THREE ESSAYS ADDRESSING ISSUES IN RETAIL CHANNELS

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Three Essays examining Empirical Issues in Marketing Channels

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ABSTRACT

My dissertation examines the effect of several changes occurring in the retail environment. In the first essay, I study competition among retail formats. I examine the phenomenon retailers call channel blurring: consumers moving their purchases from channels traditionally associated with that category to alternative channels. At one time, different retail formats served different purposes, but they are slowly becoming indistinguishable. For example, mass merchandisers are now carrying sizeable assortments of groceries and pharmaceuticals, while drug chains such are stocking their shelves with toys and household items. I examine how consumers are responding to these changes. My results show that consumers view retail formats as substitutable, that households who are more brand loyal are also more retail format loyal, and that households who purchase private labels are also format loyal.

In the second essay, I examine retail chain choice behavior at the basket level. I develop a model of retail chain choice behavior to understand what factors underlie this decision. The results show that the retailers' food price image has a bigger impact than non-food price image, and that different retailers have customers who use assortment differently. Implications of this are discussed with respect to marketing mix decisions.

In the third essay, I examine retail competition from a legal perspective by performing an empirical analysis of the case history of the Robinson-Patman Act. While the stated goal of the Act is to prevent price discrimination and level the playing field for small buyers, in reality the marketplace may not be not aligned with this goal. Anecdotal evidence suggests that Wal-Mart and others obtain better prices for the same goods when compared with small competitors. I find evidence that the Brooke Group Supreme Court ruling significantly decreased the probability of a plaintiff winning a Robinson-Patman case. The finding is particularly evident in primary-line cases and cases where the issue of competitive harm is addressed. Additionally, I find the importance of plaintiff resources changes after the Brooke Group ruling such that small plaintiffs are significantly more successful than large plaintiffs before Brooke Group but are significantly less successful after the ruling.

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1.0 DISSERTATION INTRODUCTION

Over the past several decades, the retail environment has undergone great change. We have witnessed the proliferation of the big-box retailer including the growth of Wal-Mart, club stores like Costco, and category killers like Best Buy and Lowes. These changes have resulted in a plethora of choices for the average consumer and in this dissertation I attempt to address issues associated with the changing retail environment.

These changes in the retail environment are well documented in the business and popular press but it is unclear how consumers are responding to these shifts in the competitive environment at an individual level. Consumers may respond in divergent ways as retailers add outlets and assortment options. One strategy that consumers may use is one-stop shopping in which they make the largest proportion of their purchases at larger outlets carrying a wider selection of goods. Consumers adopting such a strategy typically value the convenience offered by these large stores and forego the benefits of shopping multiple outlets. These benefits may include better prices due to greater exposure to promotions, or wider assortment options for individual categories because no one store can carry every item in a category.

The fact that these potential benefits exist implies an alternative strategy in which consumers shop multiple outlets for a given category of goods to minimize their overall cost of merchandise (e.g., Fox and Hoch 2005; Gauri, Sudhir, and Talukdar 2007). This “cherry-

picking" behavior is undesirable for retailers because one impetus for offering promotions is to drive store traffic in the hope of obtaining a larger share of consumers' requirements (Kumar and Leone 1988). Thus, if consumers are simply perusing outlets to purchase items that are on promotion, a retailer strategy of adding new categories as loss leaders may not be effective.

The changing retail environment also leads me to question the impact of these changes on the legal environment. While most marketing practitioners and academics are aware of the Robinson-Patman Act, little work in marketing has been done. Stevens (1937), in an early *Journal of Marketing* article, offers support for the Robinson-Patman Act and argues that obtaining lower input prices by negotiating with suppliers is unfair competition and that competitive advantage should be gained through production efficiency, not size. Tarpey (1972) examines several FTC cases to assess the legal liability of buyers who bargain for preferential prices under the Act. Marks and Inlow (1988) study U.S. District Court actions under Robinson-Patman from 1961 to 1986 to discern patterns in the practice of price discrimination with a focus on the impact of the Act on small business. Spriggs and Nevin (1994) analyze functional discounts and suggest that authorities should be conscious of their pro-competitive effects. This dissertation, in contrast to much previous work, does not attempt to discuss the merits of the Act or anti-trust laws in general. Rather, I take the law as a given reality and quantify how the interpretation of the law has changed after the landmark Brooke Group ruling.

1.1 SYNOPSIS OF ESSAY 1

In my first essay, I study retail competition at the highest level—competition among retail formats. I examine the phenomenon retailers call channel blurring: consumers moving their

purchases of a product category from channels traditionally associated with that category (e.g., grocery) to alternative channels (e.g., mass, club, extreme value/dollar). At one time, different retail formats such as grocery, drug, and mass merchandiser served different purposes, but they are slowly becoming indistinguishable. For example, large mass merchandisers such as Wal-Mart are now carrying sizeable assortments of grocery, pharmaceutical, and electronic products, while large drug chains such as Eckerd and CVS are stocking their shelves with toys and household items. I seek to understand how consumers are responding to these changes.

Existing work in marketing has focused mostly on competition between stores of the same format, typically grocery stores (e.g., Bell and Lattin 1998; Lal and Rao 1997). Some marketing scholars have argued that studying only grocery stores gives an incomplete picture of retail competition. Academics have studied how categories are associated with certain retail formats (Inman, Shankar and Ferraro 2004), how competitive entry affects grocery stores (Singh, Karsten and Blattberg 2006), and how aggregate household spending varies across retail formats (Fox, Montgomery and Lodish 2004). I extend this nascent area of literature by studying the intertemporal and household level factors that affect consumers' retail format choice decision, as well as study the correlates of multi-format shopping.

In the essay, I address the following two primary research questions related to retail format shopping (1) Given the growth in alternative retail formats, how are consumers splitting their purchases across retail formats (cross-format shopping)? (2)Are covariates such as shopping behaviors, demographic factors, and category-level factors associated with consumer cross-format shopping? If so, how?

To this end, I model the consumer retail format choice decision using a multinomial logit choice model and estimate it within a hierarchical Bayesian framework. The estimated model

uses a very flexible mixture of normals heterogeneity distribution. The choice model is followed up by a second analysis where I examine factors that are associated with the degree of channel blurring for a household.

My results show that consumers view retail formats as substitutable, that households who are more brand loyal are also more retail format loyal, and that households who purchase private labels are also format loyal.

1.2 SYNOPSIS OF ESSAY 2

In my second essay, I look deeper into the changing retail environment and examine household choice behavior at the basket level. I examine how households obtain their entire breadth of needs and the nature of competition among competing retailers.

I develop a multivariate probit model of household retail chain choice behavior to study the factors that underlie the chain choice decision. The factors that I examine include price image, assortment, household requirements, distance and state dependence. In estimating the model, I hope to understand how these factors affect the chain choice decision as well as quantify the effect of these factors.

Additionally, I seek to understand what factors are important in the household chain choice decision and if households use different retail chains in a complementary or competing fashion. I estimate the proposed model on a unique set of panel data from Nielsen. These data enable one of the most complete pictures of the retail environment in the marketing literature to date. I do this by utilizing three databases of information including: the complete purchase record for a given household in all retail outlets for three years, a demographic file for every household,

and a file with store characteristics and location of each retail outlet. I seek to answer the following research questions: (1) What factors are important in the retail chain choice decision? (2) Is the relationship among retailers complementary, substitutable or independent?

The results of the essay reveal several interesting insights. First, I find that the retailers' food price image has a bigger impact than its non-food price image on the store choice decision. This suggests that promotion policies should focus on these categories as they have a bigger impact on driving store traffic. Additionally, I find that different retailers have customers who use assortment differently. For example, the mass merchandiser that I analyze has customers who utilize greater assortment breadth but less assortment depth but the drug store's customers use greater depth and less breadth. Implications of this are discussed with respect to assortment expansion and deletion.

1.3 SYNOPSIS OF ESSAY 3

In the third essay, I examine retail competition from a legal perspective by performing an empirical analysis of the case history of the Robinson-Patman Act. While the stated goal of the Robinson-Patman Act is to prevent price discrimination and level the playing field for small buyers, in reality the marketplace may not be aligned with this goal. Much anecdotal evidence suggests that Wal-Mart and other big-box retailers can and do obtain better prices for the same goods when compared with small, localized competitors.

It is within the context of this environment that I examine the Robinson-Patman Act to quantify how the changes in the legal interpretation of the Act affect the outcome of cases in federal court. While other scholars have examined the effect of the Brooke Group ruling from a

legal perspective (e.g. Baker 1994; Denger and Herfort 1994), to my knowledge, this is the first attempt to empirically examine the effect of the ruling. I do this from a business prospective to quantify the actual risk faced by businesses with the goal of explaining how the Brooke Group ruling affects case outcomes.

To this end, I collect data on the outcome of Robinson-Patman Act cases in the federal court system for 25 years, from 1982 to 2006. I use this data to estimate a model where I empirically examine whether the likelihood of success for plaintiffs has decreased following the Brooke Group ruling. I account for other factors that may explain the relative success of plaintiffs by including characteristics of plaintiffs and defendants as well as characteristics from the case. Additionally, I include a structural break in the model's parameters following the *Brooke Group v. Brown & Williamson* (1993) Supreme Court ruling which allows us to study how the effect of case characteristics changes in the aftermath of this ruling.

From this analysis, I find evidence that the Brooke Group ruling significantly decreased the probability of a plaintiff winning a Robinson-Patman case. The decrease in probability is particularly evident in primary-line cases and cases where the defense raised the issue of competitive harm. Additionally, I find the importance of plaintiff resources changes after the Brooke Group ruling. While small plaintiffs are significantly more successful than large plaintiffs before Brooke Group, this result reverses afterward and large plaintiffs now do better than their small counterparts.

Together these three essays attempt to shed light on issues in retail competition. The results from these three essays will have important implications for consumers, marketers, and academics. The next three chapters present the essays of this dissertation. Essay 1 is entitled,

“Channel Blurring: A Study of Cross-Retail Format Shopping among U.S. Households.” Essay 2 is entitled, “The Role of Price Image and Assortment in Determining Retail Chain Choice.” Essay 3 is entitled, “Is the Robinson-Patman Act Dead?” These essays are followed by a discussion of the overall contribution of the dissertation, the implications for academics and marketing practitioners, and a discussion of future research opportunities.

2.0 ESSAY 1

Channel Blurring: A Study of Cross-Retail Format Shopping among U.S. Households

2.1 INTRODUCTION

As of January 31, 2008, Wal-Mart, a mass merchandise chain, operates over 2400 supercenters in the United States and has achieved a sizeable position in the U.S. grocery market with over $130 billion in grocery revenue for 2007 (*Progressive Grocer*, May 2008). While this expansion of a mass merchandise chain into the grocery channel or retail format has been impressive, the proliferation of the extreme value or "dollar store" format may be just as notable. According to Nielsen, the top five chains in the dollar store format added over 5,000 distribution points in the first five years of this decade[1]. One way in which traditional retailers— grocery stores, drug stores, and mass merchandisers other than Wal-Mart—are responding to these changes is to

[1] TD Link store count data

expand their assortment by increasing variety in areas where they have not traditionally been a competitor, including general merchandise for traditional retailers and groceries for mass merchandisers. Thus, looking at the retail market at an aggregate level, it appears that the traditional roles of the retail channels are blurring and it is becoming harder to distinguish among retail formats on the basis of assortment.

Existing work in marketing has focused mostly on competition between stores of the same format, typically grocery stores (e.g., Bell and Lattin 1998; Lal and Rao 1997). Some marketing scholars have argued that studying only grocery stores gives an incomplete picture of retail competition. Academics have studied how categories are associated with certain retail formats (Inman, Shankar and Ferraro 2004), how competitive entry affects grocery stores (Singh, Karsten and Blattberg 2006), and how aggregate household spending varies across retail formats (Fox, Montgomery and Lodish 2004). I extend this nascent area of literature by studying the intertemporal and household level factors that affect consumers' retail format choice decision, as well as study the correlates of multi-format shopping

While changes in the retail environment are well documented in the business and popular press, it is unclear how consumers are responding to these shifts in the competitive environment at an individual level. Consumers may respond in divergent ways as retailers add outlets and assortment options. One strategy that consumers may use is one-stop shopping where they make the largest proportion of their purchases at larger outlets carrying a wider selection of goods. Consumers adopting such a strategy typically value the convenience offered by these large stores and forego the benefits of shopping multiple outlets. These forgone benefits include better prices for some items due to greater exposure to promotions, or deeper assortment options for individual categories because no one store can carry every item in a category. The fact that these

potential benefits exist implies an alternative strategy in which consumers shop multiple outlets for a given category of goods to minimize their overall cost of merchandise (e.g., Fox and Hoch 2005; Gauri, Sudhir, and Talukdar 2007). This "cherry-picking" behavior is undesirable for retailers because one impetus for offering promotions is to drive store traffic in the hope of obtaining a larger share of consumers' requirements (Kumar and Leone 1988). Thus, if consumers are simply perusing outlets to purchase items that are on promotion, a retailer strategy of adding new categories to generate store traffic may not be effective.

An examination of cross-channel or cross-retail format shopping has important implications for both managers and public policy makers. From a managerial standpoint, a better understanding of consumer shopping strategies will enable managers to formulate a better marketing strategy. For instance, if most consumers are simply shopping multiple outlets to minimize their total cost for a given category, it may not make sense to expand assortment to include low margin, traffic-inducing products. However, if the majority of consumers are one-stop shoppers and buy where their overall needs can be best met, expanding assortment may be an effective strategy. I seek to shed some light on this important issue.

From a consumer perspective, I seek to determine whether changes in the environment have led to a situation where lower income groups are not experiencing the same benefits of increased retail options as the rest of the population. This situation may arise because retailers often expand into areas where the economic environment is the best, giving higher income consumers more options. Moreover, low income consumers may not have the economic means to visit multiple outlets, potentially leading to higher average costs of goods for these consumers. However, the impact of this issue may be mitigated by the proliferation of dollar stores. This format may ease problems for lower income consumers, as these outlets offer a wide assortment

of categories at low prices, but do not require the level of business needed to support a large 200,000 sq. ft. supercenter.

In this essay, I address the following primary research questions related to retail format shopping:

- Given the growth in alternative retail formats, how are consumers splitting their purchases across retail formats (cross-format shopping)?
- Are covariates such as shopping traits, demographic factors, and category-level factors associated with consumer cross-format shopping? If so, how?

To address these questions, I develop a model of the household retail format choice decision and estimate the model in a hierarchical Bayesian framework. This estimation procedure incorporates a very flexible heterogeneity distribution since I utilize a mixture of normals distribution which can approximate the shape of many distributions very well. This property of the model is important, as I expect divergent preferences for the competing retail formats among households in the dataset. I estimate the model using data from Nielsen's Homescan consumer panel from two product categories, facial tissue and laundry detergent, during the period 2001-2003. I introduce a cross-format shopping measure that I call the Channel Blurring Index, which describes the degree of multi-format shopping by a household, and explore the factors associated with this Index at a household level.

This essay contributes to the marketing literature in three important ways. First, through the theoretical development, I identify and describe both demand and supply side forces associated with retailer format decisions and consumer choice of retail format. Second, I introduce a new metric to capture cross-channel shopping. Finally, the findings offer substantive insights into the factors associated with channel choice and cross-format shopping.

2.2 THEORETICAL DEVELOPMENT

2.2.1 Grocery Store Choice Literature

Because the topic of multi-format shopping is relatively nascent and unexplored, I examine the literature from the broader area of store choice. Researchers have looked at the characteristics of retail outlets, including convenience, selection, and store attributes, to assess how these factors affect store patronage. Arnold, Oum and Tigret (1983) examine a cross-section of different cities and find that store choice drivers are heterogeneous across cities. Louviere and Gaeth (1987) study the effects of price, quality, selection, and convenience on store choice. Kumar and Karande (2000) segment retail outlets based upon the socioeconomic characteristics of the trade area and find that the effects of store environment vary across segments.

Some research has examined store choice by comparing retail outlets with different price formats. Bell and Lattin (1998) use market basket data to show that large basket shoppers prefer everyday low pricing (EDLP) over Hi-Lo stores. Bell, Ho and Tang (1998) develop a theoretical model and test it on panel data to show that price format preference is driven by consumers' efforts to minimize their total cost of shopping. Bolton and Shankar (2003) show that the EDLP vs. Hi-Lo dichotomy in price format is insufficient, and that it should be extended to more price formats that differ on four underlying dimensions: relative price, price variation, deal intensity and deal support. Lal and Rao (1997) use a theoretical model to show that EDLP and Hi-Lo stores should use different strategies to appeal to differing segments of consumers in both price and service.

Table 1

Selected Studies Related to Channel Blurring

Paper	Data	Model	Main Results
Arnold, Oum and Tigert (1983)	Survey of households in 6 cities	Multinomial logit	No seasonality of parameters. Different factors important in various cities.
Bell and Lattin (1998)	Scanner panel data, market basket	Nested multinomial logit: brand choice, purchase incidence, and store choice.	Large basket shoppers prefer EDLP over Hi-Lo stores.
Bell, Ho, and Tang (1998)	IRI shopping basket	Theoretical model of total shopping costs.	Large basket shoppers can bear higher fixed cost to obtain lower variable costs.
Bhatnagar and Ratchford (2004)	Survey, Self report data	Analytical approach using microeconomics to generate hypotheses.	Consumers minimize expected total costs.
Bolton and Shankar (2003)	Nielsen and IRI	Cluster analysis	Retailers use five different pricing policies that differ on four underlying dimensions: relative price, price variation, deal intensity and deal support.
Bucklin and Lattin (1992)	Nielsen	Nested multinomial logit	Promotion did not induce store switching in the laundry detergent category.
Fox, Montgomery and Lodish (2004)	IRI panel	Multivariate Tobit	Substitution within grocery stores stronger than across formats.
Inman, Shankar and Ferraro (2004)	Spectra	Linear regression Correspondence analysis	Categories are associated with specific channels

Table 1 Continued

Paper	Data	Model	Main Results
Kumar and Karande (2000)	A.C. Nielsen Market Metrics	Linear regression	Look at the effect of internal and external store characteristics on store performance.
Kumar and Leone (1988)	Store data	Linear regression	Some of the increases in sales during promotion to due store switching.
Lal and Rao (1997)	Survey	Theoretical model	EDLP and Hi-Lo stores should use different strategies to appeal to differing segments of consumers in both price and service.
Louviere and Gaeth (1988)	Survey/experiment	Conjoint-like analysis	Examine preference for selection, convenience, quality, and their interactions
Messinger and Narasimhan (1997)	Aggregate U.S. Supermarket Data	Theoretical model	Increases in per capita disposable income has lead to greater supermarket assortment, presumably because of a demand for time convenience
Popkowski-Leszczyc and Timmermans (1997)	Nielsen	Binary Probit	Conclude that switching is random.
Singh, Karsten and Blattberg (2006)	Frequent shopper database from a single grocery store	Joint model of inter-purchase time and basket size	Incumbent supermarket lost 17% of their volume to a Wal-Mart Supercenter

Store switching behavior has also been examined in the literature. Kumar and Leone (1988) examine retail price promotions and find that some of the sales increase during promotion is due to store switching. In contrast, Bucklin and Lattin (1992) find no store switching effect. Popkowski-Leszcyc and Timmermans (1997) examine switching among competing grocery stores and find that households with two wage earners tend to be more loyal and make less shopping trips, while households with one wage earner tend to shop more. Messinger and Narasimhan (1997) show that increases in per capita disposable income has lead to greater supermarket assortment, presumably because of a demand for time convenience.

2.2.2 Multiple Retail Format Research

While much of the work in this area focuses on grocery stores, researchers have been studying issues that span multiple retail formats. Bhatnager and Ratchford (2004) use a general model based on microeconomic theory to show the optimality of the different retail formats is dependent on membership fees, travel costs, consumption rates, perishability of products, inventory holding costs of consumers, and cost structures of retailers. Inman, Shankar, and Ferraro (2004) show that specific categories are associated with specific channels. Fox, Montgomery, and Lodish (2004) study shopping behavior across several formats, including grocery stores, mass merchandisers, and drug stores, and find that store substitution is stronger within the grocery format than across formats. Singh, Karsten and Blattberg (2006) examine the effect of the entry of a Wal-Mart Supercenter on an incumbent grocery store. They find that the incumbent store lost 17% of its sales volume to the new entrant.

