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

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ABSTRACT

Channel blurring—a phenomenon in which consumers are moving their purchases of a product category from channels or retail formats traditionally associated with that category (e.g., grocery) to alternative channels (e.g., mass, club, extreme value/dollar) and in which retailers from one channel are selling items traditionally associated with other channels—is of great interest to both manufacturers and retailers. At one time, different retail formats such as grocery, drug, and mass merchandiser served different purposes, but they are becoming indistinguishable. For example, large mass merchandisers such as Walmart are now carrying sizeable assortments of grocery, pharmaceutical, and electronic products, while large drug chains such as Walgreens and CVS are stocking their shelves with toys and household items. We seek to understand how consumers are responding to these changes. We develop a new measure that we call the Channel Blurring Index, which characterizes the degree of channel blurring for a household. We develop a model with the index as a function of demographic, behavioral, and market factors both at the overall and at the department levels. We estimate the models using data from Nielsen's Homescan consumer panel for the entire breadth of product categories over a four-year period (2004-2008) in three cities. The results from our analysis offer important substantive insights. They show that households that extensively use private label products (pay lower prices and purchase smaller baskets of goods) engage in lower (higher) levels of channel blurring. Additionally, we find that several demographic factors are associated with the level of channel blurring. Importantly, the results suggest that the drivers of channel blurring vary across departments in a retail store.

In 2013, Walmart operated over 3,100 supercenters in the United States (U.S.) and had achieved a strong position in the U.S. grocery market with over half of its $274 billion U.S. revenues coming from the grocery category (Walmart Annual Report 2013). 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 three chains in the dollar store format added over 10,000 retail locations in the first decade of the 21st century. One way in which traditional retailers— grocery stores, drug stores, and mass merchandisers other than Walmart—are responding to these changes is to expand their assortment by increasing variety in categories which they have not traditionally sold. Such examples include general merchandise for grocery retailers and grocery for mass merchandisers. Thus, at the aggregate level of the retail market, it appears that the traditional roles of the retail channels are blurring, making it hard to distinguish among retail formats on the basis of assortment.

While prior research 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), not much is known about competition across channels. 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). However, both academics and retailers lack a way to characterize the degree of cross-channel shopping among households.

An examination of cross-retail format shopping has important implications for managers. From a managerial standpoint, a better understanding of consumer shopping strategies across store formats will enable managers to formulate better marketing strategies. We know that at an aggregate level retailers are shifting to formats like supercenters, but it is unclear what the responses to shifts in the competitive environment are at an individual level.

As retailers add outlets and assortment options, consumers may respond in divergent ways. On the one hand, consumers may adopt a one-stop shopping approach and make the lion's share of their purchases at large outlets carrying a wide selection of goods. These consumers typically value the convenience offered by these large stores and forego some benefits of shopping at multiple outlet types. These benefits include lower prices, greater value from promotions, and deeper assortment in specific categories. On the other hand, consumers may shop at multiple outlets for a given product category to minimize their overall cost of merchandise (e.g., Fox and Hoch 2005; Gauri, Sudhir, and Talukdar 2008). This "cherry-picking" behavior is undesirable for retailers because a major impetus for offering promotions is to drive store traffic to obtain a large share of consumers' requirements (Kumar and Leone 1988). Thus, if consumers are simply perusing outlets to purchase items on promotion, a retailer strategy of adding new categories as loss leaders may not be effective.

In this paper, we address four key research questions related to cross-channel/retail format shopping:

- Given the growth in alternative retail formats, to what degree are consumers splitting their purchases across retail formats (cross-channel shopping)?
- How are variables such as demographic factors (e.g., household income, presence of children), behavioral factors (e.g., basket size, assortment utilization), and market factors (e.g., retail density, geographic area) associated with consumer cross-channel shopping?
- Do the levels of cross-channel shopping differ across product departments within the store?
- Are the drivers of cross-channel shopping different for various departments?

The answers to these questions have important theoretical and managerial implications. By knowing how consumers split their purchases across channels and what drives these splits, we can better understand why we observe the different purchasing patterns across retail formats. Manufacturers can use this understanding to formulate more efficient distribution strategies for their products. Similarly, determining how cross-channel shopping varies across categories and how the determinants of cross-channel shopping differ by category, researchers can better predict why one category may exhibit more or less cross-channel shopping than the other. Both manufacturers and retailers can use this understanding to reformulate the category-channel mix.

To address these questions, we first develop a measure to characterize the degree of cross-channel shopping for a household. We call this measure the Channel Blurring Index (CBI). We then develop a model in which the CBI is a function of demographic, behavioral, and market factors. We estimate the models using data from Nielsen's Homescan consumer panel for the entire breadth of product categories over a four-year period (2004-2008) in three cities, Cincinnati, Columbus, and Pittsburgh. Additionally, we estimate the model for several departments within stores to study the differences in the index and its drivers across departments.

