity, possibly at the expense of one or more existing brands.

Among the demographic attributes, I find that the coefficient of household size in baseline marginal utility is negative and statistically significant for brands B, C, and E while its effect on satiation is positive and statistically significant for brands B, C, D and E. It is not significant for the other brands. This finding implies that smaller households tend to have stronger preference for yogurt purchases than larger households, but once the purchase decisions are made, smaller households are satiated at smaller quantity and larger households at larger quantity. This result is intuitive as yogurt is something that may be consumed by each member of the household. On each shopping occasion, consumers may need to consider the preferences of each household member, and choose brand specific to each member's preferences. Relative to an individual shopper buying for herself, however, such multiple purchases involve non-trivial search costs so larger households may be reluctant to purchase different brands for everyone, but tend to purchase larger quantities of fewer brands for all members of the household.

For brand A, income has a positive and statistically significant impact on baseline marginal utility. For brand B, however, it has a negative and statistically significant impact on baseline marginal utility. This result may be due to the nature of brands A and B. Brand A is more of a niche brand that is likely to be successful among high-income households, while brand B appeals instead to low-income households. For brands A, C, and E, income has a negative and statistically significant impact on satiation. In other words, higher-income households tend to purchase smaller quantities on each shopping occasion. Easier satiation may be due to the fact that I account for multiple-variety purchases. Low-income households may not be able to purchase multiple varieties as they are forced to consider only those that offer the lowest price, or the highest price-adjusted baseline marginal utility. For high-income households, on the other hand, satiation occurs at a smaller quantity and so they tend to purchase a variety of brands with different tastes and nutritional contents simply because of their lower price sensitivity. This finding may also be due to higher-income households' greater proclivity for dining out – if more meals are purchased outside the home, they have less of a need to purchase at retail. Other coefficients of income are not statistically significant.

The age coefficient in baseline marginal utility is positive and statistically significant for brands A, B, C, D, and E and marginally significant for the new brand. Older households tend to have stronger preference for yogurt purchases than younger households as they may be more health-conscious and aware of the nutritional benefits of yogurt. The age coefficient in satiation is negative and statistically significant for the new brand and brands A and B. However, it is positive and statistically significant for brands D and E. Older households tend to be satiated at smaller quantities of the new brand and brands A and B and at larger quantity of brands D and E. This result may be simply due to the nature of each brand.

I find that education has a negative effect on baseline marginal utility for brands A and E, suggesting that lower-educated households tend to prefer these brands. Education has a positive effect on purchase quantities of brands A, B, C, and D. It may be the case that higher-educated households tend to be more efficient their shopping behavior and are better at realizing the economies of scale in shopping for groceries.

Among state-dependent variables, inventory has a positive and statistically significant impact on baseline marginal utility of brands B and C, suggesting that households with more yogurt on hand tend to have stronger preference for these brands than households with less on hand. Stockpiling by a household implies a deeper category involvement and stronger preference for the category as a whole. Based on my estimates, it appears brands B and C have the strongest stockpiling-effect, so may indeed be especially preferred by households who tend to hold larger inventories.

Loyalty has a positive and significant effect on baseline marginal utility of brand B, suggesting that households loyal to brand B tend to prefer that brand relative to others. The loyalty coefficient in satiation is positive and statistically significant for brand A, but negative and statistically significant for brand B. Households that are loyal to brand A tend to be satiated at a larger quantity, while households loyal to brand B tend to be satiated at smaller quantities. Customers of brand B may be loyal, but purchase a smaller quantity on each shopping occasion. To estimate consumers' risk attitudes consistently, it is important to control effects of state-dependent variables, even though many do not have a statistically significant on utility or satiation.

Finally, marketing mix variables play a crucial role in explaining both baseline marginal utility and satiation. Price promotion has a positive and statistically significant impact on baseline marginal utility for the new brand and brands A, B and C, suggesting that discounting prices tends to shift the indifference cut everywhere upwards. Promotion, however, has a negative and statistically significant impact on satiation for the new brand and brand C, suggesting that discounting prices tends to reduce the satiation point for a typical household. For these brands, price promotion may cause some consumers to make impulse purchases, which are typically smaller in volume and more frequent than planned purchases. On the other hand, price promotion has a positive and statistically significant impact on the satiation parameter for brand E, suggesting that households tend to purchase a larger quantity when brand E is on promotion. Unlike the other brands, brand E may not be as affected by impulse purchases.

My findings with respect to consumers' risk reduction behavior in the yogurt category have significant implications for producers, and retailers, of consumer packaged goods more generally. All manufacturers are rightly concerned with the consumer dynamic involved with the introduction of new brands. I show that consumers perceive considerable risk in trying new brands, so reduce their purchase quantities in order to limit their risk exposure. Knowing this, firms would be well-advised to either offer new brands in smaller, introductory sizes, to offer free samples wherever possible or to offer a money-back guarantee if the product is not up to expectations. Retailers have less of an incentive to sell new brands (unless they are private labels) as any new brand is likely to take space from an existing, proven brand. Much of a retailer's profit, however, is in the form of trade promotions and allowances so a manufacturer's introduction of a new product represents a strategic opportunity to cooperate and perhaps earn more than simply retail margin.

Risk-reduction behavior using purchase-quantities is typical in both the CPG and service industries. In the service industry, consumers usually make decisions about which services they choose and how much they use these services while they are exposed to the risk that expectations about these qualities will not be met. In the educational business, for example, consumers who plan to register for paid classes typically do not know whether they are satisfy with the service a school offers. Educational benefits are usually observable at least after completing a series of classes. It is possible that satiation with respect to class hours occurs at a smaller level if consumers face much uncertainty at the time of the class registration. This is similar to the risk-reduction behavior observed in the CPG market. My model has a potential to analyze consumer behaviors in many industries and open new avenues for research.

3.6 Conclusions and Implications

From a consumer perspective, the purchase of a new product involves a considerable amount of risk. How well a new product meets a consumer's prior expectations is inherently uncertain. In order to minimize the loss in expected utility associated with the risk of purchasing a brand they may find unsatisfactory in subsequent use, consumers may purchase a smaller than usual quantity on their trial purchase. Accordingly, my hypothesis is that satiation occurs at a smaller quantity when consumers try a new brand.

I test this hypothesis using a multiple-discrete \ continuous extreme value (MDCEV) model applied to household panel scanner data from the yogurt category in several major U.S. markets. With the MDCEV model, I am able to test if satiation depends on whether a brand purchased is new, or familiar to the consumer. I find that when consumers purchase a new brand for the first time, their utility function is more concave and satiation occurs at a smaller quantity, which supports my hypothesis. My findings suggest that consumers reduce the risk of a new brand by purchasing a smaller than usual quantity on their trial purchase and that slow sales of new products attributes to consumers' rational response to risk perception. Moreover, this effect differs across consumers as risk attitudes are naturally individual-specific: While some consumers are risk averse when trying new brands, others may instead prefer the excitement associated with "taking a flyer" on an unfamiliar product.

My findings have a number of practical implications. Most importantly, manufacturers of CPGs should recognize that consumers experience significant risk when contemplating the purchase of an untried-brand. Because purchasing most CPGs does not represent a major, long-term financial commitment, the nature of the risk is less financial than it is purely utility-based. Consumers have a limited number of usage occasions for most products, and do not want to be disappointed on any of them. This is particularly the case when the manufacturer is asking the consumer to give up something that is tried and true, or at least satisfactory. There are a number of ways to limit consumers' exposure to such utility risk, and I suggest some of the more obvious such as free samples, smaller package sizes, or the offer of some type of guarantee.

There are a number of avenues for future research. First, the MDCEV model used in this analysis does not consider cross-category risk-reduction effects. Consumers typically purchase brands in multiple product categories on a single purchase occasion. New brand purchases in a certain product category may influence purchase behaviors in another product category. In order to capture this effect, the model can be extended to a multiple category purchase setting by using a multiple discrete

\ continuous nested extreme value (MDCNEV) approach developed by Pinjari and Bhat (2010). Second, the MDCEV model may be useful in studying strategic pricing decisions by competing manufacturers. While prices are assumed to be exogenous solely to analyze consumers' risk-reduction behavior, it may be the case that manufacturers optimally react to consumer risk-reduction behavior in consideration of rival manufacturers' strategies. Equilibrium analysis of the interactions between utility-maximizing consumers with different risk attitudes and profit-maximizing firms may provide insight into firms' pricing strategies. I leave them for future research.

CHAPTER 4.

ESSAY 3: CONSUMER RISK BEHAVIOR AND FIRM RESPONSE

4.1 Introduction

In the consumer packaged goods (CPGs) industry, package size and price are inextricably linked. Because package prices are prominently displayed, the size of the package determines the unit-price, or the price per unit of volume for the product contained inside. Consumers tend to respond more sharply to package-prices than unit-prices, so manufacturers often use changes in package size to hide price changes. According to McIntyre (2011), for example, Heinz reduced the size of some of its ketchup products by an average of 11% and kept its package price the same, while Kraft reduced the amount of crackers in its Nabisco Premium saltines and Honey Maid graham crackers boxes by 15%, while keeping box prices the same, and PepsiCo reduced the size of its half-gallon cartons of Tropicana by 8% and, in doing so, increased the carton price by 5 to 8%. In these examples, unit prices rose with a change in package size. However, it is not clear whether these changes are driven by consumer demand, cost considerations, or recognition of the strategic nature of package sizes.

Most consumers have accurate knowledge about neither package size nor unit price, which makes them difficult to compare unit prices (Granger and Billson 1972; Russo 1977; Wansink 1996; Raghubir and Krishna 1999; Binkley and Bejnarowicz 2003). Accordingly, manufacturers may change package size, and hence unit prices, without changing the shelf price as a matter of profit-enhancing obfuscation strategy. By doing so, they are able to extract more surplus from consumers, and avoid destructive competition in shelf prices (Ellison and Ellison 2009). Moreover, Çakıra and Balagtas (2014) find that manufacturers change package size, rather than price, because consumers tend to ignore the unit-price implications of changing packages. However, they do not account for the fact that package size decisions are endogenous, and strategic. The implications ignoring these facts can be dramatic. For example, if prices and package size are strategic complements, then package-size reductions by one firm are no longer simply price increases that are likely to be ignored. Rather, other firms may lower prices, leading to fiercer price competition in the industry. In this essay, I investigate how manufacturers of CPGs choose package size and price in a competitive environment.

While both package size and price have a direct impact on manufacturers' profitability, consumers perceive them in a different way. Shelf prices are relatively clear and transparent, whereas changes in package size are rarely announced, and often hidden. As a result, consumers are less sensitive to change in package size than in price, which implies that package downsizing can serve as a more effective means of increasing profit than a change in shelf-price (Çakıra and Balagtas 2014). Further, package downsizing makes the direct comparison of unit price particularly difficult, which may lead to rise in profits (Ellison and Ellison 2009). However, they do not answer the question of whether package downsizing is, in fact, in manufacturers' interests. First, changes in package size are likely to involve costly changes in production and distribution systems. Second, and perhaps more importantly, competitors are likely to be more aware of package-size changes than consumers, and respond in appropriate ways. Therefore, it is critical to consider not only consumer responses to package-size changes, but cost and competitor reactions as well. Therefore, to explain equilibrium package-size and price outcomes, I develop a structural model of consumer demand, and manufacturers' joint decisions regarding package size and price.

There are two types of cost associated with making packages. One is variable, and the other fixed. For example, the cost of packaging materials increases if manufacturers produce larger packages. Manufacturers also incur some costs that are independent of volume, such as set-up costs, inventory costs, and distribution costs. Manufacturers may be able to increase unit prices by selling in smaller packages, but it is possible that the costs of producing a new package outweigh the higher price. In this study, I explicitly account for both types of packaging cost in estimating the effect of changing package size on profitability.

Packaging costs are clearly important in explaining package-size decisions. In an equilibrium framework, Koenigsberg, Kohli and Montoya (2010) consider the costs of producing a particular package size, as well as the consumption rate, consumption utility, and marginal value of consumption. They show that the equilibrium package size depends on the curvature of the cost function in package size, as well as the effect of package size on demand. However, they do not take into account product differentiation, or competition among firms. Competitive reactions may be as important as reactions from consumers as both interact to determine market share, and profit.

Package size is an often-overlooked attribute in models of differentiated-product demand. In fact, consumers may differ in their preference for package size for two reasons. First, consumers are generally risk-averse (Kahneman and Tversky 1979). When consumers purchase an unfamiliar product, they face the risk that it does not meet their prior expectation, so tend to choose a smaller package because doing so can minimize their exposure to uncertainty of buying a large amount of a product they don't like (Shoemaker and Shoal 1975). Smaller packages also allow consumers to match their purchase and consumption rates (Koenigsberg, Kohli, and Montoya

2010). Each package often permits several consumption occasions after purchase – consider a box of cereal or can of coffee as but two examples – so by using smaller packages, consumers can flexibility accommodate any preference for variety or deviation from planned consumption that may arise after purchase.

If consumer demand, in part, depends on package size, then manufacturers are likely to use it as a strategic variable. In a world with homogeneous consumers, manufacturers would offer only a single package size, but would face strong price competition with no differentiation. As shown in the previous chapter, however, consumers exhibit heterogeneous preferences for package size. In fact, consumers with different consumption rates, storage costs, transaction costs, and marginal utility from increased consumption prefer different package sizes (Gerstner and Hess 1987; Subramaniam and Gal-Or 2009). Therefore, manufacturers often differentiate on the basis of package size in order to attract particular market segments. For example, Kelloggs offers Special K in some 11 different package sizes, while General Mills sells Cheerios in 24 others. By doing so, they avoid direct price competition (Anderson, De Palma, and Thisse 1992).

The semi-collusion literature suggests that if firms in oligopolistic markets have multiple decision variables, price and non-price variables, they tend to compete in non-price variables, but collude in price. This is true for a range of variables, from investment in R&D and capacity (Davidson and Deneckere 1990; Fershtman and Gandal 1994; Brod and Shivakumar 1999), advertisement (Dixit and Norman 1978; Slade 1995), promotion (Richards 2007), line extension (Kadiyali, Vilcassim, and Chintagunta 1998), product-line length (Draganska and Jain 2005; Richards and Hamilton 2006), product assortment (Draganska, Mazzeo, and Seim 2009), location in geographic space (Friedman and Thisse 1993; Thomadsen 2007), and location in attribute space (Jehiel 1992; Richards, Allender, and Hamilton 2013). In each case, non-price variables can serve as strategic tools that change the nature of price competition. Despite its prominence in product design, and salience to consumers, competitive package sizing has received a little attention in the literature. In this study, I investigate how manufacturers use package size as a competitive tool, and the relationship between package size and price competition.

Accounting for the simultaneous determination of package size and price is also important from an econometric point of view. In the previous chapter, I show that consumers choose package sizes, at least in part, due to the perceived risk of a mismatch between product attributes and their own preferences. In studying the effect of package size on consumer demand, I follow the extant literature by assuming package size is exogenous, or determined in a prior stage of a multi-stage game played between consumers and product manufacturers. Instead, if firms are rational, they ought to exploit consumers' responses to the uncertainty inherent in trying any new product, and profit accordingly. Because package size is therefore endogenous, estimating consumer-response to changes in package size in a structural econometric model controls for any endogeneity bias that may otherwise arise.

This observation is often overlooked in the empirical marketing literature. Indeed, the fundamental unit of analysis is typically a brand or product line, but manufacturers offer different package sizes at different unit prices within the same product line even though each stock keeping unit (SKU) is identical in terms of formulation, flavor, and aroma (Gerstner and Hess 1987). Empirical analysis of strategic package size and price decisions, therefore, must be made at an SKU level. There are some examples of SKU-level modeling. Allenby, Shively, Yang, and Garratt (2004) develop a model of package-choice, but assume price is exogenously given so they do not address firm pricing behavior. On the other hand, Khan and Jain (2005), Cohen (2008), and Gu and Yang (2010) endogenize retailer, manufacturer, or retailer and manufacturer behaviors and investigate pricing strategies for different package sizes. They find that firms use package size as a price discrimination tool, and can earn super-normal profits by charging higher unit prices for smaller packages. But, these authors focus on pricing different, exogenously-given package sizes so are silent on how manufacturers determine package sizes as strategic variables. My structural model is built on an equilibrium concept that accounts for the interaction between consumers with heterogeneous preference for package size and profit-maximizing retailers and manufacturers, endogenizing manufacturers' simultaneous decision of package size and price.

The model includes both consumer demand, and manufacturers' optimal response to package-preferences. On the demand-side, I explicitly account for package-size preferences as well as other elements of the marketing mix. By conditioning manufacturer decisions on consumer preferences for different package sizes, I ensure that manufacturer decisions are optimal responses with respect to their expectations on how consumers will react. On the supply-side, oligopolistic manufacturers jointly set package size and wholesale prices and retailers set retail prices taking into account consumer demand, manufacturer and retailer costs, and competition in package size and price. My model allows me to derive the equilibrium package size and price, and to reveal the interdependence between them. My modeling framework is similar to that used in the product-line literature (Draganska and Jain 2005; Richards and Hamilton

2006; Richards, Allender, and Hamilton 2013; Richards and Hamilton 2014). This literature shows that prices and product line decisions are strategically linked, but do not consider the importance of more product-specific decisions. Moreover, I incorporate both manufacturer and retailer behaviors. Villas-Boas and Zhao (2005) show that it is important to consider interactions among consumers, retailers, and manufacturers because estimates of consumer preferences, manufacturer and retailer costs, and the extent of strategic interaction between manufacturers and retailers will be biased and inconsistent otherwise.

As an example of the strategic interdependence between package size and price, I apply the empirical model to store-level scanner data for the ready-to-eat breakfast cereal category in the Chicago market. I find that package size decisions by manufacturers reflect both consumer preferences, and price competition among suppliers. Consumers prefer small packages, in part due to the perceived risk, and have heterogeneous responses to package size. At the same time, the cost of producing packages of different sizes rises in a nonlinear way. I find that manufacturers respond to competitive pressure by changing not only their price, but package size as well. Specifically, manufacturers tend to downsize packages as wholesale prices rise, suggesting that changes in package size mitigate the impact of wholesale price increases. Further, the received wisdom holds that manufacturers change package sizes because it is a stealthy means of changing unit prices. However, my results suggest that this effect is only part of the reason manufacturers change prices – a weak part. Rather, manufacturers incur significant costs to change package sizes, and any change in package size is likely to incite strong price competition. Therefore, what would seem to be an intuitive result, namely that manufacturers change prices because consumers won't notice, is fundamentally incorrect because it does not take into account the cost of changing package sizes, and the strategic implications of doing so. My study is the first to endogenize package size decisions, and because changing packages is costly, reducing package sizes in response to higher costs is not always rational.

This study contributes to the empirical marketing literature by endogenizing joint decisions of package size and price. Whereas others who explain why manufacturers change package sizes consider only the response of consumers, I show that cost and strategic considerations are equally as important. On a substantive level, I show that when manufacturers change package sizes, they are responding to not only consumer preferences, but to the structure of packaging costs, and the nature of rivalry in their industry. Finally, I provide further evidence that package size changes have to the potential to be a facilitating practice for semi-collusion in prices in that offering larger package sizes tends to soften price competition, which raises wholesale margins accordingly.

The reminder of this paper is organized as follows. In the second section, I describe the econometric framework used to estimate the equilibrium package size and price. In the third section, I describe the data, and present some stylized facts drawn from my sample that motivates this study. In the fourth section, I present the estimation and simulation results and discuss how package size affects consumer demand, production costs, and competition in the market and how package size and price are related each other. I draw conclusions, explain some fundamental implications for firms and regulators in the CPG industry, and describe potential extensions in the final section.

4.2 Model

4.2.1 Overview

In this section, I describe a structural model of consumer, retailer, and manufacturer behavior. On the demand side, I employ a random utility model of consumer choice among differentiated products (Berry 1994; Berry, Levinsohn, and Pakes 1995; Nevo 2001). On the supply side, I assume that manufacturers set package size and wholesale prices, and retailers set retail prices taking into account consumer demand and manufacturer and retailer costs. I model the vertical relationship between manufacturers and retailers using a two-stage game: In the first stage, manufacturers propose a contract to retailers that specifies the wholesale price of each product. In the second stage, retailers set retail prices conditional on retailers' acceptance of that contract. I estimate this two-stage game using backward induction. Namely, I first estimate consumer demand, and then estimate the retailer profit maximization problem, and the manufacturer package-sizing and pricing decisions conditional on consumer, retailer, and competitor behaviors. I discuss each stage of the model in the following subsections.

4.2.2 Demand-Side Model

In this subsection, I describe a model consumer demand that is appropriate for studying preferences at the SKU-level. Representative consumer demand models, such as the AIDS model (Deaton and Muelbauer, 1980) or the Rotterdam Model (Theil 1965; Barten, 1964), are not appropriate for describing the demand for differentiated products like CPGs because they assume consumers purchase a little bit of every product and provide little insight into the microstructure of demand. Therefore, I use a random utility model in which consumers are assumed to make a discrete choice among differentiated products. A consumer is assumed to choose the product that provides the highest level of utility from those available in the sample, or other products from another store as the outside option. Products are differentiated by SKU, or a specific brand, flavor, and size. Different package sizes under the same brand are treated as different products because (1) consumers may vary in the amount of convenience they derive from each package size, and (2) manufacturers and retailers use different pricing strategies for different package sizes. For example, some retailers offer a volume discount, while others charge a volume premium for large packages. Consumers make hierarchical purchase decisions, first deciding whether to purchase a product from the stores in the data set or other stores, and then deciding on a specific product, conditional on store choice. Consequently, I employ a generalized extreme value (GEV) model of consumer demand (McFadden 1978).