Our work extends these literatures by exploiting the panel nature of our data to examine the intertemporal factors, as well as household level factors that drive the household retail format choice decision. In addition, we use the estimates from the retail format choice model as well as cross-sectional variables to examine the correlates of multi-format shopping. In the following section, we provide a theoretical rationale as to why consumers may engage in multi-channel shopping.

2.2.3 Drivers of Channel Blurring

Demand-Side Drivers. Evidence from consumer panel data suggests that consumers are shopping at more channels than ever before. While household penetration of the traditional channels including grocery (99%), mass merchandisers (89%) and drug stores (84%) remains high, penetration rates in alternative channels including dollar (68%) and club/warehouse (50%) are rising[2]. As households shop at more types of outlets, they will be exposed to more promotions and could switch channels from which they traditionally buy a given category (Kumar and Leone 1988). Moreover, research has shown that consumers record only about 40% of what they actually purchase on their shopping lists (Block and Morwitz 1999), which suggests that much of the decision-making process is done in the store and that in-store marketing may play an important role. These factors imply that some consumers are likely to engage in cherry-picking behavior (e.g., Fox and Hoch 2005; Gauri, Sudhir, and Talukdar 2007) and buy a given category when a deal is available at an outlet where they are shopping.

However, not all consumers are likely to engage in this behavior. Households with two wage earners and little time for shopping may be making fewer shopping trips and may be more loyal to a given store. Popkowski-Leszcyc and Timmermans (1997) find evidence for this phenomenon in the

[2] Estimated from the Neilsen Homescan panel 2001-2003.

context of grocery stores. Additionally, households may simply shop at the same format every time out of habit.

Supply-Side Drivers. Retailers and manufacturers may also be contributing to channel blurring. Retailers who are successful in one format are transferring their competencies into other formats. The transition of Wal-Mart from their traditional stores with mostly general merchandise and limited food items into Supercenters with full-fledged grocery departments is the most notable example. Kroger is developing its supercenter concept, known as Kroger Marketplace in some markets, which combines their traditional grocery assortment with a larger nonfood department and pharmacy in markets throughout the United States (*Drug Store News*, November 22, 2004). Drug stores such as Walgreens, which opened 476 stores in 2006, many with expanded assortments, are adding to the trend as well.[3] Much of this activity could simply be a response to competitive pressure.

One factor that contributes to the ability of retailers to increase the breadth of their assortment is the trend toward stores with larger footprints. The U.S. Economic Census shows an environment where the average size of a retail outlet is growing. The average size of a retail grocery facility was nearly 15,700 ft^2 in 2002 as compared to just above 8500 ft^2 ten years prior in 1992. Furthermore, the number of warehouse club stores and supercenters, at an average floor space of 140,000 ft^2, nearly doubled from 1997 to 2002. This trend toward increased size opens up shelf space opportunities for manufacturers to get their products distributed through additional outlets.

Product manufacturers have a strong incentive to respond to these changes by seeking distribution in these new outlets. By gaining additional distribution, manufacturers can reduce their dependency on individual retailers. This is an important issue, as research has shown that the balance

[3] 2006 Walgreen's Annual Report.

of power in channel relationships may be shifting toward retailers (e.g., Geylani, Dukes, and Srinivasan 2007). Anecdotal evidence supports this as well and the growth in power of Wal-Mart is well documented in the business press. Furthermore, manufacturers seek additional distribution opportunities in order to better compete with other manufacturers. If consumers shift their buying habits, such that they buy a given product category in a new retail format, and a manufacturer does not have distribution in this format, market share will be lost.

2.2.4 Channel Blurring Index

To capture the level of channel blurring for a household, I define a summary measure of cross-channel shopping that I call the Channel Blurring Index (CBI). The CBI is conceptually similar to Herfindahl Index, but differs in two important ways. First, I take the complement of the sum of squares of purchases so that greater dispersion of channel shopping has a higher Channel Blurring Index. Second, I normalize the index so that it ranges from zero to one. The following is the equation for CBI:

$$CBI = \frac{1 - \sum_{i}^{n} SOV_i^2}{1 - (1/n)} \tag{1}$$

Where n is the number of channel options in the market[4] and SOV_i is the quantity weighted share of volume of category i in the market. The index equals zero when complete channel loyalty exists and one when the volume of purchases are split equally among all channels.

In the analysis, I view CBI from two levels: aggregate and individual. This is an important distinction as the two levels of analysis may show different trends. For example, at an aggregate or

[4] Clearly, this measure is undefined when there is only one channel option in the market. However, the purpose of the measure is to be used in markets where multiple channel options exist.

market level, channels may be blurring due to the fact that additional channel options are available, or existing channels now carry a wider assortment of goods. However, at an individual level, individuals may respond to changes in aggregate assortment in one of two ways. First, consumers could use multiple retail formats to engage in cherry-picking behavior and buy their category requirements when they observe price promotions in a given retail outlet. Second, consumers could consolidate their purchases into one format by taking advantage of the breadth of assortment that many stores now offer. In the remaining sections of this essay, I perform empirical analyses to examine these issues and try to provide insight into the research questions I posed at the beginning of the essay.

2.3 DATA

To carry out this study, I utilize data from the Nielsen Homescan panel of consumers. This dataset tracks the purchases from over 125,000 U.S. households across all retail outlets. Thus, it is uniquely suited to study consumer choice behavior across retail outlets including those corporations who do not share their scanner data with marketing research services such as Nielsen. While I have data for all U.S. markets, I utilize data from only the St. Louis market to better define the competitive set for a given household. That is, the distribution intensity for a given chain varies greatly across markets and by using only one market, I eliminate these differences. The data cover the period from 2001 to 2003 and involve two product categories, facial tissue and laundry detergent.

In the empirical analyses, I analyze data at the category level rather than at the shopping basket level. Analyzing data at the category level provides for a conservative test of whether consumers are engaging in cross-format shopping. That is, it would not be surprising to find that

consumers utilize multiple retail formats for their breadth of needs as different formats specialize in different categories and consumers likely need multiple types of retailers to satisfy their needs. However, looking at basket level data may be a fruitful avenue of research and I analyze retail chain choice at the basket level in the second essay of this dissertation.

2.3.1 Demographic Variables

The Nielsen Homescan database tracks certain demographic variables along with the purchase history of consumers. I use this database in the empirical analyses because one of the objectives is to examine if demographics are associated with retail format preferences. Because retailers of different formats carry different assortments of brand, size and quality, they will likely attract different households. The demographic variables in the database include shopper gender, household income, household size and work status. I expect that these variables will be able to capture variance in preferences due to household requirements as well as time availability to shop at formats that are less convenient, but offering better prices.

2.3.2 Shopping Behaviors

Consumer shopping behaviors such as category volume purchased, brand type, time elapsed since last purchase, and average price paid are also likely to impact consumer's choice of channel or retail format (Kushwaha and Shankar 2007). Quantity of purchase or usage rate is one such shopping trait that can be measured by the total category volume purchased by the household. Households with larger category volume may purchase more from multiple retail formats to fulfill their category needs. There is considerable variation across formats with regard to the product sizes they stock. For

example, most club stores do not carry a single box of facial tissue, but are likely to carry multiple boxes in a single pack. Thus, shoppers who have the need for large quantities as well as the desire and ability to store inventory will likely buy from this format. Given that different retailers stock units of different sizes, quantity is an endogenous variable. Thus, I use a lagged quantity variable as an instrument for quantity in the model.

The type of brand and consumer retail format choice also have a similar relationship. Not all retailers stock the same set of brands, so brand preferences will have some bearing on the format decision. To parsimoniously capture the effect of the type of brand on retail format choice, I treat type of brand as a dichotomous variable--retailer or manufacturer brand. I use the lag of this variable as an instrument to account for endogeneity (e.g., Villas-Boas and Winer 1999).

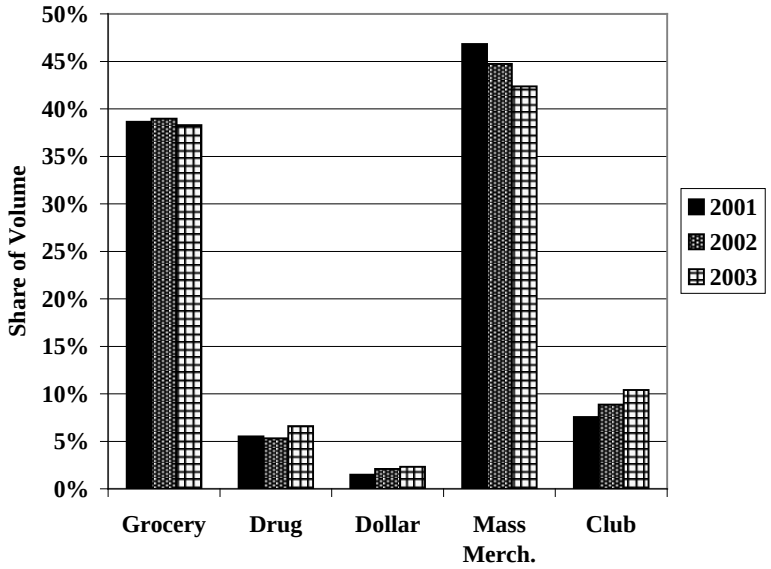
I also expect the length of time elapsed since the last purchase of the category to affect the retail format choice decision. As the time since the last category purchase becomes larger, it becomes increasingly likely that a household's inventory is depleted. In such a situation, consumers may be willing to purchase goods from retail formats that are different than their typical sources for that category. Accordingly, preference for a particular retail format should decrease as time since last purchase increases.

Average price paid will also be an important variable in the channel format choice. However, the effect of price at this level is somewhat complicated. Consumers likely have imperfect information about prices at each retailer and often must visit the store to obtain the actual pricing information. If the household inventory is depleted and if the category is needed, the consumer must either decide to purchase the category at a high price or make another shopping trip to another retailer to obtain a better price. In another scenario, consumers may be at a retail format where they

do not typically purchase the focal category, but if they observe a price promotion, they may purchase the item in that format even though they are not in immediate need of the category.

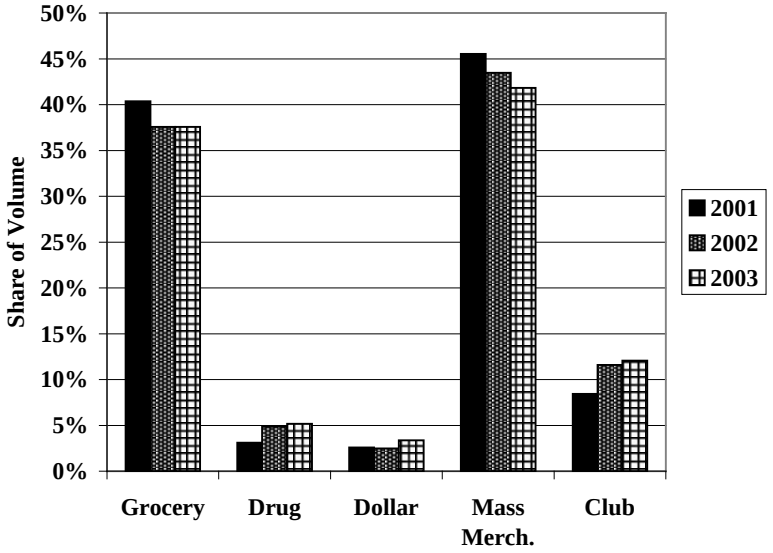
Although I have information on price paid for a particular transaction in the database, I do not have data on prices of competing brands for that purchase occasion. Thus, I use a proxy for price paid by creating a trip weighted mean price for each week in the database.

Figure 1A
Share of Volume by Channel: Facial Tissue



Aggregate CBI: 2001 = 0.778 2002 = 0.796 2003 = 0.823

Figure 1B
Share of Volume by Channel: Laundry Detergent



Aggregate CBI: 2001 = 0.776 2002 = 0.8170 2003 = 0.832

2.3.3 Descriptive Analysis

Tables 2A and 2B contain descriptive statistics for five retail formats, grocery, drug, dollar or extreme value, mass merchandise including supercenter, and wholesale club. These tables show considerable variance in characteristics across channels. Our data shows that the dollar and club formats offer the lowest prices for the categories studied. Interestingly, the club channel attracts shoppers with the highest income level and the dollar channel attracts those with the lowest income, suggesting that preference for a low price spans all income levels. Club stores also attract the largest households and have the largest quantity purchased per trip. This finding could be related to the fact that the assortment in club stores mainly comprises large quantity SKU's.

A descriptive analysis can show also show the trends in channel utilization by consumers over the three year period of our data (see Figures 1A & 1B). The facial tissue category is purchased heavily through the grocery (39%) and mass merchandising channels (45%). However, the dominant position of these two channels is in jeopardy as the combined share of volume for grocery and mass merchandise fell from 85% in 2001 to 81% in 2003. This fact is also supported by our channel blurring measure, which increases from 0.778 to 0.823 during the same period. Much of the gains in share went to the dollar and club channels, as the dollar channel grew from 1% in 2001 to 2% in 2003 and the club channel grew from 8% in 2001to 11% in 2003. The liquid detergent data show very similar trends where the grocery and mass merchandise channels are losing volume share to dollar and club stores (86% combined share in 2001 vs. 79% combined share in 2003). Thus, at an aggregate level, it appears that consumers are utilizing alternative channels at a higher rate. But what does this imply for individual behavior?

Table 2A
Trip-Weighted Descriptive Statistics for Facial Tissue

Channel	Annual Household Income	% Two-Wage Households	% Retired or Non-working households	Household Size	% Trips by Males	Mean Price per Tissue	% Private Label	Mean Quantity/Trip (# Tissues)
Grocery	$47,150	25.5%	37.3%	2.30	20.1%	$0.0105	19.4%	244
Mass	$53,471	34.1%	25.8%	2.49	15.9%	$0.0102	10.3%	323
Drug	$49,639	20.8%	42.1%	2.12	17.3%	$0.0109	16.3%	297
Dollar	$34,346	21.6%	35.9%	2.23	19.7%	$0.0079	4.6%	254
Club	$69,329	48.4%	29.0%	2.70	34.7%	$0.0084	1.6%	1,201

Table 2B
Trip-Weighted Descriptive Statistics for Laundry Detergent

Channel	Annual Household Income	% Two-Wage Households	% Retired or Non-working households	Household Size	% Trips by Males	Mean Price per Ounce	% Private Label	Mean Quantity/Trip (# Ounces)
Grocery	$50,308	31.8%	36.7%	2.47	19.4%	$0.0510	8.3%	117
Mass	$53,968	41.8%	21.6%	2.73	13.9%	$0.0489	2.2%	129
Drug	$51,110	27.7%	39.1%	2.36	15.3%	$0.0481	1.6%	123
Dollar	$41,017	32.1%	19.2%	2.22	7.3%	$0.0465	0.1%	100
Club	$69,697	50.9%	16.0%	2.81	36.3%	$0.0485	2.5%	300

At the household level, I also find support for the idea that consumers are utilizing multiple channels for their purchases(see Figures 2A & 2B). An examination of the facial tissue category shows that only 12% of households are loyal to one channel over the three years of data that I examine. Moreover, most consumers split their purchases considerably across channels, as 59% of households have Channel Blurring Indexes of 0.4 or greater. A similar trend can be observed in the liquid detergent category---18% of households are channel loyal and 55% of households have a Channel Blurring Index greater than 0.4.

These results indicate that there is a sizable segment of households who shop multiple outlets for a single category of goods. This fact is somewhat surprising. While it may expected that consumers will split their purchases across stores for their entire breadth of needs because no one store can stock all products, it is less likely that so many consumers would split their purchases of a single category across many types of outlets. Given this finding, I seek to understand the factors associated with retail format choice in the following section of this essay.

Figure 2A

Individual Channel Blurring Index: Facial Tissue

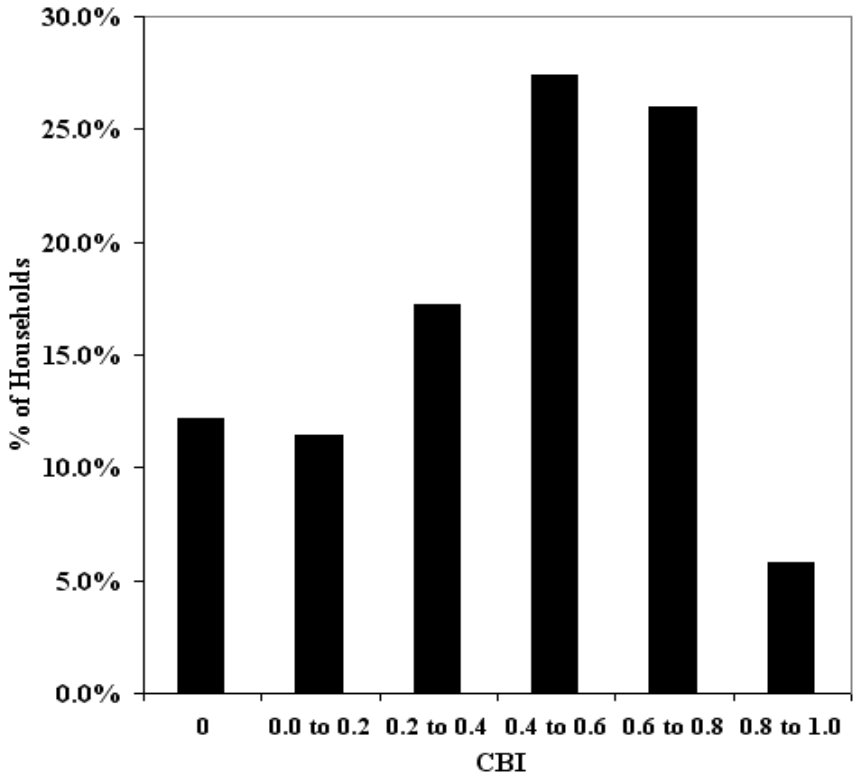
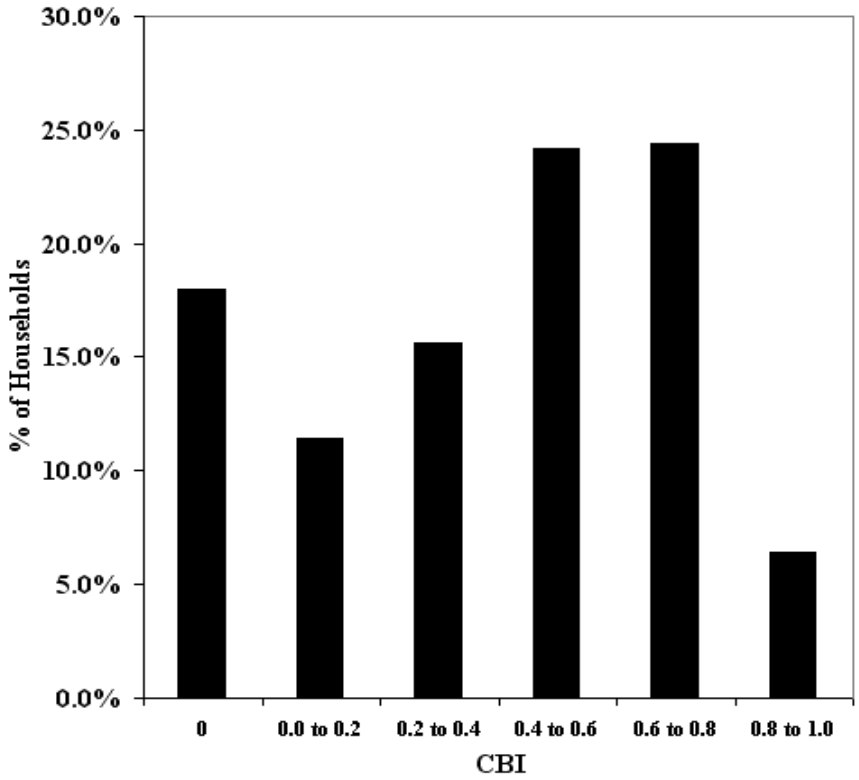


Figure 2B

Individual Channel Blurring Index: Laundry Detergent



2.4 RETAIL FORMAT CHOICE MODEL

2.4.1 Model

In this section, I develop a model to examine the factors associated with retail format choice. To this end, the specification has the retail format decision as the dependent variable. As discussed in previous sections, consumers are in an environment where many types of stores carry similar breadth of assortment and must choose among competing formats on a given purchase occasion.