Our research contributes to the marketing and retailing literatures in three important ways. First, through theoretical development, we identify and describe both demand and supply side forces associated with retailer format decisions and consumer choice of retail format. We argue that changes in both demand and supply side factors are contributing to the rise in cross-channel shopping. Second, we introduce a new measure to capture the degree of cross-channel shopping for households. This measure is useful as a summary statistic for both manufacturers and retailers. For example, manufactures could track the level of channel blurring for a particular product category over time to spot trends in purchase behavior. Finally, our findings offer substantive insights into the demographic, behavioral, and market factors associated with the degree of channel blurring by store departments within a household. These nuanced findings provide valuable insights into characteristics of households that drive cross-channel shopping.

THEORETICAL DEVELOPMENT

Grocery Store Choice Literature

Because of the relevance to the research questions we address, we examine the literature from the broader area of store choice. Several characteristics of retail outlets, including convenience, selection, and store attributes, affect store patronage. Arnold, Oum, and Tigert (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.

(Insert Table 1 here)

Prior research has also examined grocery store switching behavior. Kumar and Leone (1988) examine retail price promotions and find that some of the sales increase during promotion is due to switching among grocery stores. In contrast, Bucklin and Lattin (1992) find no store switching effect. Popkowski-Leszcyc and Timmermans (1997) examine switching among grocery stores and find that households with two wage earners tend to be more loyal and make fewer shopping trips, while households with one wage earner tend to shop more. Messinger and Narasimhan (1997) show that increases in per capita disposable income have led to greater supermarket assortment, presumably because of a demand for time convenience. Furthermore, research on cherry picking (e.g., Fox and Hoch 2005; Gauri, Sudhir, and Talukdar 2008) is relevant to our study as one motivation to engage in channel blurring is to obtain lower prices.

Much of this literature examines 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 consumers' efforts to minimize their total cost of shopping drives their price format preferences. Bolton and Shankar (2003) find that the EDLP vs. Hi-Lo dichotomy 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 price and service strategies to appeal to different consumer segments.

Multiple Retail Format Research

While much of the work in this domain focuses on grocery stores, some researchers have studied issues that span multiple retail formats. Bhatnagar and Ratchford (2004) use a general model based on microeconomic theory to show that the optimality of the different retail formats depends 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) report that specific categories are associated with specific channels, while 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 Walmart Supercenter on an incumbent grocery store and find that the incumbent store lost 17% of its sales volume to the new entry. Ailawadi et al. (2010) examine incumbent retailers' reactions to the entry of a Walmart store and the impact of these reactions on the retailers' sales.

Drivers of Channel Blurring

Demand-Side Drivers. Evidence from our 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, consumers record on shopping lists only about 40% of what they actually purchase (Block and Morwitz 1999), suggesting 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 2008) 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 presumably less 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 context of grocery stores. They show that households where both the male and female heads of household are working and with a longer time since their last shopping trip are more likely to return to the same store.

Supply-Side Drivers. Retailers and manufacturers are also contributing to channel blurring. Retailers who are successful in one format are transferring their competencies into other formats. The transition of Walmart from their mass merchandise stores into Supercenters with

[2] We define penetration rate as the proportion of households from our dataset that make one or more purchase in a given channel during the final year of our dataset.

full-fledged grocery departments is the most notable example. In some markets, Kroger is continuing to develop its supercenter concept, known as Kroger Marketplace, which combines their traditional grocery assortment with a large nonfood department and pharmacy (*Drug Store News* 2011). Drug stores such as Walgreens, which opened over 1,600 stores in the last five years, many with expanded assortments, are adding to the trend as well.[3]

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 just over 16,600 ft^2 in 2007 compared to just above 10,300 ft^2 in 1997.[4] Furthermore, the number of warehouse club stores and supercenters, at an average floor space of around 140,000 ft^2, nearly tripled from 1997 to 2007. This trend toward increased size opens up shelf space opportunities for manufacturers to gain distribution 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 the balance of power in channel relationships may be shifting toward retailers (e.g., Geylani, Dukes, and Srinivasan 2007). Anecdotal evidence supports this trend as well and the growth in power of Walmart is well documented in the business press. Furthermore, manufacturers seek additional distribution opportunities 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 if a manufacturer does not have distribution in this format, the manufacturer's market share will suffer.

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[3] 2013 Walgreen's Annual Report.

[4] Data on the 1997, 2002, and 2007 Economic Census obtained from http://factfinder.census.gov/servlet/DatasetMainPageServlet?_program=ECN accessed on November 3, 2011.

In light of the various demand and supply side drivers of channel blurring, consumers can respond in a variety of ways. At one extreme, consumers can use multiple retail formats relatively equally to engage in cherry-picking behavior and buy their category requirements when they observe price promotions in a given retail outlet. In the context of channel blurring, this behavior would produce high levels of channel blurring at the household level. At the other extreme, consumers could consolidate their purchases into one format by taking advantage of the breadth of assortment that many stores now offer—leading to a low level of channel blurring at the household level.