Formally, the utility from household h purchasing product $i \in I$ (under brand name $b \in B$) from store $j \in J$ at time t is represented by:

$$u_{hijt} = \alpha_{hb} + \beta_{ht} p_{ijt} + f(q_{it}) + \psi d_{ijt} + \omega (p_{ijt} \times d_{ijt}) + \xi_{ijt} + \tau_{hijt} + (1 - \sigma) \varepsilon_{hijt}, \quad (4.1)$$

where α_{hb}, β_{ht}, ψ, ω and σ are parameters to be estimated, p_{ijt} is the shelf price, $f(\cdot)$ is a contribution to utility by purchase quantity, q_{it} is package size, d_{ijt} is a binary discount variable that takes a value of one if the product's price is reduced by at least 10% from one week to the next and then returned to its previous value in the following week, zero otherwise, $p_{ijt} \times d_{ijt}$ is an interaction term between the price and the discount variable, ξ_{ijt} is an iid error term that reflects product attributes that are relevant, but unobserved to the econometrician, such as brand loyalty, advertising, and display, ε_{hijt} is a household- product-, store-, and time-specific iid error term that reflects unobserved consumer heterogeneity, and τ_{hijt} is an error term such that the entire error term, $\tau_{hijt} + (1 - \sigma)\,\varepsilon_{hijt}$ is extreme-value distributed (Cardell 1997). The GEV scale parameter σ is bounded between zero and one and measures the correlation among stores. As σ approaches one, the correlation of utility among stores goes to one and stores are regarded as perfect substitutes. As σ approaches zero, on the other hand, the correlation among stores goes to zero.

Package size may have a significant impact on utility. Because consumers choose a particular package size depending on their perception of risk (Shoemaker and Shoal 1975) and convenience (Koenigsberg, Kohli, and Montoya 2010), I explicitly account for utility from purchasing a particular package size by including $f\,(q_{it})$. The inclusion of package size into utility is consistent with the empirical marketing literature (Allenby, Shively, Yang and Garratt 2004; Khan and Jain 2005; Cohen 2008; Gu and Yang 2010; Çakıra and Balagtas 2014). Because the precise way in which package size enters utility is unknown, I approximate it using a general polynomial form. That is, to arrive at a closed form formula for $f\,(q_{it})$, I approximate it by a second-order Taylor series expansion (TSE) to obtain:

$$f\,(q_{it}) = f\,(0) + f^{'}\,(0)\,q_{it} + \frac{f''\,(0)}{2}q_{it}^{2}. \tag{4.2}$$

I assume contribution to utility is zero if quantity is zero, so $f\,(0) = 0$ and equation (4.2) is then written as:

$$f\,(q_{it}) = \gamma_{1ht}q_{it} + \gamma_{2t}q_{it}^{2}, \tag{4.3}$$

where γ_{1ht} $(= f^{'}(0))$ and γ_{2ht} $(= \frac{f''(0)}{2})$ are parameters to be estimated.[1] Because consumers prefer smaller packages (Shoemaker and Shoal 1975; Allenby, Shively, Yang and Garratt 2004; Khan and Jain 2005; Cohen 2008; Gu and Yang 2010; Koenigsberg, Kohli, and Montoya 2010; Çakıra and Balagtas 2014), I expect that $\gamma_{1ht} \leq 0$. Even if consumers prefer a smaller package, most of them may not accept something as small as a single-portion size. Packages that are too small increase purchase frequency and raise transactions costs prohibitively. At the same time, packages that are too large are difficult to store, and increase the likelihood of spoilage. Therefore, it is reasonable to assume that $\gamma_{2t} \geq 0$.

Although the GEV model captures different degrees of substitution among products across groups, it still suffers from the independent of irrelevant alternatives (IIA) property within each group, which generates an unrealistic substitution pattern. To overcome this problem, I allow the brand-specific intercept, the marginal utility of income, and the marginal utility of package size to vary across households in a random way (Berry, Levinsohn, and Pakes 1995; Nevo 2001). This assumption also captures unobserved heterogeneity in brand preference, price responsiveness, and preference for different package sizes. Formally, the brand-specific intercept is assumed to be normally distributed across households, so that:

$$\alpha_{hb} = \alpha_0 + \sum_{b=1}^{B-1} \alpha_{1b} x_b + \sigma_\alpha \iota_h, \ \iota_h \sim N(0,1), \tag{4.4}$$

where α_0, α_{1b} and σ_α are parameters to be estimated, x_b is the binary variable that takes one if product i is brand b, and zero otherwise, and ι_h is a household-specific

[1] Draganska and Jain (2005) use a similar approach to derive the functional form of the relationship between utility and product-line length. In each case, there is no theoretical prior, so approximating a general polynomial form is a reasonable way to proceed.

random component capturing brand preference. Similarly, the marginal utility of income is assumed to be normally distributed across households, so that:

$$\beta_{ht} = \beta_0 + \sum_{k=1}^{K} \beta_k y_{kt} + \sigma_\beta \kappa_h, \ \ \kappa_h \sim N(0,1), \tag{4.5}$$

where β_k's and σ_β are parameters to be estimated, y_{kt}'s are mean household demographic attributes at time t, and κ_h is a term capturing household-specific random variation in price response. Finally, I assume the marginal utility of package size differs across households, so that:

$$\gamma_{ht} = \gamma_0 + \sum_{k=1}^{K} \gamma_k y_{kt} + \sigma_\gamma \lambda_h, \ \ \lambda_h \sim N(0,1), \tag{4.6}$$

where γ_k's and σ_γ are parameters to be estimated and λ_h is a household-specific term that captures random variation in package size. Equations (4.4), (4.5), and (4.6) allow me to incorporate unobserved consumer heterogeneity that may be important in determining consumers' product choice behavior. With these random coefficients, the elasticities are the function of the attributes of all the choices rather than the one in question and the one changed. That is, the elasticities depend on the specification of variables and mixing distribution, which generates a more realistic substitution pattern.

The utility associated with the outside option is specified as follows:

$$u_{h00t} = \varepsilon_{h00t}. \tag{4.7}$$

When a household chooses the outside option, it implies that they do not purchase any of the products $i \in I$ sold at store $j \in J$. With an outside good, households are allowed to substitute to other goods. In its absence, a simultaneous change in the price of all products leads to no change in aggregate consumption.

Following Berry, Levinsohn, and Pakes (1995) and Nevo (2001), I decompose equation (4.1) into the mean part that varies over products and stores, but not households, and the idiosyncratic part that varies over products, stores and households, or:

$$u_{hijt} = \delta_{ijt}\left(x_b, y_{kt}, p_{ijt}, q_{it}, d_{ijt}, \xi_{ijt}; \alpha, \beta, \gamma\right) + \phi_{hijt}\left(\iota_h, \kappa_h, \lambda_h; \sigma\right) + \varepsilon_{hijt}, \tag{4.8}$$

where $\delta_{ijt}(\cdot)$ is the mean part and $\phi_{hijt}(\cdot)$ is the idiosyncratic part. I define the density of ι_h, κ_h and λ_h as $g_1(\iota)$, $g_2(\kappa)$ and $g_3(\lambda)$ respectively. By integrating over the distributions of $g_1(\iota)$, $g_2(\kappa)$ and $g_3(\lambda)$, I derive the market share of product i in store j at time t as:

$$s_{ijt} = \iiint \frac{\exp\left(\delta_{ijt} + \phi_{hijt}\right) / (1-\sigma)}{D_J^{\sigma}\left(\sum\limits_{j \in J} D_J^{1-\sigma}\right)} g_1(\iota)\, g_2(\kappa)\, g_3(\lambda)\, d\iota d\kappa d\lambda, \tag{4.9}$$

where $D_J = \sum\limits_{i \in I} \exp\left(\delta_{ijt} + \phi_{hijt}\right) / (1-\sigma)$.

In equation (4.1), ξ_{ijt} are unobservable to the econometrician, but known to consumers, retailers, and manufacturers. The retail prices determined by the interactions among them are potentially correlated with unobserved demand shocks, which yield biased estimates. To address this issue, I estimate equation (4.9) via simulated maximum likelihood (SML) method combined with the control function approach (Train 2009; Pertin and Train 2010; Park and Gupta 2009). The detailed estimation method is described in the next section.

4.2.3 Supply-Side Model

Pricing and package-size decisions by CPG manufacturers depend critically on consumer response, and cost considerations. In modeling supply decisions, manufacturers set package sizes and wholesale prices taking into account the structure of their own costs, and retailer responses, while retailers pass-through manufacturers' package size decisions and set prices to consumers taking into account their costs and the nature of consumer demand. Manufacturers are assumed to compete horizontally among themselves in both package sizes and wholesale prices. Others find that consumers base their store selection decisions not only on prices charged for a single product category, but also on their basket price and store's non-price attributes such as store location, service quality, and product variety (Arnold, Oum, and Tigert 1983; Bell, Ho, and Tang 1998; Bell and Lattin 1998; Bawa and Ghosh 1999; Briesch, Chintagunta, and Fox 2009). Following Slade (1995), Besanko, Gupta, and Jain (1998), and Sudhir (2001), therefore, I assume that retailers behave as local monopolists in my model. Manufactures and retailers interact vertically according to a manufacturer-Stackelberg assumption (Sudhir 2001). Assuming manufacturers are able to set prices and package sizes first is well-supported by the empirical literature on vertical supply relationships (Besanko, Dubé and Gupta 2003; Villas-Boas and Zhao 2005; Draganska and Klapper 2007; Villas-Boas 2007). I solve the model using backward induction by first estimating the second-stage retail pricing decision, and then the first-stage package size and wholesale price equations. In the reminder of this section, I derive the subgame perfect Nash equilibrium in package sizes and prices to this channel game. To simplify notation, I drop time subscript t in the subsequent discussion.

Consider first the pricing decision facing retailer j. Following Slade (1995), Besanko, Gupta and Jain (1998) and Sudhir (2001), I assume that retailers behave as local monopolists. That is, retailer j carrying I products chooses the optimal retail prices p_i that maximize category profit. The profit maximization problem for retailer

j is written as:

$$\pi^j = \max_{p_i} Q \sum_{i=1}^{I} (p_i - r_i)\, s_i - F_j,\ \forall j, \tag{4.10}$$

where Q is the size of the total market, s_i is the market share of product i, r_i is the retailing marginal costs for product i, and F_j is the fixed cost for retailer j. I assume the retailing costs are captured by a normalized quadratic unit cost function (Diewert and Wales 1987), so the marginal cost is given by the following linear combination of retailing input prices:

$$r_i = \nu_0^r + \nu_1^r w_i + \sum_{l=2}^{L^r} \nu_l^r z_{li}^r, \tag{4.11}$$

where ν_l^r's are parameters to be estimated, w_i is the wholesale price for product i paid by retailer j, z_{li}^r's are other retailing input prices for selling product i.[2] Because retailer j pass-through manufacturers' package size decisions and choose retail price p_i to maximize its category profit, retailer j's first order condition for product i is obtained by differentiating equation (4.10) with respect to p_i, so that:

$$\frac{\partial \pi^j}{\partial p_i} = s_i + \sum_{i=1}^{I} (p_i - r_i) \frac{\partial s_i}{\partial p_i} = 0,\ \forall i, j. \tag{4.12}$$

Equation (4.12) is then solved for retailer j's margin, which gives, in matrix notation:

$$p - r = -(\Omega)^{-1} s, \tag{4.13}$$

where $p = (p_1, \ldots, p_I)^T$, $r = (r_1, \ldots, r_I)^T$, $s = (s_1, \ldots, s_I)^T$ and Ω is an $I \times I$ matrix of share derivatives with respect to all retail prices where the (i, j) element is given

[2] The normalized quadratic unit cost function for product i is $C_i = \mu_1^T z + \mu_2 y_i + \frac{1}{2}\left(z^T \mu_3 z + z^T \mu_4 y_i\right)$ where y_i is the output of product i and z is the vector of normalized input prices. So, the marginal cost for product i, $\frac{\partial C_i}{\partial y_i}$ is written by the linear combination of normalized prices, which supports my linear specification of marginal costs.

by $\frac{\partial s_j}{\partial p_i}$. Equation (4.13) indicates that retail margins are the inverse functions of the share derivatives with respect to retail prices weighted by market share.

Manufacturer m offers products I_m (i.e. $\sum_{m=1}^{M} I_m = I$) and is assumed to compete in package sizes and wholesale prices in Bertrand-Nash fashion. Following Koenigsberg, Kohli and Montoya (2010), I assume that manufacturers make simultaneous decisions regarding package size and price. Setting package prices and sizes together is both reasonable and descriptive of business practice as manufacturers target a specific price per unit of measure for each SKU – a policy that is only possible if prices and package sizes are determined together. Consequently, the profit maximization problem facing manufacturer m is written as:

$$\pi^m = \max_{w_i, q_i} Q \sum_{i=1}^{I_m} (w_i - c_i) s_i - F_m - \sum_{i=1}^{I_m} h(q_i), \tag{4.14}$$

where c_i is the marginal cost for product i, F_m is the fixed cost of manufacturer m and $h_m(q_i)$ is the package-size cost function for a package of size q_i. In this equation, package costs are assumed to be separable from c_i and F_m. Package size may also affect manufacturers' variable costs of production, but this effect is likely to be minimal. Moreover, my focus is the influence of package size on fixed costs such as set-up costs, inventory costs and distribution costs so the primary effect of packaging costs is independent of production volume.[3] As in the retailers' profit maximization problem, I assume the marginal cost for product i is arisen from a Normalized Quadratic unit cost function (Diewert and Wales 1987). So, the marginal cost for product i is written

[3]I include product-specific intercepts into my supply-side model. These intercepts control for the variations of the variable costs associated with producing packages.

as:

$$c_i = \nu_0^m + \sum_{l=1}^{L^m} \nu_l^m z_{li}^m, \tag{4.15}$$

where ν_l^m's are parameters to be estimated, z_{li}^m's are input prices for selling product i.

Again, the exact form of packaging costs is not known, *a priori*, but they can be approximated by a TSE. Applying a TSE to an arbitrary function of package size implies:

$$h(q_i) = h(0) + h'(0)\, q_i + \frac{h''(0)}{2} q_i^2, \tag{4.16}$$

or:

$$h(q_i) = \theta_0 + \theta_1 q_i + \theta_2 q_i^2, \tag{4.17}$$

where θ_0 $(= h(0))$, θ_1 $(= h'(0))$, and θ_2 $(= \frac{h''(0)}{2})$ are parameters to be estimated. The fixed cost associated with producing and distributing packages may be neither simply increasing nor decreasing. Packages that are too small and too large may require special packaging technology, excessive costs associated with setting up the production line, or special handling in the distribution system and shelf display. Consequently, I expect that the fixed packaging cost function is convex, or $\theta_0 > 0$, $\theta_0 > 0$, and $\theta_0 > 0$.

With this objective function, I then consider manufacturer m's pricing decision problem. Differentiating equation (4.14) with respect to w_i, manufacturer m's first order condition for product i is written as:

$$s_i + \sum_{k=1}^{I_m} \left((w_i - c_i) \sum_{l=1}^{I} \frac{\partial s_i}{\partial p_l} \frac{\partial p_l}{\partial w_k} \right) = 0, \ \forall i. \tag{4.18}$$

In equation (4.18), $w_i - c_i$ represents manufacturer margin for product i and $\frac{\partial s_i}{\partial p_l}\frac{\partial p_l}{\partial w_k}$ represents the change in the market share of product i in response to the change in the wholesale price of product k. The change in wholesale price affects all retail prices, which in turn influences the market share of the product in question. Notice that equation (4.18) includes the retail-wholesale pass-through term, $\frac{\partial p_l}{\partial w_k}$ that is not observable in the data set.[4] Following Sudhir (2001), Villas-Boas and Zhao (2005) and Villas-Boas (2007), the retail-wholesale pass-through term is recovered by totally differentiating equation (4.12) to yield (in matrix notation):

$$\Theta = G^{-1}\Omega, \tag{4.19}$$

where Θ is an $I \times I$ matrix with (i, j) element given by $\frac{\partial p_i}{\partial w_j}$ and G is an $I \times I$ matrix with (i, j) element given by:

$$g_{ij} = \frac{\partial s_i}{\partial p_j} + \sum_{k=1}^{I} (p_k - r_k) \left(\frac{\partial s_k^2}{\partial p_i \partial p_j} \right) + \frac{\partial s_j}{\partial p_i}, \ \forall i, j. \tag{4.20}$$

In equation (4.20), $\frac{\partial s_i}{\partial p_j}$ represents the change in the market share of product i in response to the change in the retail price of product j, $p_k - r_k$ is the retail margin of product k, and $\frac{\partial s_k^2}{\partial p_i \partial p_j}$ is the change in $\frac{\partial s_k}{\partial p_i}$ in response to the change in the retail price of product j. As shown in equation (4.19), the retail-wholesale pass-through matrix, Θ is obtained by the product of the inverse of the matrix, G and the matrix of share derivatives with respect to all retail prices. Equation (4.18) is then solved for manufacturer m's margin using the matrix Θ to find (in matrix notation):

$$w - c = -\left(\left(G^{-1}\Omega \right) \Omega * I_N \right)^{-1} s, \tag{4.21}$$

where I_N is an $I \times I$ identity matrix and $*$ is an element-by-element multiplication. Equation (4.21) implies that manufacturer margins depend on the inverse functions

[4] I assume that retailer does not know the terms of the contract between manufacturers and other retailers. This implies that $\frac{\partial p_l}{\partial w_k} = 0$ if p_l is the retail price in one retailer and w_k is the wholesale price offered to other retailers. The derivatives are not necessarily equal to zero if p_l is the retail price in one retailer and w_k is the wholesale price offered to the same retailer. I describe how this is revealed in the subsequent discussion.

of the share derivatives with respect to wholesale prices weighted by market share. As discussed above, the share derivatives with respect to wholesale prices are the function of the G matrix and the share derivatives with respect to all retail prices.

Retailers and manufacturers are assumed to know the structure of the game and set retail prices and wholesale prices according to equations (4.13) and (4.21), respectively. As Villas-Boas and Zhao (2005) and Draganska and Klapper (2007) note, however, it is possible that the actual outcome of this game differs from theoretical predictions due to asymmetric market information, regulations, and supply constraints. Accordingly, I allow for deviations from either profit-maximizing retail prices, or Bertrand-Nash wholesale prices by using "conduct parameters." Specifically, equations (4.13) and (4.21) are written as:

$$p - r = -\left(\left(\frac{1}{\rho}\right)\Omega\right)^{-1} s \tag{4.22}$$

and

$$w - c = -\varphi\left(\left(G^{-1}\Omega\right)\Omega * I_N\right)^{-1} s, \tag{4.23}$$

where ρ and φ are conduct parameters to be estimated. The conduct parameters represent how the equilibrium outcomes respond to the changes in demand conditions expressed in elasticity terms. Also, each of the conduct parameters measures the extent of deviation from Bertrand-Nash pricing conduct. If $\rho = \varphi = 0$, then both retailers and manufactures set prices competitively. If $\rho = \varphi = 1$, then retailers set prices as perfect local monopolists, and manufactures as perfect Bertrand-Nash competitors. In each case, $\rho > 1$ and $\varphi > 1$ imply retailers and manufactures exercise greater market power.[5] The last case is likely to happen if retailers or manufactures

[5] Corts (1999) points out the conduct parameters are biased because the estimation based on the static conjectural variations approach cannot be independent of any

compete in non-price attributes such as service quality, advertisement, and product assortment and set price collusively.

Finally, I consider the package-size decisions of manufacturer m. Differentiating equation (4.14) with respect to q_i, manufacturer m's first order condition for product i is given by:

$$Q \sum_{k=1}^{I_m} (w_k - c_k) \frac{\partial s_k}{\partial q_i} - \theta_1 - 2\theta_2 q_i = 0, \ \forall i. \tag{4.24}$$

In equation (4.24), $w_k - c_k$ represents manufacturer margin for product k and $\frac{\partial s_k}{\partial q_i}$ represents the change in the market share of product k in response to the change in the package size of product i. Equation (4.24) is then solved for manufacturer m's optimal package size to find:

$$q = \eta_0 + \eta_1 Q \Gamma (w - c), \tag{4.25}$$

where $q = (q_1, \ldots, q_I)^T$, η_0 $(= -\frac{\theta_1}{2\theta_2})$ and η_1 $(= \frac{1}{2\theta_2})$ are parameters to be estimated,[6] Γ is an $I \times I$ matrix of share derivatives with respect to all package sizes with (i, j) element given by $\frac{\partial s_j}{\partial q_i}$. Because $\Gamma(w - c)$ is the products of the share derivatives with respect to package size and the estimates of manufacturer competitive response to changes in demand conditions expressed in price elasticity terms, η_1 measures the effect of competition and package size substitutability on equilibrium package sizes. Although the own-share derivative is expected to be negative and the cross-share share derivative to be positive in sign, the sign of η_1 is an empirical question as it depends on both Γ and $w - c$.

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dynamic oligopolistic behaviors. I acknowledge this issue. But, there are no other methods to measure market power.

[6] θ_0 is not identified in my econometric model. But, it does not have any impacts on the subsequent discussion.

In summary, the retailer and manufacturer decisions are characterized by equations (4.22), (4.23), and (4.25), respectively. My intent is to reveal how manufacturers use package size and price as complementary tools in strategic competition. The interaction between the equilibrium wholesale prices determined by equation (4.23) and the equilibrium package sizes determined by equation (4.25) is my primary concern. Because explicitly including cross-response parameters between package-size and price makes the model econometrically intractable, I conduct a series of simulations to determine their joint equilibrium realizations. By conducting the simulations, therefore, I examine how manufacturers respond to a change in their competitive environment caused by package downsizing. Equations (4.22), (4.23), and (4.25) involve in many factors such as market shares and own- and cross-share derivatives with respect to all retail prices, wholesale prices, and package sizes, so simulation is an effective way to show how the outcome variables of interest are determined in equilibrium. To conduct the simulation, the parameters in equations (4.22), (4.23), and (4.25) are required.