I specify a random utility model where the utility for a given format is specified at a household level. For format choice, the deterministic component of household h's utility for format j for category c on shopping trip t is given by:

$$U_{hjct} = \alpha_{jc} + \beta X_{hjct} + \varepsilon_{hjct} \qquad (2)$$

Where α_{jc} is the format-category-specific constant, ε_{hjct} is the error term, and the variables of the matrix X_{hjct} are:

$Lag\_QTY_{hct} =$ Category volume purchased by household h on last purchase occasion.

$Lag\_Brand_{hct} =$ Indicator variable which takes the value of 1 if a manufacturer's brand was purchased on the last purchase occasion by household h and 0 if a retailer brand was purchased.

$IPT_{hct} =$ Interpurchase time in days since last category purchase by household h.

$Lag\_Format_{hjct} =$ Effect of state dependence where this indicator variable takes the value of 1 if j was the last retail format where category purchase was made, and 0 otherwise.

$Price\ Index_{hjct} =$ Trip weighted average category price for category c, in format j at time t.

In the case of the quantity and brand variables, lag specifications were used to control for the endogeneity issue (e.g., Villas-Boas and Winer 1999).

The probability of format choice is given by the familiar multinomial choice model as follows:

$$P_{hct}(j) = \frac{\exp(U_{hjct})}{\sum_{J} \exp(U_{hjct})} \tag{3}$$

To capture household level format preferences, I estimate this model in a hierarchical Bayesian framework using a mixture of normals heterogeneity distribution. Details of the MCMC algorithm can be found in Rossi, Allenby and McCulloch (2005, Chapter 5).

This estimation procedure allows for a very flexible heterogeneity distribution, as the mixture of normals distribution can approximate many shapes very well. This method is highly appropriate for this analysis because I expect wide variation in format preference across households, some households with strong preference for a given format and other households with weak or no preference for that format. Additionally, the model allows for fixed effects so that observed sources of heterogeneity can also be modeled. The heterogeneity distribution of the coefficients is modeled as follows:

$$\beta_h = Z_h\ \delta + u_h \tag{4}$$

Where δ are the coefficients for the fixed effects, and Z_h is a mean-centered matrix of the following fixed effect variables:

Gender: Proportion of shopping trips made by female shoppers in household h,

HH_Size: Number of members in household h,

Dual Income: An indicator variable that takes the value of 1 if the household has two working adult members,

Retired: An indicator variable that takes the value of 1 if the household has zero working adult members,

Income: Household income level.

u_h is the heterogeneity distribution and the basis of this distribution is given as follows:

$$\mu_h \sim N(\mu_{ind_h}, \Sigma_{ind_h}) \tag{5}$$

$$ind_h \sim Multinomial_K(pvec) \tag{6}$$

Where ind_h is an indicator latent variable for the component from which household h is taken and it takes integer values 1 to K, K is the number of mixture components, and pvec is a vector of mixture probabilities of length K.

To estimate the posterior distribution of the parameters of the model, I made 50,000 draws with the MCMC algorithm. The first 25,000 draws were used as a burn-in period and the final 25,000 were used for inference. An inspection of a plot of the log likelihood and parameters showed that steady state was reached by this point. Furthermore, I used defaults for priors where possible, except for the prior precision on the normal component means. As suggested in Rossi, Allenby and McCulloch (2005, p. 150), I used a prior precision of .0625 and standardized the non-indicator variables of the X matrix. This prior setting results in greater shrinking of household level parameters, which is a more conservative estimate that allows for the probability that households with short purchase histories may patronize formats not observed in the period of the data.

Moreover, the number of mixture components for the heterogeneity distribution must be specified. Since I model the heterogeneity distribution as continuous rather than as segments as is done in a finite mixture model (e.g., Kamakura and Russell 1989), the task is to include enough

components in the mixture to allow for adequate flexibility to fit the actual heterogeneity distribution. Hence, I do not need to run models with every possible number of components in the mixture to see where a selection criterion is minimized. Rather, I run models with both five and ten mixture components and find no appreciable difference in posterior estimates. Based on this analysis, I conclude that a five-component mixture is adequate to capture the unobserved heterogeneity. Thus, I report the results from the five component mixture.

2.4.2 Results

Model Comparison Results. Prior to presenting the coefficients and substantive results from the final model, I examine several alternative specifications for the retail format choice model. I examine two alternative models for each product category. Model 1 is a multinomial logit model without heterogeneity. Model 2 is a multinomial logit model with a normal heterogeneity distribution rather than a mixture of normals distribution. Model 3 is the full model with both observed sources of heterogeneity and a mixture of normals heterogeneity distribution.

I compare the models using three criteria: log marginal density, hit probability, and hit rate. Log marginal density is an in-sample criterion and hit probability and hit rate test the predictive ability of the model. I calculate the log marginal density using the approximation developed by Newton and Raftery (1994). I developed the predictive measures using the final two purchases of each household as a holdout sample. Hit probability is the mean probability of the chosen alternative in the holdout sample and hit rate is the proportion of instances in the holdout sample where the alternative with the highest probability is chosen by the household.

Table 3A

Facial Tissue Model Fit

Model Description	In Sample Log Marginal Density*	Out of Sample Hit Probability	Out of Sample Hit Rate
Multinomial Logit without Heterogeneity	-9737.0	47.4%	59.2%
Hierarchical Model with Normal Heterogeneity	-6309.1	61.8%	68.8%
Hierarchical Model with Mixture of Normals Heterogeneity	-6256.7	63.5%	70.0%

Table 3B

Laundry Detergent Model Fit

Model Description	In Sample Log Marginal Density*	Out of Sample Hit Probability	Out of Sample Hit Rate
Multinomial Logit without Heterogeneity	-8160.8	40.4%	52.8%
Hierarchical Model with Normal Heterogeneity	-5046.4	56.5%	62.6%
Hierarchical Model with Mixture of Normals Heterogeneity	-4978.5	58.5%	64.2%

* Calculated using the method of Newton and Raftery (1994)

Tables 3A & 3B show the model fit statistics for the facial tissue and laundry detergent categories. Several results are consistent across both categories. First, the full model with fixed effects and mixture of normals heterogeneity is superior to the other specifications across both categories and all three criteria. Second, while the models with normal heterogeneity and mixture of normals heterogeneity perform similarly in-sample, the out-of-sample fit criteria show marked improvement when the mixture of normals distribution is used. Third, the hit rate is relatively high for both the categories, underscoring the utility of the model specification in household level prediction.

Estimation Results. Tables 4 and 5 report the hierarchical parameter estimates and their standard errors for the facial tissue and laundry detergent categories. Given the flexible nature of the model, the mean and standard error do not convey all of the information in the estimation procedure.

Therefore, I provide histograms of the household level retail format-specific parameters in Figures 3 and 4.

For the estimation, I chose the grocery format as the base since it is the traditional format where these categories of goods are purchased. Interestingly, grocery still has a strong effect, as the drug, dollar and club coefficients are negative across both the product categories. Mass merchandisers have coefficients near zero, indicating that the preference for this format is not different from that for the grocery format. The distributions of household-level parameters show that while the overall results indicate that the lower volume formats (drug, dollar and club) have negative preference coefficients, there are households with strong preference toward these formats. For example, the distribution of club coefficients shows that many households have highly negative coefficients for this format, but there is a small group that prefers this format. This finding likely reflects the split between households who have memberships at these clubs and those that do not.

Table 4

Facial Tissue Estimation Results

	Intercept	Gender	HH_Size	Dual Income	Retired (Non-Working)	Income	Category Volume
Drug	-1.99	-0.44	-0.46	-0.50	1.12	-0.11	-0.14
	(0.30)	(0.02)	(0.02)	(0.01)	(0.06)	(0.02)	(0.01)
Dollar	-3.09	-0.08	0.25	0.40	0.02	-0.35	-0.99
	(0.41)	(0.03)	(0.02)	(0.02)	(0.02)	(0.05)	(0.02)
Mass	0.03	0.00	0.02	-0.02	0.03	0.00	-0.05
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
Club	-4.10	0.12	0.12	0.24	-0.57	0.19	0.29
	(0.54)	(0.08)	(0.01)	(0.04)	(0.01)	(0.04)	(0.05)
QTY_Drug	0.06	0.06	0.43	-0.36	0.23	-0.01	0.02
	(0.03)	(0.02)	(0.08)	(0.02)	(0.03)	(0.01)	(0.01)
QTY_Dollar	-0.27	-0.06	0.17	0.00	-0.36	0.09	-0.05
	(0.05)	(0.01)	(0.03)	(0.04)	(0.02)	(0.04)	(0.04)
QTY_Mass	0.15	-0.01	-0.25	-0.14	-1.09	0.29	-0.10
	(0.02)	(0.01)	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)
QTY_Club	-0.21	0.09	-0.16	-0.49	0.98	0.26	2.24
	(0.04)	(0.03)	(0.01)	(0.02)	(0.01)	(0.01)	(0.03)
Brand_Drug	0.03	-0.03	-0.09	0.04	0.23	0.00	0.05
	(0.03)	(0.02)	(0.04)	(0.02)	(0.03)	(0.01)	(0.02)
Brand_Dollar	-0.63	0.58	-1.08	-0.34	-0.54	0.06	0.15
	(0.07)	(0.03)	(0.01)	(0.05)	(0.01)	(0.02)	(0.04)
Brand_Mass	0.02	-0.02	-0.02	-0.55	0.91	-0.02	1.38
	(0.02)	(0.01)	(0.01)	(0.04)	(0.04)	(0.02)	(0.02)
Brand_Club	-0.04	-0.01	0.10	-0.09	-0.17	0.08	-0.07
	(0.04)	(0.04)	(0.01)	(0.03)	(0.03)	(0.03)	(0.05)
IPT_Drug	-0.34	0.18	-1.22	0.32	1.56	-0.31	-0.28
	(0.03)	(0.01)	(0.04)	(0.01)	(0.03)	(0.01)	(0.08)
IPT_Dollar	-0.38	-0.08	-0.16	0.08	-0.66	-0.26	-0.46
	(0.06)	(0.04)	(0.02)	(0.05)	(0.02)	(0.03)	(0.05)
IPT_Mass	0.03	0.00	-0.33	-0.17	-0.03	-0.10	0.01
	(0.01)	(0.06)	(0.05)	(0.02)	(0.04)	(0.01)	(0.01)
IPT_Club	-0.31	0.13	-0.39	0.09	0.67	-0.12	-0.08
	(0.03)	(0.03)	(0.01)	(0.01)	(0.03)	(0.05)	(0.04)
State Dependence	0.09	0.02	-0.45	-0.23	-0.57	0.02	0.53
	(0.05)	(0.02)	(0.04)	(0.01)	(0.02)	(0.02)	(0.01)
Price	-0.08	0.09	-0.14	0.03	1.11	0.00	0.02
	(0.02)	(0.04)	(0.02)	(0.02)	(0.01)	(0.03)	(0.00)

Table 5

Detergent Estimation Results

	Intercept	Gender	HH_Size	Dual Income	Retired (Non-Working)	Income	Category Volume
Drug	-3.04	-1.72	-0.24	-0.13	0.24	-0.26	0.16
	(0.32)	(0.04)	(0.03)	(0.02)	(0.06)	(0.04)	(0.02)
Dollar	-2.39	-0.05	0.28	1.61	-1.17	-0.84	0.84
	(0.29)	(0.05)	(0.02)	(0.01)	(0.01)	(0.03)	(0.02)
Mass	-0.04	-0.15	-0.15	0.06	-0.05	0.07	-0.03
	(0.05)	(0.01)	(0.02)	(0.01)	(0.01)	(0.03)	(0.03)
Club	-3.34	0.01	-1.18	0.16	-0.33	0.40	-0.18
	(0.39)	(0.06)	(0.04)	(0.06)	(0.02)	(0.04)	(0.02)
QTY_Drug	-0.66	-0.06	-0.33	-0.25	0.73	-0.04	0.25
	(0.04)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
QTY_Dollar	-0.36	-0.06	0.12	-0.04	0.17	-0.03	0.04
	(0.03)	(0.01)	(0.07)	(0.04)	(0.04)	(0.03)	(0.04)
QTY_Mass	0.01	-0.33	1.16	-0.46	0.71	-0.07	0.12
	(0.05)	(0.04)	(0.03)	(0.02)	(0.02)	(0.01)	(0.02)
QTY_Club	-0.15	-0.07	0.32	-0.29	-1.07	0.48	-0.95
	(0.04)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.04)
Brand_Drug	0.28	0.05	0.07	-0.01	0.28	-0.02	-0.06
	(0.02)	(0.03)	(0.04)	(0.07)	(0.04)	(0.03)	(0.02)
Brand_Dollar	-1.76	0.25	0.05	-0.99	0.18	0.19	-0.13
	(0.04)	(0.02)	(0.01)	(0.05)	(0.01)	(0.02)	(0.02)
Brand_Mass	0.00	0.03	0.04	-0.35	-1.00	0.51	-1.04
	(0.01)	(0.01)	(0.01)	(0.03)	(0.04)	(0.02)	(0.02)
Brand_Club	-0.52	0.04	-0.11	-0.02	0.06	-0.17	-0.03
	(0.06)	(0.04)	(0.02)	(0.04)	(0.01)	(0.02)	(0.03)
IPT_Drug	-0.49	0.26	-0.67	0.24	-0.47	-0.08	-0.09
	(0.06)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)
IPT_Dollar	-0.51	0.03	-0.19	-0.11	-0.14	-0.28	1.64
	(0.03)	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)	(0.06)
IPT_Mass	0.01	0.12	-0.09	0.01	-0.29	0.03	0.02
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.03)	(0.01)
IPT_Club	-0.25	-0.22	-0.04	0.03	0.74	0.01	0.15
	(0.05)	(0.01)	(0.01)	(0.00)	(0.04)	(0.03)	(0.05)
State Dependence	0.26	-0.05	-0.17	-0.39	0.23	0.03	-0.01
	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)	(0.02)	(0.01)
Price	-0.07	-0.09	-0.02	0.03	0.25	0.01	0.06
	(0.01)	(0.03)	(0.02)	(0.01)	(0.01)	(0.03)	(0.00)

The distribution of household-level coefficients for the mass merchandise format for facial tissue gives a better description of actual preference than the point estimate in Table 4. While the mean coefficient is 0.03, there are large portions of mass far away from zero, as the distribution appears to have two modes: one near -2 and one near 2. This result indicates that there are large portions of the market with strong preferences (positive and negative) for the mass merchandise format, which would not be evident from an analysis that did not take this heterogeneity into account.

The lag quantity coefficients show interesting results for the club format. Since club features the same products in larger quantities, buying a large quantity on a previous trip would intuitively suggest that a household may be more likely to buy from a club store on the next trip. Surprisingly, the results show the opposite trend as the average coefficient is negative (facial tissue coefficient = -0.22, standard error = 0.04; detergent coefficient = -0.15, standard error = 0.04). This finding suggests that consumers may use the club format for large stock-up trips and use other formats to fill in between these trips. This pattern of behavior is also evident from the inter-purchase time coefficients, where shorter inter-purchase times are associated with a higher probability of a club store trip. This result is somewhat counterintuitive. If a household were exclusively using the club format, it would have a longer inter-purchase time due to the large quantities offered at club stores.

Figure 3

Facial Tissue: Distribution of Household-Level Coefficients

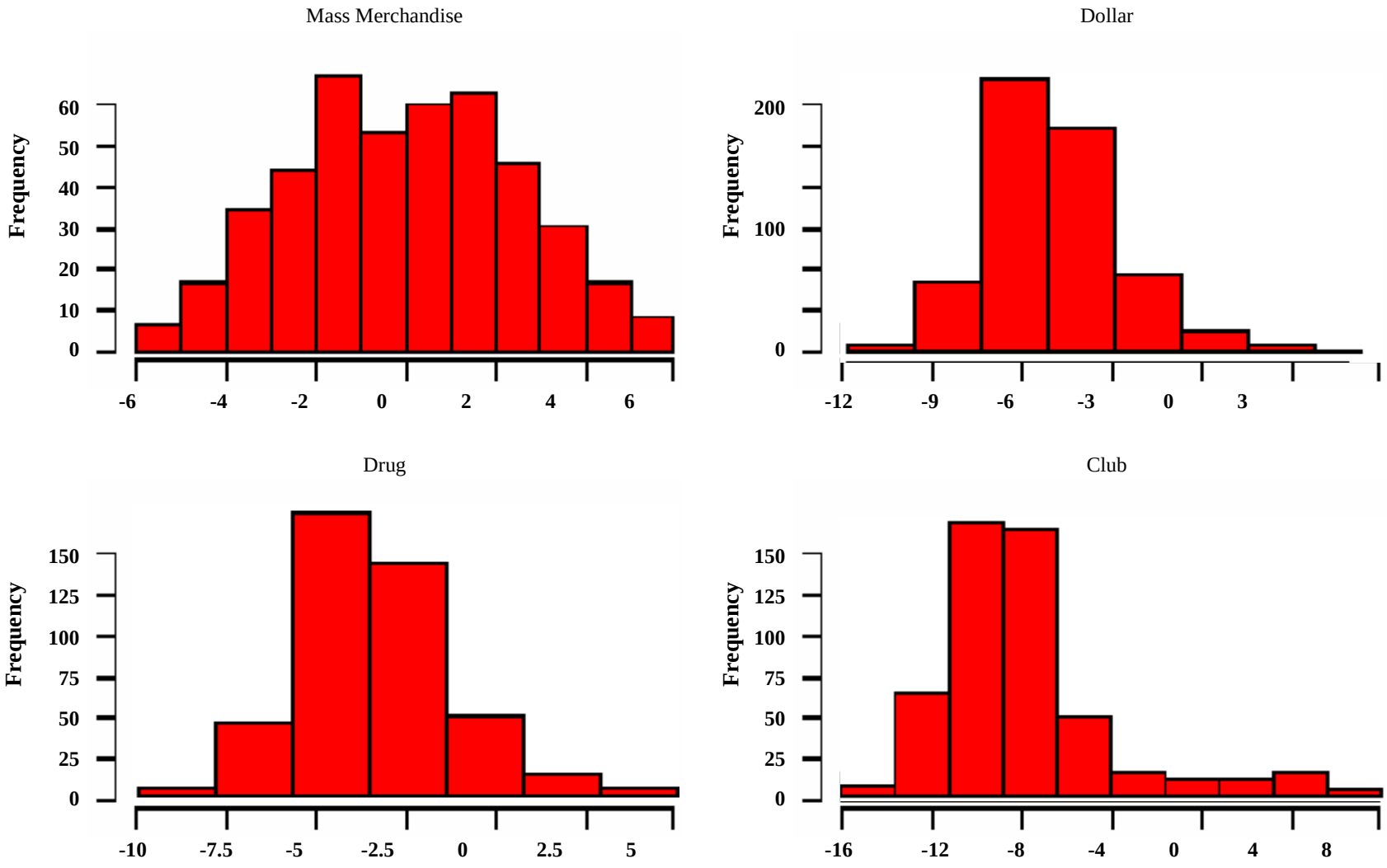
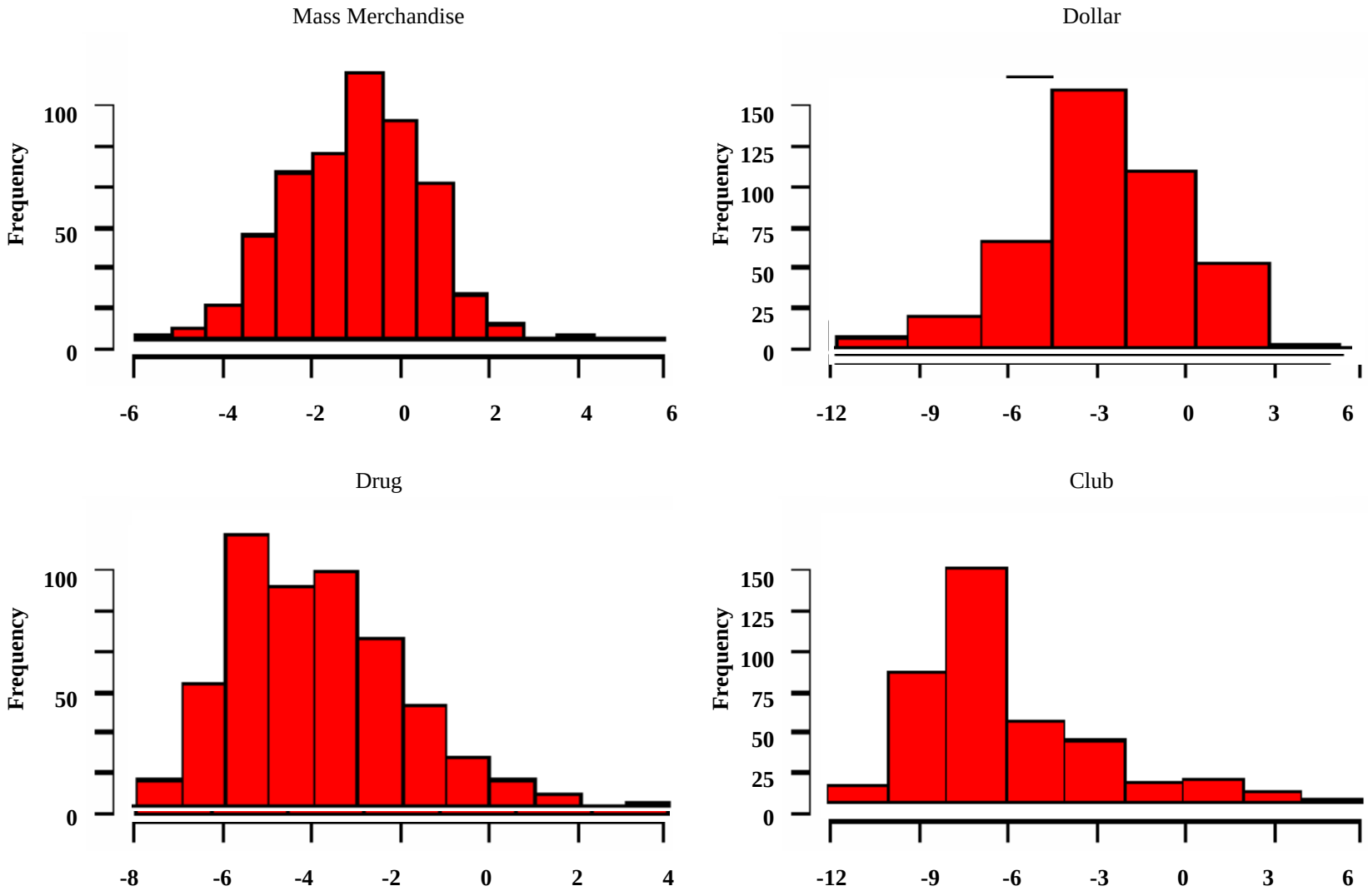