Channel Blurring Index

To determine the channel blurring level, we need to define a measure that captures the level of dispersion in purchases across retail channels. Properties needed in such a measure include the ability to detect not only whether shoppers are using multiple channels but also to what degree. To get at the degree of dispersion, a simple measure such as the number of channels utilized will not suffice. The requirements of our measure lead us to existing measures of industry concentration for a measure of channel blurring. Industry concentration measures are relevant to our study because we are essentially looking at the level of concentration of purchases within channels. The most widely used measure of industry concentration is the Herfindahl Index. Thus, we define a summary measure of cross-channel shopping similar to the Herfindahl Index. We call this measure, the Channel Blurring Index (CBI).

The CBI is conceptually similar to the Herfindahl Index but differs in two important ways. First, we take the complement of the sum of squares of purchases so that the index is positively related to channel blurring. That is, the index increases as the level of channel blurring increases. This property is necessary as we study the level of dispersion rather than the level of concentration. Second, we normalize the index so that it ranges from zero to one.

The CBI captures the degree which households split their purchases across types of outlets over a period of time. The index equals zero when complete channel loyalty exists and one when the dollar values of purchases are split equally among all channels. Thus, the measure cannot be calculated continuously because as the time increment for calculating the CBI tends toward zero, the CBI also tends toward zero. The following is the equation for CBI:

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

where n must be greater than one and is defined as the number of channel options in the market and SOR_i is the dollar share of a household's requirements obtained in channel i.

In this manuscript, we view the unit of analysis for CBI as the household. However, the usefulness of this measure is not limited to just analyzing CBI at the household level. The CBI can be calculated at an aggregate or market level. This analysis may show that channels are blurring either because additional channel options are available, or because existing channels carry a wider assortment of goods. However just because channels are blurring at an aggregate level does not imply that households are using multiple channels to fulfill their needs. At the household level, individuals can respond to changes in aggregate assortment by consolidating their purchases more into one channel or by increasing the number of channels they use for shopping. Thus, the aggregate market-level CBI may be increasing while the average household CBI is decreasing. In addition to the aggregate and household level, the CBI can be calculated at the category, product, or segment level to produce further insights.

A CONCEPTUAL MODEL OF CHANNEL BLURRING

In the following sections, we present a conceptual model of the variables that are likely to be associated with the level of channel blurring within a household. The variables comprise demographic, behavioral, and market factors. In the following sections, we discuss the rationale behind each variable and the expected relationship with the CBI. Figure 1 contains a graphical depiction of the expected relationships in our conceptual model.

(Insert Figure 1 about here)

Demographic Factors

Household Income. Household income is reported by Nielsen as a range value. We use the midpoint of this range as the measure of income in our model. We expect that higher income households will exhibit lower levels of channel blurring behavior. This expectation is predicated on the belief that households that earn a higher income will incur a higher fixed cost of shopping and will choose a more efficient strategy of shopping in fewer channels (e.g., Popkowski-Leszcyc and Timmermans 1997). Thus, these shoppers will forgo the benefits of searching for better prices and will engage in one-stop shopping.

Two Wage Earners. In addition to household income, we also include a variable indicating whether a household has two wage earners. We believe the number of wage earners differs from total household income. While the variables are correlated, they do not measure the same construct. Total income measures the level of monetary resources, whereas the number of people working within the household indicates time available for shopping. Households with two wage earners likely suffer from a deficiency of available shopping time. Thus, we believe households with two wage earners will engage in lower levels of channel blurring.

Retired Households. We represent households with retired or unemployed members as an indicator variable. We believe that these households will exhibit a shopping behavior different from households with members who are working. The mechanism through which retirement status affects channel blurring may be complex. On one hand, households with retired members may have extra time to make multiple shopping trips to different channels. On the other hand, making multiple shopping trips requires resources and capabilities to travel to these shopping outlets and navigate different stores. Furthermore, relative to other households, households with retired members have greater shopping experience and may have stronger preferences for their favorite shopping outlets and will less likely experiment with new formats. We believe that overall, retired households will be associated with lower levels of channel blurring.

Presence of Children. We include the presence of children as an indicator variable in our model. The presence of children in a household creates divergent pressure on the tendency to engage in channel blurring. On the one hand, households with children may have an incentive to engage in channel blurring due to greater need for assortment and price sensitivity as children and adults often have different category needs and children stretch monetary resources. On the other hand, children place an additional time burden on the household as there are a greater number of activities that the household must complete. We believe that the time pressure children create for shopping is more dominant, so we expect this variable to be negatively associated with channel blurring.

Behavioral Factors

Lag Channel Blurring Index. We calculate the CBI for each household for each quarter, allowing us to study the variation in the measure over time and to assess how changes in other variables affect the level of channel blurring.[5] However, we do anticipate that the observations

[5] The choice of quarter as the unit of analysis is somewhat arbitrary. We believe that this level of analysis allows adequate number periods to assess whether a household utilized multiple formats--but not too much time that it did not allow for their behavior to change over time. As a robustness check, we reestimated a model with the year as the unit of analysis. The results, reported in Appendix A, are substantively similar to the results of the model with quarter as the unit of analysis.

from each quarter will not be independent, rather they should follow an AR(1) process. Thus, we include the lagged value of the dependent variable in the model with the expectation that it will be positively associated with the current value of the CBI, consistent with studies using similar indexes (e.g., Anderson, Fornell, and Lehmann 1994).