4.2.4 Estimation and Identification

The equilibrium model is estimated in two stages. In the first stage, I estimate the demand model (equation (4.9)), and in the second stage, conditional on the demand estimates, the supply model (equations (4.22), (4.23), and (4.25)) is estimated. While fully simultaneous estimation may be more efficient, this two-stage approach provides consistent demand estimates regardless of the assumptions made regarding the supply-side model (Yang, Chen, and Allenby 2003). On a practical level, two-stage estimation also renders a highly complex model of consumer, retailer, and manufacturer interactions tractable to estimate. In this subsection, I describe the estimation methods used for both the demand and supply models.

Identification of retailer and manufacturer conduct in structural models such as this can never be proven conclusively, but rests on the logic of the identification strategy, and the quality of the estimation results. For the current model, market share and retail price vary across product, retailer, and time, which easily identify price-response parameters (table 4.1). Although package size changes less often, and in a discrete way, over the sample period, manufacturers offer a variety of package sizes. The average package size is 16.1 ounces and the standard deviation is 3.6 ounces. So, cross-sectional variation is enough to identify the package-size-response parameters. With respect to wholesale prices, others rely on implicitly-estimated wholesale price variation (Villas-Boas and Zhang 2005; Draganska and Klapper 2007; Villas-Boas 2007), so identifying manufacturer is inherently more questionable than in this study. Because I use observed wholesale prices, which vary substantially over time and across products (table 4.1), identifying manufacturer behavior is much easier (Nakamura and Zerom 2010). Moreover, input prices for both retailers and manufacturers are highly volatile over the sample period (figure 4.1 and table 4.3), so variations in input costs enable me to identify key parameters of the demand and supply models. However, note that the retail prices and manufacturer and retailer margins are likely to be endogenous.

For the demand model, retail prices are likely to be endogenous in store-level retail scanner data. Because unobserved (to the econometrician) factors such as advertisement, in-store promotion, and shelf placement are known to consumers, retailers, and manufacturers, observed prices are likely to be correlated with unobserved demand shocks, which may yield inconsistent estimators. There are two approaches to address this endogeneity issue. One is to use a simulated generalized method of moments (SGMM) approach (Berry, Levinsohn, and Pakes 1995), and the other is the control function approach (Park and Gupta 2009; Petrin and Train 2010). I employ the control function approach, because SGMM tends to be sensitive to sampling error and, as a result, requires multiple markets and multiple stores in each market (Berry, Linton and Pakes 2004). Further, the control function approach has been shown to be useful in contexts similar to mine (Park and Gupta 2009).

The control function approach is intended to introduce a proxy variable that accounts for the unobserved factors, ξ_{ijt} affecting retail prices, such that the remaining variations in retail prices, p_{ijt} independent of the error term, ε_{hijt} and the standard estimation approaches is consistent. For illustration purposes, I rewrite equation (4.8) as:

$$u_{hijt} = V\left(x_b, y_{kt}, p_{ijt}, q_{it}, d_{ijt}, \iota_h, \kappa_h, \lambda_h; \alpha, \beta, \gamma, \sigma\right) + \xi_{ijt} + \varepsilon_{hijt}. \tag{4.26}$$

Suppose the endogenous price variable, p_{ijt} is expressed as a linear combination of n observed instruments, v_{ijtn} and an unobservable factor, π_{ijt}, so that:

$$p_{ijt} = \sum_{n=1}^{N} \chi_n v_{ijtn} + \pi_{ijt}, \tag{4.27}$$

where χ_n's are parameters to be estimated and ε_{hijt} and π_{ijt} are independent of p_{ijt}, but ε_{hijt} and π_{ijt} are correlated. The correlation between ε_{hijt} and π_{ijt} reflects the price endogeneity problem. I decompose ε_{hijt} into the mean part conditional on π_{ijt} and the deviation part that is independent of π_{ijt}: $\varepsilon_{hijt} = E\left(\varepsilon_{hijt}|\pi_{ijt}\right) + \widetilde{\varepsilon}_{hijt}$. The conditional expectation is a function of π_{ijt}, and is called the control function, denoted by $CF\left(\pi_{ijt}\right)$. With the conditional expectation term, or control function, and the deviation part, equation (4.26) is written as:

$$u_{hijt} = V\left(x_b, y_{kt}, p_{ijt}, q_{it}, d_{ijt}, \iota_h, \kappa_h, \lambda_h; \alpha, \beta, \gamma, \sigma\right) + \xi_{ijt} + CF\left(\pi_{ijt}\right) + \widetilde{\varepsilon}_{hijt}. \tag{4.28}$$

Because $\widetilde{\varepsilon}_{hijt}$ is independent of p_{ijt}, standard simulated maximum likelihood (SML) is applicable.

For the control function $(CF(\pi_{ijt}))$, I use the residuals from equation (4.27) i.e. $\widehat{\pi}_{ijt} = p_{ijt} - \sum_{n=1}^{N} \widehat{\chi}_n v_{ijtn}$. Specifically, the control function approach takes a two-step process. In the first step, the variable that is thought to be endogenous is regressed on exogenous instruments to generate a vector of residuals. In the second step, the demand model is estimated using the residuals as an explanatory variable. Because the IV residuals account for unobservable factors in prices that may be correlated with errors in the demand equation, this method controls for the potential implied bias, and provides consistent demand estimates. I then use SML to estimate the full model, including the control function (Train 2009; Petrin and Train 2010). SML uses random draws from the distributions that reflect consumer heterogeneity so, to aid in the computational speed and efficiency of estimation, I use 100 Halton draws (Bhat 2003).

Effective demand instruments must be correlated with price, but not the unobservable factors. As suggested by Villas-Boas (2007) and Draganska and Klapper (2007), the set of instrumental variables includes a variety of cost, brand, and dynamic variables. First, manufacturer and retail level input prices such as grain prices, sugar prices, wholesale prices, gas prices, diesel prices, and wages are used because input prices are likely to be correlated with retail prices, but not the unobservable demand factors. Second, brand specific intercepts account for unobservable supply factors that influence retail prices. Third, lagged share values are likely to be correlated with current-period prices, but only weakly correlated with current-period demand shocks (Villas-Boas and Winer 1999). This set of instruments explains 36.3% of the total variation in the endogenous retail price and produces an F statistic is 186.5, which implies that the instruments are not weak (Staiger and Stock 1997).

Instruments for the supply model are also required because retailer and manufacturer margins in the price and package-size equations are also likely to be endogenous. Again, factors such as supply contracts, supply constraints, and retailer marketing strategies are known to retailers and manufacturers, and so influence margins at both levels, but are unobservable to the econometrician. The control function approach is used again, as in the demand model. In the first-stage IV regression, endogenous margins are regressed on exogenous instruments to again obtain a set of residuals. The set of residuals is then used as an explanatory variable in the price and package-size equations, which provides consistent estimates of the key parameters of interest. To take advantage of the efficiency gains arising from contemporaneous correlation among the supply-side equations, seemingly unrelated regressions (SUR) is used to estimate the supply-side model with the control function.

In the supply model, the instruments must be correlated with margins, but not correlated with the unobservable factors in the price and package-size equations. On an intuitive level, supply instruments are variables that shift the demand curve and, hence, identify equilibrium points on the supply curve. I use the set of instruments well-accepted in the literature (Draganska and Klapper 2007; Villas-Boas 2007). For the manufacturer margin, demographic variables such as household income, household size, age, educational attainment, and employment status are used to capture variation in demand. Second, retail input prices are used as instruments because variations in retail costs are likely to influence the derived-demand for breakfast cereal by retailers. Third, lagged margins are used because they are likely to be correlated with current margins, but not with the unobservable factors. Fourth, manufacturer-specific binary variables capture idiosyncratic supply factors that are unobservable to the econometrician, but are known to retailers and manufacturers. Finally, binary variables accounting for seasonal effects are included to account for temporal variation that may be important in determining manufacturers' margins. For the retailer margin, demographic variables, lagged margins, and store-specific binary variables are used, following the same general logic as with the manufacturer-margin equation. This set of instruments explains 1.8% of the total variation in the endogenous manufacturer margin and 91.0% of the retailer margin. The F statistics are 15.6 for the first-stage IV regression for the manufacturer margin, and 15,507 for the retailer margin, respectively. Because each of these F statistics is greater than 10, I again conclude that the instruments are not weak in the sense of Staiger and Stock (1997).

4.3 Data Description

I estimate the empirical model using store-level scanner data (IRI Infoscan) from the ready-to-eat breakfast cereal category for the Chicago market. Specifically, the data consists of 156 weeks (April 2007 - March 2010) of supermarket chain-level retail sales of ready-to-eat breakfast cereal. The data set includes UPC level unit sales and dollar sales sold in two major supermarket chains in Chicago: Dominicks and Jewel. Each product-alternative is defined as an SKU. For tractability, I focus on 35 major SKUs, subject to the restriction that each product is sold in both stores. All other SKUs are assumed to be in the outside option. The outside option is the difference between total market sales and the sales captured by the data, where the total market is defined as the population of Chicago multiplied by per capita consumption. Per capita consumption is calculated by assuming each consumer in the Chicago market has an average serving-size per day as in Nevo (2001). Defining the outside option this way means that the model captures not only the IRI-products excluded from the analysis, but also those sold in stores that do not provide their sales data to IRI.

The breakfast cereal category represents an ideal case-study of package size and pricing strategy. First, breakfast cereals are frequently purchased and consumed by a wide variety of consumers, so the distribution of preferences help identify the demand parameters. Second, there are two major manufacturers, General Mills and Kelloggs, which are well-understood to compete strategically using multiple tools – an observation that also helps identify competitive interactions at the manufacturer level. Finally, manufacturers often change the size of their packages relative to manufacturers who sell products in cans or bottles, and variation in package size is necessary to identify the core parameters of interest.

The manufacturer pricing data is provided by Promodata, Inc., and includes the price charged by manufacturers before allowances are applied, markups charged by wholesalers to retailers, the effective date of new case prices, "deal allowances," or off-invoice items offered to retailers by the wholesaler, the type of promotion suggested by the wholesaler to the retailer, and the allowance date. For the analysis, I define the wholesale price as the price charged to the retailer net of any allowances. One limitation of this data set is that it captures prices charged by wholesalers to non-self-distributing retailers. While some retailers do indeed self-distribute, I assume that the wholesale price is likely to be highly correlated with that charged to self-distributing retailers. There are two reasons why this is a valid assumption. First, the Robinson-Patman Act requires any deals offered in a market to be offered to all (Richards and Hamilton 2014). Second, manufacturers typically do not want to build ill-will among their retail customers by offering deals that differ sharply between competitors. Although wholesale price information is proprietary, the risk that competitive information may be shared among retail buyers is often not worth the small benefit that can be earned by discriminating among buyers. At the very least, compared with existing methods of imputing wholesale prices (Villas-Boas and Zhao 2005; Villas-Boas 2007), the resulting error is likely to be minimal.

Variation in wholesale prices, market shares, and retail prices is critical to identify the parameters of interest in the empirical model. Table 4.1 shows the market share, retail price per ounce, and wholesale price per ounce of the 35 products in each store. The data in table 4.1 reveals that market shares vary across package size and retailer, and that manufacturers set different prices for different package sizes even within the same product line. Within each product line, manufacturers can either charge a discount or a premium for product sold in smaller packages. This table shows that retailers and manufacturers generally charge higher unit prices for smaller packages, which is consistent with the finding by Gerstner and Hess (1987). Consumers may have heterogeneous package-size preferences, and my previous findings show that consumers tend to prefer smaller packages. Retailers and manufacturers may understand this fact, albeit implicitly, and adopt different marketing strategies for each package size.

Table 4.1
Share, Retail Price, and Wholesale Price Across Product and Retailer

		Dominicks						Jewel					
		Choice share (%)		Retail price per oz. ($)		Wholesale price per oz. ($)		Choice share (%)		Retail price per oz. ($)		Wholesale price per oz. ($)	
Manufacturer	Choice alternative	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
General Mills	Honey Nut Cheerios 14/12.25 oz.	0.253	0.233	0.253	0.049	0.253	0.023	0.768	0.909	0.274	0.063	0.253	0.023
	Honey Nut Cheerios 20/17 oz.	0.147	0.109	0.254	0.046	0.223	0.011	0.365	0.285	0.276	0.054	0.224	0.011
	Cheerios 10/8.9 oz.	0.235	0.263	0.337	0.078	0.298	0.018	0.625	0.666	0.370	0.077	0.299	0.018
	Cheerios 15/14 oz.	0.227	0.213	0.250	0.049	0.235	0.015	0.742	1.096	0.248	0.056	0.235	0.015
Kelloggs	Frosted Flakes 14 oz.	0.130	0.106	0.216	0.046	0.222	0.008	0.622	0.889	0.221	0.067	0.222	0.008
	Frosted Flakes 17 oz.	0.085	0.066	0.226	0.042	0.204	0.007	0.501	0.711	0.216	0.064	0.204	0.007
	Rice Krispies 12 oz.	0.131	0.073	0.260	0.053	0.255	0.012	0.388	0.431	0.299	0.079	0.255	0.012
	Rice Krispies 18 oz.	0.062	0.032	0.229	0.038	0.211	0.007	0.228	0.215	0.256	0.059	0.211	0.007
	Froot Loops 15/12.2 oz.	0.108	0.082	0.235	0.051	0.235	0.031	0.386	0.563	0.269	0.080	0.234	0.030
	Froot Loops 19.7/17 oz.	0.049	0.032	0.224	0.036	0.194	0.020	0.176	0.265	0.240	0.059	0.194	0.020
	Frosted Mini-Wheats 18 oz.	0.141	0.088	0.181	0.037	0.173	0.007	0.352	0.330	0.191	0.048	0.173	0.007
	Frosted Mini-Wheats 24 oz.	0.101	0.095	0.172	0.032	0.145	0.005	0.337	0.289	0.164	0.038	0.145	0.005
	Special K Red Berries 12 oz.	0.117	0.064	0.280	0.041	0.261	0.008	0.329	0.383	0.301	0.068	0.261	0.008
	Special K Red Berries 16.7 oz.	0.069	0.026	0.269	0.035	0.241	0.003	0.302	0.284	0.273	0.053	0.241	0.003
	Special K Original 12 oz.	0.090	0.043	0.281	0.039	0.262	0.008	0.280	0.257	0.302	0.067	0.262	0.008
	Special K Original 18 oz.	0.050	0.019	0.253	0.035	0.223	0.003	0.224	0.173	0.253	0.050	0.223	0.003
	Cocoa Krispies 17.5/16.5 oz.	0.089	0.060	0.186	0.039	0.182	0.011	0.356	0.401	0.203	0.057	0.182	0.011
	Apple Jacks 15/12.2 oz.	0.082	0.060	0.233	0.050	0.237	0.029	0.353	0.529	0.268	0.079	0.236	0.028
	Apple Jacks 19.1/17 oz.	0.037	0.022	0.225	0.033	0.197	0.018	0.162	0.234	0.245	0.057	0.197	0.018
	Raisin Bran 20 oz.	0.164	0.119	0.155	0.034	0.151	0.005	0.423	0.558	0.167	0.042	0.151	0.005
	Raisin Bran 25.5 oz.	0.096	0.092	0.157	0.029	0.129	0.004	0.266	0.292	0.154	0.034	0.129	0.004
	Raisin Bran Crunch 18.2 oz.	0.082	0.035	0.218	0.034	0.177	0.004	0.238	0.279	0.197	0.046	0.177	0.004
	Corn Flakes 12 oz.	0.063	0.072	0.278	0.040	0.206	0.009	0.246	0.158	0.274	0.055	0.206	0.009
	Corn Flakes 18 oz.	0.081	0.043	0.186	0.037	0.173	0.005	0.207	0.195	0.211	0.052	0.173	0.005
	Crispix 12 oz.	0.077	0.033	0.282	0.055	0.252	0.009	0.199	0.229	0.319	0.072	0.252	0.009
Post	Honey Bunches of Oats 16/14.5 oz.	0.128	0.119	0.210	0.053	0.197	0.024	0.329	0.302	0.213	0.055	0.197	0.025
	Honey Bunches of Oats 21/19/18 oz.	0.088	0.051	0.207	0.043	0.177	0.023	0.177	0.095	0.220	0.039	0.177	0.023
	Honey Bunches of Oats with Almonds 16/14.5 oz.	0.123	0.123	0.208	0.053	0.198	0.024	0.314	0.317	0.212	0.055	0.198	0.024
	Honey Bunches of Oats with Almonds 21/19/18 oz.	0.078	0.054	0.204	0.044	0.177	0.022	0.152	0.090	0.219	0.040	0.178	0.022
	Fruity Pebbles 13/11 oz.	0.099	0.112	0.241	0.059	0.226	0.031	0.217	0.264	0.234	0.067	0.226	0.030
	Cocoa Pebbles 13/11 oz.	0.089	0.108	0.239	0.061	0.226	0.031	0.187	0.232	0.234	0.067	0.227	0.031
Quaker Oats	Oatmeal Squares 16 oz.	0.141	0.082	0.219	0.049	0.193	0.028	0.148	0.201	0.279	0.049	0.193	0.028
	Cap'N Crunch Crunch Berries 15 oz.	0.053	0.059	0.236	0.066	0.201	0.030	0.221	0.375	0.256	0.071	0.201	0.030
	Cap'N Crunch 16 oz.	0.063	0.069	0.221	0.062	0.189	0.028	0.208	0.370	0.241	0.066	0.189	0.028
	Cap'N Crunch 22 oz.	0.040	0.029	0.198	0.039	0.153	0.019	0.127	0.117	0.195	0.044	0.153	0.019

The data summary also reveals that fully 15 out of 35 products changed package size once during the sample period, so co-variations in package size and price are at least conceptually identified in the data. In fact, the discrete nature of package-size changes helps make this case more clearly. Table 4.2 compares market share, retail price, and wholesale price before and after changes in package size. When manufacturers downsize packages, most retail prices, and all wholesale prices, rise. For example, when Kelloggs changed the size of the Froot Loops package from 15 ounces to 12.2 ounces, the retail price increased from \$0.224 per ounce to \$0.243 per ounce in Dominicks, and from \$0.226 per ounce to \$0.295 per ounce in Jewel. Therefore, retailers clearly do not intend to hold unit prices constant after a change in package size. Further, along with this package downsize, Kelloggs raised the wholesale price of Froot Loops from \$0.198 per ounce to \$0.258 per ounce. This simple comparison shows that manufacturers apparently use changes in packaging to mount implicit changes in price. However, despite the price increases, each product in table 4.2 gains market share after the package-size change. For example, Froot Loops increased its market share from 0.087% to 0.121% in Dominicks and from 0.355% to 0.404% in Jewel. In what seems like an act of marketing magic, package downsizing allowed manufacturers to raise not only market share, but prices, and margins as well. If this example holds more generally, however, then it begs the question as to why manufacturers do not downsize more often. There may be something important such as demand, cost, or strategic considerations that the summary in table 4.2 does not take into account. Therefore, formal econometric estimation, to identify the simultaneous interaction of all possible motivations to change package size, or not, is necessary.

Table 4.2
Share, Retail Price, and Wholesale Price Before and After Changes in Package Size

			Dominicks		Jewel	
Manufacturer	Choice alternative	Variable	Before	After	Before	After
General Mills	Honey Nut Cheerios 14/12.25 oz.	Choice share (%)	0.170	0.259	0.632	0.777
		Retail price per oz. ($)	0.277	0.252	0.250	0.276
		Wholesale price per oz. ($)	0.219	0.256	0.219	0.256
	Honey Nut Cheerios 20/17 oz.	Choice share (%)	0.134	0.148	0.330	0.366
		Retail price per oz. ($)	0.240	0.256	0.251	0.278
		Wholesale price per oz. ($)	0.194	0.226	0.194	0.226
	Cheerios 10/8.9 oz.	Choice share (%)	0.472	0.222	0.584	0.626
		Retail price per oz. ($)	0.289	0.341	0.351	0.372
		Wholesale price per oz. ($)	0.273	0.301	0.273	0.301
	Cheerios 15/14 oz.	Choice share (%)	0.255	0.224	0.421	0.762
		Retail price per oz. ($)	0.237	0.252	0.250	0.248
		Wholesale price per oz. ($)	0.220	0.236	0.220	0.236
Kelloggs	Froot Loops 15/12.2 oz.	Choice share (%)	0.087	0.121	0.355	0.404
		Retail price per oz. ($)	0.224	0.243	0.226	0.295
		Wholesale price per oz. ($)	0.198	0.258	0.198	0.257
	Froot Loops 19.7/17 oz.	Choice share (%)	0.053	0.045	0.181	0.171
		Retail price per oz. ($)	0.211	0.233	0.207	0.261
		Wholesale price per oz. ($)	0.171	0.209	0.171	0.209
	Cocoa Krispies 17.5/16.5 oz.	Choice share (%)	0.086	0.090	0.432	0.304
		Retail price per oz. ($)	0.192	0.182	0.186	0.214
		Wholesale price per oz. ($)	0.171	0.189	0.171	0.189
	Apple Jacks 15/12.2 oz.	Choice share (%)	0.075	0.086	0.333	0.364
		Retail price per oz. ($)	0.219	0.242	0.229	0.292
		Wholesale price per oz. ($)	0.203	0.259	0.202	0.258
	Apple Jacks 19.1/17 oz.	Choice share (%)	0.042	0.034	0.162	0.160
		Retail price per oz. ($)	0.217	0.230	0.221	0.261
		Wholesale price per oz. ($)	0.177	0.210	0.177	0.210
Post	Honey Bunches of Oats 16/14.5 oz.	Choice share (%)	0.106	0.134	0.286	0.339
		Retail price per oz. ($)	0.203	0.212	0.204	0.216
		Wholesale price per oz. ($)	0.170	0.204	0.170	0.204
	Honey Bunches of Oats 21/19/18 oz.	Choice share (%)	0.092	0.083	0.165	0.200
		Retail price per oz. ($)	0.204	0.212	0.231	0.197
		Wholesale price per oz. ($)	0.168	0.196	0.167	0.197
	Honey Bunches of Oats with Almonds 16/14.5 oz.	Choice share (%)	0.100	0.129	0.282	0.320
		Retail price per oz. ($)	0.202	0.209	0.200	0.215
		Wholesale price per oz. ($)	0.170	0.205	0.170	0.205
	Honey Bunches of Oats with Almonds 21/19/18 oz.	Choice share (%)	0.082	0.071	0.139	0.177
		Retail price per oz. ($)	0.203	0.206	0.231	0.194
		Wholesale price per oz. ($)	0.170	0.196	0.169	0.196
	Fruity Pebbles 13/11 oz.	Choice share (%)	0.096	0.107	0.202	0.255
		Retail price per oz. ($)	0.245	0.228	0.247	0.199
		Wholesale price per oz. ($)	0.215	0.266	0.213	0.259
	Cocoa Pebbles 13/11 oz.	Choice share (%)	0.086	0.100	0.174	0.217
		Retail price per oz. ($)	0.244	0.225	0.247	0.201
		Wholesale price per oz. ($)	0.215	0.266	0.213	0.263

Estimating costs, however, requires detailed data on input prices that comprise retailer and manufacturer costs. Both retailer and manufacturer costs are functions of a number of input prices specific to their production processes. Retailers' costs consist of average weekly commercial gas prices, average weekly diesel prices, as well as the wholesale prices described above. Manufacturers' costs include average weekly industrial gas prices, average weekly diesel prices, and average weekly prices of agricultural commodity inputs such as corn, wheat, oats, rice, malt, and sugar. Manufacturers use some of these grains for producing each product. Using volume sales of each product as a weight, I combine grain prices into a single measure and use it for the estimation. The gas price data is from the U.S. Department of Energy (2011) and is smoothed to produce weekly series from the native monthly series, while agricultural commodity prices are from the U.S. Department of Agriculture, Economic Research Service (2011). Figure 4.1 depicts the time series plot and table 4.3 reports the mean and the standard deviation of the input prices. Note that the value of week one is normalized to 100 in each series of costs. These graphics reveal substantial variation in input prices over time and the fact that some important input prices rose over the sample period. For example, sugar prices rise consistently, while the prices of other inputs rise until around week 65, and decrease afterward. Rising input prices, in turn, provide ample motivation for manufacturers to seek innovative ways to raise margins.