Figure 4

Detergent: Distribution of Household-Level Coefficients

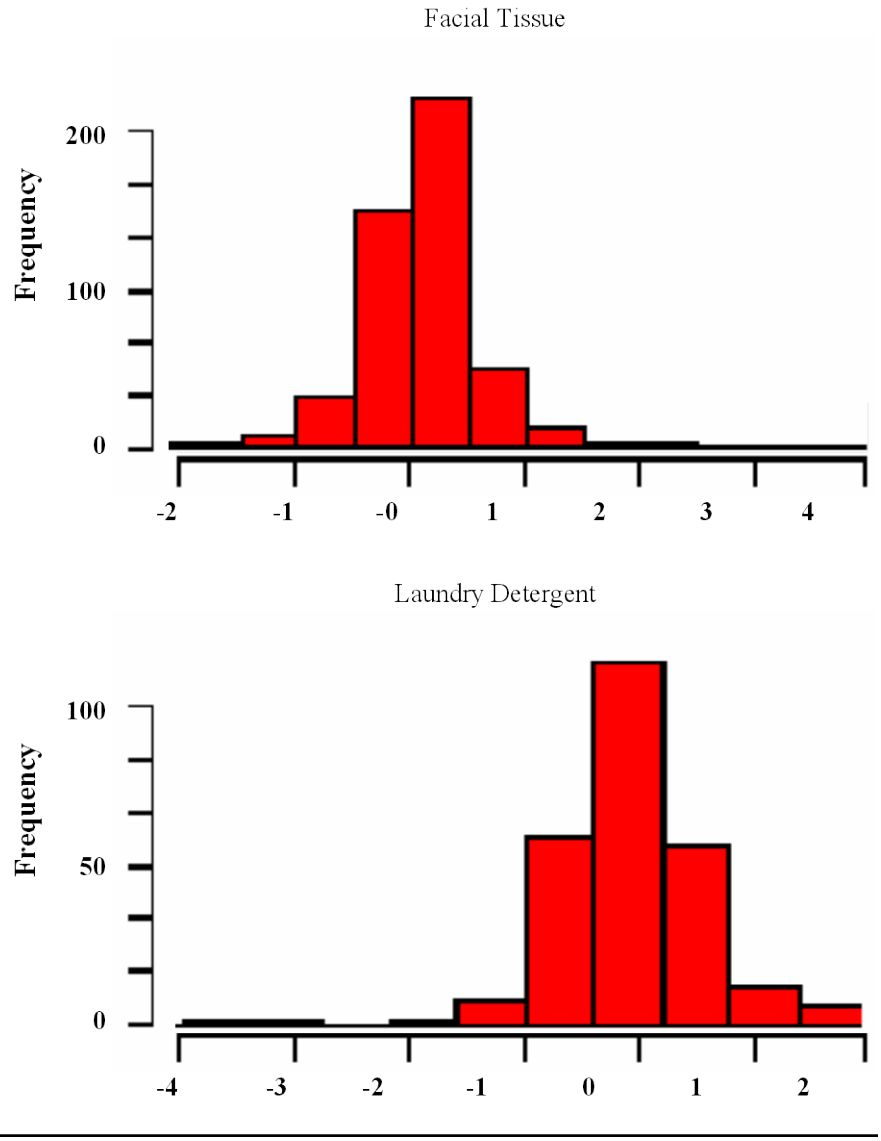


Another interesting result that transcends the categories is the relative unimportance of state dependence. This is surprising in light of the fact that brand and SKU choice models typically show strong effects for state dependence (e.g., Seetharaman, Ainslie and Chintagunta 1999; Inman, Park and Sinha 2007). However, state dependence effects are often less pronounced when the effects of heterogeneity are modeled (Roy, Chintagunta, and Haldar 1996). The results show little importance for the last format utilized (facial tissue = 0.09; detergent = 0.26). Figure 5 shows that this result is true for the majority of households, as much of the mass of the distribution of household-level state dependence parameters is located close to zero. This finding adds to the growing evidence from the model that consumers view different formats as substitutes for the chosen categories.

The price coefficients from both categories are close to zero. This result suggests that most consumers do not choose retail format based upon weekly price fluctuations at retailers. This result could have occurred for one of several reasons. First, the cost of obtaining information across multiple retailers is both time and effort intensive. Second, consumers most likely form a price image based on more than one product category. This price image is, in turn, embedded in their preference for a given retail format.

Figure 5

Distribution of Household-Level Coefficients: State Dependence



Demographic Effects. The effects of household level demographic characteristics are also reported in Tables 4 and 5. In this section, I focus on the effects of demographics on the retail format intrinsic value coefficients, as the demographics for the other coefficients offer less intuition into consumer behavior.

The results show that across categories retired or non-working households have a stronger preference for the drug format. This preference could be because this format is relatively convenient

and it carries an assortment that is important to this group of consumers. The convenience factor may play a role since drug stores have many more distribution points than formats such as club, and travel may be difficult for this group of consumers due to health (in the case of retired households) or transportation (in the case of non-working households) issues. Furthermore, the assortment offered at the drug format, which includes pharmaceuticals, may drive store trips for this group which could also explain the greater preference toward this format. More detailed data would need to be collected to determine the exact cause of this relationship.

In addition, I find that lower income households have a preference for the dollar format. This result is consistent with the descriptive analysis and is likely due to the fact that relatively low prices can be obtained in this format and there are a large and growing number of distribution points for consumers to frequent.

Household-Level Results. I find that some households show preference toward multiple formats. For example, Household 50 utilizes four formats for each category and shows high preference for three formats in each category with coefficients of 0.67 (dollar), 0.21 (mass) -4.37 (drug) and -6.17 (club) for facial tissue and -3.30 (dollar), 0.14 (mass), -0.18 (drug) and -9.98 (club) for detergent. Additionally, Household 187 utilizes both mass merchandisers and grocery stores for both categories, but doesn't use any of the three other formats. This household has preference coefficients of -9.48 (dollar), -0.45 (mass) -4.35 (drug) and -3.87 (club) for facial tissue and -4.88 (dollar), -.42 (mass), -8.87 (drug) and -6.00 (club) for detergent. Hence, there is evidence that some households have strong preference for multiple formats and utilize multiple types of stores for a particular category. This finding, together the high Channel Blurring Index for many households, suggests that it may be important to look at the characteristics of multi-format shoppers. In the following section, I use the household level coefficients generated from the retail format choice

model with cross-sectional household level characteristics to examine their impact on the degree of channel blurring.

2.5 MULTI-FORMAT SHOPPING MODEL

While the previous section presents a model of the retail format choice decision for a given choice occasion, I also am interested in the factors associated with multi-format shopping behavior. I address this issue by examining the household level data in a cross-sectional analysis. To do this, I utilize the household-level coefficients generated from the retail format choice model as independent variables in the model to predict the degree of multi-format shopping. Because the coefficients for quantity, interpurchase time, and brand type provide estimates of how preferences change due to intertemporal factors, I do not use these coefficients in this stage. Instead, I provide cross-sectional measures for these factors as described below.

2.5.1 Model

I wish to study the degree of channel blurring at the individual level, so I estimate a model in which CBI is the dependent variable. I create a separate model for each category and estimate them as a system of seemingly unrelated regressions (SUR). The model for the CBI of household h for category c is given as follows:

$$CBI_{hc} = \alpha + \beta X_{hc} + \eta_{hc} \qquad (6)$$

where α is an intercept term and the variables of the X_{hc} matrix are:

HH Drug Coefficient: Posterior mean drug coefficient from format choice model,

HH Dollar Coefficient: Posterior mean dollar coefficient from format choice model,

HH Mass Coefficient:	Posterior mean mass coefficient from format choice model,
HH Club Coefficient:	Posterior mean club coefficient from format choice model,
HH State Dep. Coef:	Posterior mean state dependence coefficient from format choice model,
HH Price Coefficient:	Posterior mean price coefficient from format choice model,
Dual Income:	An indicator variable which takes the value of one if there are two working adults in the household and zero otherwise,
Retired:	An indicator variable which takes the value of one if there are zero, working adults in the household and zero otherwise,
Household Size:	Number of members in household h,
Household Income:	Household income level,
% Male:	The percent of shopping trips from the households that were done by males,
% Private Label:	Proportion of HH volume that was a retailer's brand rather than a manufacturer's brand,
Brand Blurring Index:	An index calculated in an analogous method to the Channel Blurring Index but with brands purchased rather than retail format utilized,
IPT:	Average inter-purchase time for household h,
Category Volume:	Quantity of category purchases in equivalent units, and
	η is an error term.

2.5.2 Results

The results of the SUR analysis with CBI as a dependent variable are shown in Table 6. The household-level demographic variables provide little intuition into the channel blurring phenomenon, as only Retired and Household Income are statistically significant and this finding holds for one category—laundry detergent.

Table 6

Multichannel Shopping Estimation Results

	Facial Tissue				Laundry Detergent			
Parameter	Estimate	Std. Error	P-Value		Estimate	Std. Error	P-Value	
Intercept	0.770	0.081	<.0001	*	0.431	0.064	<.0001	*
Dual Income	0.057	0.034	0.094		0.051	0.038	0.182	
Retired	0.057	0.031	0.072		-0.072	0.033	0.030	*
HH Size	-0.006	0.010	0.556		-0.016	0.014	0.253	
HH Income	0.001	0.001	0.174		-0.001	0.001	0.036	*
% Shopping trips by Males	-0.046	0.041	0.258		0.048	0.051	0.352	
% Private Label	-0.154	0.041	0.000	*	-0.264	0.081	0.001	*
Brand Blurring Index	0.183	0.033	<.0001	*	0.148	0.035	<.0001	*
Avg. Interpurchase Time	0.001	0.000	0.049	*	0.001	0.000	0.034	*
Category Volume	0.000	0.000	0.092		0.000	0.000	0.146	
HH Drug Coefficient	0.038	0.006	<.0001	*	0.008	0.008	0.274	
HH Dollar Coefficient	0.031	0.006	<.0001	*	-0.007	0.006	0.201	
HH Mass Coefficient	-0.030	0.006	<.0001	*	-0.013	0.006	0.050	*
HH Club Coefficient	0.020	0.007	0.002	*	-0.065	0.013	<.0001	*
HH State Dependence Coefficient	-0.109	0.014	<.0001	*	-0.151	0.017	<.0001	*
HH Price Coefficient	-0.029	0.019	0.132		0.023	0.025	0.361	

The shopping behaviors and preference coefficients, however, provide more interesting results. The mean interpurchase time, mass and club preference, state dependence, % private label, and Brand Blurring Index are significant across both categories. The mean interpurchase time results imply that longer interpurchase times are associated with higher levels of channel blurring. The results for the preference coefficients are mixed. For the mass merchandise format, greater preference is associated with lower levels of channel blurring. This finding suggests that consumers who have high

preference for this format use it as their primary format and are loyal to the format. This is also the case with the club format for laundry detergent. However, for the drug, dollar and club formats in the facial tissue category, high preference is associated with greater channel blurring. This result indicates that preference for these formats occurs together with preference for another format, which leads to greater channel blurring.

The results also indicate that the brand purchased has interesting results for channel blurring. First, I find that households who buy a greater proportion of their category requirement from private label brands engage in less channel blurring. This suggests that private labels may offer one avenue to build format or store loyalty. Second, I find that households who have greater dispersion of brand purchases also have a greater dispersion of format choices. This finding suggests that consumers who are less format loyal are also less brand loyal. This finding implies that loyalty may be a household level trait that extends beyond brands and into retail formats as well.

Table 7

Loyalty Analysis-% of Households

	Facial Tissue	Laundry Detergent	Both Categories
Brand and Format Loyal	3.8%	8.2%	1.0%
Only Brand Loyal	10.6%	15.8%	4.4%
Only Format Loyal	8.4%	9.8%	3.2%
Neither Brand nor Format Loyal	77.2%	66.2%	91.4%

To gain a deeper understanding of this result, I examine loyalty at the household level in Table 7. While on average, higher brand loyalty is associated with higher format loyalty, very few households are completely format and brand loyal across categories. In fact, only 1% of households buy the same brand in the same format on every purchase occasion for both categories. However, 3.8% and 8.2% of households are completely format and brand loyal for the facial tissue and laundry detergent categories, respectively. This result implies a very simple decision process for these

households. Furthermore, 10.6% and 15.8% of households are brand loyal but not format loyal for the facial tissue and detergent categories, respectively. This result suggests that many households either have a preferred brand that they buy when needed regardless of location or that the household shops multiple formats to obtain their preferred brand at better prices. I also observe that 8.4% and 9.8% of households are format loyal, but not brand loyal for facial tissue and laundry detergent, respectively. Thus, they are loyal to the format but respond to in-store marketing efforts or have a preference for variety. Finally, 77.2% of the facial tissue market and 66.2% of the laundry detergent market are neither brand nor format loyal, which implies that these are competitive categories for both retailers and manufacturers.

2.6 DISCUSSION

2.6.1 Summary

Taken together, the results attempt to address the two research questions I posed at the beginning of the essay. The results show that household level heterogeneity in retail format preference explains much of retail format choice decision. Interestingly, many of the household-level preference distributions were multimodal, indicating wide variance in preference across households. The results also shed light on the profiles of households with preference for a particular format. Retired and non-working households have greater preference for the drug format and lower income households prefer the dollar format.

Surprisingly, I find that the importance of state dependence is low. This result, along with the results from studying the intertemporal pattern of quantity and inter-purchase times, suggests that consumers use different formats as substitutes for one another. This finding has important implications for how retailers view competition.

The analysis of the factors associated with the degree of channel blurring shows that shoppers who buy a greater proportion of private label goods tend to be more format loyal and engage less in channel blurring. This interesting result suggests that strong private label brands may enable lower competition among retailers. Furthermore, households who have a high degree of dispersion in brand purchases also have high Channel Blurring Indexes. This finding implies that loyalty is a household level trait and some consumers are habitually loyal while others look for good deals at the brand and retailer level.

2.6.2 Implications for Marketers

The results of this essay have important implications for marketers. First, retailers should consider using private label products as a way to build loyalty among its consumer base. It appears that there is a segment of consumers that uses private label brands in a way to shop in an efficient manner. They enjoy a low price associated with retailer brands without having to search across multiple stores to get a low price. Retailers who have a wide assortment of these goods may be able to attract and retain this group of customers. There is an opportunity for several formats in the categories examined, as both dollar and club formats have low share of private label brands sold in their outlets. Second, retailers should realize that competition is not just within format, as consumers use different formats as substitutes for one another. While most retailers are very aware of the threat posed by Wal-Mart Supercenters, competition is also growing in the form of dollar stores and warehouse clubs. Consequently, existing retailers should include an analysis of these cross-format competitors in their strategic planning efforts. Third, the results suggest that some consumers shop across formats to obtain better prices for goods, engaging in cherry-picking behavior. This finding suggests that loss-leader strategy aimed at generating store traffic should be used carefully.

Furthermore, the results have implications for product manufacturers and marketers of national brands. First, on average, consumers who are loyal to retail formats are also more loyal to brands. Thus, manufacturers should try to create cooperative marketing plans with retailers where they have a strong position in an effort to best serve and maintain this strong relationship. I also find that about 10-15% of consumers are brand loyal but not format loyal. This result is important and should be studied in detail as it may imply that consumers are searching across formats to obtain the best price for a given brand. If this is the case, manufacturers should coordinate their marketing efforts across retailers in order to maximize their profits for this group.

Figure 6

Household Loyalty Types

Brand Blurring Index	Channel Blurring Index: High*	Channel Blurring Index: Low
High	**Opportunists** (29% Tissue, 24% Detergent)	**Channel Loyal** (23% Tissue, 22% Detergent)
Low	**Brand Loyal** (17% Tissue, 21% Detergent)	**Habitually Loyal** (31% Tissue, 33% Detergent)

*High Channel Blurring and Brand Blurring Index is > 0.5

The results suggest that both retailers and manufactures can benefit from analysis of CBI in their markets. In Figure 6, I present a table of household loyalty types each of which requires different marketing actions. Both the categories have fairly large segments of households that I

consider to be habitually loyal--they buy the same brand in the same format. In categories where this segment is large, both manufacturers and retailers benefit from maintaining this business, so cooperative marketing campaigns could be undertaken through vehicles such as shared advertising or point-of-purchase coupons. However, the second largest group in each category is what I call opportunists. These consumers buy multiple brands in multiple formats, suggesting that they buy when they find an attractive deal. In categories where there are large groups of these consumers, competition is likely to be intense and the introduction of a retailer brand may be a good strategy as brand preferences do not appear to be that strong.

I also find a group of households who appear to have strong preference for one brand but are willing to buy it at multiple retail formats. This finding suggests that these consumers are willing to shop around for a better deal for their preferred brand. When a large segment of this type of consumer exists, the loss-leader strategy may be attractive, but could backfire due to cherry-picking. Finally, there are consumers who prefer a retail format, but are willing to buy multiple brands. These consumers respond to in-store marketing and in this case, manufacturers should adopt a push strategy by offering trade promotions to retailers.