Trip Chaining. Trip chaining is a variable used to describe whether a household shops at multiple outlets in a given day. It is a count variable that represents the number of days in the previous quarter the household shopped at more than one outlet. We argue that households who visit more stores on a given shopping trip engage in a higher level of channel blurring. To account for the potential endogeneity of trip chaining and other behavioral variables, we use a lagged variable.

Basket Size. We measure basket size by the mean dollar value of the shopping basket for a household across visits in a given quarter. We expect that households which buy larger baskets will engage in lower levels of channel blurring as large baskets indicate one-stop shopping (e.g., Bell and Lattin 1998). Large basket shoppers tend to try to minimize the fixed cost of shopping and will likely exhibit a lower degree of channel blurring.

Private Label Share. We measure private label share as the mean dollar share of private label goods in the household’s basket. We include this variable since the use of private label goods signals that the household is price sensitive. More price sensitive households will likely engage in greater search behavior, so will exhibit higher levels of channel blurring.

Price Index. We measure price index of a household for a given category by computing the mean price paid by the household and dividing it by the mean price paid by the entire sample of households. To realize lower prices in a category, households will engage in cherry picking behavior and shop at many outlets, searching for the best deal (e.g., Fox and Hoch 2005; Gauri, Sudhir, and Talukdar 2008). Thus, price index will exhibit a negative relationship with channel blurring index.

Assortment. We examine the role of a household's purchase assortment on the level of channel blurring. We conceptualize assortment as a variable with two dimensions: assortment breadth and assortment depth. We calculate breadth as the percentage of all product categories a household purchases in a given quarter. We operationalize depth as ratio of the average number of SKUs a household purchases in a purchased category in a given quarter and the total number of available SKUs in the categories purchased in that quarter. We believe that both measures of assortment will be associated with higher levels of channel blurring because greater assortment indicates variety seeking behavior that is positively related to shopping across formats.

Market Factors

Retail Density. A factor that may affect a household's level of channel blurring is the availability of various retail formats in a given vicinity. Households close to different types of retail outlets will have a greater opportunity to engage in channel blurring and thus will be associated with higher levels of channel blurring. We operationalize this variable as the number of retail format types within a five-mile radius of the household's home.[6]

Geographical Market. Our panel of data are structured such that the measures are at the household level but the data are cross-nested within geographical markets and quarters. To control for unobserved heterogeneity across the three markets, we add fixed effects for each geographical market. We have no a priori belief about the level and direction of differences across cities, but we seek to account for differences between cities due to unobserved factors such as market-level preferences, consistent with Shankar and Bolton (2004).

[6] We conducted a robustness check using a 10 mile radius and the substantive results do not change.

Time Trend. We account for any potential effect of time by allowing for fixed effects for each quarter. Because this is a control variable, to simplify the exposition of our results, we do not report its effect in the results tables.[7]

EMPIRICAL STUDY

In this section, we first discuss the model specification and estimation procedure for the CBI model. We then present the descriptive results followed by the model estimation results. Finally, we provide several sets of results that reveal additional insights by examining CBI at the department level (dry groceries, frozen foods, health and beauty aids).

Data

To carry out the study, we utilize data from the Nielsen Homescan panel of consumers. The panel is uniquely suited to study consumer choice behavior across retail outlets. Panelists record their purchases across all the retail formats. The panel tracks purchases from over 125,000 U.S. households across all retail outlets. However, our dataset represents a subset of this panel as we worked with Nielsen to select cities that were representative of the growth in channel options over the time period of our data (2004-2008). This selection process yielded the following cities: Cincinnati, Columbus, and Pittsburgh. The final dataset contains data from 2,086 panelists that made over 600,000 shopping trips.

Model Specification and Estimation

We use the CBI as the dependent variable. The construction of the dependent variable is such that ordinary least squares estimation is inappropriate because the range of the dependent variable is bounded between zero and one. Therefore, an alternative specification is needed.

[7] We report these results in Appendix A.

Models characterized by a dependent variable that can take the value of zero or one have traditionally been modeled by a generalized linear model with a logit link function, also known as logistic regression. Our dependent variable is similar to this but rather than following a binomial distribution, it can take any value between zero and one. Thus, a more general specification is needed.

The characteristics of our dependent variable are such that they are similar to a probability distribution in that the measure is continuous and can take any value between 0 and 1. For this reason, we believe that our dependent variable is best characterized via a beta distribution. Additionally, our model specification accounts for dependencies within the error structure of the data. Thus, our overall model specification is characterized as a generalized linear mixed model with a beta distribution on the dependent variable and a logit link function.