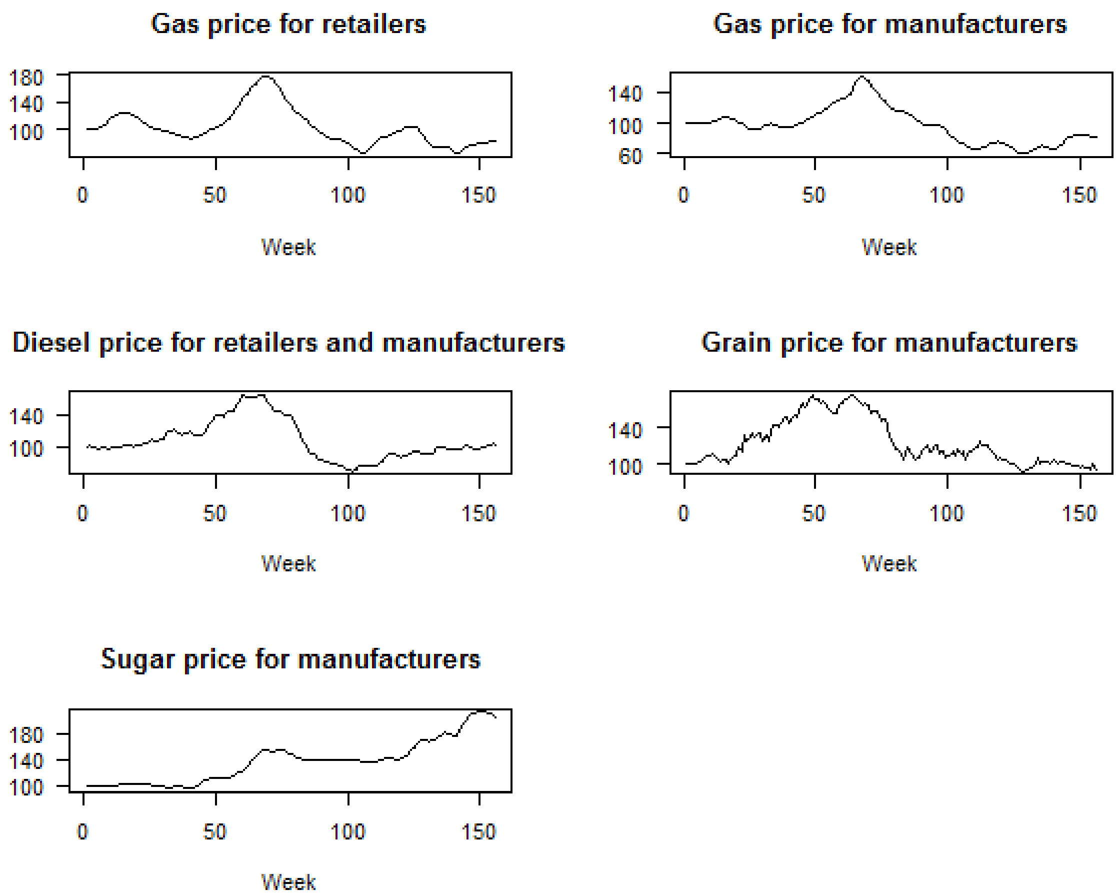

Figure 4.1
Input Costs

Table 4.3
Input Costs

Variable	Mean	Std. dev.
Gas price for retailers	103.506	27.090
Gas price for manufacturers	96.981	23.948
Diesel price for retailers and manufacturers	107.387	24.701
Grain price for manufacturers	123.944	25.156
Sugar price for manufacturers	136.903	32.775

Note: Grain price is the weighted average of main grain prices.
Week 1's value is normalized to 100 in each series.

Demand also depends on observed heterogeneity, or variation in household demographic and socioeconomic attributes. For the demand model and the first-stage

IV regressions in the supply-side model, I include mean household income, household size, age, educational attainment (which assumes a value of one if a householder is college-graduate or more, zero otherwise), and employment status, which is defined as the number of workers in a household. Each is smoothed to produce a weekly series from the native yearly observations obtained from the U.S. Bureau of Census (2011). Table 4.4 presents the mean and the standard deviation of each demographic variable. Each of these variables capture variation in demand-shifting demographic attributes over time, which is useful in estimating the demand-side model and constructing instruments for retailer and wholesaler margins. Of these variables, household income, educational attainment, and employment status are relatively variable over the sample period, while household size and averge age are less so. Clearly, this pattern was influenced by the Great Recession of 2008 - 09.

Table 4.4
Demographic Variables

Variable	Mean	Std. dev.
Household income ($,000)	67.934	1.107
Household size	2.606	0.004
Age	42.007	0.264
Educational attainment of a householder	0.322	0.012
Employment (number of workers in a household)	1.092	0.018

4.4 Results and Discussion

In this section, I present the results obtained by estimating the structural models described in the previous section. The parameter of primary interest in my demand model is package-size response. My hypothesis is that consumers prefer smaller packages and preference for package size is heterogeneous among consumers. The key parameters in the supply model, on the other hand, are the coefficient estimates for the margin variables, or how retail and manufacturer conduct affect package size and pricing in equilibrium. Prior to presenting the results from the supply model, however, I first present the estimates obtained from the demand model, and interpret their implications for the structure of package-size demand. Next, I describe the estimates from the supply-side of the model, and explain how the costs of increasing package size present practical limitations to manufacturers' ability to respond to consumers' demand for variety in package sizes. Finally, I discuss the strategic implications of changing package sizes, and draw some more general findings for CPG manufacturers and retailers.

4.4.1 Demand Results

I first establish the validity of the maintained demand model by conducting specification tests of the random-coefficient nested logit model relative to the simple-logit alternative. Table 4.5 reports the estimation results from the fixed-coefficient nested logit model, random-coefficient nested logit model without control function, and random-coefficient nested logit model with control function respectively. First, I compare the random-coefficient nested logit model with the fixed-coefficient specification. To test the validity of the random-coefficient specification, I conduct a likelihood ratio (LR) test in which the random-coefficient logit model is the alternative, and the fixed-coefficient nested logit model is the null specification. The LR test statistic is 28,811 with 3 degrees of freedom, so the null is rejected in favor of the alternative specification. Moreover, the standard deviations of the random parameters in the random-coefficient nested logit model are all significant, so I conclude that the random-coefficient specification outperforms the fixed-coefficient version.

Table 4.5
Estimation Results of Demand Model

		Fixed-coefficient nested logit model with control function		Random-coefficient nested logit model without control function		Random-coefficient nested logit model with control function	
	Variable	Estimate	t value	Estimate	t value	Estimate	t value
Brand preference	Constant	-1.109^*	-4.611	-0.202^*	-10.170	2.280^*	44.025
	Honey Nut Cheerios	0.784^*	16.966	0.191^*	23.782	0.779^*	85.066
	Cheerios	0.866^*	15.879	0.583^*	103.342	1.053^*	72.278
	Frosted Flakes	0.259^*	6.858	0.442^*	99.865	0.548^*	67.015
	Rice Krispies	0.456^*	10.859	0.600^*	169.065	0.314^*	22.799
	Froot Loops	0.168^*	4.472	0.411^*	159.946	0.759^*	103.892
	Frosted Mini-Wheats	0.233^*	5.566	0.033^*	10.258	0.458^*	58.498
	Special K Red Berries	0.616^*	12.767	0.673^*	202.605	1.252^*	121.049
	Special K Original	0.501^*	11.093	0.247^*	65.963	0.519^*	57.914
	Cocoa Krispies	0.069	1.476	-0.001	-0.187	0.252^*	24.818
	Apple Jacks	0.100^*	2.658	0.177^*	83.244	0.370^*	53.636
	Raisin Bran	0.080	1.677	-0.022^*	-5.478	0.380^*	34.452
	Raisin Bran Crunch	0.221^*	4.997	-0.128^*	-9.013	0.476^*	45.855
	Corn Flakes	0.190^*	5.119	0.218^*	63.296	0.449^*	58.945
	Crispix	0.419^*	7.302	0.188^*	48.654	0.817^*	52.044
	Honey Bunches of Oats	0.230^*	6.224	0.387^*	120.589	0.699^*	102.837
	Honey Bunches of Oats with Almonds	0.143^*	3.916	0.053^*	9.085	0.319^*	56.377
	Fruity Pebbles	-0.020	-0.444	0.144^*	31.633	-0.178^*	-12.051
	Cocoa Pebbles	-0.099^*	-2.150	-0.189^*	-6.879	0.187^*	27.300
	Oatmeal Squares	0.400^*	8.439	0.334^*	68.684	0.769^*	73.241
	Cap'N Crunch Crunch Berries	0.046	1.017	-0.012^*	-2.019	0.641^*	89.438
Marketing mix	Discount	0.682^*	12.036	0.201^*	16.769	0.175^*	15.987
	Price	-0.525^*	-8.806	-0.003	-0.209	-0.037^*	-2.934
	Package size	0.845^*	3.689	-0.334^*	-5.143	-0.157^*	-2.746
	Package size squared	-0.037^*	-3.991	0.011^*	4.114	0.004	1.432
Interaction terms	Price × discount	-0.026^*	-11.833	-0.007^*	-15.609	-0.006^*	-15.707
	Price × household income	0.681^*	7.893	0.017	0.778	0.021	1.130
	Package size × household income	-1.468^*	-4.388	0.323^*	3.431	0.275^*	3.320
	Package size squared × household income	0.058^*	4.321	-0.010^*	-2.428	-0.007	-1.877
Std. dev. of random parameters	Constant	–	–	0.059^*	69.869	0.396^*	304.292
	Price	–	–	0.028^*	309.551	0.016^*	93.647
	Package size	–	–	0.089^*	885.100	0.019^*	213.126
Within store correlation	GEV scale parameter	0.537^*	36.412	0.854^*	367.991	0.880^*	403.890
Control function	IV regression residuals	0.038^*	6.524	–	–	0.009^*	6.258
Estimate of std. dev.	Std. dev.	–	–	0.176^*	226.179	0.159^*	94.101
Simulated log likelihood at convergence		$-10,147$		$3,108$		$4,258$	

Note: An asterisk indicates significance at a 5% level.

Next, I investigate the dimensions of the endogeneity problem, and examine whether the control function is able to adequately address the issue. From the results reported in table 4.5, which shows estimates obtained without the control function, it is clear that the estimated coefficients are different from those of the random-coefficient nested logit model with control function. In particular, if the endogeneity problem is ignored, the marginal utility of income (or price coefficient) is much smaller. This finding is inconsistent with prior studies of breakfast-cereal demand (Nevo 2001; Richards and Hamilton 2014) so represents evidence of apparent endogeneity bias. Further, I conduct a regression-based endogeneity test (Wooldridge 2010). The t-statistic for the IV regression residuals in table 4.5 indicates that the control parameter is statistically different from zero, which indicates that the control function effectively corrects for the endogeneity bias that would otherwise be present.

The third test is a t-test of the GEV scale parameter. If the scale parameter is not significantly different from zero, then consumers do not regard stores as different sources of cereal, and a simple logit model would suffice. The t-statistic for the GEV scale parameter shows that it is statistically different from zero, which suggests that the nested logit specification is superior to the simple logit. In summary, therefore, these specification tests support the validity of the random-coefficient nested logit model, so this model is used to calculate demand elasticities, which form key inputs to the manufacturer and retail supply equations estimated in the second-stage.

The demand model provides several findings that are of practical and theoretical importance. First, the GEV scale parameter is close to one, which implies that breakfast cereals are highly substitutable for each other. Although this result would be somewhat surprising if the model were estimated only at the brand level, recall that the data includes several SKUs of the same brand. It is perhaps not surprising, therefore, that different SKUs of the same brand are highly substitutable. Further, the sample cereals are all from the same broad sub-category of products – family and children cereals – so they are likely to be relatively substitutable by construction.

Second, the standard deviation of the random price coefficient is significant, which suggests that the marginal utility of income differs among consumers. Therefore, unobserved heterogeneity is an important feature of the breakfast cereal market. While this result is consistent with others that use cereal for their subject matter (Nevo 2001; Richards and Hamilton 2014), it is perhaps more important in an SKU-level model as it suggests that consumers respond to price changes within the same brand-family in substantially different ways.

Third, the discount variable is positive and the interaction term between the discount variable and the price variable is negative. This means that a temporary price discount causes demand to shift outward and rotate counter-clockwise, or become more elastic when a retailer promotes the item through a temporary price reduction. Finding that demand becomes more elastic is both intuitive and consistent with the literature on retail price promotions. Although expected, this finding is important for retail practice as it implies that margins fall significantly during promotion periods as consumers become more sensitive to promotional price changes and are, therefore, more willing to substitute to other products.

Fourth, and perhaps most important, the coefficient on the package size variable is negative, suggesting that consumers prefer a smaller package. This finding is consistent with Khan and Jain (2005), Cohen (2008), and Gu and Yang (2010). Consumers prefer smaller packages because they allow consumers to match purchase volumes more closely to consumption rates (Koenigsberg, Kohli, and Montoya 2010). An alternative interpretation is that smaller packages reduce the risk that purchases fail to meet consumers' prior expectations of how the product is likely to perform in terms of taste, nutrition, texture, or any other salient attribute (Shoemaker and Shoal 1975). Further, the interaction term between the package size variable and income is positive, suggesting that higher income consumers tend to prefer larger packages. This is consistent with Cohen (2008) as higher-income households tend to purchase larger packages on each shopping occasion perhaps because any mismatch between their purchase and consumption plans, or their perception of the risk associated with a poor attribute match may be trivial for them. It also may be the case that higher income families simply have larger homes, more storage, and the ability to reduce transactions costs by buying packages that will last for many consumption occasions. In addition, the standard deviation of the random package-size coefficient is statistically significant, which implies that package-size preferences are heterogeneous among cereal shoppers, as expected. If consumers differ in their demand for packages of different sizes, then this finding may explain manufacturers' motivation for offering different package sizes within the same product line.

These estimates also allow me to calculate the optimal package size for each cereal brand. According to the package-size / utility relationship shown in figure 4.2, package size has a nonlinear, concave effect on utility. Moreover, the demand estimates imply and the estimates imply an optimal package size of 12.0 ounces. In the sample of cereals used here, for example, some of the more popular brands – Honey Nut Cheerios 12.25-ounce box, Rice Krispies 12-ounce box, Froot Loops 12.2-ounce box, and others – are sold in near optimal sizes. However, this optimal size is derived using only demand-side estimates. In the following subsection, I discuss the optimal package size that incorporates supply-side costs and competition among manufacturers.

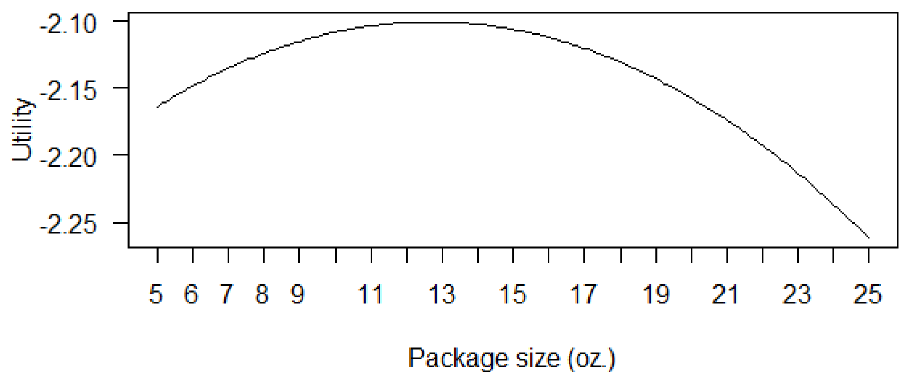

Figure 4.2
Effect of Package Size on Utility

Whether each package-size is priced optimally depends on the own-price and cross-price elasticities with other brands and other SKUs within the same brand. Table 4.6 shows the matrix of own- and cross-price elasticities for a few of the products in the sample offered by General Mills and Kelloggs in Dominicks, while table 4.7 reports similar estimates for SKUs sold in Jewel. Clearly, the random-coefficient nested logit model is not subject to the IIA property of simple logit models as all cross-price elasticities differ, and reveal a greater willingness among consumers to substitute among like products. That is, substitution across products is stronger for products with similar package sizes relative to those with different package sizes. For example, the first row of tables 4.6 and 4.7 shows that a price change for Honey Nut Cheerios 14/12.25-ounce box has a greater impact on the share of Cheerios 15/14-ounce box than Cheerios 10/8.9-ounce box, Frosted Flakes 14-ounce box than Frosted Flakes 17-ounce box and so on. Compared with the results reported in tables 4.6 and

4.7, the substitution patterns differ slightly from one store to the next, which again shows the value of using a GEV specification.

Table 4.6

Price Elasticities of Demand in Dominicks

With respect to:		Response of: Honey Nut Cheerios 14/12.25 oz.	Honey Nut Cheerios 20/17 oz.	Cheerios 10/8.9 oz.	Cheerios 15/14 oz.	Frosted Flakes 14 oz.	Frosted Flakes 17 oz.	Rice Krispies 12 oz.	Rice Krispies 18 oz.	Froot Loops 15/12.2 oz.
Honey Nut Cheerios 14/12.25 oz.	Estimate	−3.699	0.179	0.151	0.226	0.251	0.222	0.214	0.197	0.229
	t value	−10.986	12.185	10.280	15.398	17.089	15.103	14.565	13.427	15.598
Honey Nut Cheerios 20/17 oz.	Estimate	0.102	−3.612	0.049	0.113	0.137	0.138	0.101	0.150	0.118
	t value	10.849	−10.395	5.265	12.093	14.630	14.729	10.771	15.966	12.631
Cheerios 10/8.9 oz.	Estimate	0.463	0.290	−2.306	0.372	0.396	0.317	0.465	0.287	0.435
	t value	26.157	16.366	−5.109	20.997	22.396	17.892	26.290	16.222	24.548
Cheerios 15/14 oz.	Estimate	0.195	0.171	0.089	−3.785	0.215	0.192	0.169	0.184	0.194
	t value	14.763	12.970	6.739	−11.297	16.268	14.519	12.828	13.950	14.686
Frosted Flakes 14 oz.	Estimate	0.095	0.089	0.054	0.100	−4.172	0.100	0.101	0.096	0.115
	t value	14.115	13.176	7.971	14.746	−14.334	14.732	14.895	14.233	17.021
Frosted Flakes 17 oz.	Estimate	0.059	0.061	0.027	0.062	0.066	−3.962	0.049	0.071	0.059
	t value	12.737	13.143	5.829	13.397	14.206	−12.633	10.516	15.329	12.763
Rice Krispies 12 oz.	Estimate	0.135	0.112	0.103	0.129	0.152	0.123	−4.056	0.117	0.163
	t value	15.669	12.908	11.924	14.951	17.587	14.224	−11.695	13.504	18.838
Rice Krispies 18 oz.	Estimate	0.044	0.057	0.022	0.050	0.056	0.062	0.041	−4.209	0.049
	t value	11.784	15.234	5.905	13.474	15.051	16.592	11.026	−13.433	13.151
Froot Loops 15/12.2 oz.	Estimate	0.089	0.081	0.059	0.088	0.112	0.088	0.112	0.085	−4.172
	t value	14.460	13.103	9.596	14.367	18.195	14.355	18.231	13.754	−13.137

Note: Each entry represents the percentage change in the share of column product with respect to a percentage change in the price of row product. Standard errors are computed using a bootstrap method (Cameron and Trivedi 2005).