2.6.3 Implications for Consumers

The results imply two strategies for consumers to obtain lower overall prices for their category requirements. The first strategy comprises shopping at one format and buying low-cost private label goods. This is effective because it involves low search costs, as obtaining information on weekly prices and promotions may be effort-intensive. The second strategy involves shopping at multiple formats and buying items when they are on promotion at lower prices. Greater research which strategy is more effective and what types of consumers engage in each strategy.

Because club stores and mass merchandisers offer relatively low prices, but have limited distribution points, I believe that lower income consumers may be disadvantaged in their ability to shop at value based formats. However, the retail format choice model and descriptive analysis show that the dollar format offers both low prices and attracts lower income consumers. This finding, together with the fact that dollar store distribution points are growing rapidly, suggests that consumers of all income strata are able to benefit from the increased competition in the retail industry.

2.6.4 Limitations and Future Research

While this study provides a look into cross-format shopping among consumers, it is limited in that it only looks at two categories in one geographic market. Future research should examine whether there are category differences or differences across markets. The categories I examine are necessities which are relatively storable. Furthermore, differences in brand preferences across markets have been researched (Bronnenberg, Dubé, and Dhar 2007) and found to be important. Channel preferences will likely vary across markets as well. Additionally, the data were limited in the information available in the causal environment. It would be interesting to analyze data on advertising exposure to understand its effect on store trips. This research looks at cross-format shopping for a given category. Complementary research that examines within-format competition as well as across-format competition at the shopping basket level would be useful. It would also be interesting to study the dynamic effects of store competition to see how consumers' utilization of different formats evolves as a function of store entry, changes in assortment, and new products.

3.0 ESSAY 2

The Role of Price Image and Assortment in Determining Retail Chain Choice

3.1 INTRODUCTION

In the contemporary retail environment, consumers are faced with many retail options. As I show in the first essay of this dissertation, many households show a high preference for multiple retailers across different retail channels for a given category. But, how do households use these multiple retailers to obtain their whole breadth of needs?

Existing work in marketing has examined the store choice decision at the household level. Bell and Lattin (1998) examine retailers of different price formats and show that large basket shoppers prefer EDLP over Hi-Lo stores. Fox, Montgomery and Lodish (2004) look at preference for different retailers and find that substitution is stronger within the grocery format than across retail formats. Briesch, Chintagunata and Fox (2008) show that while the preference for low prices is universal, assortment preferences vary across households. In this essay, I examine the role of price image and assortment to see how these factors play a role in store

choice and also examine the structure of competition among retailers. To this end, I conceptualize a model where consumers can purchase from multiple retailers in a given timeframe. Thus, I can examine whether the relationship among retailers is complementary, substitutable, or independent (e. g. Manchanda, Ansari, and Gupta 1999).

In this essay, I seek to answer the following two research questions. (1) What factors are important in the retail chain choice decision? (2) Is the relationship among retailers complementary, substitutable or independent? In the following sections of this essay, I first develop the model that is estimated. This is followed by a description of the data and a presentation of the results. Finally, I discuss what these results imply for retailers and discuss future research opportunities.

3.2 CONCEPTUAL MODEL

The choice of which retail chains to patronize is a complex process that will likely be influenced by many factors. In the following section I briefly review the literature to develop a conceptual model for the retail chain choice decision.

3.2.1 Basket Size and Composition

The role of basket size has been studied previously in the marketing literature. Bell and Lattin (1998) find that large basket shoppers prefer the everyday low pricing format over stores that over more promotions. This effect of basket size is likely due to some underling phenomenon such as the price dispersion of the store. Bhatnagar and Ratchford (2004) study store choice across retail formats and find that the optimality of a format is dependent upon inventory holding

costs, among other things. Thus, preference for certain chains, such as wholesale clubs, may depend on a household's desire and ability to inventory products.

Additionally, the composition of the basket will influence the retail chain choice decision. Inman, Shankar and Ferraro (2004) show that categories are associated with certain retail formats which in turn leads consumers to purchase those categories in the associated format. While, many chains have overlapping assortment, considerable differences still exist in the focus of the assortment across retailers. Thus, basket size and composition will likely play a role in the chain choice decision. I develop an expected basket size measure that is used in the model to address this concept. It is measured for both food and non-food items to address the role of basket composition in the chain choice decision.

3.2.2 Price

Price will clearly be a factor in the chain choice decision. Given the rise of low cost retailers such as Wal-Mart, the retail market has become increasingly focused on price. But, what role will price play at the basket level. The role of price at the category level has been extensively studied (e.g., Guadagni and Little 1983). When choosing an item from a set of competing brands at this level, consumers can easily calculate the tradeoffs. However, at the basket-level the tradeoff becomes more difficult. Consumers are not exposed to competing prices without visiting other outlets, so price information is less readily available. Additionally, the basket of goods that a consumer purchases is not static and will change from week to week.

Marketing academics have addressed this issue in previous studies. Bell, Ho, and Tang (1998) find that consumers can lower their variable cost (i.e. price) but pay higher fixed costs in terms of distance traveled and time needed to shop. Briesch, Chintagunta, and Fox (2008) model

the basked as a collection of categories that have a probability of being included in the subsequent shopping trip. Thus, the effect of price is built up from the category level. They find that the role of price is small compared to other factors such as assortment and convenience.

3.2.3 Assortment

Assortment plays an interesting role in the chain choice decision. Messinger and Narasimham (1997) argue that as time costs increase, a large assortment becomes more important. So, there may be a tradeoff between assortment and convenience. Briesch, Chintagunta, and Fox(2008) find that the less important assortment is to a consumer's store choices, the more the consumer values convenience and vice versa. Additionally, self-report studies show that assortment is an important variable in the store choice decision (e.g. Arnold, Roth and Tigert 1981; Arnold, Oum and Tigert 1983). I include two measures of assortment in my model of retail chain choice: assortment breadth and depth. Addressing assortment in this manner allows me to examine the tradeoff between these two concepts that appears to exist in the marketplace.

3.2.4 Convenience

The density of stores within a chain as well as the location of households leads to an environment where chains differ in terms of their relative convenience to shoppers. Bell, Ho and Tang (1998) explore the tradeoff between the fixed and variable costs of shopping and find that consumers minimize their total cost of shopping. In this conceptualization convenience, or lack thereof, is a fixed cost of shopping. Others have found an important role for convenience as well e.g. Arnold, Roth and Tigert 1981; Arnold, Oum and Tigert 1983). However, Singh, Hansen, and

Blattburg (2006) find that the effect of distance is quite small. I account for the effect of convenience in the model by including the distance to the closest outlet of a given chain.

3.2.5 Habit

Consumers will likely develop a habit over time and patronize the same chains as they learn about the price and assortment levels of each store. Brand and SKU choice models typically show strong effects for state dependence (e.g., Seetharaman, Ainslie and Chintagunta 1999; Inman, Park and Sinha 2007) and it is likely that this will play a role in chain choice as well. I include whether or not the chain was used in the previous time period as a variable in the model.

3.3 MODEL

3.3.1 Consumer Store Choice and Utility Function

I consider a market in which there is a set of households (H) that purchase from a set of retail chains (J) and where household purchases are observed over a timespan (T). For each time period t, households must choose the retail chains from which they make their purchases. I let the indicator variable D_{hjt} represent the choice of whether household h patronizes retail chain j in time period t as follows,

$$D_{hjt} = \begin{Bmatrix} 1, \text{ if chain j is utilized} \\ 0, \text{ otherwise} \end{Bmatrix} \tag{1}$$

Since consumers are uncertain about the environment that they will encounter when arriving at chain j, consumers will maximize their expected utility based upon the environment they anticipate they will encounter:

$$U_{hjt} = \beta_1 + \beta_2 Q_{hft} + \beta_3 Q_{hnt} + \beta_4 P_{hnjt} + \beta_5 P_{hfjt} + \\ \beta_6 AB_{ht} + \beta_7 AD_{ht} + \beta_8 Dist_{hj} + \beta_9 RM_h + \beta_8 SD_{hjt} + \varepsilon_{hjt} \quad (2)$$

Where Q_{hft} and Q_{hnt} is the demand for food and non-food items respectively for household h in period t, P_{hfjt} is the price image of food products needed at time t, P_{hnjt} is the price image of non-food products needed at time t, AB_{ht} is the household-level assortment breadth requirement, AD_{ht} is the household-level assortment depth requirement, $Dist_{hj}$ is a measure of the distance to chain j for household h, RM_h is a measure of how remote household h is, and SD_{hjt} is a measure of state dependence for household h to chain j at time t.

3.3.2 Consumer Purchase Quantity Decision

I assume consumer weekly needs for food and non-food items are exogenously given and follow an auto-regressive process. Conceptualizing quantity in this way controls for the simultaneity problem where quantity may also be affected by the store choice decision. In order to determine how consumer demand influences store choice, I create an expression for the expected quantity of both food and nonfood products that will be required during the next shopping occasion. The quantity of food and non-food items needed are expressed as the following

$$Q_{hft} = \gamma_f + \delta_f X_{hft} + \psi_{hft} \quad (3)$$

$$Q_{hnt} = \gamma_n + \delta_n X_{hnt} + \psi_{hnt} \quad (4)$$

where γ_f and γ_n are intercept coefficients, δ_f and δ_n are estimated parameters, and the variables of the X_{hft} and X_{hnt} matrices are as follows:

$Lag\_Q_{ht} =$ Number of items (food items for matrix X_{hft} and nonfood for matrix X_{hnt}) purchased during the last purchase occasion.

Seasonality= Avg. Qty. of food or non-food items purchased by all households in a given week.

HH_Size= Number of members in household h.

Income= Annual income of household h.

Inventory= Inventory level of food or non-food items for household h at time t.

I model inventory using the normal recursive relationship (e.g., Gönül and Srinivasan 1996) as follows:

$$Inv_{ht} = Inv_{ht-1} + PurQty_{ht-1} - \text{Consumption}_{ht-1} \quad (5)$$

Where separate inventory levels are estimated for food and non-food items, Inv_{ht-1} is the inventory level carried by household h at time t-1, $PurQty_{ht-1}$ is the number of items purchased by household h at time t-1, and $\text{Consumption}_{ht-1}$ is the consumption by household h since time t-1. I assume that consumption is constant and the inventory is bounded on the lower end at zero.

I expect errors across equations (3) and (4) to be correlated because of random shocks at the household level that are unobserved in the data, thus I allow for these errors to be correlated by using a seemingly unrelated regression (SUR) estimation.

3.3.3 Price Image

Included in the utility function is the perceived price image of the retail chain. I model price image rather than simply including current price because in the context of retail chain choice, consumers will be uncertain about what prices they will encounter in a given chain due to price fluctuations over time and imperfect recall of prices prior to entering a store. To account for this, I let PI_{hjt} denote the price image of household h for chain j at time t. The definition of price image is conditional on whether the chain was visited in a given week. If the chain was visited, I define price image as a weighted combination of the current period average basket price and the price image of the household at time t-1. If no chain visit was made, price image is not updated. The expression for price image is given as follows:

$$PI_{hjt} \mid (D_{hjt} = 1) = \alpha PI_{hjt-1} + (1-\alpha) P_{jt} \qquad (6)$$

$$PI_{hjt} \mid (D_{hjt} = 0) = PI_{hjt-1}$$

The operationalization of price image in this manner is problematic for two reasons. First, because consumer baskets will differ across time, the average price may vary due to basket fluctuations rather than price fluctuations. Second, certain items may carry more weight in determining the price image of the store. I do two things to mitigate these issues. First, I mean center all items to the category weighted mean price. This will give a more accurate depiction of whether the basket price is indeed high or low, Second, I allow for separate price image processes for both food and non-food items to capture differences across categories. This will allow the test of whether food or non-food price-image has a greater role in determining store choice.

3.3.4 Assortment

Given that retailers position themselves in the market in different formats with different types of assortment, I expect that the assortment level of a retailer will affect the probability of choice for that retailer. However, I do not have information on the store-level. I only have the observed purchase behavior of a subset of the stores' customers. Using this information I could construct an assortment index based on what all of the customers in aggregate purchase but, this information is a noisy signal of the actual assortment of the store and is of little use.

Given this, I create household level measures of assortment to see how household assortment requirements affect store choice. The two measures of assortment address two different types of requirements. The first measure is a measure of breadth of assortment. This measure is created by observing how many different categories a household purchases over the course of the dataset. The Homescan panel contains 1068 categories, and I normalize this construct so that the breadth of assortment ranges from 0 to 1.

The second measure of assortment measures the depth of assortment that a given household uses. This measure is created by observing the total number of SKUs that a household purchases and then dividing that by the number of categories that were purchased. Households that utilize a greater number of SKUs per category could be engaging in variety seeking or simply be willing to use multiple SKUs in a substitutable manner.

3.3.5 Distance

Distance is an important variable in the model as it is a measure of how convenient the store is for a given household. In order to measure distance to retailers from households, I obtained the

geocode for each household and retailer in the market. Distance is then measured to each retailer by using the great circle distance formula, which is simply the distance measured from point to point on the Earth. Because many chains will have multiple retail outlets, I measure distance to the retailer as the closest outlet or the outlet utilized for that purchase occasion.

I also include a second measure of distance in the model which is a variable that I call remoteness. This measure is included because I believe that distance will not simply influence choice in a linear manner. Rather, I observe that some households are not convenient to any of the stores that I examine and may behave differently than households in more populous areas. My point can best be considered through an example. Household 1 who is 5 miles from Grocery #1 and 1 mile from Grocery #2 may strongly value the convenience of Grocery chain #2. However, Household 2, who is 20 miles from Grocery #1 and 25 miles from Grocery #2, may not consider distance to be as important as both stores are relatively inconvenient. Moreover, households who are more remote may have a preference for a retailer with certain characteristics such as a considerable breadth of assortment. Thus, the level of remoteness of a household may lead to a greater probability of choice for a given retailer. The remoteness measure is created by taking the minimum distance to any of the chains that are examined.

3.3.6 State Dependence

The model also includes a measure of state dependence to examine the effect of previous shopping behavior. I expect that where consumers shopped in previous weeks will have an influence on where consumers shop in the current period. This variable takes the value of 1 if the chain was patronized in the previous time period and is 0 otherwise.

3.3.7 Estimation

For the estimation, I employ a simulated maximum likelihood method where I assume that the errors across models follow a multivariate normal distribution. This gives rise to a multivariate probit model. The probability that a household visits chain j at time t is given by the following equation:

$$P(D_{hjt} = 1) = \Phi(V_{hjt}) \qquad (7)$$

Where Φ is the cumulative standard normal distribution and V_{hjt} is the deterministic portion of the utility function U_{hjt}. In the estimation procedure I allow the error terms to be correlated, making this a multivariate probit model and, the likelihood to be maximized it the following:

$$LogL(\alpha) = \sum_{h=1}^{H}\sum_{j=1}^{J}\sum_{t=1}^{T} D_{hjt} * Log[P(D_{hjt} = 1 \mid \alpha)] \qquad (8)$$

3.4 DATA DESCRIPTION

The data for this study was obtained from the Nielsen Company and it comes from two of their products: Homescan and TD Linx. The Homescan panel tracks the purchases from over 125,000 U.S. households across all retail outlets. For the current study, a subset of the data was used as the dataset is comprised of all panelist purchases from the Pittsburgh market for the years 2005-2007. This dataset contains information about the overall basket size and composition at the department level as well as detailed information about each individual item that is purchased. Additionally, the data contains information about the demographics and location of the individual panelists.

The other portion of data comes from the Nielsen TD Linx dataset. This data contains comprehensive information about the store location, sales volume, physical characteristics, and departments within the stores. Using this information along with the Homescan panel, I can obtain precise distances to each store for each panelist. This is superior to many previous papers (e.g., Briesch, Chintagunta and Fox 2008) that operationalize distance using Zip Code centroids.

Using these data sources, I am able to construct a complete purchase history of a given household across all retailers that sell the products of interest. The analysis utilizes data from a wide range of categories. All of the typical consumer staples like items from dry grocery non-food item departments including items like toner cartridges for printers and kitchen gadgets are contained in the dataset. The dataset contains the purchase history of 582 panelists and represents over 250,000 store visits.

3.5 RESULTS

3.5.1 Store Patronage

In Table 8, I include the percentage of houses that patronize each of the stores in a given week. The table shows the patronage level at the six chains that are included in the model, whose names are disguised in order to maintain confidentiality. I examine one store from each format: grocery, mass merchandise, dollar stores, drug stores, and club stores as well as a second grocery store. A second grocery store is examined because the grocery market is more fragmented and represents a high proportion of the total sales for the dataset. The visits for these six chains represent 48% of the total trips in the market studied.

Table 8

Households Visiting Each Chain

Chain	% of Households Making Trips in a Given Week
Mass #1	32.9
Grocery #1	31.3
Grocery #2	12.6
Dollar #1	9.8
Drug #1	9.1
Club #1	6.1

3.5.2 Quantity Process

Table 9 shows the results for the quantity process estimation. Overall the model predicts reasonably well as the system-weighted R^2 is 0.40. For the food quantity process, all predictor variables were significant except for the household income. This makes sense as greater income may not lead to a larger quantity of food items being purchased. The effect of income would likely lead to substitution to higher priced items rather than an increase in primary demand for food. Interestingly, the household inventory was positively associated with food demand. This is counterintuitive as one may expect that the level of food inventory would be negatively associated with demand. This may have occurred because this model is estimated across households and the inventory level is correlated with weekly average household purchase quantity.

The results for the non-food quantity process are substantively similar except that the effect of household size is smaller and the effect of income is now significant. These findings make sense as the effect of non-food items is different than the effect of food items. This is the

case, because food items are affected by the ability to physically consume the product whereas non-food items are not. Thus, I would expect household size to have a smaller effect on quantity and income to now have a positive effect on the quantity of non-food items purchased.

Table 9
Quantity Process Estimation Results

	Food		Non-Food	
	Parameter	P-Value	Parameter	P-Value
Intercept	-9.305	<.0001	-3.430	<.0001
Lag Quantity	0.069	<.0001	0.037	<.0001
Seasonality	0.984	<.0001	1.033	<.0001
Household Inventory	0.024	<.0001	0.007	<.0001
Household Size	2.837	<.0001	0.675	<.0001
Income	0.004	0.5663	0.020	<.0001

3.5.3 Retail Chain Choice Results

The results of the retail chain choice model estimation can be in Table 10. I will present the results in two sections. First, I will discuss the results of the individual chain estimations, and then I will examine the correlation structure of the error terms in the model to comment on the competitive relationship among firms.

Grocery #1. The Grocery #1 results can be found in the first column of Table 3. The estimation shows that all of the independent variables except remoteness and food price image significantly affect the probability of a store visit. Among all stores that I study, it appears that distance has the greatest impact on store visits for this chain. I calculated simulated probabilities from the model parameters to quantify the impact of each independent variable because of scale differences across variables. In doing so, I find that households that are 5 miles from Grocery

Chain #1 have a 55% probability of a store visit and that this probability drops to 48% when the distance is increased to 10 miles.

The biggest impact on store visits is the state dependence variable. The probability of a store visit is 55% if the chain was visited in the previous time period but this probability drops to only 24% if the chain was not visited in the previous week. Other interesting findings for this chain were the assortment variables. I found that households that preferred greater depth in assortment were relatively likely to visit grocery stores but those households who preferred greater breadth of assortment were less likely to visit Grocery Chain #1. This is a counterintuitive finding given that this chain does have a considerable breadth of assortment as defined by the Nielsen categories. A complete list of the simulated probability studies can be found in Table 11.

Grocery #2. The results of Grocery Store #2 differ from Grocery Store #1 in several important ways. First, the food price image is now statistically significant and important. Table 11 shows that if the food price image is -1 the probability of a store visit is 55% but if the food price image increases to 1, the probability of a store visit drops to 21%. Also, like Grocery Chain #1, households with a greater breadth requirement have a greater probability of a store visit, but unlike Grocery chain #1, households who utilize less of the assortment depth, on average, have a greater probability of a chain visit. Like all chains, the state dependence variable is important. If the chain was not patronized in the previous week, the probability of a chain visit is only 2% but this probability increases to 24% if a chain visit was made.