The beta distribution is given by the following expression:

$$\pi(y,p,q) = \frac{\Gamma(p+q)}{\Gamma(p)\Gamma(q)} y^{p-1}(1-y)^{q-1}, 0 < \mathrm{y} < 1 \qquad (2)$$

where $p > 0$, $q > 0$ and $\Gamma(\cdot)$ is the gamma function. The model is described in detail by Ferrari and Cribari-Neto (2004). To create an estimable model, the beta distribution is reparameterized such that the following relationships are true:

$$\mu = \frac{p}{(p+q)} \text{ and } \varphi = p + q \qquad (3)$$

Under this parameterization and using a logit link function, a linear model can be derived where we estimate a set of standard parameters (β) well as a scale parameter (ϕ). Due to the logit link function, the regression parameters can be interpreted via an odds ratio.

Descriptive Results

Prior to presenting our main model, we present descriptive results using the CBI. Figure 2 shows a histogram of the mean household level CBI. This figure shows that households exhibit a wide variety of behaviors with respect to channel utilization and the median household CBI is 0.469. Figure 3 shows the trend in market-level CBI over time. We create this measure at the market level and it represents the aggregate usage of the various channels that we study. Our data suggest that at an aggregate level, the level of channel blurring is increasing over time.

We also examine differences in CBI across product types. To do this, we separate purchases into departments as defined by Neilsen. We then calculate the aggregate department level CBI and report it in Figure 4. We find that non-food categories such as health and beauty aids and general merchandise exhibit the highest CBI, while perishable food items such as dairy and produce have the lowest CBIs. Overall, these descriptive analyses show the utility of our measure for examining channel blurring at household, market, and product levels.

(Insert Figures 2-4 about here)

Model Results

The descriptive statistics for the data appear in Table 2 and the model results are in Table 3. Overall, the model fits well with a pseudo R^2 value of 0.577.

(Insert Tables 2 and 3 about Here)

Demographic Variables. We examined the effects of several demographic variables on the CBI. We find that as compared to one wage earner households, both retired ($\beta = -.030$, $p < .001$) and two wage earner households blur less ($\beta = -.044$, $p < .001$). For the retired households, the lower CBI may be due to the high fixed costs of shopping at multiple outlets or because retired people are less likely to try new experiences. As argued earlier, two wage earner households likely suffer from a lack of available time to shop at multiple outlets and thus forgo the benefits of shopping at multiple channels to have a more efficient shopping routine.

Households with children have higher CBI levels (β = .012, $p < .01$). This finding may be indicative of the greater breadth of needs that larger households have for fulfilling the needs of household members. Finally, we find that households with a higher level of income have lower CBI levels (β = -.001, $p = .010$).

Behavioral Variables. The second block of variables included in the table are the behavioral variables. As evidenced by the coefficient on the lagged dependent variable, households exhibit a high degree of habit in their behavior, as the previous period's CBI measure is a significant predictor of the current period's value (β = 2.687, $p < .001$). We also see a positive association between the number of trips made per shopping day and the level of the CBI as evidenced by the Trip Chaining variable (β = .177, $p < .001$). This finding suggests that blurring occurs when households make multiple trips in one day. Basket size in dollar value is negatively associated with CBI (β = -.702, $p < .001$), revealing that households who buy larger baskets in a given trip tend to be more loyal to a given channel than other households.

Contrary to our expectation, we find that households that purchase a high proportion of private label goods in dollar value have lower CBIs (β = -.063, $p < .001$). We believed that purchases of private label goods would indicate price sensitivity and that price sensitive households would engage in greater search behavior and have higher CBIs. However, the opposite finding suggests that stores should consider using private label merchandise as a way to build loyalty. This is an important finding because customers who purchase private label goods may not need to shop around once they find low prices through private label goods.

We also find that households that have high price indexes are associated with lower levels of channel blurring (β = -.002, $p = .001$). This is consistent with our expectation and suggests that households that obtain the lowest prices are the ones that utilize the most channels.

We also examine a household's assortment utilization to assess its effect on channel blurring. We find that assortment breadth utilization ($\beta = .000$, $p = .531$) is not associated with channel blurring, but assortment depth is ($\beta = -.074$, $p < .001$). This finding implies that households using more depth of assortment use fewer channel options for their purchases, perhaps because a single store carries a depth of assortment that addresses those households' needs.

Market variables. We expected proximity of a household to multiple channels will lead to higher levels of channel blurring. Our results do not support this notion as we find that higher levels of retail density are associated with lower levels of channel blurring ($\beta = -.001$, $p < .001$). Finally, we see some difference in the overall levels of channel blurring across geographic markets; Pittsburgh ($\beta = .074$, $p < .001$) has a high level of CBI while Cincinnati ($\beta = 0.006$, $p = .430$) is not distinguishable from Columbus.

Department-Level Results

To determine whether the drivers of household level channel blurring differ across product categories within the store, we reconstruct our data set at the department level. We present the results from three separate departments that represent a variety of different types of goods and vary in the aggregate level of channel blurring: dry grocery, frozen foods, and health and beauty aids. The largest five categories from each of these departments appear in Table 4. The estimation results are in Tables 5A-5C.