Table 4.7
Price Elasticities of Demand in Jewel

With respect to:		Response of: Honey Nut Cheerios 14/12.25 oz.	Honey Nut Cheerios 20/17 oz.	Cheerios 10/8.9 oz.	Cheerios 15/14 oz.	Frosted Flakes 14 oz.	Frosted Flakes 17 oz.	Rice Krispies 12 oz.	Rice Krispies 18 oz.	Froot Loops 15/12.2 oz.
Honey Nut Cheerios 14/12.25 oz.	Estimate	−3.622	0.211	0.145	0.255	0.262	0.244	0.201	0.208	0.225
	t value	−10.099	11.091	7.634	13.439	13.764	12.811	10.560	10.953	11.825
Honey Nut Cheerios 20/17 oz.	Estimate	0.102	−3.437	0.046	0.117	0.120	0.139	0.089	0.130	0.093
	t value	9.180	−9.087	4.175	10.537	10.829	12.502	8.041	11.720	8.419
Cheerios 10/8.9 oz.	Estimate	0.596	0.405	−2.159	0.518	0.498	0.387	0.514	0.367	0.478
	t value	25.882	17.582	−4.433	22.496	21.636	16.810	22.320	15.923	20.737
Cheerios 15/14 oz.	Estimate	0.182	0.163	0.083	−3.901	0.214	0.195	0.133	0.186	0.164
	t value	11.512	10.340	5.264	−11.967	13.579	12.356	8.426	11.805	10.396
Frosted Flakes 14 oz.	Estimate	0.124	0.110	0.054	0.169	−3.752	0.143	0.105	0.109	0.133
	t value	11.380	10.140	4.946	15.539	−12.762	13.129	9.642	10.031	12.228
Frosted Flakes 17 oz.	Estimate	0.087	0.098	0.033	0.098	0.108	−4.058	0.094	0.095	0.128
	t value	10.796	12.089	4.055	12.141	13.293	−14.137	11.637	11.711	15.875
Rice Krispies 12 oz.	Estimate	0.125	0.109	0.079	0.126	0.138	0.124	−3.250	0.095	0.106
	t value	12.927	11.304	8.242	13.032	14.288	12.886	−8.004	9.827	10.988
Rice Krispies 18 oz.	Estimate	0.055	0.070	0.028	0.067	0.067	0.075	0.040	−3.812	0.052
	t value	9.742	12.302	4.891	11.851	11.787	13.209	7.098	−10.777	9.210
Froot Loops 15/12.2 oz.	Estimate	0.085	0.073	0.047	0.089	0.104	0.110	0.095	0.067	−3.516
	t value	11.833	10.226	6.582	12.380	14.583	15.320	13.301	9.393	−9.529

Note: Each entry represents the percentage change in the share of column product with respect to a percentage change in the price of row product. Standard errors are computed using a bootstrap method (Cameron and Trivedi 2005).

If prices and package sizes are determined simultaneously, package-size elasticities are also of practical importance to manufacturers and retailers alike. Table 4.8 presents the matrix of own- and cross-package-size elasticities in Dominicks and table 4.9 reports those in Jewel. The package size elasticities are smaller than price elasticities, which is consistent with the finding of Çakıra and Balagtas (2014). This finding implies that consumers are relatively insensitive to changes in package size and likely pay more attention to changes in price. However, the fact that most of them are statistically significant from zero suggests that these elasticities are not to be ignored. Own-package-size elasticities tend to be negative and cross-package-size elasticities be positive. Negative own package-size elasticities confirm the finding that consumers prefer smaller package sizes, in general, while the positive cross effects suggest that larger package sizes for one SKU cause the utility from another SKU to rise, as expected if consumers prefer smaller packages.

Table 4.8

Package-Size Elasticities of Demand in Dominicks

With respect to:		Response of: Honey Nut Cheerios 14/12.25 oz.	Honey Nut Cheerios 20/17 oz.	Cheerios 10/8.9 oz.	Cheerios 15/14 oz.	Frosted Flakes 14 oz.	Frosted Flakes 17 oz.	Rice Krispies 12 oz.	Rice Krispies 18 oz.	Froot Loops 15/12.2 oz.
Honey Nut Cheerios 14/12.25 oz.	Estimate	−0.579	−0.003	0.101	0.036	0.035	0.003	0.060	−0.008	0.042
	t value	−3.798	−0.331	13.262	4.711	4.536	0.338	7.883	−1.034	5.476
Honey Nut Cheerios 20/17 oz.	Estimate	0.047	−0.685	0.050	0.038	0.040	0.014	0.049	0.004	0.041
	t value	10.545	−4.638	11.400	8.617	9.172	3.197	11.084	0.987	9.337
Cheerios 10/8.9 oz.	Estimate	0.116	−0.013	−0.310	0.052	0.044	−0.007	0.138	−0.019	0.078
	t value	15.494	−1.742	−1.954	7.024	5.844	−0.918	18.521	−2.488	10.477
Cheerios 15/14 oz.	Estimate	0.060	0.004	0.074	−0.618	0.042	0.010	0.059	−0.001	0.046
	t value	9.149	0.630	11.191	−4.286	6.417	1.514	8.989	−0.158	6.945
Frosted Flakes 14 oz.	Estimate	0.029	0.003	0.035	0.021	−0.606	0.006	0.034	0.000	0.028
	t value	7.640	0.880	9.140	5.550	−4.116	1.506	8.726	0.052	7.253
Frosted Flakes 17 oz.	Estimate	0.025	0.006	0.023	0.021	0.020	−0.696	0.023	0.005	0.020
	t value	10.559	2.407	9.363	8.509	8.309	−4.728	9.456	1.969	8.390
Rice Krispies 12 oz.	Estimate	0.034	−0.001	0.071	0.020	0.021	0.001	−0.609	−0.004	0.031
	t value	8.198	−0.256	17.086	4.850	5.136	0.233	−3.857	−1.063	7.519
Rice Krispies 18 oz.	Estimate	0.019	0.005	0.018	0.016	0.017	0.007	0.019	−0.699	0.017
	t value	9.796	2.499	9.488	8.447	8.599	3.844	9.988	−4.384	8.574
Froot Loops 15/12.2 oz.	Estimate	0.024	0.001	0.038	0.016	0.018	0.002	0.032	−0.002	−0.620
	t value	7.476	0.248	11.797	5.077	5.744	0.776	10.052	−0.581	−4.176

Note: Each entry represents the percentage change in the share of column product with respect to a percentage change in the package size of row product. Standard errors are computed using a bootstrap method (Cameron and Trivedi 2005).

Table 4.9
Package-Size Elasticities of Demand in Jewel

		Response of:								
With respect to:		Honey Nut Cheerios 14/12.25 oz.	Honey Nut Cheerios 20/17 oz.	Cheerios 10/8.9 oz.	Cheerios 15/14 oz.	Frosted Flakes 14 oz.	Frosted Flakes 17 oz.	Rice Krispies 12 oz.	Rice Krispies 18 oz.	Froot Loops 15/12.2 oz.
Honey Nut Cheerios 14/12.25 oz.	Estimate	−0.527	−0.009	0.103	0.030	0.030	−0.004	0.060	−0.015	0.042
	t value	−3.519	−0.922	10.291	2.996	2.973	−0.398	6.030	−1.515	4.192
Honey Nut Cheerios 20/17 oz.	Estimate	0.045	−0.598	0.049	0.032	0.031	0.008	0.046	−0.006	0.034
	t value	9.206	−4.071	9.873	6.538	6.386	1.657	9.328	−1.127	6.878
Cheerios 10/8.9 oz.	Estimate	0.130	−0.026	−0.240	0.049	0.042	−0.016	0.162	−0.031	0.093
	t value	14.326	−2.894	−1.529	5.373	4.591	−1.717	17.745	−3.376	10.168
Cheerios 15/14 oz.	Estimate	0.048	−0.005	0.060	−0.518	0.033	0.002	0.043	−0.008	0.032
	t value	5.345	−0.511	6.686	−3.653	3.726	0.214	4.854	−0.903	3.548
Frosted Flakes 14 oz.	Estimate	0.033	−0.005	0.038	0.025	−0.509	−0.001	0.035	−0.011	0.025
	t value	4.158	−0.687	4.841	3.129	−3.557	−0.149	4.421	−1.367	3.194
Frosted Flakes 17 oz.	Estimate	0.035	0.003	0.027	0.027	0.031	−0.592	0.043	−0.003	0.040
	t value	6.237	0.502	4.826	4.832	5.495	−4.112	7.630	−0.561	7.145
Rice Krispies 12 oz.	Estimate	0.037	−0.004	0.077	0.018	0.019	−0.000	−0.586	−0.007	0.042
	t value	7.668	−0.758	16.114	3.785	3.929	−0.044	−3.726	−1.549	8.645
Rice Krispies 18 oz.	Estimate	0.027	0.006	0.027	0.023	0.023	0.011	0.023	−0.663	0.023
	t value	8.525	1.794	8.560	7.253	7.470	3.394	7.472	−4.188	7.210
Froot Loops 15/12.2 oz.	Estimate	0.026	−0.002	0.041	0.015	0.017	0.002	0.038	−0.005	−0.587
	t value	6.274	−0.455	9.896	3.630	4.168	0.576	9.334	−1.107	−3.982

Note: Each entry represents the percentage change in the share of column product with respect to a percentage change in the package size of row product. Standard errors are computed using a bootstrap method (Cameron and Trivedi 2005).

While these demand results are of considerable interest themselves, the objective of this analysis is to determine how consumer preferences for package size condition manufacturer decisions to offer SKUs that differ in terms of their package size, how they are to be priced, and how retailers pass-through manufacturer price changes to the consumer level.

4.4.2 Supply Results

I use the demand estimates reported in table 4.5 to calculate market shares and share derivatives with respect to all retail prices, wholesale prices, and package sizes. The share derivatives are then substituted into the supply model in (4.18) and (4.20), which are, in turn, used to estimate retailer pricing, manufacturer pricing, and manufacturer package-size equations (4.22), (4.23), and (4.25). In these equations, retail and manufacturer margins are likely to be endogenous and the supply estimates biased if no consideration is made for the simultaneous nature of margins, prices, and package sizes. To overcome this problem, I again use the control function approach in which endogenous margins are regressed on exogenous instruments to obtain the residuals, and the set of residuals is then used as an explanatory variable in the price and package-size equations.

Once the control function is brought into the supply model, the model is estimated by SUR. I begin by conducting specification tests on the proposed model, followed by the interpretation of the parameters. First, an LR test is used to compare the supply-side model against a naïve model that consists of only constants. The LR statistic is $9,082$ which is chi-square distributed with 48 degrees of freedom. Therefore, the naïve model is rejected in favor of the maintained supply-side specification and I conclude that the supply-side model fits the data better than no model at all.

Second, I compare the results of the model with and without instrumental variables to show the extent of bias present if endogeneity is not properly accounted for. In tables 4.10, 4.11, and 4.12, I present the estimation results from the supply model without the control function. In the non-instrumented model, the estimated Wu-Hausman test statistic value is 57.7 and its p-value is 15.9%, which suggests that the null hypothesis that the margins are exogenous is marginally rejected. However, the conduct parameter in manufacturer price equation is negative when the endogeneity problem is ignored. This implies that the equilibrium prices decrease in response to an upward shift of demand curve as the conduct parameter measures how the equilibrium prices respond to changes in demand conditions. Because this is somewhat nonsensical, I conclude that the margins are endogenous and the instrumental variables are necessary.

Table 4.10
Estimation Results of Retail Price Equation

	Without control function		With control function	
Variable	Estimate	t value	Estimate	t value
Constant	−0.02788*	−4.95194	−0.08857*	−3.71108
Wholesale price	0.84693*	63.23896	0.83921*	61.77331
Gas price	0.00257*	8.64330	0.00252*	8.44014
Diesel price	0.00246*	1.97324	0.00192	1.47619
Dominicks	0.02780*	7.80918	0.07363*	4.15347
Changes in demand conditions expressed in price elasticity terms (conduct parameter)	0.00031*	12.23968	0.00065*	4.93713
Control function	–	–	−0.00035*	−2.64728
R-squared	0.30421		0.30465	

Note: An asterisk indicates significance at a 5% level.

Table 4.11
Estimation Results of Manufacturer Price Equation

	Without control function		With control function	
Variable	Estimate	t value	Estimate	t value
Constant	0.12784*	77.84321	0.12667*	76.75785
Grain price index	0.00017*	14.13380	0.00017*	14.07076
Sugar price	0.00094*	41.72521	0.00093*	41.59300
Gas price	−0.00004	−0.33396	0.00038*	2.72575
Diesel price	−0.00811*	−16.29583	−0.00903*	−17.46899
Honey Nut Cheerios 14/12.25 oz.	0.09518*	74.88158	0.09605*	75.41021
Honey Nut Cheerios 20/17 oz.	0.06896*	54.27917	0.06979*	54.81494
Cheerios 10/8.9 oz.	0.14192*	111.48315	0.14271*	111.94102
Cheerios 15/14 oz.	0.07786*	61.27645	0.07872*	61.82441
Frosted Flakes 14 oz.	0.06368*	50.12701	0.06321*	49.75700
Frosted Flakes 17 oz.	0.04848*	38.17313	0.04797*	37.76948
Rice Krispies 12 oz.	0.09795*	77.04688	0.09749*	76.70135
Rice Krispies 18 oz.	0.05645*	44.43834	0.05594*	44.04769
Froot Loops 15/12.2 oz.	0.07760*	61.07116	0.07711*	60.68731
Froot Loops 19.7/17 oz.	0.03960*	31.17929	0.03907*	30.76236
Frosted Mini-Wheats 18 oz.	0.01716*	13.51119	0.01666*	13.11865
Frosted Mini-Wheats 24 oz.	−0.00847*	−6.67310	−0.00903*	−7.11268
Special K Red Berries 12 oz.	0.10439*	82.08394	0.10398*	81.80539
Special K Red Berries 16.7 oz.	0.08566*	67.40121	0.08516*	67.01260
Special K Original 12 oz.	0.10469*	82.32606	0.10426*	82.02871
Special K Original 18 oz.	0.06817*	53.66124	0.06765*	53.24779
Cocoa Krispies 17.5/16.5 oz.	0.02574*	20.27169	0.02525*	19.88392
Apple Jacks 15/12.2 oz.	0.07944*	62.50691	0.07899*	62.17007
Apple Jacks 19.1/17 oz.	0.04239*	33.37497	0.04186*	32.95906
Raisin Bran 20 oz.	−0.00437*	−3.44068	−0.00488*	−3.84363
Raisin Bran 25.5 oz.	−0.02354*	−18.53669	−0.02410*	−18.97915
Raisin Bran Crunch 18.2 oz.	0.02147*	16.90724	0.02094*	16.49502
Corn Flakes 12 oz.	0.05018*	39.50188	0.04967*	39.11366
Corn Flakes 18 oz.	0.01796*	14.14720	0.01745*	13.74733
Crispix 12 oz.	0.09583*	75.39032	0.09527*	74.93579
Honey Bunches of Oats 16/14.5 oz.	0.04049*	31.88232	0.04088*	32.23282
Honey Bunches of Oats 21/19/18 oz.	0.02254*	17.75398	0.02289*	18.05549
Honey Bunches of Oats with Almonds 16/14.5 oz.	0.04117*	32.41819	0.04156*	32.77113
Honey Bunches of Oats with Almonds 21/19/18 oz.	0.02327*	18.32754	0.02363*	18.63141
Fruity Pebbles 13/11 oz.	0.06851*	53.92753	0.06891*	54.31890
Cocoa Pebbles 13/11 oz.	0.06894*	54.26704	0.06935*	54.66081
Oatmeal Squares 16 oz.	0.03868*	30.45738	0.03870*	30.54063
Cap'N Crunch Crunch Berries 15 oz.	0.04569*	35.97406	0.04578*	36.12051
Cap'N Crunch 16 oz.	0.03335*	26.26534	0.03338*	26.34480
Changes in demand conditions expressed in price elasticity terms (conduct parameter)	−0.00000	−0.68636	0.00003*	6.68000
Control function	–	–	−0.00003*	−6.80347
R-squared	0.84868		0.84946	

Note: An asterisk indicates significance at a 5% level.
The Estimate coefficient for manufacturer margin is −3.8E−07 when the endogeneity problem is ignored.

Table 4.12
Estimation Results of Manufacturer Package-Size Equation

	Without control function		With control function	
Variable	Estimate	t value	Estimate	t value
Constant	16.05090*	459.39162	16.05106*	459.37376
Market size × package-size elasticities × competitive response to changes in demand conditions	3.05082*	3.37186	3.25769*	3.37530
Control function	–	–	0.00009	0.67250
R-squared	0.00113		0.00118	

Note: An asterisk indicates significance at a 5% level.

After determining the preferred specifications for the manufacturer price and package-size equations, and the retail price equation, I then interpret the estimates from each in turn. In general, the supply-model estimates provide reasonable results in terms of goodness of fit and economic and statistical significance. First, recall that the retail price equation examines the relationship between retail prices and retail costs and demand conditions expressed in elasticity terms. Table 4.10 shows the estimates obtained for the retail pricing equation. In terms of goodness-of-fit, the results in this table show that the variables used in this equation explain 30.5% of the total variation in retail price. Further, the t-statistic for the IV regression residuals indicates that the residual parameter is statistically different from zero, suggesting that the control function approach again addresses the expected endogeneity of retail margins in the expected way. Retail cost variables such as wholesale price, gas price, and diesel price variables are all positive, suggesting that retailers tend to charge higher prices as costs increase. Each cost variable is statistically significant, except for diesel price, so the cost component of the model appears to fit the data well.

The extent of strategic behavior is estimated through the conduct parameter. In table 4.10, the conduct parameter is statistically different from, but close to, zero, which suggests that the retail market is more competitive than the maintained assumption in which retailers act as a local monopolist. Nevertheless, retailers still have non-zero margins. The small conduct parameter implies that retail prices are relatively unresponsive to changes in demand induced by price changes by other retailers. My estimated retail-conduct parameter is smaller than those estimated for other product categories such as ketchup (Villas-Boas and Zhao 2005), ground coffee (Draganska and Klapper 2007), and fluid milk (Richards, Allender, and Hamilton

2012). It may be the case that most retailers use the pricing of breakfast cereals as a means of increasing store traffic (Walters and MacKenzie 1988) because breakfast cereals are frequently purchased by consumers across all income strata. Retailers may recognize that a price increase in breakfast cereals causes adverse effects not only on the category, but across the entire store, so are reluctant to change prices even if they experience a significant growth in demand.

Next, I interpret the estimates from the manufacturer price equation. With this equation, I investigate whether variation in wholesale prices is explained by variation in input prices such as grain, sugar, gas, or diesel prices, other product specific costs, and the demand conditions facing manufacturers. Table 4.11 reports the estimation results from manufacturer price equation. The estimated goodness-of-fit statistics are again good as variation in the explanatory variables explains fully 84.9% of the total variation in wholesale price. A t-test on the IV regression residuals implies that the control function approach appropriately accounts for any endogeneity of the implied margin term. Therefore, the conduct parameter is estimated consistently. All variables are statistically significant and the coefficient estimates for the cost variables are largely intuitive. Each cost coefficient, except for the price of diesel fuel, has a positive effect on wholesale prices, suggesting that manufacturers set higher prices when costs rise.

Manufacturers appear to price competitively in the cereal market. Specifically, the price equation estimates show that the conduct parameter is positive and significant, but very close to zero, indeed only 5.2% of the retail conduct parameter. Therefore, competition in the cereal market appears to be stronger among manufacturers than among retailers. One reason for this finding may be that manufacturers have little bargaining power in the face of rising private-label share. Private labels are particularly strong in the cereal category, and constitute one of the primary pricing challenges facing manufacturers. As a result, manufacturers are less responsive to changes in demand than are retailers. Another reason why the manufacturer conduct parameter is relatively small may be the presence of high and rising production costs. Although my model controls for concurrent variation in manufacturing costs, if manufacturers expect higher production costs in the future, they may price more competitively than otherwise would be the case in order to maintain market share. This dynamic would appear through the conduct parameter. Another reason why I find more deviation from Bertrand pricing than others in this literature may be the fact that I also control for changes in package size. Failing to account for changes in package size may mean that much of the competitive response in unit prices is subsumed in package-size changes in more traditional analyses. I return to this issue after interpreting the results obtained from the package-size equation.

Estimates of the package-size equation reveal how manufacturers choose package size in response to the estimate of competitive response and pack-size elasticities.[7] Estimates of the manufacturer package-size equation imply that manufacturers simultaneously consider how manufacturers competitively respond to varying demand conditions, and consumers' tendencies to substitute among package sizes. The results obtained from estimating this equation are shown in table 4.12. In this case, the control function parameter is not significant, perhaps because the null hypothesis of exogeneity is only marginally rejected. But, as discussed above, I assume that the endogeneity problem is present on logical grounds, and retain the control function

[7] The variation in the market size is negligible small.

despite its lack of significance. In terms of the quality of the specification, the explanatory variables account for 0.1% of the total variation in package size. Although this coefficient of determination is small, variations in package size are clearly driven by many random factors. Moreover, the remaining parameter estimates suggest that this model captures some of the more important determinants of package size.

The coefficient of the interaction term between market size, package-size elasticities, and estimate of competitive response to changes in demand conditions expressed in price elasticity terms is positive and significant.[8] This parameter captures the competitive response of manufacturers to changes in rivals' package sizes, so is interpreted in a manner analogous to the pricing conduct parameter above.[9] In other words, the parameter measures the slope of the manufacturer reaction function in package-size space such that a positive estimate indicates package sizes are strategic complements, and a negative estimate indicates they are strategic substitutes. The positive estimate is intuitive. Recall that the own-package-size elasticities of demand are negative and the manufacturer conduct parameter is positive. So, the positive coefficient means that an increase in wholesale price of one product leads to an increase in competitive response, *ceteris paribus*, which causes a reduction in package size of that product. This negative relationship between price and package size explains the

[8]For the purpose of illustration, I ignore the effect of the market size variable and consider manufacturer package-size equation with two products, so that: $q_1 = \eta_0 + \eta_1 \left[(w_1 - c_1) \frac{\partial s_1}{\partial q_1} + (w_2 - c_2) \frac{\partial s_2}{\partial q_1} \right]$ and $q_2 = \eta_0 + \eta_1 \left[(w_1 - c_1) \frac{\partial s_1}{\partial q_2} + (w_2 - c_2) \frac{\partial s_2}{\partial q_2} \right]$ where η_1 is positive, $\frac{\partial s_1}{\partial q_1}$ and $\frac{\partial s_2}{\partial q_2}$ are negative, and $\frac{\partial s_2}{\partial q_1}$ and $\frac{\partial s_1}{\partial q_2}$ are positive. This simplification helps to understand the discussion in this paragraph.