Table 10

Chain Choice: Estimation Results

	Grocery #1		Grocery #2		Mass Merch #1		Drug #1		Club #1		Dollar #1	
	Parameter	P-Value	Parameter	P-Value	Parameter	P-Value	Parameter	P-Value	Parameter	P-Value	Parameter	P-Value
Intercept	-0.156	0.543	-0.406	0.009	-1.628	<.0001	-1.635	<.0001	-1.737	<.0001	-0.665	<.0001
Predicted Food Quantity	0.023	<.0001	0.020	<.0001	0.014	<.0001	-0.012	<.0001	0.002	0.474	0.009	0.001
Predicted Non-Food Quantity	0.010	0.011	0.036	<.0001	0.024	<.0001	0.041	<.0001	0.028	<.0001	-0.010	0.048
Food Price Image	-0.153	0.102	-0.454	<.0001	-0.174	<.0001	-0.038	0.017	-0.035	0.071	-0.453	<.0001
Non-Food Price Image	-0.040	0.020	-0.026	0.000	-0.013	0.203	0.020	0.003	-0.025	<.0001	-0.040	0.298
Assortment Breadth	-1.756	<.0001	-1.789	<.0001	1.045	<.0001	-2.209	<.0001	1.990	<.0001	-0.118	0.701
Assortment Depth	0.112	<.0001	-0.074	0.000	-0.086	<.0001	0.201	<.0001	-0.215	<.0001	-0.008	0.743
Distance	-0.036	<.0001	-0.009	<.0001	-0.001	0.102	-0.006	<.0001	-0.002	0.065	0.000	0.655
Remoteness	-0.001	0.127	-0.005	0.043	0.010	<.0001	0.000	0.421	0.000	0.650	-0.006	<.0001
State Dependence	0.840	<.0001	1.378	<.0001	0.628	<.0001	0.802	<.0001	0.262	<.0001	1.269	<.0001

Table 11

Simulated Probabilities

	Groc #1	Groc #2	Mass #1	Drug #1	Club #1	Dollar #1
P(Trip|Food Basket =20)	0.59	0.21	0.18	0.21	0.08	0.18
P(Trip|Food Basket=10)	0.50	0.16	0.15	0.24	0.08	0.16
P(Trip|Non-Food Basket =10)	0.59	0.21	0.18	0.21	0.08	0.18
P(Trip|Non-Food Basket=5)	0.57	0.16	0.15	0.15	0.06	0.20
P(Trip|Food Price Image=1)	0.59	0.21	0.18	0.21	0.08	0.18
P(Trip|Food Price Image=-1)	0.71	0.55	0.29	0.23	0.09	0.50
P(Trip|Non-Food Price Image=1)	0.59	0.21	0.18	0.21	0.08	0.18
P(Trip|Non-Food Price Image=-1)	0.62	0.23	0.19	0.19	0.09	0.20
P(Trip|HH Uses 40% of Categories)	0.55	0.24	0.20	0.15	0.12	0.18
P(Trip|HH Uses 20% of Categories)	0.68	0.36	0.15	0.28	0.06	0.19
P(Trip|HH Uses 4 SKUs/Categories)	0.59	0.21	0.18	0.21	0.08	0.18
P(Trip|HH Uses 2 SKUs/Categories)	0.51	0.26	0.23	0.11	0.17	0.19
P(Trip|Distance=5 Miles)	0.55	0.24	0.20	0.15	0.15	0.18
P(Trip|Distance=10 Miles)	0.48	0.22	0.20	0.15	0.15	0.18
P(Trip|Remoteness =20 miles)	0.59	0.19	0.22	0.21	0.08	0.16
P(Trip|Remoteness=10 miles)	0.59	0.21	0.19	0.21	0.08	0.17
P(Trip|Trip Last Week)	0.55	0.24	0.20	0.15	0.12	0.18
P(Trip|No Trip Last Week)	0.24	0.02	0.07	0.03	0.07	0.02

Mass Merchandiser #1. The results of the Mass Merchandiser #1 estimation show that all factors are statistically significant except for distance and non-food price image. The effect of distance is interesting. If a model is estimated without the remoteness variable, the effect of distance was actually positive and statistically significantly. I surmised that this was because households that were not close to any of the chains were using mass merchandiser #1 as a source for a large proportion of their baskets. Thus, because competitive distances were not in the model, the model captured this effect via a positive relationship for the distance parameter. A parsimonious way to capture the effect of competitive distances was to include the remoteness variable in the model. When this variable was included, the effect of distance became negative and nonsignificant, and the remoteness variable was positive and significant. The effect of remoteness was such that households who were 10 miles from any of the chains had a 19% probability of a store visit and households who were 20 miles from any of the chains had a 22% probability of visiting mass merchandiser #1.

The assortment variables were also interesting for mass merchandiser #1. Households that had utilized a wider breadth of assortment but less depth of assortment had a higher likelihood of patronizing mass merchandiser #1. This is in line with the strategy of typical mass merchandisers, especially in the age of the supercenter concept, as many of these firms carry many product categories at the expense of category depth. The assortment variables were relatively important as households that used 40% of the breadth of categories had a 20% probability of a chain visit while those households who used only 20% of the breadth of assortment had a 15% probability of store visit. For the assortment depth variable, households who used an average of 4 SKUs/category had an 18% probability of store visit while those that used only 2 SKUs/category had a 23% probability of store visit.

Drug #1. All of the independent variables except remoteness are statistically significant for Drug Chain #1. One interesting trend is that Drug Chain #1 attracts households with a smaller food basket requirement. This is the only chain where this is the case. All else equal, you might expect households with greater requirements to make more visits to all chains. However, presumably due to the positioning or assortment of Drug Chain #1 households with smaller food requirements visit Drug Chain #1 with greater probability. The probability that a household with an expected food demand of 10 items would have 24% probability of visiting the chain whereas a household with an expected food demand of 20 items would have 21% probability of a chain visit.

The effect of assortment on the patronage probability of Drug Chain #1 is such that the households with lower breadth requirements but greater depth requirements visit the chain with greater probability. Households that utilize 40% of the assortment breadth have a 15% probability of store visit while those that utilize 20% of the assortment breadth have a 28% probability of store visit. For assortment depth, households that use 4 SKUs/category on average, have a 21% probability of a chain visit while those households that use 2 SKUs/category on average have only an 11% of chain visit.

Club #1. For Club Chain #1, non-food basket size, non-food price image, the assortment variables and state dependence were statistically significant. Interestingly, neither of the food variables or distance variables were statistically significant. Thus, it appears that within the context of this market, distance was not an important factor for the club chain. Consistent with the strategy of many club stores, households that utilize greater category breadth but lower category depth had a greater probability of visiting this chain. Households that used 40% of the category breath had a 12% probability of a chain visit while those that used 20% of the breadth

only had a 6% probability of a chain visit. Households that used an average of 4 SKUs/category had an 8% chance of chain visit whereas those that used 2 SKUs/category had a 17% probability of store visit.

The other factor that had a large impact on chain visit was state dependence where households that visited the chain in the previous week had a 12% probability of a chain visit but those who hadn't visited the chain only had an 8% probability of a chain visit. While this is a relatively large shift in probability, it appears smaller than most of the other chains. This may be due to the fact that the frequency of visit to club stores is less and a one week lag may not capture this effect entirely.

Dollar #1. Food and non-food basket size, food price image, remoteness, and state dependence were the statistically significant factors for Dollar Chain #1. Interestingly, neither of these assortment variables were significant for this chain in contrast to the other five chains. However, the effect of food price image and state dependence appears to be somewhat large. Instances where the food price image was -1 showed that the household had a 50% probability of a chain visit but when the food price image was 1, the probability dropped to 18%. Also, if the chain was visited in the previous week, the probability of a visit was 18% while when no chain visit was made, the probability of a chain visit dropped to 2%.

Competition Structure. By examining the error term structure of the multivariate probit model, the nature of the competition among firms that I studied can be examined. I classify the competition into three different groups: substitutes (negative correlation), complements (positive correlation), and independent (non-significant correlation). Table 12 contains the results of this analysis.

Two sets of chains have substitutable relationships: Mass Merchandiser #1–Drug #1 and Mass Merchandiser #1—Grocery #1. Additionally, Drug #1 and Grocery #1 have a complementary relationship. This set of results suggests an interesting competitive structure as some households use Grocery #1 in conjunction with Drug #1 to fill out their baskets while other households replace both of these chains with Mass Merchandiser #1. Based on the other coefficients from the estimation, it appears that those who prefer depth may use a combination of the Grocery #1 and Drug Chain #1 while those who prefer breadth and perhaps one-stop shopping use Mass Merchandiser #1. These insights suggest ways for these retailers to expand or reduce their assortment.

Drug Chain #1 and Grocery #2 have complementary relationships with several other chains. It appears that these chains often are used in conjunction with other chains are not used to obtain a households entire breadth of needs. These results suggest that these chains do not fill the role as the primary source for most households. Rather, people are using them to fill some other role such as to exposure to greater assortment or promotional pricing opportunities.

Table 12
Competitive Relationship

Correlation	Parameter	P-Value	Relationship
#1 Grocery-#2 Grocery	0.02	0.240	Independent
#1 Grocery-#1 Mass	-0.04	0.010	Substitutes
#1 Grocery-#1 Drug	0.10	<0.001	Complements
#1 Grocery-#1 Club	-0.03	0.304	Independent
#1 Grocery-#1 Dollar	0.03	0.179	Independent
#2 Grocery-#1 Mass	0.07	<0.001	Complements
#2 Grocery-#1 Drug	0.08	0.002	Complements
#2 Grocery-#1 Club	-0.01	0.605	Independent
#2 Grocery-#1 Dollar	0.01	0.691	Independent
#1 Mass-#1 Drug	-0.11	<0.001	Substitutes
#1 Mass-#1 Club	0.17	<0.001	Complements
#1 Mass-#1 Dollar	0.03	0.141	Independent
#1 Drug-#1 Club	-0.02	0.519	Independent
#1 Drug-#1 Dollar	0.06	0.037	Complements
#1 Club-#1 Dollar	-0.05	0.118	Independent

3.6 DISCUSSION

3.6.1 Summary and Generalizations across Chains

In this essay, I examine the factors that affect the retail chain choice at the household level for the household's entire basket of needs. I estimated a multivariate probit model to quantify the role that various factors play in this decision. The model was estimated at the chain level and the following generalizations can be observed from the model:

- State dependence has the largest impact on trip probability across chains.
- Food price image has a bigger impact than non-food price image for most chains.
- The impact of assortment across chains varies in interesting ways.

- Distance plays a small role in the chain choice process.
- With a few exceptions, households with larger requirements have a higher probability of trips to the various chains.

I found that many factors were important in the chain choice decision but the role of state dependence was the largest factor for most chains. This seems to suggest that habit is an important factor in the chain choice decision. Interestingly, food price image played an important role in the choice decision for most chains but non-food price image was often of smaller magnitude. This suggests that the price of food plays a bigger role in the store choice decision and this may have implications for pricing strategy.

The role of assortment varies in interesting ways across chains. The mass merchandiser and club store attract customers who use a greater breadth of assortment but less depth in assortment. This is consistent with the strategy typically employed by these types of stores. For the drug chain and grocery chain #1 households who use a greater level of depth but use a lower level of breadth have a greater probability of a store visit. This too may have implications for these retailers as many grocery and drug stores are expanding breadth of their assortment and need to be careful not to jeopardize their current customer base if they sacrifice depth to achieve this breadth.

Interestingly, distance plays a small role for all chains except Grocery #1. This suggests the relative unimportance for convenience in the chain choice decision. Future research should examine this further to see if a better conceptualization of distance could better explain the role of convenience. I only observe where the households live not where they work or other factors that may explain why a chain may be convenient to the household. Finally, I find that households

with larger demand for food or non-food items typically have a greater probability of a chain visit.

3.6.2 Implications for Marketers

This research provides several interesting implications for the retail industry. First, I believe the fact that food price image plays a greater role in chain choice than non-food price image is an important insight for retailers. This may mean that food prices matter more to consumers or that they are easier to compare across retailers. Either way, promotions and low prices should be utilized for food categories rather than non-food categories to help drive store traffic. Non-food prices may be less important and could be higher to maximize profits.

Second, the assortment results suggest ways for retailers to expand or trim their assortment to satisfy their customer base. If a given chain's customers prefer greater depth rather than breadth, assortment decisions can be made accordingly. Clearly, other considerations such as category profitability will drive this as well, but these results could provide additional information.

Finally, an analysis such as this could be useful for retailers to discovery which firms they are in competition with and which firms are used in a complementary fashion with their chain. Knowing this information could provide a firm with data detailing how to compete with the other chains. If a chain is a substitute for your chain, you may want to develop a plan to attract the customers directly from that firm. However, knowing a firm has a complementary relationship with your firm may also provide insights for competition. You could study why this relationship exists and examine what role that firm is providing for your customers that you are not. If this can be discovered, additional opportunities could be created with existing customers.

3.6.3 Future Research

While this essay provided some interesting initial insights into the retail chain choice decision, future research should be done in this area to add to these results. First, future research should incorporate heterogeneity into models of the chain choice decision. A model that estimates latent segments or a continuous representation of heterogeneity may provide additional insights into whether differences in the importance of the variables exist across households.

Second, research should be done to see how consumers arrange their trips in a temporal manor. For example, if multiple trips are made in one week, are they all on the same day and in a similar location. This line of research may further explain the role of convenience in the chain choice decision and may be particularly important in light of the recent increase in energy costs.

Finally, research into role of assortment should be undertaken to see if certain types of categories have more importance in the chain choice decision. This may provide some insight to retailers to help them expand their assortments in the ongoing channel blurring phenomenon. The retail environment continues to evolve over time and should be a fruitful research area for many years.

4.0 ESSAY 3

Is the Robinson-Patman Act Dead?

4.1 INTRODUCTION

The Robinson-Patman Act (the RP Act) was passed in 1936 in order to combat a new and growing threat to the independent retailer: the chain store. In essence, the act prohibits suppliers from discriminating in price among competing buyers and buyers from knowingly receiving discriminatory prices. While there are defensible forms of price discrimination, the act was put in place to protect independent retailers from the significant buying power of the larger chain stores. Given the existence of this statute, I would expect that the retail environment would continue to have strong independent retailers competing with chain stores. However, this is not the reality that is observed.

The current environment is such that large chains are dominating across all types of retailers. Examples of this supremacy can be seen in formats like grocery stores, which are dominated by chains like Kroger's, Publix and now Wal-Mart, and also drug stores where large

chains like CVS, Walgreen's, and Rite-Aid have a large market share. The relative power of chains can be best seen in drug stores where the total store count declined by 8% from 1997-2002 but the store count of the three largest chains increased by 44%. Additionally, grocery stores have seen a considerable concentration of power as well. In 1997 the top 4 chains had 20.4 % of the store count and this increased to 32.5% in just 5 years[5].

Moreover, there is evidence to suggest that firms are using their size to pressure suppliers to achieve lower input prices. One prominent contemporary example is Wal-Mart, who is currently the largest retailer in the United States. While much of its growth in power has been attributed to its logistical and operational efficiency, suppliers also suggest that Wal-Mart uses its size to gain better prices (Facenda 2004). Wal-Mart expects and gets the lowest price in the market and suppliers trying to do otherwise may suffer dire consequences (e.g., Useem 2003; Smith 2002). In this essay, I seek to understand why THE RP ACT is failing to meet its intended goal and whether it is still relevant to business practitioners.

When the RP Act was enacted the prevailing populist attitude was that protecting small businesses from larger chain stores was an important goal. Over time, that attitude has changed and with it, the meaning of competitive harm under the RP Act. Originally, competitive harm meant showing that a competitor was injured. Thus, if price discrimination led to a company going out of business or losing profits due to declining market share, competitive harm could be proven. However, this interpretation changed over time and ultimately a new standard for proving competitive harm was formed in the *Brooke Group v. Brown & Williamson*[6] case which was decided in 1993. In this case, the Supreme Court made clear its interpretation of the Act and heightened the standard for showing competitive injury for plaintiffs seeking damages.

[5] Data from 1997 & 2002 U.S. Economic Censuses and Company Annual Reports
[6] Brooke Group Ltd. v. Brown & Williamson Tobacco Corp. (92-466), 509 U.S. 209 (1993)

After Brooke Group, showing competitive harm requires showing that a rival priced below their costs and had a reasonable prospect of recouping their investment in below cost pricing. To show that a firm recouped their investment in below cost pricing, plaintiffs must show that as a consequence of the price discrimination consumers ultimately pay higher prices. Recoupment could occur in any market but one scenario where recoupment is likely is if the price discrimination drives a competitor from the market and a monopoly is created. Then, the surviving competitor can raise prices and enjoy monopoly profits. Thus, competitive harm no longer means harming a competitor, it means harming the consumers of the goods. This ruling clarified the government's position on the RP Act and made the act more consistent with other antitrust statutes such as the Sherman Act. However, in doing this, it seems the Supreme Court has made gaining relief under the act much more difficult; thereby leading us to question whether the act is still relevant to businesses.

It is within the context of this environment that I examine the Robinson-Patman Act to quantify how the changes in the legal interpretation of the Act affect the outcome of cases in federal court. While other scholars have examined the effect of the Brooke Group ruling from a legal perspective (e.g. Baker 1994; Denger and Herfort 1994), to my knowledge, this is the first attempt to empirically examine the effect of the ruling, quantifying the actual risk faced by businesses with the goal of explaining how the Brooke Group ruling affects case outcome.

To this end, I collect data on the outcome of the RP Act cases in the federal court system for 25 years from 1982 to 2006. I use this data to estimate a model where I empirically examine whether the likelihood of success for plaintiffs has decreased following the Brooke Group ruling. I account for other factors that may explain the relative success of plaintiffs by including characteristics of plaintiffs and defendants as well as characteristics from the case. Additionally,

I include a structural break in the model's parameters following the *Brooke Group v. Brown & Williamson* Supreme Court ruling which allows us to study how the effect of case characteristics changes in the aftermath of this ruling. From this analysis, I find evidence that the Brooke Group ruling significantly decreased the probability of a plaintiff winning a Robinson-Patman case. The decrease in probability is particularly evident in primary-line Robinson-Patman cases and cases where the defense brought up the issue of competitive harm. Additionally, I find the importance of plaintiff resources changes after the Brooke Group ruling. While small plaintiffs are significantly more successful than large plaintiffs before Brooke Group, this result reverses afterward and large plaintiffs do better than their small counterparts.

Much has been written about the RP Act since its passage in 1936. Economists and antitrust lawyers have long debated the merits of and problems with the RP Act. For example, early discussions address whether the RP Act is pro- (Posner 1976) or anti-competitive (Bork 1978; 376-410). Economists have also examined the implications of the RP Act for welfare distribution and market efficiency. Ross (1984), for example, empirically argues that the RP Act may have harmed grocery chains without any benefit to other firms. Katz (1987) and O'Brien and Shaffer (1994) theoretically measure the welfare effects of prohibiting price discrimination in intermediate goods markets, such as wholesale. These writings have focused on the RP Act from the perspective of antitrust economics. As such, they attempt to resolve, in a broad sense, whether the RP Act is good for economic efficiency.

The marketing literature has previously examined the implications of antitrust law for channel management. In particular, the discriminate use of slotting allowances has been a subject of debate (e.g., Bloom, Gundlach, & Cannon 2000; Sudhir & Rao 2006). Some authors argue that prohibiting retailers from charging slotting allowances can be viewed as a means of leveling

the playing field for smaller competitors (Gundlach & Bloom 1998). Sullivan (1997) suggests, in contrast, that the use of slotting fees is not anticompetitive.

While most marketing practitioners and academics are aware of the RP Act, little work in marketing has been done. Stevens (1937), in an early *Journal of Marketing* article, offers support for the RP Act and argues that obtaining lower input prices by negotiating with suppliers is unfair competition and that competitive advantage should be gained through production efficiency not size. Tarpey (1972) examines several FTC cases to assess the legal liability of buyers who bargain for preferential prices under the RP Act. Marks and Inlow (1988) study U.S. District Court actions under the RP Act from 1961 to 1986 to discern patterns in the practice of price discrimination, with a focus on the impact of the RP Act on small business. Spriggs and Nevin (1994) analyze functional discounts and suggest that authorities should be conscious of their pro-competitive effects. This essay, in contrast to much previous work, does not attempt to discuss the merits of or anti-trust laws in general. Rather, I take the law as a given reality and quantify how the law has changed after the landmark Brooke Group ruling.