(Insert Table 4 and Tables 5A-5C about here)

Dry Groceries. The dry groceries department is a group of items that have a moderate level of aggregate channel blurring. It contains a group of diverse items, such as ready-to-eat cereal and soft drinks that can be purchased in bulk and stored for a relatively long time such that advanced planning and stocking up may occur. It also contains relatively perishable items like bread that cannot be stored for extended periods. The analysis shows several interesting findings. In this department, private label share has a positive effect on channel blurring ($\beta = .057$, $p < .001$). Additionally, like the health and beauty aids department, the role of price index is positive ($\beta = .048$, $p < .001$). Also, in a reversal from the analysis across product categories, households with children have lower levels of channel blurring ($\beta = -.018$, $p < .001$).

Frozen Foods. The frozen foods department is strongly associated with the grocery category. It has a lower level of aggregate channel blurring than the other departments. The results from the analysis of this department are largely consistent with those of the overall analysis, but there are a few notable exceptions. The households which utilize a greater assortment depth in this department have lower levels of channel blurring ($\beta = -.018$, $p < .001$) compared to an insignificant effect of assortment depth on channel blurring for the overall store. Additionally, contrary to the results of the overall store, households with children have a lower level of blurring for this department ($\beta = -.028$, $p < .001$).

Health and Beauty Aids. The health and beauty aids department is interesting to study for two reasons. First, it has a higher level of channel blurring than those of the other departments. Second, it contains many items people purchase with high immediacy. That is, many of these purchases are not planned well in advance and consumers may purchase many of these items more on convenience or impulse than on price. Examples of these categories include cold and pain remedies noted on Table 3. This results for this department exhibit many differences from those for the overall store. First, several of the variables, including basket size, two wage earners, and households with children that were significant for the overall store, are insignificant for this department ($p < 0.10$). Second, the roles of the price index ($\beta = .044$, $p < .001$) and retired households ($\beta = .025$, $p < .001$) reverse for this department. The price index finding supports the idea that channel blurring for this department is not driven by price but by need immediacy. Finally, as in the case for frozen foods, we find a negative effect of assortment breadth on channel blurring (β = -.007, $p < .001$).

DISCUSSION

Summary of Key Results

Taken together, the results attempt to answer the four research questions we posed at the beginning of the manuscript. We first develop a measure to characterize the degree of channel blurring that we call the CBI. We then perform a descriptive analysis to show that the level of channel blurring varies across households and types of products and is increasing over time.

Our analysis of the relationship between the CBI and demographic, behavioral, and market factors reveals several interesting results. First, shoppers who buy a greater proportion of private label goods tend to be more loyal to retail formats and engage less in channel blurring. This result suggests that strong private label brands may lower competition among retailers. Second, we find that households who pay lower prices for their goods engage in higher levels of channel blurring. Thus, engaging in cross-format shopping may be a way for customers to minimize the amount they pay for their basket of goods. However, an interesting finding from our departmental analysis suggests that this is not universally true. Some departments show the opposite effect as households that have higher channel blurring indexes actually pay greater prices. Third, we find that large basket shoppers engage in less channel blurring. Finally, we find several demographic traits are associated with the level of channel blurring and that retired households, two-wage earner households and high income households have lower levels of channel blurring while those households with children have higher levels of channel blurring.

Implications for Marketers

Our results have important implications for marketers. First, retailers should consider using private labels as a way to build loyalty among their customers. There exists 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 in their outlets.

Second, because of the high level of channel blurring observed among households, retailers should realize that competition is not just within format and consumers use different formats as substitutes. While most retailers are aware of the threat posed by Walmart 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, our results suggest that some consumers shop across formats to obtain better prices for goods, engaging in cherry-picking behavior. This finding implies that a loss-leader strategy aimed at generating store traffic should be used carefully.

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 and obtaining information on weekly prices and promotions across channels may be effort-intensive. The second strategy involves shopping at multiple formats and buying items when they are on promotion at lower prices. Future research can address which strategy is more effective under which conditions and what types of consumers engage in each strategy.

Because club stores and mass merchandisers offer relatively low prices, but have limited distribution points, low income consumers may be disadvantaged in their ability to shop at value based formats. However, an analysis of our dataset shows that the dollar format offers both low prices and attracts low income consumers. This finding, together with the trend of dollar store distribution points growing rapidly, suggests that consumers of all income strata can benefit from the increased competition in the retail industry.

Limitations and Future Research

Our study has limitations that future research could address. First, while our study provides insights into cross-format shopping among consumers, the empirical analysis is limited to three geographic markets. Future research should examine whether differences in CBI exist across markets just like differences in brand preferences (Bronnenberg, Dubé, and Dhar 2007). Second, our data did not have information on advertising. It would be interesting to analyze data on advertising exposures to understand their effect on store trips. Third, the unit of our empirical analysis of cross-format shopping is the household. Complementary research can examine cross-format shopping at the category level. Generalizations about the types of categories exhibiting high cross-channel competition would be important to both retailers and manufacturers.