[9]Of course, this interpretation does not carry the same intuition that a value of 0 implies no strategic response, and a value of 1 indicates Bertrand behavior. The precise value of the parameter depends on the units of measure for the product at hand.

common observation that firms simultaneously raise prices and downsize packages. The result implies that manufacturers use changes in package size to mitigate the effects of changes in input prices, passing wholesale price increases onto retailers in an indirect way.

In terms of the interactions in package size among manufacturers, the intuition of my finding is that when one package is reduced in size, the wholesale price of that product increases. Also, according to the demand results, the cross-package-size elasticities of demand are positive. Taken together, a decrease in one package size then leads to an increase in its wholesale price, and so the appropriate competitive response to that product, *ceteris paribus*, is an increase in competitors' package sizes. Larger packages from competitors' products imply a decline in wholesale price for that product because there is a negative relationship between price and package size. That is, a package downsizing for one product causes a decline in competitors' wholesale prices, which intensifies competition among manufacturers. The opposite case occurs when package size rises. When one manufacturer increases the size of his product, the wholesale price of that product decreases, implying a reduction in competitive response. Because the cross-package-size elasticities are positive, an increase in the size of one package, *ceteris paribus*, leads to a reduction in competitors' package sizes, which in turn leads to an increase in competitors' wholesale prices. That is, a rise in package size softens price competition among manufacturers. In sum, a positive conduct-parameter estimate in the package-size equation implies wholesale prices and package sizes are strategic complements, and a decrease in package size intensifies price competition, reducing manufacturers' incentives to make smaller packages for fear of inciting a destructive competitive response. For reasons that will be made clear below, I demonstrate the nature of strategic rivalry among manufacturers using a counterfactual, numerical simulation that also incorporates the cost of changing package sizes.

Packaging costs are important determinants of the incentive to change package size as well. Estimates of the package-size equation describe the shape of the cost function in package size, and permit the derivation of an optimal package (see figure 4.3). Figure 4.3 shows that costs decrease until the optimal package size of 16.1 ounces, and then increase afterward. Evidently, packages that are too small may require special packaging technology, excessive costs associated with adjusting the production line, or special handling in the distribution system and shelf display. For similar reasons, manufacturers incur higher costs if packages are too large. In the current sample, for example, Special K Red Berries 16.7-ounce box, Oatmeal Squares 16-ounce box, and Cap'N Crunch 16-ounce box, etc. are sold in sizes that are very nearly optimal. Recall that the optimal size based on demand estimates alone was 12.0 ounces. Due to competition among manufactures and packaging costs, the optimal package size is more likely greater than the size that consumers prefer. This result suggests that brand managers must consider both the demand and supply effects associated with changes in package size. For example, Kelloggs reduced the size of its cereal boxes of Apple Jacks from 19.1 ounces to 17.0 ounces and 15.0 ounces to 12.2 ounces, respectively. Based on the costs associated with the larger size, Kelloggs can expect both an increase in share and a reduction in cost. In the latter case, on the other hand, Kelloggs can expect an increase in share, but must incur the cost of switching to the new packages. This result suggests that package downsizing is not always effective, both due to competition among manufacturers, that reduces the marginal benefit of changing package size, and higher marginal costs associated with producing larger packages. Ultimately, however, the incentive to change package size depends on the equilibrium effect on margins.

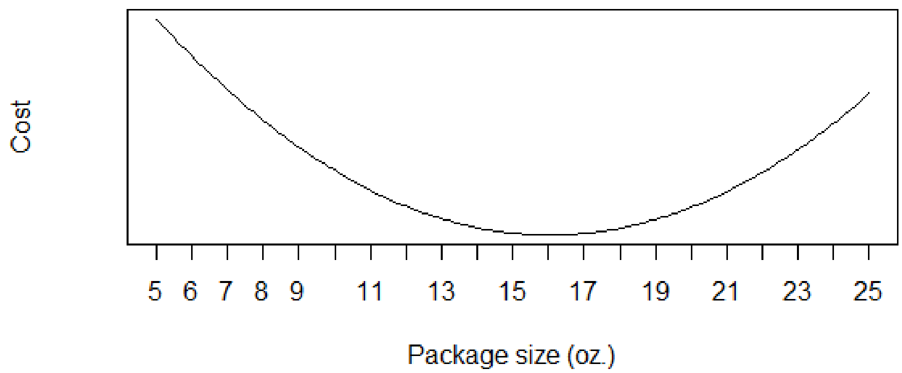

Figure 4.3
Fixed Cost Associated with Making Packages of Different Sizes

Because my model describes equilibrium outcomes in the breakfast cereal market, I am able to calculate implied margins on both the retailer and manufacturer level, and simulate changes in each margin based on either shocks to the market, or under alternative assumptions for the estimated parameters. According to equations (4.22) and (4.23), the price-cost margins are calculated as the product of the demand conditions expressed in elasticity terms and the conduct parameters. Using the estimated retail and manufacturer conduct parameters, the results in table 4.13 show a base-case simulation for each implied cost and margin. As the results in this table show, manufacturer margins are smaller than retail margins, while the high retail margins are mainly due to the store-specific factors associated with the Jewel chain. Apparently, Jewel shoppers are unusually loyal and are willing to pay more for national brands from this chain, relative to the competition. Table 4.14 compares implied retail margins and costs of Dominicks with Jewel, and shows that the implied margin for Jewel is in fact 3.5 times greater than Dominicks. Jewel may have market power either because it more effectively uses non-price store attributes such as store location, assortment size, and service quality. In fact, Jewel has been the biggest grocer in Chicago area and had more than 20% of market share in 2007.[10] Moreover, 68 out of 186 local Jewel stores were remodeled from 2008 to 2010 to build new displays, and bigger meat and deli departments (Sterrett 2009). This renovation might contribute further to the development of Jewel's apparent strategic advantages. Importantly, these results show that competition in package size can act as a facilitating practice for enhanced market power in the output market. More generally, competition in non-price attributes is likely to soften price competition and increase market power. For example, firms use strategic variables such as product-line length (Draganska and Jain 2005; Richards and Hamilton 2006), location in geographic space (Friedman and Thisse 1993; Thomadsen 2007), and location in attribute space (Jehiel 1992; Richards, Allender, and Hamilton 2013). Competition in each of these variables, like rivalry in package size, changes the nature of price competition so conclusions regarding price competition alone are highly misleading.

[10] Data describing Jewel's financial performance is not available because it is a part of Albertsons, which is privately held.

Table 4.13
Implied Costs and Margins Across Product

	Retailer		Manufacturer	
Product	Cost	Margin	Cost	Margin
Honey Nut Cheerios 14/12.25 oz.	0.19460	0.08013	0.25147	−0.00016
Honey Nut Cheerios 20/17 oz.	0.17005	0.07976	0.22521	0.00011
Cheerios 10/8.9 oz.	0.23307	0.08878	0.29813	−0.00143
Cheerios 15/14 oz.	0.17948	0.07923	0.23415	0.00003
Frosted Flakes 14 oz.	0.16833	0.07831	0.21863	0.00078
Frosted Flakes 17 oz.	0.15396	0.07811	0.20339	0.00060
Rice Krispies 12 oz.	0.19651	0.08159	0.25291	0.00123
Rice Krispies 18 oz.	0.15974	0.07865	0.21137	0.00108
Froot Loops 15/12.2 oz.	0.17936	0.07962	0.23253	0.00067
Froot Loops 19.7/17 oz.	0.14541	0.07824	0.19449	0.00067
Frosted Mini-Wheats 18 oz.	0.12766	0.07700	0.17208	0.00102
Frosted Mini-Wheats 24 oz.	0.10404	0.07643	0.14639	0.00062
Special K Red Berries 12 oz.	0.20169	0.08169	0.25940	0.00207
Special K Red Berries 16.7 oz.	0.18454	0.07990	0.24058	0.00090
Special K Original 12 oz.	0.20192	0.08176	0.25969	0.00179
Special K Original 18 oz.	0.16957	0.07905	0.22307	0.00058
Cocoa Krispies 17.5/16.5 oz.	0.13518	0.07731	0.18067	0.00099
Apple Jacks 15/12.2 oz.	0.18103	0.08009	0.23441	0.00149
Apple Jacks 19.1/17 oz.	0.14781	0.07833	0.19728	0.00067
Raisin Bran 20 oz.	0.10920	0.07632	0.15054	0.00103
Raisin Bran 25.5 oz.	0.09087	0.07614	0.13132	0.00086
Raisin Bran Crunch 18.2 oz.	0.13053	0.07766	0.17637	0.00078
Corn Flakes 12 oz.	0.15492	0.08085	0.20509	0.00119
Corn Flakes 18 oz.	0.12787	0.07738	0.17288	0.00100
Crispix 12 oz.	0.19390	0.08479	0.25070	−0.00016
Honey Bunches of Oats 16/14.5 oz.	0.14810	0.07801	0.19630	0.00010
Honey Bunches of Oats 21/19/18 oz.	0.13095	0.07783	0.17832	0.00011
Honey Bunches of Oats with Almonds 16/14.5 oz.	0.14877	0.07793	0.19698	0.00010
Honey Bunches of Oats with Almonds 21/19/18 oz.	0.13164	0.07772	0.17905	0.00011
Fruity Pebbles 13/11 oz.	0.17230	0.07930	0.22433	0.00001
Cocoa Pebbles 13/11 oz.	0.17270	0.07921	0.22477	0.00006
Oatmeal Squares 16 oz.	0.14465	0.07914	0.19412	0.00009
Cap'N Crunch Crunch Berries 15 oz.	0.15124	0.07962	0.20120	0.00134
Cap'N Crunch 16 oz.	0.14073	0.07862	0.18881	0.00004
Cap'N Crunch 22 oz.	0.11098	0.07721	0.15542	0.00011

Table 4.14
Implied Costs and Margins Across Retailer

Retailer	Cost	Margin
Dominicks	0.19375	0.03551
Jewel	0.12016	0.12287

On the other hand, the relatively low level of manufacturer margins is somewhat surprising. One reason why this may be the case is that, over the sample period, manufacturers experienced a significant rise in input costs, especially grain prices, that they were evidently reluctant to pass on to consumers. In fact, the implied manufacturer cost is higher than the retail cost. At the same time, consumers expected higher cereal prices due to rising commodity costs, so retailers accommodated these expectations by increasing retail prices. This finding is consistent with the recent literature on consumer search and pass-through (Tappata 2009; Chandra and Tappata 2011; Gómez, Richards, and Lee 2013) that suggests asymmetric pass-through is largely due to retailers accommodating consumer expectations of likely retail price changes, and not the undue exercise of market power.

The results in table 4.13 also reveal a substantial difference in margins between small and large packages. For example, although there is some variation among brands, the margin for smaller packages is generally greater than for larger packages – a finding that is consistent with the notion that retailers offer a volume discount by reducing margins on larger packages. If they are indeed rational, retailers and manufacturers likely know that consumers prefer smaller packages, and charge higher prices per unit of volume relative to larger packages.

My primary hypothesis is that manufacturers use price and package size as complementary tools in strategic competition with one another, so the interaction between them is key to explaining market outcomes in an inherently strategic environment. In order to better understand the strategic relationship between price and package size, I conduct a counterfactual simulation and investigate how manufacturers adjust package size and price in response to a package downsizing by a competitor. As discussed above, changes in package size have a significant effect on consumer demand, which in turn influences market share, and retail and manufacturer margins. Because equations (4.22), (4.23), and (4.25) imply that retailers' price decisions and manufacturers' price and package-size decisions depend critically on their respective competitive response to rivals' behaviors, it is likely that retailers and manufacturers strategically respond to competitors' package-size decisions using package size, price, or both. Simulation determines exactly how they are related, in a comprehensive, strategic sense that takes into account consumer response and cost considerations as well.

Consider one example. Suppose General Mills reduces the size of a Cheerios 15/14-ounce box by 10%. Because the optimal package size from a consumer perspective is 12.0 ounces, General Mills can expect to gain market share. But, in equilibrium, competitors react using both price and package size. Package downsizing by one firm provides an incentive for the others to change package size in response, but competitors also recognize that a change in package size is costly. Therefore, competitors may respond to an observed downsizing not by changing package size, but by changing wholesale prices. According to equation (4.23), wholesale price is determined by input costs and competitive reactions. A change in the size of one package affects the state of competition, and ultimately, the wholesale price of other products. Because many factors are involved, simulating the market equilibrium provides an answer to exactly how competitors interact in price and package size.

To see why simulation is necessary, I derive the response in wholesale prices due to a package downsizing. Whether wholesale prices increase or decrease depends on how consumers respond to the change in price of the simulated product size (small package) and the original product (larger package). For the purpose of illustration, consider the case with two products and ignore the retail-wholesale pass-through terms. Suppose the first product is downsized. Then, the wholesale price of the second product is written as:

$$w_2 - c_2 = \frac{\frac{\partial s_1}{\partial w_2}}{\frac{\partial s_1}{\partial w_1}\frac{\partial s_2}{\partial w_2} - \frac{\partial s_2}{\partial w_1}\frac{\partial s_1}{\partial w_2}} s_1 - \frac{\frac{\partial s_1}{\partial w_1}}{\frac{\partial s_1}{\partial w_1}\frac{\partial s_2}{\partial w_2} - \frac{\partial s_2}{\partial w_1}\frac{\partial s_1}{\partial w_2}} s_2, \tag{4.29}$$

which implies that a change in w_2 is determined by $\frac{\partial s_1}{\partial w_1}$, $\frac{\partial s_1}{\partial w_2}$, $\frac{\partial s_2}{\partial w_1}$, and $\frac{\partial s_2}{\partial w_2}$. If $\frac{\partial s_1}{\partial w_1}\frac{\partial s_2}{\partial w_2} - \frac{\partial s_2}{\partial w_1}\frac{\partial s_1}{\partial w_2}$ increases, $\frac{\partial s_1}{\partial w_2}$ decreases, or $\frac{\partial s_1}{\partial w_1}$ increases, *ceteris paribus*, w_2 decreases. But, it is impossible to derive a systematic relationship between wholesale price and share derivatives in an analytical way. So, I reveal the interaction between wholesale prices and package sizes via numerical simulation.

Using the estimated demand and supply parameters, I calculated equilibrium prices, margins, and market shares at both the retailer and manufacturer levels under the scenario described above. Table 4.15 reports the percent change in retail price-cost margins, manufacturer price-cost margins, equilibrium retail prices, equilibrium wholesale prices, and equilibrium package sizes relative to their original values. This table shows that competitors generally lower wholesale prices in response to package downsizing. Package size and wholesale price are, therefore, strategic complements. For example, if General Mills reduces the size of a box of Cheerios, Kelloggs reduces the price of Rice Krispies 12-ounce box by 0.078%, Rice Krispies 18-ounce box by 0.124%, and Froot Loops 15/12.2-ounce box by 0.180%. Therefore, competitors lower wholesale prices in response to the downsizing of one product. Downsizing sharpens price competition, and dramatically reduces the incentives for manufacturers to reduce package size. For example, in this simulated market, General Mills lowers the price of Cheerios in an equilibrium response to competitor reactions, which further reduces the margin of the targeted product. What simple demand analysis suggests may be a good strategy to cover a cost increase, therefore, achieves exactly the opposite result.

Table 4.15
Percent Change of Retail Price, Retail Margin, Wholesale Price, Package Size, and Manufacturer Margin

	Retailer		Manufacturer		
Product	Retail price (%)	Retail margin (%)	Wholesale price (%)	Package size (%)	Manufacturer margin (%)
Honey Nut Cheerios 14/12.25 oz.	−0.002	−0.006	−0.660	−1.334	−1046.935
Honey Nut Cheerios 20/17 oz.	0.002	0.005	−0.278	−0.349	−574.573
Cheerios 10/8.9 oz.	0.001	0.004	−8.646	−3.199	−1804.722
Cheerios 15/14 oz.	0.084	0.263	−0.951	−1.015	−6522.209
Frosted Flakes 14 oz.	0.002	0.005	−0.065	−0.039	−18.520
Frosted Flakes 17 oz.	0.003	0.008	−0.029	0.007	−9.784
Rice Krispies 12 oz.	0.002	0.006	−0.078	0.018	−16.212
Rice Krispies 18 oz.	0.002	0.005	−0.124	0.005	−24.406
Froot Loops 15/12.2 oz.	0.020	0.064	−0.180	0.026	−63.277
Froot Loops 19.7/17 oz.	0.002	0.007	−0.022	0.001	−6.428
Frosted Mini-Wheats 18 oz.	0.005	0.011	−0.140	−0.006	−23.864
Frosted Mini-Wheats 24 oz.	0.006	0.012	−0.030	0.004	−7.155
Special K Red Berries 12 oz.	−0.004	−0.013	−0.174	0.061	−22.043
Special K Red Berries 16.7 oz.	0.001	0.003	−0.064	0.005	−17.159
Special K Original 12 oz.	−0.004	−0.013	−0.116	0.038	−16.897
Special K Original 18 oz.	0.002	0.008	0.012	−0.001	4.546
Cocoa Krispies 17.5/16.5 oz.	0.004	0.011	−0.137	0.003	−25.200
Apple Jacks 15/12.2 oz.	−0.016	−0.050	−0.189	0.031	−29.997
Apple Jacks 19.1/17 oz.	0.003	0.008	−0.037	0.002	−10.827
Raisin Bran 20 oz.	0.006	0.012	−0.157	0.002	−22.948
Raisin Bran 25.5 oz.	0.006	0.012	−0.133	0.003	−20.028
Raisin Bran Crunch 18.2 oz.	0.004	0.011	−0.075	−0.001	−16.807
Corn Flakes 12 oz.	−0.004	−0.014	−0.167	0.014	−28.857
Corn Flakes 18 oz.	0.004	0.011	−0.136	−0.001	−23.719
Crispix 12 oz.	0.012	0.041	0.355	−0.116	559.204
Honey Bunches of Oats 16/14.5 oz.	0.003	0.009	0.001	0.000	2.229
Honey Bunches of Oats 21/19/18 oz.	0.004	0.011	0.001	0.000	2.224
Honey Bunches of Oats with Almonds 16/14.5 oz.	0.003	0.009	0.001	0.000	2.493
Honey Bunches of Oats with Almonds 21/19/18 oz.	0.004	0.011	0.001	0.000	2.201
Fruity Pebbles 13/11 oz.	0.000	0.001	−0.001	0.000	−10.612
Cocoa Pebbles 13/11 oz.	0.000	0.001	0.001	0.000	3.961
Oatmeal Squares 16 oz.	0.001	0.002	−0.001	0.000	−2.545
Cap'N Crunch Crunch Berries 15 oz.	0.001	0.002	0.097	−0.001	14.620
Cap'N Crunch 16 oz.	0.002	0.006	−0.005	0.000	−23.447
Cap'N Crunch 22 oz.	0.005	0.012	0.000	0.000	−0.150

Competitors respond by increasing the size of their packages. For example, Kelloggs increases the size of a Rice Krispies 12-ounce box by 0.018%, Rice Krispies 18-ounce box by 0.005%, and Froot Loops 15/12.2-ounce box by 0.026%. Recalling the negative relationship between the wholesale price and size of the same package, and the fact that competitors react to package downsizing by reducing their wholesale price, competitors will increase their package sizes in response to a downsizing by a rival. That said, the percentage change in package size is small. Because equilibrium package size is a function of the estimates of the competitive response and the response in market share with respect to package size, and this product is small, competitors may recognize that price is more effective tool for covering cost increases in this case.

Retailers respond to package downsizing in a different way. The smaller Cheerios package size attracts more consumers because consumers prefer smaller packages. As a result, retailers can charge a higher price on the new Cheerios 15/14-ounce box and the retail margin for the Cheerios 15/14-ounce box increases. In fact, the retail price of Cheerios 15/14-ounce box increases by 0.084% and the retail margin by 0.263%. Rising retail prices in response to package downsizing is a common observation, as noted in the introduction. At the same time, retailers tend not to change the prices for other products in a meaningful way. For example, retailers change the price of Rice Krispies 12-ounce box only by 0.002%, Rice Krispies 18-ounce box by 0.002%, and Froot Loops 15/12.2-ounce by 0.020%. Because retailers maximize category profit rather than brand profit, they do not have an incentive to change retail prices except for the product being downsized. As a result of package downsizing, retailers can expect two positive effects. First, the retail margin for the downsized product increases. Second, one of the major retail costs – wholesale price – decreases because price competition among manufacturers is sharpened. As a result, we have the somewhat paradoxical result that retailers can benefit more from package downsizing than manufacturers.

For manufacturers, the optimal reaction to package downsizing is to lower wholesale prices. In other words, package size and price are strategic complements. Package downsizing intensifies price competition among manufacturers and reduces manufacturer margins. Therefore, package downsizing may not be in manufacturers' best interests when strategic interactions are taken into account. Because manufacturers implicitly understand the equilibrium response to downsizing, this finding may explain why package downsizing is relatively rare. Manufacturers recognize the deeper consequences associated with package downsizing, so tend to rely on raising wholesale prices instead.