An examination of this issue is important to marketers for several reasons. First, my findings will have implications in how marketers set their prices. The current interpretation of the RP Act may mean that it is better to maximize profits rather than to avoid price discrimination. I am not advocating breaking the law, rather, the current view is that price discrimination is good for competition when it leads to lower consumer prices. Second, marketing educators should examine how they present the RP Act in their courses. Most introductory marketing textbooks include a section about the Act and simply give the advice that price discrimination is illegal. This advice may train managers to be risk averse in their pricing policies. Finally, my findings have implications for those companies who are contemplating

pursuing a Robinson-Patman case. Because I find that the relative success of plaintiffs differs under different scenarios, marketers should use this information to help decide whether a Robinson-Patman case is a worthwhile investment.

In the following sections of this essay, I first provide a brief description of the RP Act and what is prohibited by the Act. Then I review the history of the act to provide a rationale for why I think that the act is declining in importance and how the Brooke Group ruling has affected case outcomes. Next, I provide a justification for the model specification and formally test how the Brooke Group ruling has affected the outcome of RP Act cases. Finally, I conclude with discussion of the results and the implications for marketers and marketing academics.

4.2 SUMMARY OF WHAT THE ROBINSON-PATMAN ACT FORBIDS

The RP Act has been criticized for its lack of focus, obscure language and excessive discretion to the FTC without guidelines for enforcement (Edwards 1959). As a result, a simple reading of the statement of the Act does not provide a sharp description of what practices are forbidden.

The first major section of the Act is section 2(a) which prohibits sellers from engaging in price discrimination when the buyers are competitors themselves. A typical case under 2(a) involves a supplier offering discounts to a price sensitive intermediary that is not available to other competitors. Franchisors who sell to independents as well as to franchisees may have a strong incentive to discriminate in this way, for example. Because independents are not typically contractually bound to their supplier, they are free to shop for the cheapest price, a privilege not available to the franchisee. An examination of twenty-five years (1982-2006) of case history

showed that the vast majority (82.2%) of cases had allegations falling under section 2(a)[7]. This high percentage is likely due to the fact that price discrimination is essentially forbidden in this part of the Act. Accordingly, whenever an action is brought under any section of the Act, it also often involves section 2(a).

Another major section of the Act is section 2(f) which states that it is unlawful for a person in commerce to *knowingly* induce or receive discrimination in price. In this case, the buyer will violate section 2(f) only if she knew that the seller was offering terms that violate section 2 (a).[8] For example, Wal-Mart has been accused of knowingly inducing its suppliers to offer discounts which are not available to smaller retailers.[9] . Interestingly, only 10.1% of the cases contained allegations under section 2(f). This low percentage may reflect the difficulty to prosecute section 2(f) cases, because to be liable under this section, the requirements for a section 2(a) violation must also be established.

Sections 2(c), 2(d), and 2(e) prohibit sellers and buyers from using brokerage, allowances, and services to accomplish indirectly what sections 2(a) and 2(f) directly prohibit (Clark 1995). Section 2(c) prohibits a seller from paying to or receiving from a buyer anything of value as a commission, brokerage fee or other compensation, or any allowance or discount in lieu thereof, except for services rendered. Sections 2(d) and 2(e) prohibit a seller from granting advertising and promotional allowances or services to a buyer unless these allowances or services are made available to all buyers. Sections 2(c), (d) and (e) were present in 18.4, 7.4 and 10.1 percent of the cases, respectively.

Although the RP Act was enacted to prevent price discrimination, engaging in price discrimination, *per se*, is not a violation of the act. There are certain jurisdictional requirements

[7] A given case may involve multiple sections.
[8] See for example, *A&P vs. FTC*, 440 U.S. 69, (1979).
[9] See *Tires Inc. of Broward v. Goodyear Tire & Rubber Co.*, 295 F. Supp. 2d 1349 (S.D. Fla. 2003).

that must be fulfilled in order for the price discrimination to fall under the RP Act. These requirements are statements written into the act that must be fulfilled in order to have a case for which the RP Act applies. While the requirements are unchanged, the interpretation and relative importance of the requirements change over time. For example, the Act applies to tangible goods, not to discrimination in services. The implications of this requirement are important given the trend of the U. S. economy toward the service sector. The RP Act simply does not apply to most transactions in some of the largest sectors of the economy.

4.3 THE DECLINE IN IMPORTANCE OF THE ROBINSON-PATMAN ACT

4.3.1 FTC Enforcement Policy

The RP Act may be enforced by three different constituents: private parties, the Department of Justice, and the Federal Trade Commission (FTC). The Department of Justice typically enforced the criminal provisions of the Act while the FTC enforced the civil provisions. Private parties can and do bring their own cases with the possible outcome of treble damages as well as attorney fees. The Department of Justice has not enforced the criminal provisions of the Act since the 1960's and the FTC has decreased its activity in civil enforcement as well. In the early history of the act, the FTC did devote considerable resources toward enforcement. For example, in the 1965-1968 timeframe, the FTC investigated an average of 97 complaints and filed 27 cases annually. However, that number declined throughout the next several decades such that the FTC has only filed one case since 1992[10].

[10] 2007 Antitrust Modernization Commission Report and Recommendations April 2007

This lack of enforcement was not because of coincidence or changes in the way that companies do business rather it reflects changes in the way the RP Act was viewed. Originally, the Act was viewed positively because it had a cause that many at the time felt was important (e.g., Stevens 1937). The RP Act was put in place to protect smaller businesses from the buying power of larger chain stores. The popular view in the 1930s was that big business was a problem and the enemy of consumers. Chain stores were feared, so much so that many states enacted taxes for companies who opened multiple outlets in a given state. An example of chain store tax is the Texas statute where retailers who had more than 50 stores in the state were taxed $750 dollars per outlet (Ross 1984).

Over time this view changed as economic analysis improved and calls were made to better align the RP Act with the broader antitrust laws. The purpose of antitrust laws inherently is to increase competition. By trying to reduce price competition and help certain buyers, many viewed the RP Act as a deterrent to competition. In fact, as early as the 1955 report by the Attorney General's National committee to Study Antitrust Laws, the courts of the United States were being urged to reconcile the position of the RP Act with other antitrust laws. The federal government periodically commissioned reports such as the 1955 study and most come to the same conclusion that aligning the RP Act with the other antitrust laws was an important goal. The FTC has adopted a position similar to these committees and as such they have backed away from government enforcement of the act. Additionally, the Department of Justice in a 1977 report indicated their position on the act by saying that it was based on "questionable economic assumptions prevalent in the 1930s[11]." In spite of the lack of government enforcement, the RP Act remains law and private parties can and do pursue cases in the federal court system.

[11] Report on the Robinson-Patman Act, United States Department of Justice, 1977

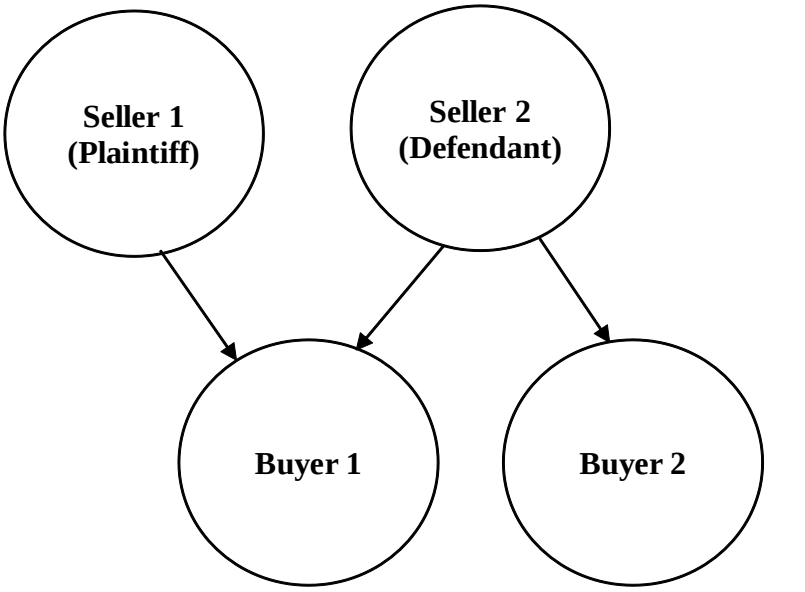
4.3.2 Competitive Harm

Competitive harm is perhaps the most complex and debated issue of the RP Act since it was enacted. Section 2(a) of the act prohibits price discrimination that injures any level of competition in distribution. Therefore, if a plaintiff fails to show that competition was harmed, the case is dismissed. The burden of proving harm to competition is on the plaintiff, thus, the issue of harm to competition is salient in many cases, as defendants will often make a motion to dismiss based on the fact that competition was not harmed, leaving plaintiffs with the burden of showing that it was. The most common RP Act cases are primary-line and secondary-line violations. In primary-line violations, competition between different sellers may be injured when one of them engages in price discrimination while selling to at least one of their common customers. Figure 7 shows a typical primary-line discrimination scenario. In this simple example there are two sellers denoted as Seller 1 and Seller 2 who are both selling to a common buyer known as Buyer 1. If, for example, Seller 1 has a price of $2.00 per unit and Seller 2 has a price of $1.50 per unit for Buyer 1 and Seller 2 is also selling to a second buyer (Buyer 2) at a higher price of $2.00 per unit, a primary-line price discrimination claim may be possible, if the jurisdictional requirements of the RP Act are fulfilled. In this claim, Seller 1 would be the plaintiff and Seller 2 would be the defendant.

In secondary-line violations, competition between customers of a seller may be lessened if the seller differentiates between them in price. Figure 8 shows a typical secondary-line discrimination scenario. In this simple example there are two buyers denoted as Buyer 1 and Buyer 2 who are both buying from a common seller known as Seller 1. Let’s say for example that Seller 1 has a price of $2.00 per unit to Buyer 1 and a price of $1.50 per unit to Buyer 2. If

the other requirements of the act are satisfied, Buyer 2 may be able to state a secondary-line price discrimination claim against Seller 1 under section 2a and Buyer 2 under section 2f. But, to properly assert an RP Act violation, a plaintiff must do more than show a mere price difference; they must show competitive harm as well.

Figure 7
Typical Primary-Line Case



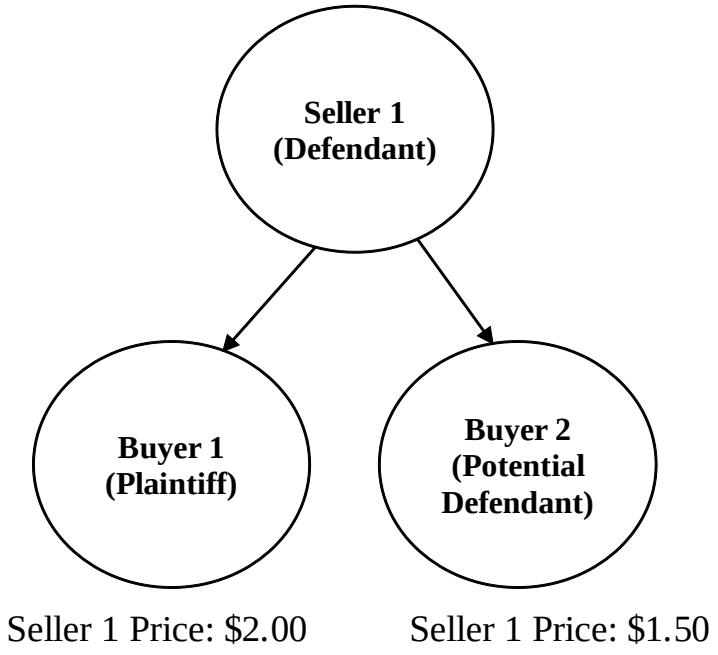
Seller 1 Price: $2.00 Seller 2 Price: $2.00
Seller 2 Price: $1.50

To establish competitive harm in secondary-line violation, the plaintiff has two lines of attack. The first requires the plaintiff to show that price discrimination caused damage to competition, not simply damage to a competitor. Two conditions are necessary to establish this. The first is whether the "favored" buyer and the "disfavored" buyer are competing for the same customers. If not, then the RP Act is not violated. The interpretation of what the same customers constitute was clarified in *Volvo v. Reeder*[12] where the Supreme Court ruled that the same customers meant that both competing buyers must sell to common customers not just into the

[12] Volvo Trucks North America, Inc. v. Reeder-Simco GMC, Inc., 126 S. Ct. 860 (2006).

same market. Second, the plaintiff must prove either loss of downstream sales or that the disfavored buyer was forced to reduce its output price to retain sales[13]. This then must ultimately lead to higher prices for the customers of the two buyers. Because this chain of causality is difficult to show, directly showing competitive harm in a secondary-line is not an easy task.

Figure 8
Typical Secondary-Line Case



As an alternative to directly showing competitive injury, a plaintiff can utilize the "Morton Salt" inference to establish a violation (*FTC* v. *Morton Salt Co.,* 334 U.S. 37, 43). Under this method, injury can be inferred if the disparity in price is sufficiently large and occurred over a substantial amount of time. Admittedly, the Morton Salt rule may appear inconsistent with the notion of preventing unfair competition. In fact, many argue that the Morton Salt rule does the opposite by punishing efficient buyers and protecting inefficient ones (Stancil 2004). Nevertheless, the precedent remains and has been used successfully. In *Flash*

[13] See for example, *Falls City Indus., Inc. v. Vanco Beverage, Inc.,* 460 U. S. 428 (1983)

Elecs. v. Universal Music, 312 F. Supp. 2d 379 (E.D.N.Y 2004), the RP Act claim survived a motion to dismiss with the judge stating that, "a prohibited effect on competition may be inferred from evidence that an individual competitor suffered injury from 'a substantial price difference over time.'"

The judicial interpretation of primary-line injury under the RP Act has evolved over the course of the Act's history. The original interpretation of the act was that injury to a competitor and injury to competition was synonymous. Consequently, if the price discrimination by the defendant was shown to cause injury to another competitor (e.g., lost profits, exit business) then an RP Act case could be proven. An early case where this position is laid out is Utah Pie Co. v. Continental Baking Co., 386 U. S. 685 (1967). In this case, the Supreme Court reversed an appeals court ruling that overturned a jury ruling for the plaintiff.

Utah Pie was a private party case where the plaintiff was a regional pie baker facing increased competition by national bakers. Continental Baking, a large pie baker, slashed its price in the Salt Lake City market below the cost to make the pies in order to gain market share. Other large pie bakers in the market slashed their prices as well. Utah pie responded to this by filing a price discrimination suit seeking an injunction and treble damages.

The original trial ended in a jury ruling for Utah pie but the Court of Appeals overturned this verdict. The Supreme Court decided to hear the case and held that showing below cost pricing was enough to show "predatory intent" and that the jury ruling in favor of the plaintiff was warranted. Critics at the time felt that this ruling made showing predatory pricing too easy (e.g., Bowman 1967; Elzinga and Hogarty 1978). The main argument of the detractors was that declining prices are inherently good for consumers. And, unless a price war creates a monopoly or a market structure where one competitor has significant market power such that prices are

subsequently raised, a market where prices are declining is a sign of healthy competition. It is this type of competition that antitrust laws were put in place to try to foster.

4.3.3 Brooke Group vs. Brown and Williamson

It was twenty-five additional years until the high court decided to revisit the issue of competitive harm in primary-line RP Act cases. In the intervening years, many argued that showing competitive harm in RP Act cases should have the same requirements as showing injury inflicted by predatory pricing schemes actionable under section 2 of the Sherman Act. There are two prerequisites for a plaintiff seeking to establish a competitive injury under the Sherman Act. First, the plaintiff must prove that the prices complained of are below an appropriate measure of its rival's costs. Second, the plaintiff must show that the competitor has a dangerous probability of recouping its investment in below cost prices.[14] In order to show that the investment in below cost prices could be recouped, a plaintiff must be able to show that consumer prices ultimately increased to a level above where they before the discrimination and that this high price level is sustainable. *Utah Pie* only required showing that a defendant lowered prices to a level that were below the cost to make the goods. The second requirement of showing recoupment is a much higher hurdle.

The interpretation of competitive harm in primary-line cases was brought in line with the Sherman Act by the Supreme Court in *Brooke Group Ltd. v. Brown & Williamson Tobacco Corp*. (92-466), 509 U.S. 209 (1993). This case involved two cigarette manufacturers who were among the six largest competitors in the market. Brooke Group faced declining market share in the cigarette industry and tried to boost its sagging market share by introducing a generic

[14] See *Brooke Group Ltd. v. Brown & Williamson Tobacco Corp.*, 509 U.S. 209, 222, 125 L. Ed. 2d 168, 113 S. Ct. 2578 (U.S. 1993).

cigarette to the market. Brown and Williamson responded to this by introducing its own line of generic cigarettes at the same price as Brooke Group. However, when the two companies were utilizing the same distributor, Brown and Williamson offered discriminatory rebates.

Brooke Group's theory of price discrimination was that this action by Brown and Williamson would force Brooke Group to retreat from the generic market and ultimately lead to higher consumer prices for generic cigarettes. In their case, Brooke Group effectively showed that Brown and Williamson priced below cost and also argued that this was irrational without the prospect of recoupment, but they did not show that Brown and Williamson could actually recoup their investment in below cost pricing. The Supreme Court ruled that because Brooke Group could not show that the actions of Brown and Williamson ultimately would lead to higher prices for generics, they were not entitled to relief under the RP Act. The court ruled this way because they felt that maintaining supracompetitive prices, at the scale needed, was highly unlikely given the cigarette market structure.

The cigarette market structure at the time was such that Brown and Williamson's market share of the entire cigarette market never exceeded 12% and that there were several other large competitors in the market such as Philip Morris and R. J. Reynolds. These other large manufacturers could easily enter the generic market segment if prices became sufficiently attractive. Given this, the court felt that Brown and Williamson would not have a reasonable prospect of recouping their investment in below cost pricing therefore consumers were not harmed, rather they benefited from the below cost pricing.

The court stopped short of saying that recoupment was impossible in an oligopoly but indicated that recoupment was unlikely unless the pricing scheme ultimately created a monopoly. The fact that they did not adopt a "Chicago School" view and consider any instance of predatory

pricing in an oligopoly as irrational was encouraging to some commentators (Baker 1994). However, most view the Brooke Group ruling as a major blow that seriously dwindled the possibility of a plaintiff winning a primary-line RP Act case (e.g. Denger and Herfort 1994; Glazer 1994).

In order to substantiate the legal analysis that the Brooke Group ruling was deleterious to the prohibitions of the RP Act, I empirically examine whether the likelihood of a plaintiff winning an RP Act case has decreased after the ruling. To my knowledge, this is the first such attempt to empirically measure the effect of the Brooke Group ruling. I do this by examining a data set created from twenty-five years of federal cases (1982-2006) where an RP Act claim was made.

4.4 EMPIRICAL STUDY

4.4.1 Model

To test how the Brooke Group ruling has changed the outcome of Robinson-Patman Act cases, I develop a model where the case outcome is the dependent variable given as follows:

Y= 1 if the case is ruled for the Plaintiff

Y=0 if the case is ruled for the Defendant.

Cases that are classified as rulings for the defendant include several legal outcomes: summary judgment for the defendant, dismissal of the plaintiff's claims, and jury rulings for the defendant.

Rulings for the plaintiff include: summary judgment for the plaintiff, failure to dismiss the plaintiff's claims[15] and jury rulings for the plaintiff.

The model that I estimate is a probit model. The goal of this analysis is to show whether the Brooke Group ruling changed the outcome of RP Act cases and also to show how the ruling impacts the effect of various case characteristics. That is, I want to show if case characteristics and plaintiff and defendant characteristics play a role in case outcome and if that role changes in the aftermath of the Brooke Group decision. In the following sections I provide a justification for the independent variables that are included in the model and provide the expectation of what I should find upon estimating the model.

Brooke Group Ruling. I include a variable in the model that indicates whether the case occurred before or after the Brooke Group ruling. This variable is used in two ways. First, I include the variable in the model by itself as a main effect. Second, I use it to create interaction variables with all other variables in the model. These interaction variables allow us to examine whether the effects of the independent variables change after the Brooke Group ruling.