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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 the grocery format 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	The effects of internal and external store characteristics on store performance are significant.
Kumar and Leone (1988)	Store data	Linear regression	Some of the increases in sales during promotion are due to store switching.
Lal and Rao (1997)	Survey	Theoretical model	EDLP and Hi-Lo stores should use different price and service strategies to appeal to different consumer segments.
Louviere and Gaeth (1987)	Survey/experiment	Conjoint-like analysis	Preferences for selection, convenience, quality, and their interactions are different.
Messinger and Narasimhan (1997)	Aggregate U.S. Supermarket Data	Theoretical model	Increases in per capita disposable income have led to greater supermarket assortment, presumably because of a demand for time convenience.
Popkowski-Leszczyc and Timmermans (1997)	Nielsen	Binary Probit (repeat or not repeat)	Conclude that switching is random.
Singh, Karsten, and Blattberg (2006)	Frequent shopper database from a single grocery store	Joint model of IPT and basket size	Incumbent supermarket lost 17% of its sales volume to a Walmart Supercenter.

Table 2
Descriptive Statistics

	Variable	Mean	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	CBI_t	0.456	1														
2	CBI_{t-1}	0.456	0.629	1													
3	Retired HH	0.714	-0.015	-0.017	1												
4	Two Wage Earners	0.085	-0.023	-0.018	-0.481	1											
5	Households with Children	0.187	0.001	-0.005	0.074	-0.018	1										
6	Household Income	43.245	-0.056	-0.055	-0.150	0.225	0.049	1									
7	Trip Chaining	5.521	0.219	0.290	0.033	-0.024	0.051	-0.106	1								
8	Basket Size	46.739	-0.128	-0.163	-0.050	0.065	-0.006	0.113	-0.046	1							
9	Private Label Share	0.226	-0.061	-0.099	0.010	-0.011	0.009	-0.143	0.041	-0.061	1						
10	Price Index	1.045	0.002	0.014	0.003	0.001	-0.001	0.018	-0.017	0.023	-0.035	1					
11	Assortment Breadth	95.141	0.072	0.123	-0.139	0.116	0.033	0.147	0.130	0.162	-0.001	-0.020	1				
12	Assortment Depth	1.586	0.010	0.035	-0.131	0.091	0.005	0.078	0.070	0.137	-0.061	-0.020	0.660	1			
13	Retail Density	3.050	-0.069	-0.070	0.002	-0.032	-0.035	0.029	-0.097	-0.027	-0.023	0.009	-0.143	-0.017	1		
14	Pittsburgh	0.279	0.064	0.065	-0.070	0.039	-0.106	-0.054	0.017	-0.008	-0.071	0.004	0.001	0.011	0.011	1	
15	Columbus	0.465	-0.020	-0.026	-0.057	0.038	-0.066	0.053	-0.038	0.041	-0.007	0.001	0.030	0.025	-0.026	-0.072	1

Table 3

Model Estimation Results-Overall

	Parameter	Std. Error	P-Value
Intercept	-1.467	0.018	<0.001
CBI_{t-1}	2.687	0.008	<0.001
Retired HH	-0.030	0.004	<0.001
Two Wage Earners	-0.044	0.007	<0.001
Households with Children	0.012	0.004	0.002
Household Income	-0.001	0.000	0.010
Trip Chaining	0.177	0.007	<0.001
Basket Size	-0.001	0.000	<0.001
Private Label Share	-0.063	0.015	<0.001
Price Index	-0.002	0.001	0.001
Assortment Breadth	0.000	0.000	0.531
Assortment Depth	-0.074	0.008	<0.001
Retail Density	-0.001	0.000	<0.001
Pittsburgh	0.074	0.006	<0.001
Columbus	0.006	0.007	0.430

N = 28,607

Table 4
Top Categories by Department

Dry Groceries
1. Bread
2. Ready-to-Eat Cereal
3. Soft Drinks
4. Canned Soup
5. Cookies

Frozen Foods
1. Ice Cream
2. Frozen Pizza
3. Frozen Novelties
4. Frozen Potatoes
5. Frozen Dinners

Health and Beauty Aids
1. Toothpaste
2. Pain Remedies-Headache
3. Shampoo
4. Deodorants
5. Cold Remedies-Adult

Table 5A

Model Estimation Results-Dry Grocery Department

	Parameter	Std. Error	P-Value
Intercept	-1.434	0.022	<0.001
CBI_{t-1}	2.424	0.010	<0.001
Retired HH	-0.037	0.005	<0.001
Two Wage Earners	-0.011	0.008	0.175
Households with Children	-0.018	0.005	0.000
Household Income	-0.004	0.000	<0.001
Trip Chaining	0.221	0.011	<0.001
Basket Size	-0.001	0.000	<0.001
Private Label Share	0.057	0.015	<0.001
Price Index	0.048	0.006	<0.001
Assortment Breadth	-0.001	0.000	<0.001
Assortment Depth	-0.020	0.006	0.002
Retail Density	-0.001	0.000	<0.001
Pittsburgh	0.071	0.007	<0.001
Columbus	-0.024	0.009	0.007