Next, consider the opposite case. How do manufacturers optimally react to package upsizing? My simulation result implies that if manufacturers increase the size of their packages, competitors are likely to raise their wholesale prices. Again, this is a manifestation of the finding that package size and wholesale prices are strategic complements. Package upsizing is not a common business practice. However, if we consider the brand rather than the UPC as a fundamental unit of analysis, launching a large package can be regarded as package upsizing. In order to capitalize on a volume premium, manufacturers often introduce large packages as additions to an existing product line, which increases the average package size of the product line, and has the same effect as package upsizing. Competitors respond to the upsizing by raising their wholesale prices, softening price competition among manufacturers and raising manufacturer margins. This insight is not new, but is another example of a more general phenomenon from the industrial organization literature. Firms in oligopolistic markets are likely to compete in non-price variables such as investment in capacity and R&D, advertisement, and location in attribute space in order to facilitate implicit collusion in price (Dixit and Norman 1978; Davidson and Deneckere 1990; Jehiel 1992). Competition in package size and price in the breakfast cereal market is an example of semi-collusion when multiple strategic tools are available.

This simulation demonstrates that changes in package size affect retail and manufacturer margins, and nature of competition among manufacturers. Package size and price are strategic complements. If a manufacturer downsizes its package, competitors lower wholesale prices in response. Price competition is sharpened and manufacturer margins are reduced. If a manufacturer upsizes its package, on the other hand, competitors raise wholesale prices, price competition is softened, and manufacturer margins rise. The underlying mechanism of this outcome is consumers' responses to changes in price and package sizes. Whether package size and price are strategic complements or substitutes depends on the response of market share with respect to wholesale prices. Further, if consumers were more sensitive to changes in package size, manufacturers would use package size more often than wholesale price in order to cover a production-cost increase. Finally, I find that retailers gain more from package downsizing than manufacturers. Strategic interactions among manufacturers and between retailers and manufacturers play a critical role in explaining equilibrium package size, and price decisions.

My findings have broad implications, both for manufacturers and retailers. First, my findings highlight the importance of package choice. If pricing is a primary concern for CPG marketers, package size should be of equal importance. I show that both package size and price have substantial effects on manufacturers' profitability – effects that are not independent, but inextricably linked through the cost of production and the way these changes alter the competitive environment among manufacturers. Second, consumers prefer small packages, but their preference is subject to a considerable amount of heterogeneity. Manufacturers, therefore, would be well-advised to launch at least one small-pack product, and multiple package sizes to meet consumers' diverse tastes regarding package size, particularly during the introduction phase. Consumers' taste for small packages means that both manufacturers and retailers can charge higher prices for small-packages due to consumers' preference for flexibility, and their aversion to the risk of buying a product they don't like. Third, manufacturers' package-size decisions depend not only on the derived demand from retailers, but on responses from rivals, and the costs associated with making different packages. Contrary to the literature on this point, CPG managers may have an incentive to downsize packages according to consumers' demand for package size, but doing so may not always yield the desired outcome. If production costs rise and manufacturers wish to restore margins by reducing package size and raising unit prices, then not only will they experience higher packaging costs, but the competitive response from rivals may mean that margins, in fact, fall in response. In this case, CPG managers should be aware of the direct costs associated with downsizing, understand competitors' reactions to downsizing, and anticipate consumer responses should the chosen size be below the optimal level.

There are implications that go beyond my specific application to the CPG industry. Although conventional economic thought holds that price is all-important, the evident salience of package size suggests that prices are relevant only in the context of usage patterns. The way consumers use products or services make price changes more or less important, and may, in fact, dominate the relevance of prices. For example, consider a travel agent marketing cruises in the Caribbean. Although the "price" of a cruise can be denominated in either the total price for the entire experience, or a price per day of sailing, consumers are likely to have a strong preference for a trip duration that fits with their lifestyle. Whereas retired people are more likely to favor longer excursions, younger, working professionals seeking a few days of sun and relaxation would prefer shorter trips. The "price" of the cruise in these examples is clearly relevant only in terms of the greater consideration of how large a package is offered.

Similarly, life insurance, retirement plans, and restaurant meals are all services that are offered as packages – packages that serve as points of competition among suppliers, and address, or not, consumers' preferences for specific package sizes. For example, when people choose a life insurance, they are interested in insurance premium as well as fees. Risk-averse people may prefer a higher-premium life insurance while risk-loving people may be satisfied with a lower-premium life insurance. Because the amount of insurance premium involves people's risk attitudes, how insurance companies set the premium for each insurance is critical to understand how the life insurance market works. People's choice of retirement plan is similar. When people choose 401(k) plan, for example, they tend to consider not only how much they have to pay for fees, but also how their personal assets are managed, and how much they can expect to receive in the future. People who are willing to accept risk and aim to gain high returns may prefer high-risk high-return investments. On the other hand, people who seek to avoid risk or people who have a long-term life plan may choose low-risk low-return investment. Finally, consumers consider many factors when they choose a restaurant meal. Especially, for health-conscious people, caloric content is one of the important choice attributes for the entire meal package. Such consumers are likely to choose a meal by considering both price and caloric content, so if a restaurant chooses to offer lower-calorie meal choices, they may charge a higher price, and earn a larger margin. In this case, which is common practice, particularly among fast-casual, chain-restaurants, restaurants may compete in caloric content, and collude in price.

4.5 Conclusions and Implications

In this chapter, I investigate how manufacturers choose package size and unit-price, or the price per unit volume. Package size and price are important elements of the marketing mix because consumers observe both package size and package price directly, but must infer the unit price. Whereas others regard this disconnect between package prices and unit-prices, or "actual" prices as an opportunity for manufacturers to pass hidden price increases on to consumers, the reality of the situation is not as simple. Indeed, when cost and strategic considerations are taken into account, actual manufacturer behavior is likely to be exactly the opposite.

My primary concern is how manufacturers make package size and pricing decisions in consideration of consumer preferences, production and distribution costs, and strategic interactions among manufacturers. To that end, I develop a structural model of interactions among consumers, retailers, and manufacturers when both package size and price are supplier-decision variables. Consumers make discrete choices among differentiated products, while manufacturers set package size and wholesale prices, and retailers pass-through manufacturers' package size decisions and set retail prices taking into account consumer demand and manufacturer and retailer costs. In this way, I model the process of product design and pricing as a simultaneous decision of how large a package to offer, and what unit-price to charge. As a structural model of market equilibrium, my model reveals the interdependence of manufacturer package-size and pricing decisions, with optimal responses from competitors in both dimensions.

I apply this model to store-level scanner data from the ready-to-eat breakfast cereal category from two major retailers in the Chicago market. I find that package size is an important attribute in a consumer's choice among cereal SKUs, and that these purchase decisions condition manufacturers' production decisions. Specifically, consumers prefer small packages, in part, due to the perceived risk, but their preference for package size is heterogeneous. So, that explains why manufacturers offer multiple packages within the same product line. When manufacturers offer a particular package size, they consider consumer demand, the costs associated with making packages, and potential competitive responses from rivals. Consequently, equilibrium package size outcomes result not only from consumer preferences, but from more complex responses from manufacturers to their perceived incentives.

My results overturn what has become a received wisdom in the literature. The fact that consumers tend to over- or under-estimate package size allows manufacturers to use changes in package size as obfuscation strategy (Granger and Billson 1972; Russo 1977; Wansink 1996; Raghubir and Krishna 1999; Binkley and Bejnarowicz 2003; Ellison and Ellison 2009). Moreover, others find package downsizing is an effective way for manufacturers to maintain margins in the face of cost increases, because consumers are less responsive to changes in package size than to changes in price

(Çakıra and Balagtas 2014). However, I show that manufacturers may be better off raising prices, and leaving package sizes alone. On the surface, package downsizing may mitigate the effect of an input-price increase, but also generates a strategic reaction from competitors. If a package is downsized, competitors tend to lower their wholesale prices in response. Price competition in the wholesale market is intensified, and manufacturer margins decrease. This dynamic explains why downsizing is a relatively rare event, and not a common occurrence as the consumer-response literature would lead us to believe.

I also find that retailers may benefit from package downsizing more than manufacturers. Retailers can charge consumers a higher price for the downsized product because consumers prefer smaller packages. Retailers can also expect lower costs as wholesale-price competition reduces their purchasing costs. If the packages are upsized, on the other hand, competitors raise their wholesale prices, and wholesale margins rise at the expense of retailers. Package downsizing intensifies price competition among manufacturers, while package upsizing softens price competition. As a consequence, introducing line-extensions with larger packages allows manufacturers to potentially collude in setting prices.

My findings are consistent with the more general literature on semi-collusion in components of the marketing mix. Advertising, capacity investment, and product-line length are all ways suppliers can soften price competition – essentially drawing competitor attention away from prices, and toward some other means of competing. As another example of this more general line of research, I show that package size is a facilitating practice that has the potential to enhance manufacturer market power.

Nor are the implications of my research limited to the CPG market. I argue that many types of service – retirement plans, insurance contracts, and vacations are but three – are offered as packages so are subject to the same insights that I highlight here. Package-size or complexity and service-price are inextricably linked, and are likely both sources of competitive rivalry. Making such services "smaller" in the sense of offering a more narrow range of benefits, or coverage levels, may seem an obvious way to raise margins, but may in fact have the opposite result. Larger, more complex service contracts are logical result of competition in package size and price.

There are a number of avenues for future research. First, I estimate my demand model using market-level data, so cannot include many household-level features that may have an influence on package choice behaviors. Second, consumers in my model are assumed to be myopic. However, it is possible that consumers are forward-looking and choose a particular package size depending on their knowledge of product quality and retailers' temporary price discounts (Erdem, Imai and Keane 2003; Sun 2005; Hendel and Nevo 2006; Osborne 2011). It would be worthwhile to consider how manufacturers choose package size in response to consumers' dynamic package choice behavior. These questions are left for future research.

CHAPTER 5.

CONCLUSIONS AND IMPLICATIONS

In this dissertation, I examine how purchasers of consumer packaged goods, or CPGs, behave under uncertainty, and how suppliers optimally react. Uncertainty affects consumers' and suppliers' decision-making processes in both direct and indirect ways, a full consideration of which helps explain common observations, or even overturn received wisdom. I consider three sources of uncertainty and how optimal behavior by agents throughout the CPG supply chain can explain three stylized facts in the retailing industry. First, food retailers choose a pricing strategy, or price format, that is either every-day-low-price (EDLP) or promotion-based pricing (HILO). Each generates a different pattern of price variation, or form of uncertainty, which tends to attract different types of shoppers. Second, consumers face uncertainty even after choosing a store. When consumers purchase a new product, they do not know *a priori* whether they will like it. The product they purchase or, more precisely, the package it comes in, will reflect their preferences for the risk that the new product will not meet their needs. New product purchases are a clear source of uncertainty. Third, I endogenize supplier behaviors so that manufacturer and retailer response to consumer uncertainty becomes, in essence, another form of uncertainty. By endogenizing supplier behaviors, I show that conventional wisdom regarding manufacturer pricing amidst cost uncertainty, is almost completely wrong.

In the first essay, I offer a new explanation for how different store formats – EDLP and HILO – can coexist, even though retailing is relatively competitive. In the retailing economics literature, the notion that consumers choose stores based on the size of their shopping basket is of the order of a stylized fact. However, EDLP and HILO stores differ not only in the average price offered, but EDLP prices vary less over time than do HILO prices. If retailing were perfectly competitive, then conventional economic theory would lead us to expect one format to dominate the market. In local retail markets, however, EDLP and HILO stores coexist. The first essay reconciles this seeming paradox by considering consumers' preferences for risk. I develop a two-stage, incentive compatible experiment to measure subjects' risk preferences, and to examine how their attitudes toward risk influence their preference for store price format. My model reveals the relationship between consumer heterogeneity in risk preference and store choice decisions. In particular, more risk-averse consumers are more likely to choose EDLP stores while risk-loving consumers prefer HILO stores. Risk-averse consumers seek to avoid variation in retail prices. On the other hand, risk-loving consumers tend to take advantage of price variation as they are willing to search in order to find the best deal. My findings suggest that retailers' pricing strategies allow consumers with different risk preferences to self-select among store price formats, and consequently different store-price formats are able to coexist despite the relatively competitive nature of food retailing. Because store price format is defined by variations in prices, my explanation is more fundamental than conventional explanations that rely on shopping-basket size.

In the second essay, I extend the notion that consumers respond optimally to risk to the context of new product choice. New products promise to deliver benefits that existing products do not. However, approximately 80% of new products ultimately fail. The second essay provides a fundamental explanation why. Namely, while others examine the role of advertising and packaging as signals of embodied quality, they do not answer the question as to why consumers are reluctant to accept new products. Simply, consumers are uncertain whether they will like a new product. Accordingly, they tend to choose smaller quantities, or smaller packages, of new products compared to those that they have purchased in the past. I explain this observation as a manifestation of risk-averting behavior by utility-maximizing consumers. I use a multiple-discrete / continuous extreme value (MDCEV) model of demand applied to household-level panel scanner data for the yogurt category to test this theory. I find that when consumers try a new product, their utility function is more concave and satiation occurs at a smaller quantity, suggesting that consumers reduce the risk associated with the trial purchase of a new product by choosing a smaller quantity. My finding suggests that slow sales of a new product can be explained as a rational response from risk-averse consumers. The obvious implication of this finding is that CPG marketers would be well-advised to design appropriate marketing strategies to reduce consumers' risk, such as offering smaller packages and trial coupons for new products, or offering a money-back guarantee should the consumer not like the product.

In the third essay, I delve deeper into the question of package size to examine how manufacturers are likely to optimally respond to the risk-averting consumers I found in the second essay. In this essay, I attempt to reconcile the observation that manufacturers offer a variety of package sizes within a same product line, and yet change package sizes only rarely in spite of empirical evidence that consumers tend to ignore changes in package size and are, therefore, apparently willing to absorb the higher unit-prices that result. I explain this observation as an equilibrium outcome of firms that set package sizes and prices simultaneously when considering consumer response, packaging costs, and potential rival reactions. If a firm's choice of package size reflects consumers' risk preferences, and all manufacturers share this realization, then all suppliers are likely to use package size as a strategic tool. I test this theory by estimating a structural model of consumer, retailer, and manufacturer interaction using store-level scanner data from the ready-to-eat breakfast cereal category. I find that consumers prefer smaller packages, and that their preference for package size is heterogeneous. Because package size preferences are important demand-shifters, manufacturers are able to use packaging as a competitive tool, and the heterogeneity of package preferences provides manufacturers an incentive to offer multiple package sizes within a same product line. Manufacturers choose package size conditional on consumer demand, packaging costs, and strategic responses from rivals. My estimates show that package size and price are strategic complements. In other words, if manufacturers reduce package sizes, competitors lower their prices in response, and price competition becomes sharper. On the other hand, if manufacturers sell larger packages, competitors will raise prices, and price competition is softened. While existing studies that consider only consumer demand for different package sizes suggest that consumers are insensitive to changes in package size, and that package downsizing is therefore an effective profit-enhancing tool, my findings suggest manufacturers are not able to change package sizes without considerable cost, and without inciting damaging price-competition from competitors. As a result, changes in package size are infrequent, and tend not to produce the desired result.

In the first two essays, I establish a link between consumers' risk perceptions and their store and product choice patterns. In the final essay, I examine how suppliers optimally react to risk-averse consumer behavior. The primary implication from the first two essays is that consumers face significant risk when they make the most basic choices required of them on a daily basis, so suppliers – manufacturers and retailers

– can be expected to adopt marketing strategies that both limit consumers' risk exposure and exploit their risk-averse behaviors. Package downsizing is one example. In the final essay, however, I show that simple conclusions based on a consideration of consumer behavior alone can be misleading because manufacturer choices can trigger competitive responses that often thwart the original objective. In the context of the third essay, manufacturers are reluctant to reduce the size of their products because package downsizing makes sharpens price competition and reduces margins, which is opposite the original intent. Recognition of the strategic nature of package sizes is therefore critical to understanding how CPG markets operate.

The attitudes towards risk addressed in this dissertation are fundamental, general characteristics of consumer behavior in nearly every purchase environment. In insurance markets, for example, risk-averse consumers may prefer a higher-deductible health plan while risk-loving consumers are satisfied with a lower-deductible. Insurance products not only help consumers diversify risk, but also screen consumers with different risk attitudes, just like package sizes and store formats. Heterogeneity in risk preferences can also explain the proliferation of insurance products just as they can explain why manufacturers offer so many different package sizes, and Walmart hasn't completely dominated the retail grocery industry. As a second example of the fundamental nature of my findings, consider the service industry. When choosing services, consumers usually make decisions about which services to use, and how much to use them. If consumers are uncertain about service quality, they may exhibit risk-reduction behavior by choosing a limited cable package, a slower internet speed, a conservative haircut, or a three-day vacation to a city they haven't visited before. The framework used in this dissertation is, therefore, not limited to the CPG market, but has broader implications for choices, and firm performance, in many other markets.

WORKS CITED

Ackerberg, D. (2003). Advertising, learning and consumer choice in experience good markets: A structural empirical examination. *International Economic Review, 44(3),* 1007–1039.

Allenby, G. M., Shively, T. S., Yang, S, & Garratt, M. J. (2004). A choice model for packaged goods: Dealing with discrete quantities and quantity discounts. *Marketing Science, 23(1),* 95–108.

Anand, B. N., & Shachar, R. (2011). Advertising, the matchmaker. *The RAND Journal of Economics, 42(2),* 205–245.

Anderson, S. P., De Palma, A., & Thisse, J. F. (1992). *Discrete choice theory of product differentiation.* MIT press.

Anderson, L. R., Freeborn, B. A., & Hulbert J. P. (2012). Risk aversion and tacit collusion in a Bertrand duopoly experiment. *Review of Industrial Organization, 40(1),* 37–50.

Anderson, L. R., & Mellor, J. M. (2008). Predicting health behaviors with an experimental measure of risk preference. *Journal of Health Economics, 27(5),* 1260–1274.

Arnold, S. J., Oum, T. H., & Tigert, D. J. (1983). Determinant attributes in retail patronage: Seasonal, temporal, regional, and international comparisons. *Journal of Marketing Research, 20(2),* 149–157.

Barten, A. P. (1964). Consumer demand functions under conditions of almost additive preferences. *Econometrica: Journal of the Econometric Society, 33(1–2),* 1–38.

Bawa, K., & Ghosh, A. (1999). A model of household grocery shopping behavior. *Marketing Letters, 10(2),* 149–60.

Becker, G. M., DeGroot, M. H., & Marschak, J. (1964). Measuring utility by a single response sequential method. *Behavioral Science, 9(3),* 226–232.

Bell, D. R., Ho, T., & Tang, C. S. (1998). Determining where to shop: Fixed and variable costs of shopping. *Journal of Marketing Research, 35(3),* 352–369.

Bell, D. R., & Lattin, J. M. (1998). Shopping behavior and consumer preference for store price format: Why "large basket" shoppers prefer EDLP. *Marketing Science, 17(1),* 66–88.

Berry, S. (1994). Estimating discrete-choice models of product differentiation. *RAND Journal of Economics, 25(2),* 242–262.

Berry, S., Levinsohn, J., & Pakes, A. (1995). Automobile prices in market equilibrium. *Econometrica, 63(4),* 841–890.

Berry, S., Linton, O. B., & Pakes, A. (2004). Limit theorems for estimating the parameters of differentiated product demand systems. *The Review of Economic Studies, 71(3),* 613–654.

Besanko, D., Dubé, J. P., & Gupta, S. (2003). Competitive price discrimination strategies in a vertical channel using aggregate retail data. *Management Science, 49(9),* 1121–1138.

Besanko, D., Gupta, S., & Jain, D. (1998). Logit demand estimation under competitive pricing behavior: An equilibrium framework. *Management Science, 44(11),* 1533–1547.

Bhat, C. R. (2003). Simulation estimation of mixed discrete choice models using randomized and scrambled Halton sequences. *Transportation Research Part B: Methodological, 37(9),* 837–855.

Bhat, C. R. (2005). A multiple discrete-continuous extreme value model: Formulation and application to discretionary time-use decisions. *Transportation Research Part B: Methodological, 39(8),* 679–707.

Bhat, C. R. (2008). The multiple discrete-continuous extreme value (MDCEV) model: Role of utility function parameters, identification considerations, and model extensions. *Transportation Research Part B: Methodological, 42(3),* 274–303.

Binkley, J. K., & Bejnarowicz, J. (2003). Consumer price awareness in food shopping: the case of quantity surcharges. *Journal of Retailing, 79(1),* 27–35.

Borle, S., Boatwright, P., Kadane, J., B., Nunes, J., C., & Shmueli, G. (2005). The effect of product assortment changes on customer retention. *Marketing Science, 24(4),* 616–622.

Briesch, R. A., Chintagunta, P., & Fox, E. J. (2009). How does assortment affect grocery store choice? *Journal of Marketing Research, 46(2),* 176–189.

Brod, A., & Shivakumar, R. (1999). Advantageous Semi-Collusion. *The Journal of Industrial Economics, 47(2),* 221–230.

Bucklin, R., E., Gupta, S., & Siddarth, S. (1998). Determining segmentation in sales response across consumer purchase behaviors. *Journal of Marketing Research, 35(2),* 189–197.

Byzalov, D., & Shachar, R. (2004). The risk reduction role of advertising. *Quantitative Marketing and Economics, 2(4),* 283–320.

Çakıra, M., & Balagtas, J. V. (2014). Consumer response to package downsizing: Evidence from the Chicago ice cream market. *Journal of Retailing, 90(1),* 1–12.

Cameron, A. C., & Trivedi, P. K. (2005). *Microeconometrics: methods and applications.* Cambridge university press.

Cardell, N. S. (1997). Variance components structures for the extreme-value and logistic distributions with application to models of heterogeneity. *Econometric Theory, 13(2),* 185–213.

Chandra, A., & Tappata, M. (2011). Consumer search and dynamic price dispersion: an application to gasoline markets. *The RAND Journal of Economics, 42(4),* 681–704.

Charness, G., & Gneezy, U. (2012). Strong evidence for gender differences in risk taking. *Journal of Economic Behavior and Organization 83(1),* 50–58.

Chen, T., Sun, B., & Singh, V. (2009). An empirical investigation of the dynamic effect of Marlboro's Permanent pricing shift. *Marketing Science, 28(4),* 740–758.