This method of constructing the variables means that the coefficients of the model can be interpreted in the following manner. The main effects parameters of all of the independent variables will be the magnitude of the effect of that variable before the Brooke Group ruling. The interaction of the independent variable and the Brooke Group indicator variable will be the change in effect of that variable after Brooke Group. Thus, to get the magnitude of the effect of the variable after Brooke Group, the main effect and interaction variable must be added together.

[15] I recognize that there is a censoring issue in these cases because additional rulings for a given case may occur after the data collection is completed. However I do not have data on the status of the case as to whether it was subsequently settled out of court or if future motions are pending in front of Federal Court. As more time passes from these rulings we become more confident that no future rulings are pending. Two facts mitigate this issue. First, I update the database with rulings from existing cases through 1/31/08, so that all cases have at least two years of additional time for appeals court rulings. Second, any rulings that are erroneously classified as rulings for the plaintiff work counter to our main hypothesis as we are looking for a tougher environment after Brooke Group.

The expectation is that I will not find a significant main effect for the Brooke Group variable because the Brooke Group ruling will only apply to cases that have certain characteristics. Thus, I expect that the effect of the Brooke Group ruling will be seen in the interaction variables.

Type of case. One aspect that should impact the relative success of plaintiffs is the type of case: primary-line or secondary-line. This needs to be taken into account because as was explained in the previous section of this manuscript, the judicial interpretation of competitive harm is different for primary and secondary-line cases. Because of the different standards, I do not have a strong expectation of whether primary-line cases or secondary-line cases will be more likely to be ruled for the plaintiff. However, after the Brooke Group ruling the probability of a ruling for the plaintiff should decrease most in primary-line cases.

No harm to competition defense. The issue of competitive harm was explained in detail in a previous section of this manuscript. This variable is included in the model because the change in interpretation of competitive harm by the Brooke Group ruling should lead to a decrease in success for plaintiffs in cases where a competitive harm ruling was made. While there are other defenses available to defendants (e.g., meeting competition, cost justification), these defenses are not addressed in the Brooke Group ruling thus should not change because of the Brooke Group ruling. Therefore, I aggregate cases with all other defenses into one category and put cases where competitive harm was used in the other category. A summary of the prevalence of defenses used in RP Act cases is contained in Table 13.

Table 13
Prevalence of Defenses in RP Act Cases

Defense	% of Cases
Cost Justification/ Functional Discount	5.3
Changing Market Conditions	0.3
Meeting Competition	1.6
Functional Availability	4.7
Fee for Services Rendered	5.7
No Harm to Competition	42.3

Resources. I believe that resources will play an important and interesting role in the outcome of RP Act cases. The measure of resources that we include in the model is company revenues. I classify both plaintiffs and defendants as large if their revenues are greater than 50 million dollars a year. The role of resources is complicated by the history of the act. On one hand, the Act is written and may be interpreted in a way to protect small companies. An example of this is the aforementioned Morton Salt rule, which is recognized as a way to remove the burden of proving market-wide competitive injury for small retailers.[16] Accordingly, being smaller may not be such a burden for a plaintiff. On the other hand, involvement in an RP Act case is undoubtedly a costly endeavor. In order to successfully win a case as a plaintiff, a prima facie case must first be presented to Federal District Court. This may involve multiple motions and briefs to the court. If the prima facie case is made, a jury trial may be held where expert testimony may be required. This suggests that receiving relief under the RP Act is a resource intensive process. Thus, it may be reasonable to expect that firms with greater resources to expend on litigation will have greater success as both plaintiffs and defendants.

[16] See *American Booksellers v. Barnes and Nobel*, 135 F. Supp. 2d 1031 (2001 N.D. Cal.).

Moreover, I expect that the Brooke Group ruling will change the way resources impact the outcome of cases. First, because this ruling places the additional burden of showing recoupment on the plaintiffs, the resources that a plaintiff has may become more important after the ruling. This will make the probability of receiving a favorable ruling after the Brooke Group case more likely for large plaintiffs as compared to smaller plaintiffs. Second, I believe that the Brooke Group ruling will have an opposite effect on defendants. The logic for this is that defeating an RP Act allegation may have become easier. Because of the heightened competitive harm standard, it may be a good strategy for defendants to make an early motion to dismiss based on the fact that there was no competitive harm. Furthermore, the burden of proving competitive harm is on the plaintiff and, if they are unable to do so, the case will end quickly and the resources available to defendants will become less important. Thus, after the Brooke Group ruling large defendants may no longer be better positioned in RP Act cases.

Industry. Industry was used in the model because characteristics of the industry may lead to greater success in pursuing an RP Act case. I classify cases into two broad industries: consumer goods and industrial goods which is consistent with the history of the act. The Act was originally targeted at retail chain stores, which sell consumer goods; hence the judicial interpretation of the Act may lead to an environment where companies in the consumer goods industry have an advantage when pursuing RP Act cases. Thus, I predict that cases in the consumer goods industry will have a greater probability of being ruled for the plaintiff.

However, after the Brooke Group ruling showing recoupment may be tougher in the consumer goods industry. In general, there are more firms competing in consumer markets as compared to industrial markets which are characterized by large buyers and sellers (Kotler and Armstrong 2007). As is evidenced by the Brooke Group ruling, showing recoupment is tougher

when more firms are present in an industry. This is true because competing firms decrease the likelihood that a company can raise prices to a supracompetitive level. Consequently, after the Brooke Group ruling the probability of a ruling for plaintiffs in the consumer goods industry should decrease.

4.4.2 Data

The dataset for this manuscript was constructed by searching for all cases that involved an RP Act ruling during the twenty-five year period from 1982-2006. This time period reflects a sizable and relatively equal amount of time before and after the Brooke Group ruling. In order to find the RP Act cases, I searched the Academic Lexis-Nexus database for federal cases where the RP Act was mentioned. From this search, I examined every record that was returned to see if the case had an RP Act ruling or merely mentioned the Act for some other purpose.

After filtering out cases where the RP Act was merely mentioned, I merged cases where there were multiple rulings at possibly different levels of federal court such that each set of plaintiffs and defendants only represented one case in the final dataset. The case outcome was determined by the most recent ruling in the case. So, for example, if a case was initially ruled for the plaintiff but overturned by the Court of Appeals, the case was recorded as a ruling for the defendant in the final database. The additional variables used in the model were coded by reading the cases. When information that was required was not available from the case record, I searched for other sources for that data.

Information about plaintiff and defendant revenue was not typically contained within the case record. In order to find this data, I searched other sections of the Lexis-Nexus database as

well as the Business and Company Resource Center. This search often returned a value for the actual revenue or a range within which the company revenue was contained. However, not every company could be located from these sources. In these cases, I performed a general internet search to find the data, and if this did not provide the information, I used my judgment to classify the companies as large or small. Typically, when I couldn't find revenue information it was because the company was a small retailer who operated from one location. Therefore, I could reasonably classify them as a small plaintiff or defendant. After performing the data collection process, the final dataset contained 298 cases. Table 14 has summary statistics of the data for both before and after the Brooke Group ruling.

Table 14
Descriptive Statistics Before and After Brooke Group

Variable	Before	After
Number of Cases	153	145
No Harm to Competition Defense was used	41%	51%
Plaintiff Over 50 Million in Revenue	24%	17%
Defendant over 50 Million in Revenue	65%	77%
Consumer Goods Industry	67%	45%
Primary-Line Case	27%	22%

4.4.3 Results

Table 15 presents the coefficient estimates, standard error and p-values from the estimation of the model. The results can be interpreted such that negative coefficients indicate a greater probability of a ruling for the plaintiff and the interaction variables are the change in magnitude of the parameters after the Brook Group ruling.

Main Effect of Brooke Group Ruling. Confirming expectations, I find no main effect of the Brooke Group ruling. However, if I examine the predicted probabilities generated by the

model, I do find a shift toward a lower probability of a ruling for the plaintiff. The model shows that the overall probability of a ruling for the plaintiff was 35% before the Brooke Group ruling but dropped to 23% after the ruling (see Figure 9). So, while the main effect of the Brooke Group parameter is not significant, the overall probability shifts toward the plaintiffs after Brooke Group. The combination of these results indicates that the ruling did not have a general effect of making it tougher on plaintiffs; rather, the effect was confined to cases with certain characteristics.

Table 15
Robinson-Patman Estimation Results

	Parameter Estimate	Standard Error	p-Value
Intercept	0.782	0.272	0.004
No Harm to Competition Defense	-0.741	0.236	0.002
Consumer Goods Industry	-0.344	0.242	0.156
Small Plaintiff	0.677	0.350	0.053
Small Defendant	0.381	0.258	0.140
Primary-Line Case	-0.805	0.289	0.005
Brooke Group	0.161	0.426	0.705
Brooke Group X No Harm to Competition Defense	0.832	0.340	0.015
Brooke Group X Consumer Goods	-0.158	0.346	0.649
Brooke Group X Small Plaintiff	-0.943	0.472	0.046
Brooke Group X Small Defendant	-0.475	0.408	0.244
Brooke Group X Primary-Line	1.692	0.492	0.001

Type of Case. Prior to the Brooke Group ruling, I expected to find no difference in the probability of success for plaintiffs but afterward, my expectation was that the probability of rulings for the plaintiff would decrease in primary-line cases. The results confirm my expectation. Interestingly, the main effect of the Primary-Line variable has a negative coefficient, indicating that before Brooke Group Primary-Line cases were more likely to be ruled

for the plaintiff than Secondary-Line cases. However, the Brooke Group X Primary-Line interaction coefficient shows a large positive effect, indicating a shift in probability toward rulings for the defense after Brooke Group. The magnitudes of these results are difficult to interpret from the coefficient estimates, thus, to better understand the results, I use the predicted probabilities generated by the model (See Figure 9). By separately examining primary-line cases, I find the predicted probability of a ruling for the plaintiff drops from 58% to 6%. This shows how unlikely it is to win Primary-Line RP Act case after Brooke Group and the large magnitude of the change in primary-line cases shows the importance of the Brooke Group ruling. Interestingly, the change in probability for Secondary-Line Cases was negligible, indicating the Brooke Group ruling had no effect on these cases.

Figure 9

Effect of Type of Case on Predicted Probability of Ruling for Plaintiff

Type of Case	Before Brooke Group	After Brooke Group	Total
Primary-Line	58%	6%	35%
Secondary-Line	28%	27%	27%
Total	35%	23%	29%

No Harm to Competition Defense. Similar to the primary-line variable, I had no expectation before the Brooke Group ruling but afterward I expect cases where competitive harm rulings were made to have a greater probability of being ruled for the plaintiff. The findings support this expectation as I find that the No Harm to Competition parameter is significant and negative and that the Brooke Group X No Harm to Competition Defense parameter is significant and positive. Thus, before Brooke Group, compared to cases without a competitive harm ruling, cases with a competitive harm ruling were more likely to be ruled for the plaintiff. The

interaction parameter indicates this effect is nullified after the ruling. The predicted probabilities in Figure 4 help to determine the magnitude of the change. Before the Brooke Group ruling, cases with a competitive harm defense were ruled for the plaintiff 52% of the time with cases without the defense were ruled for the plaintiffs 24% of the time. This trend reverses after the ruling as cases with a competitive harm defense were ruled for the plaintiff 20% of the time but cases without a competitive harm defense were ruled for plaintiffs 25% of the time. This supports my position that the change in competitive harm standard by Brooke Group lead to less success for plaintiffs in RP Act cases.

Figure 10

Effect of Competitive Harm on Predicted Probability of Ruling for Plaintiff

No Harm to Competition Defense	Before Brooke Group	After Brooke Group	Total
Yes	52%	20%	35%
No	24%	25%	24%
Total	35%	23%	29%

Resources. I included company revenue as an independent variable in the model to account for the amount of resources that a company has to expend on a case. Our expectation was that resources would be important for both plaintiffs and defendants but, after the Brooke group ruling resources would become more important for plaintiffs and less important for defendants. Our results only support the view that resources become more important for plaintiffs after Brooke Group. Interestingly, I also find a significant effect for plaintiff size before the Brooke group ruling. The result implies that before Brooke Group compared to small plaintiffs, it was harder for large plaintiffs to win RP Act cases. However, the significant effect

for the Large Plaintiff X Brooke Group interaction implies that the advantage of small plaintiffs decreases after Brooke Group. In Figure 5, the predicted probabilities generated by the model are shown.

The model predicts that before Brooke Group, small plaintiffs win 39% of the time while large plaintiffs only win 25% of the time. After the ruling, this trend reverses and I find that large plaintiffs win 28% of the time but small plaintiffs only win 22% of the time. This is consistent with my theorizing that resources would become more important after Brooke Group. Surprisingly, I did not find any effect of defendant size. Thus, I find no support that it has become easier for defendants after Brooke Group.

Figure 11

Effect of Plaintiff Size on Predicted Probability of Ruling for Plaintiff

Plaintiff Size	Before Brooke Group	After Brooke Group	Total
Large	25%	28%	26%
Small	39%	22%	30%
Total	35%	23%	29%

Industry. I classified cases as coming from two broad industries: consumer goods and industrial goods. The prediction was that because of the history of the act, it would be advantageous for plaintiffs to have cases in the consumer goods industry. However, after the Brooke Group ruling it would be more difficult for plaintiffs in the consumer goods industry because of the recoupment requirement. Surprisingly, my model indicates no significant effect of industry.

4.5 DISCUSSION

4.5.1 Summary

In this essay, I examined an antitrust law that holds in important place in the marketing discipline known as the Robinson-Patman Act. This law has typically been introduced in marketing courses because it affects pricing which is an important activity traditionally under the scope of marketing. Our observation was that the market place reality was not aligned with the original goal of the Act which was to protect small independent businesses from the power of larger chain stores. In contrast to an environment where small businesses were flourishing, I saw that large retailers were increasing their dominance in the market and that they were gaining pricing power over their rivals and suppliers. Thus, I set out to uncover why this was the case.

In reviewing the history of the act, I found that economists and legal scholars began to argue for bringing the RP Act in line with the broader body of antitrust laws including the Sherman Act (e.g., Bowman 1967). The basis of their argument was that antitrust laws were put in place to protect competition (i.e. consumers) and not individual competitors. Over time, this argument gained support and culminated with the landmark *Brooke Group vs. Brown and Williamson* Supreme Court Ruling. This ruling required that plaintiffs show below cost pricing and a reasonable prospect of recoupment in order to prove competitive harm in a primary-line case. Legal scholars have debated the importance of this ruling from a legal perspective but as marketers I analyzed this ruling from an empirical perspective to quantify how it affected the actual outcome of RP Act cases.

I found that after the Brooke Group ruling, winning an RP Act case has become significantly tougher for plaintiffs. However, the model shows that there was no main effect of

the Brooke Group ruling; rather the effects were isolated to primary-line cases and cases where a competitive harm determination was made. The effect of type of case was particularly strong as the predicted probability of a ruling for the plaintiff decreased sharply in Primary-Line cases after the ruling. This finding suggests that businesses facing price discrimination as defined in a primary-line scenario have little legal recourse to protect them. Given the resources required to pursue an RP Act case, undertaking a primary-line case may be an unwise investment.

Additionally, I find that cases that had a competitive harm determination and occurred after the Brooke Group ruling were significantly more likely to be ruled for the defendant than for the plaintiff. This suggests that a proper course of action for defendants in RP Act cases would be to make an early motion to dismiss or for summary judgment on the grounds that competition was not harmed by the purported price discrimination. This will lead to a quick resolution of the case in many instances and will undoubtedly lead to cost savings for defendants.

Finally, I found that after the Brooke Group ruling, it has become significantly less likely for small plaintiffs receive favorable rulings as compared to large plaintiffs. Thus, viewing the act as a protector of small businesses may not be an accurate depiction. If the law offers less protection to this group, the value of keeping the law on the books in its current form is diminished.

4.5.2 Implications for Marketers

The decreased probability of actually receiving legal relief from the RP Act suggests several important implications for marketers. First, because I show that obtaining a ruling for the plaintiff is particularly hard in primary-line RP Act cases; managers should incorporate this knowledge when deciding whether to pursue a primary-line RP Act case. The resources needed

to carry out an RP Act case are not trivial. In one example where attorney fees for an RP Act case were sought in Federal Court, the fees incurred by the plaintiff were well over $1,000,000[17]. Given this reality, the resources may be better spent on differentiating themselves from competitors or on engaging in more competitive pricing, for example. This is true because the current competitive harm standard suggests that the courts are willing to let the free market take its own course without legal intervention. Thus, expending resources on such a case may not be the best option.

Second, because of recoupment standard put into place by Brooke Group, managers should be willing to take a more aggressive approach to their pricing policies. These policies should not consider the RP Act as banning price discrimination, rather they should view pricing through the ultimate effect on consumers. If a discriminatory pricing policy ultimately leads to lower consumer prices, it will be viewed positively by the legal system and will not be subject to penalties under the act. Thus, I do not advocate breaking the law; I simply suggest it should be viewed in light of the Brooke Group ruling.

Finally, marketing academics should communicate how the interpretation of the Act has changed to the next generation of managers. Given the difficulty in showing competitive harm under the RP Act, we should no longer simply indicate that a law exists that prevents price discrimination (e.g. Boone and Kurtz 2008). Instead, we should highlight the conditions where the RP Act is applicable and give the possible benefits of price discrimination. This will prevent managers from being risk averse in their pricing policies and may ultimately increase consumer welfare.

[17] See *Hasbrouck v. Texaco*, 631 F. Supp. 258 (1986)

4.5.3 Conclusion

The Robinson-Patman Act has been a controversial antitrust law since its enactment in 1936. The Brooke Group ruling by the Supreme Court in 1993 brought an end to much of the controversy by bringing the interpretation of primary-line competitive harm in synch with the broader antitrust laws. Moreover, in doing this, the courts have made life much more difficult for plaintiffs. Given the reality of this environment, small businesses have little recourse when they are the victim of price discrimination, especially in certain types of cases. While the ability of companies to offer discriminatory prices to some of their customers may ultimately benefit consumers in the form of lower prices, the small businesses that fail in the process are a legacy in some part created by the interpretation of the RP Act.

5.0 CONCLUSION

This dissertation, in three essays, examines the impact of the changes in the retail landscape on the competitive and legal retail environment. In this dissertation, I have made three contributions to the literature. First, I develop a new measure that characterizes how consumer purchases are spread across retail formats. This measure, which I call the Channel blurring Index, can be calculated at the household, segment or aggregate level. It can be used to characterize the behavior of shoppers and understand whether purchases are concentrated in one format or if households are spreading their purchases around.

The second contribution of this dissertation is to better understand the factors that drive the store choice decision. In essay 1, I look at the store choice decision at the highest level: the retail format choice. I estimate a choice model at the category level and find that household level preferences for formats can be explained by demographic and shopping behavioral variables. Additionally, I find the factors that are associated with greater levels of channel blurring. This analysis shows that those households that buy a higher proportion of private label goods tend to have greater format loyalty. In essay 2, I look at the store choice decision at the chain level. Several interesting insights are derived from this analysis. First, I find that food price image has a larger effect on chain choice as compared to non-food price image. This has implications for

promotion policies of retailers as they may want to focus more resources on food categories rather than non-food categories. Second, assortment breadth and depth affects different chains in divergent ways. This finding has implications for retailers wishing to expand or trim assortment.

The third contribution that this dissertation makes is that I find that the Robinson-Patman Act has declined in importance. By empirically examining the case history of the act, I find that after the landmark Brooke Group vs. Brown and Williamson case, obtaining relief under the Act has become much more difficult. This is especially important with respect to primary line cases. Given this finding and the heightened recoupment standard put into place by Brooke Group, managers should be willing to take a more aggressive approach to their pricing policies. Managers should think that the Robinson-Patman Act bans price discrimination; rather they should look at the pricing policy's ultimate effect on consumers. If a discriminatory pricing policy ultimately leads to lower consumer prices, it will be viewed positively by the legal system and will not be subject to penalties under the act. Thus, I do not advocate breaking the law; I simply suggest that the law should be viewed in light of the Brooke Group ruling.

This dissertation tries to build on existing retailing knowledge and to provide managers with insights that they can use in their stores. I think that the retailing industry will be a fruitful area of research and moving beyond issues such as brand choice and into other areas will benefit many.

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