Cohen, A. (2008). Package size and price discrimination in the paper towel market. *International Journal of Industrial Organization, 26(2),* 502–516.

Corts, K. S. (1999). Conduct parameters and the measurement of market power. *Journal of Econometrics, 88(2),* 227–250.

Crosetto, P., & Filippin, A. (2013). The "bomb" risk elicitation task. *Journal of Risk and Uncertainty 47(1),* 31–65.

Davidson, C., & Deneckere, R. (1990). Excess capacity and collusion. *International Economic Review, 31(3),* 521–541.

Deaton, A., & Muellbauer, J. (1980). An almost ideal demand system. *The American economic review,* 70(3), 312–326.

Diewert, W. E., & Wales, T. J. (1987). Flexible functional forms and global curvature conditions. *Econometrica, 55(1),* 43–68.

Dixit, A., & Norman, V. (1978). Advertising and welfare. *The Bell Journal of Economics, 9(1),* 1–17.

Dohmen, T., & Falk, A. (2011). Performance pay and multidimensional sorting: Productivity, preferences, and gender. *The American Economic Review, 101(2),* 556–590.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., & Wagner, G., G. (2011) Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the European Economic Association 9(3),* 522–550.

Draganska, M., & Jain, D. C. (2005). Product-line length as a competitive tool. *Journal of Economics & Management Strategy, 14(1),* 1–28.

Draganska, M., & Klapper, D. (2007). Retail environment and manufacturer competitive intensity. *Journal of Retailing, 83(2),* 183–198.

Draganska, M., Mazzeo, M., & Seim, K. (2009). Beyond plain vanilla: Modeling joint product assortment and pricing decisions. *Quantitative Marketing and Economics, 7(2),* 105–146.

Dubé, J-P. (2004). Multiple discreteness and product differentiation: Demand for carbonated soft drinks. *Marketing Science, 23(1),* 66–81.

Dubé, J-P. (2005). Product differentiation and mergers in the carbonated soft drink industry. *Journal of Economics and Management Strategy, 14(4),* 879–904.

Eckel, C., C., & Grossman, P., J. (2002). Sex differences and statistical stereotyping in attitudes toward financial risk. *Evolution and Human Behavior 23(4),* 281–295.

Eckel, C., C., & Grossman, P., J. (2008). Forecasting risk attitudes: An experimental study using actual and forecast gamble choices. *Journal of Economic Behavior and Organization 68(1),* 1–17.

Ellickson, P. B., & Misra, S. (2008). Supermarket pricing strategies. *Marketing Science, 27(5),* 811–828.

Ellison, G., & Ellison, S. F. (2009). Search, obfuscation, and price elasticities on the internet. *Econometrica, 77(2),* 427–452.

Erdem, T. (1998). An empirical analysis of umbrella branding. *Journal of Marketing Research, 35(3),* 339–351.

Erdem, T., Imai, S., & Keane, M. P. (2003). Brand and quantity choice dynamics under price uncertainty. *Quantitative Marketing and Economics, 1(1),* 5–64.

Erdem, T., Katz, M., & Sun, B. (2010). A simple test for distinguishing internal reference price theories. *Quantitative Marketing and Economics, 8(3),* 303–332.

Erdem, T., & Keane, M. P. (1996). Decision-making under uncertainty: Capturing dynamic brand choice processes in turbulent consumer goods markets. *Marketing Science, 15(1),* 1–20.

Erdem, T., Keane, M. P., & Sun, B. (2008). A dynamic model of brand choice when price and advertising signal product quality. *Marketing Science, 27(6),* 1111–1125.

Erdem, T., & Sun, B. (2002). An empirical investigation of the spillover effects of advertising and sales promotions in umbrella branding. *Journal of Marketing Research, 39(4),* 408–420.

Erdem, T., Zhao, Y., & Valenzuela, A. (2004). Performance of store brands: A cross-country analysis of consumer store-brand preferences, perceptions, and risk. *Journal of Marketing Research, 41(1),* 86–100.

Fershtman, C., & Gandal, N. (1994). Disadvantageous semicollusion. *International Journal of Industrial Organization, 12(2),* 141–154.

Fox, E. J., Montgomery, A. L., & Lodish, L. M. (2004). Consumer shopping and spending across retail formats. *The Journal of Business, 77(S2),* S25–S60.

Friedman, J. W., & Thisse, J. F. (1993). Partial collusion fosters minimum product differentiation. *The RAND Journal of Economics, 24(4),* 631–645.

Gerstner, E., & Hess, J. D. (1987). Why do hot dogs come in packs of 10 and buns in 8s or 12s? A demand-side investigation. *The Journal of Business, 60(4),* 491–517.

Gneezy, U., & Potters, J. (1997). An experiment on risk taking and evaluation periods. *The Quarterly Journal of Economics 112(2),* 631–645.

Gómez, M. I., Richards, T. J., & Lee, J. (2013). Trade promotions and consumer search in supermarket retailing. *American Journal of Agricultural Economics, 95(5),* 1209–1215.

Granger, C. W., & Billson, A. (1972). Consumers' attitudes toward package size and price. *Journal of Marketing Research, 9(3),* 239–248.

Gu, Z., & Yang, S. (2010). Quantity-discount-dependent consumer preferences and competitive nonlinear pricing. *Journal of Marketing Research, 47(6),* 1100–1113.

Guadagni, P. M., & Little, J. D. C. (1983). A logit model of brand choice calibrated on scanner data. *Marketing Science, 2(3),* 203–238.

Harrison, G. W., List, J. A., & Towe, C. (2007). Naturally occurring preferences and exogenous laboratory experiments: A case study of risk aversion. *Econometrica, 75(2),* 433–458.

Hauser, J. R., & Wernerfelt, B. (1990). An evaluation cost model of consideration sets. *Journal of Consumer Research, 16(4),* 393–408.

Hendel, I. (1999). Estimating multiple-discrete choice models: An application to computerization returns. *Review of Economic Studies, 66(2),* 423–446.

Hendel, I., & Nevo, A. (2006). Measuring the implications of sales and consumer inventory behavior. *Econometrica, 74(6),* 1637–1673.

Ho, T., Tang, C. S., & Bell D. R. (1998). Rational shopping behavior and the option value of variable pricing. *Management Science, 44(12),* 145–160.

Holt, C. A., & Laury, S. K. (2002). Risk aversion and incentive effects. *The American Economic Review, 92(5),* 1644–1655.

Horowitz, J., K. (2006). The Becker-DeGroot-Marschak mechanism is not necessarily incentive compatible, even for non-random goods. *Economic Letters 93(1),* 6–11.

Horsky, D., & Nelson, P. (1992). New brand positioning and pricing in an oligopolistic market. *Marketing Science, 11(2),* 133–153.

Jehiel, P. (1992). Product differentiation and price collusion. *International Journal of Industrial Organization, 10(4),* 633–641.

Kadiyali, V., Vilcassim, N., & Chintagunta, P. (1998). Product line extensions and competitive market interactions: An empirical analysis. *Journal of Econometrics, 89(1),* 339–363.

Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica, 47(2),* 263–291.

Kane, T. J., & Rouse, C. E. (1995). Labor-market returns to two- and four-year college. *The American Economic Review, 85(3),* 600–614.

Karni, E., & Safra, Z. (1987). "Preference reversal" and the observability of preferences by experimental methods. *Econometrica, 55(3),* 675–685.

Khan, R. J., & Jain, D. C. (2005). An empirical analysis of price discrimination mechanisms and retailer profitability. *Journal of Marketing Research, 42(4),* 516–524.

Kim, J., Allenby, G. M., & Rossi, P. E. (2002). Modeling consumer demand for variety. *Marketing Science, 21(3),* 229–250.

Koenigsberg, O., Kohli, R., & Montoya, R. (2010). Package size decisions. *Management Science, 56(3),* 485–494.

Kuhfeld, W. (2010). Experimental design and choice modeling macros. Retrieved from http://support.sas.com/resources/papers/tnote/tnote_marketresearch.html.

Lal, R., & Rao, R. (1997). Supermarket competition: The case of every day low pricing. *Marketing Science, 16(1),* 60–80.

Lejuez, C., W., Read, J., P., Kahler, C., W., Richards, J., B., Ramsey, S., E., Stuart, G., L., Strong, D., R., & Brown, R., A. (2002). Evaluation of a behavioral measure of risk taking: The balloon analogue risk task (BART). *Journal of Experimental Psychology: Applied 8(2),* 75–84.

Lusk, J. L., & Coble, K. H. (2005). Risk perceptions, risk preference, and acceptance of risky food. *American Journal of Agricultural Economics, 87(2),* 393–405.

Louviere, J. J. (1988). *Analyzing decision making: Metric conjoint analysis.* Newbury Park, CA: Sage Publications.

Louviere, J. J., Hensher, D. A., & Swait, J. (2000). *Stated choice methods: Analysis and applications.* Cambridge, U.K.: Cambridge University Press.

Louviere, J. J., & Woodworth, G. (1983). Design and analysis of simulated consumer choice or allocation experiments: An approach based on aggregate data. *Journal of Marketing Research, 20(4),* 350–367.

McIntyre, D. (2011, April 4). U.S. companies shrink packages as food prices rise. *DailyFinance,* Retrieved from http://www.dailyfinance.com/2011/04/04/u-s-companies-shrink-packages-as-food-prices-rise/.

McFadden, D. (1978). *Modelling the choice of residential location* (75–96). Institute of Transportation Studies, University of California.

Mehta, N., Chen, X., & Narasimhan, O. (2008). Informing, transforming and persuading: disentangling the multiple effects of advertising on brand choice decisions. *Marketing Science, 27(3),* 334–355.

Mehta, N., Rajiv, S., & Srinivasan, K. (2003). Price uncertainty and consumer search: A structural model of consideration set formation. *Marketing science, 22(1),* 58–84.

Meyer, R, J., & Sathi, A. (1985). A multiattribute model of consumer choice during product learning. *Marketing Science, 4(1),* 41–61.

Muthukrishnan, A., V., Wathieu, L., & Xu, A., J. (2009). Ambiguity aversion and the preference for established brands. *Management Science, 55(12),* 1933–1941.

Nakamura, E., & Zerom, D. (2010). Accounting for incomplete pass-through. *The Review of Economic Studies, 77(3),* 1192–1230.

Narayanan, S., & Manchanda, P. (2009). Heterogeneous learning and the targeting of marketing communication for new products. *Marketing Science, 28(3),* 424–441.

Nelson, P. (1970). Information and consumer behavior. *Journal of Political Economy, 78(2),* 311–329.

Nevo, A. (2001). Measuring market power in the ready-to-eat cereal industry. *Econometrica, 69(2),* 307–342.

Nguyen, Q., & Leung P. (2009). Do fishermen have different attitudes toward risk? An application of prospect theory to the study of Vietnamese fishermen. *Journal of Agricultural and Resource Economics, 34(3),* 518–538.

Nielsen. (2009). Behind Walmart's success Nielsen's 2008 year-end review looks at the numbers. *Newswire,* Retrieved from http://www.nielsenbusinessmedia.com/us/en/newswire/2009/behind-walmart%C3%A2%C2%80%C2%99s-success-nielsens-2008-year-end-review-looks-at-the-numbers.html.

Oppewal, H., & Koelemeijer, K. (2005). More choice is better: Effects of assortment size and composition on assortment evaluation. *International Journal of Research in Marketing, 22(1),* 45–60.

Osborne, M. (2011). Consumer learning, switching costs, and heterogeneity: A structural examination. *Quantitative Marketing and Economics, 9(1),* 25–70.

Park, S., & Gupta, S. (2009). Simulated maximum likelihood estimator for the random coefficient logit model using aggregate data. *Journal of Marketing Research, 46(4),* 531–542.

Petrin, A., & Train, K. (2010). A control function approach to endogeneity in consumer choice models. *Journal of Marketing Research, 47(1),* 3–13.

Phaneuf, D. J. (1999). A dual approach to modeling corner solutions in recreation demand. *Journal of Environmental Economics and Management, 37(1),* 85–105.

Pinjari, A. R., & Bhat, C. R. (2010). A multiple discrete-continuous nested extreme value (MDCNEV) model: Formulation and application to non-worker activity time-use ant timing behavior on week days. *Transportation Research Part B: Methodological, 44(4),* 562–583.

Point of Purchase Advertising International. (2012). *2012 shopper engagement study media topline report.*

Raghubir, P., & Krishna, A. (1999). Vital dimensions in volume perception: can the eye fool the stomach?. *Journal of Marketing research, 36(3),* 313–326.

Richards, T. J. (2007). A nested logit model of strategic promotion. *Quantitative Marketing and Economics, 5(1),* 63–91.

Richards, T. J., Allender, W. J., & Hamilton, S. F. (2012). Commodity price inflation, retail pass-through and market power. *International Journal of Industrial Organization, 30(1),* 50–57.

Richards, T. J., Allender, W. J., & Hamilton, S. F. (2013). Rivalry in price and location by differentiated product manufacturers. *American Journal of Agricultural Economics, 95(3),* 650–668.

Richards, T. J., & Hamilton S. F. (2014). Variety pass-through: An examination of the ready-to-eat breakfast cereal market. *Review of Economics and Statistics,* Retrieved from http://dx.doi.org/10.1162/REST_a_00447.

Richards, T. J., Gómez, M. I., & Pofahl, G. (2012). A multiple-discrete/continuous model of price promotion. *Journal of Retailing, 88(2),* 206–225.

Roberts, J, H., & Urban G, L. (1988). Modeling multiattribute utility, risk, and belief dynamics for new consumer durable brand choice. *Marketing Science, 34(2),* 167–185.

Russo, J. E. (1977). The value of unit price information. *Journal of Marketing Research, 14(2),* 193–201.

Seetharaman, P. B. (2004). Modeling multiple sources of state dependence in random utility models: A distributed lag approach. *Marketing Science, 23(2),* 263–271.

Shankar, V., & Bolton, R, N. (2004). An empirical analysis of determinants of retailer pricing strategy. *Marketing Science, 23(1),* 28–49.

Shoemaker, R. W., & Shoaf, F. R. (1975). Behavioral changes in the trial of new products. *Journal of Consumer Research, 2(2),* 104–109.

Slade, M., E. (1995). Product rivalry with multiple strategic weapons: An analysis of price and advertising competition. *Journal of Economics and Management Strategy, 4(3),* 445–476.

Smith, H. (2004). Supermarket choice and supermarket competition in market equilibrium. *Review of Economic Studies, 71(1),* 235–263.

Staiger, D., & Stock, J. H. (1997). Instrumental variables regression with weak instruments. *Econometrica, 65(3),* 557–586.

Sterrett, D. (2009, February 23). Jewel spruces up to fight Wal-Mart. *Crain's Chicago Business,* Retrieved from http://www.chicagobusiness.com/article/20090221/ISSUE01/100031351/jewel-spruces-up-to-fight-wal-mart#.

Subramaniam, R., & Gal-Or, E. (2009). Research note - quantity discounts in differentiated consumer product markets, *Marketing Science, 28(1),* 180–192.

Sudhir, K. (2001). Structural analysis of manufacturer pricing in the presence of a strategic retailer. *Marketing Science, 20(3),* 244–264.

Sun, B. (2005). Promotion effect on endogenous consumption. *Marketing Science, 24(3),* 430–443.

SymphonyIRI Group. (2012a, April). 2011 new product pacesetters: An eye into the future of CPG. *Times and Trends.*

SymphonyIRI Group. (2012b, May). Shopper marketing: Every decision begins & ends with the shopper. *Times and Trends.*

Thomadsen, R. (2007). Product positioning and competition: The role of location in the fast food industry. *Marketing Science, 26(6),* 792–804.

Train, K. (2009). *Discrete choice methods with simulation.* Cambridge university press.

Theil, H. (1965). The information approach to demand analysis. *Econometrica: Journal of the Econometric Society, 33(1),* 67–87.

Tappata, M. (2009). Rockets and feathers: Understanding asymmetric pricing. *The RAND Journal of Economics, 40(4),* 673–687.

U.S. Census Bureau. (2011). *American fact finder.* Retrieved from http://factfinder2.census.gov/faces/nav/jsf/pages/index.xhtml.

U.S. Census Bureau. (2014). *Monthly Retail Trade Report.* Retrieved from http://www.census.gov/retail/.

U.S. Department of Agriculture Economic Research Service (2011). *Data products.* Retrieved from http://www.ers.usda.gov/data-products/.aspx.

U.S. Department of Energy. (2011). *Natural gas prices.* Retrieved from http://www.eia.gov/naturalgas/data.cfm.

Villas-Boas, S. B. (2007). Vertical relationships between manufacturers and retailers: Inference with limited data. *The Review of Economic Studies, 74(2),* 625–652.

Villas-Boas, J., M., & Winer, R., S. (1999). Endogeneity in brand choice models. *Management Science, 45(10),* 1324–1338.

Villas-Boas, J., M., & Zhao, Y. (2005). Retailer, manufacturers, and individual consumers: Modeling the supply side in the ketchup marketplace. *Journal of Marketing Research, 42(1),* 83–95.

von Haefen, R. H., & Phaneuf, D. J. (2005). Kuhn–Tucker demand system approaches to non-market valuation. In Scarpa, R., & Alberini, A. A. (Eds.), *Applications of Simulation Methods in Environmental and Resource Economics* (pp. 135–157). Springer.

Wales, T. J., & Woodland, A. D. (1983). Estimation of consumer demand systems with binding non-negativity constraints. *Journal of Econometrics, 21(3),* 263–285.

Walters, R. G., & MacKenzie, S. B. (1988). A structural equations analysis of the impact of price promotions on store performance. *Journal of Marketing Research, 25(1),* 51–63.

Wansink, B. (1996). Can package size accelerate usage volume?. *The Journal of Marketing, 60(3),* 1–14.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data.* MIT press.

Yang, S., Chen, Y., & Allenby. G. M. (2003). Bayesian analysis of simultaneous demand and supply. *Quantitative Marketing and Economics, 1(3),* 251–275.

APPENDIX A

EXPERIMENT INSTRUCTIONS

A.1 OVERVIEW

You are to choose where to go shopping for your favorite grocery items from several different types of food and household essentials. In this experiment, you will pick a number of items from several different categories and have an amount of money to spend (each of the number of items, number of categories, and budget are determined during the game). I refer to this basket of goods as your "bundle." There will be 9 questions. Each choice represents a supermarket that has the following 3 attributes: (1) total bill, (2) the number of brands available in each category, and (3) the driving time to the supermarket. Assume you do not know the exact price charged for each product before going to a store. That is, you do not know which products will be on sale, so your total bill is not known prior to checking out. Therefore, the "total bill" attribute reflects both the usual price and sale price, but you only know that sometimes you pay the sale price and sometimes the regular price. In each question, please indicate the decision you would make based on your own preferences. Alternatively, you may choose not to shop at either supermarket listed in that question. Please carefully examine each option before you make a decision and click on the decision that you would make based on your own preferences. Assume that the options in each question are the only ones available to you. Do not compare choices across questions.

A.2 COMPENSATION

You will start with a budget to spend on your chosen bundle. The budget will vary depending on the shopping game, but will be sufficient to purchase whatever bundle you prefer. Please choose between one of the three bundles or to not shop at all. I will then assign a value to each bundle that reflects not just the price of the items you purchase, but the cost of travel, and the value of having access to a larger selection. If you select not to shop, the value of the bundle is 0 EU as you do not go shopping. I will then draw a number at random between 0 EU and your total budget for that question. If the value of the bundle you have selected is above this random draw, then you will get the value of the bundle, but pay an amount equal to the random draw. If the value of the bundle is below the random draw, then you keep your entire budget and pay nothing. For example, if your budget is 30 EUs, the value of the bundle is 20 EUs, and the random number is 10 EUs, then you will pay 10 EUs out of your budget, but receive 20 EUs back. Think of this as getting 20 EUs in groceries for a price of 10 EUs. You will then receive 40 EUs (30 EUs − 10 EUs + 20 EUs) at the end of the game. If your budget is 30 EUs, the value of the bundle is 10 EUs and the random number is 20 EUs, then you keep 30 EUs in payment at the end of the game. In this way, it is in your interest to make the choice that best reflects the importance you place on grocery prices, the ability to select from among many brands, and the cost of traveling to the store. After you finish making all choices, I will randomly pick one choice that determines your payoff. Call this the "payoff choice." All choices have an equal probability of being chosen for payment, so please carefully choose the bundle that most reflects your preference in all the choice occasions.

A.3 SHOPPING BASKET SIZE AND TOTAL BUDGET

Assume the followings in the next nine questions that appear within this web page.

- Items: 12 items – You will go shopping for your favorite 12 grocery items.
- Budget: 26.00 EUs – You have 26.00 EUs to spend.

- Categories: 12 categories – You are allowed to buy one item from each of the following 12 categories, bacon, butter, margarine, ice cream, soda crackers, liquid detergent, ground coffee, hot dogs, soft drinks, granulated sugar, tissue, and paper towels.
- You know your favorite item(s) in all of these 12 categories even if you usually do not buy anything from one or some of them.

APPENDIX B

IRB APPROVAL LETTER

ASU Knowledge Enterprise Development

Office of Research Integrity and Assurance

To:	Timothy Richards 1226 S. La
From:	Mark Roosa, Chair Soc Beh IRB
Date:	03/06/2013
Committee Action:	**Exemption Granted**
IRB Action Date:	03/06/2013
IRB Protocol #:	1302008790
Study Title:	Store Price Format Study

The above-referenced protocol is considered exempt after review by the Institutional Review Board pursuant to Federal regulations, 45 CFR Part 46.101(b)(2) .

This part of the federal regulations requires that the information be recorded by investigators in such a manner that subjects cannot be identified, directly or through identifiers linked to the subjects. It is necessary that the information obtained not be such that if disclosed outside the research, it could reasonably place the subjects at risk of criminal or civil liability, or be damaging to the subjects' financial standing, employability, or reputation.

You should retain a copy of this letter for your records.