Table 5B

Model Estimation Results-Frozen Foods Department

	Parameter	Std. Error	P-Value
Intercept	-0.607	0.038	<0.001
CBI_{t-1}	1.177	0.013	<0.001
Retired HH	-0.023	0.007	<0.001
Two Wage Earners	-0.039	0.011	0.000
Households with Children	-0.028	0.007	<0.001
Household Income	0.000	0.001	0.790
Trip Chaining	0.095	0.029	0.001
Basket Size	-0.002	0.000	<0.001
Private Label Share	-0.051	0.015	0.001
Price Index	0.121	0.011	<0.001
Assortment Breadth	-0.018	0.001	<0.001
Assortment Depth	-0.106	0.006	<0.001
Retail Density	-0.001	0.000	<0.001
Pittsburgh	0.054	0.009	<0.001
Columbus	0.045	0.011	<0.001

Table 5C

Model Estimation Results-Health and Beauty Aids Department

	Parameter	Std. Error	P-Value
Intercept	-0.745	0.029	<0.001
CBI_{t-1}	1.031	0.010	<0.001
Retired HH	0.025	0.006	<0.001
Two Wage Earners	0.002	0.009	0.835
Households with Children	-0.001	0.005	0.782
Household Income	0.004	0.000	<0.001
Trip Chaining	0.208	0.020	<0.001
Basket Size	0.000	0.000	0.854
Private Label Share	-0.063	0.013	<0.001
Price Index	0.044	0.007	<0.001
Assortment Breadth	-0.007	0.000	<0.001
Assortment Depth	-0.063	0.010	<0.001
Retail Density	0.002	0.000	<0.001
Pittsburgh	0.029	0.007	<0.001
Columbus	0.034	0.009	<0.001

Figure 1
Conceptual Model of Factors that Affect Level of Channel Blurring

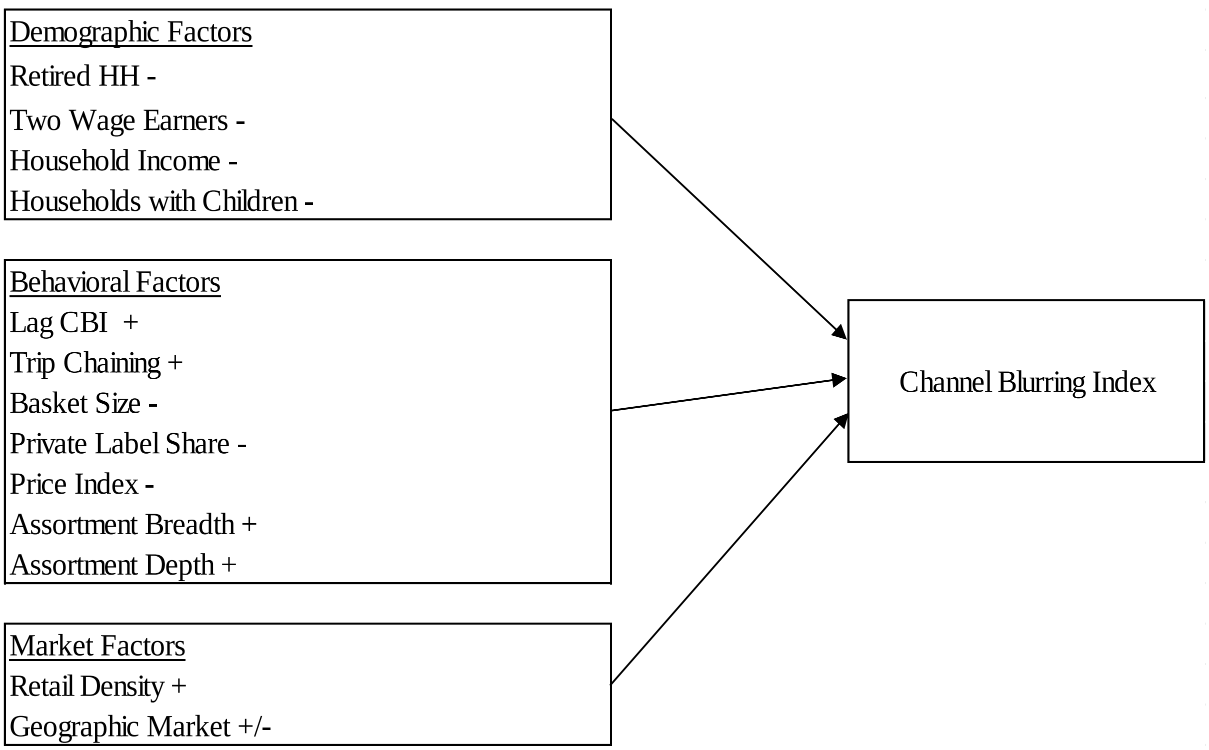


Figure 2
Histogram of Average Household CBI

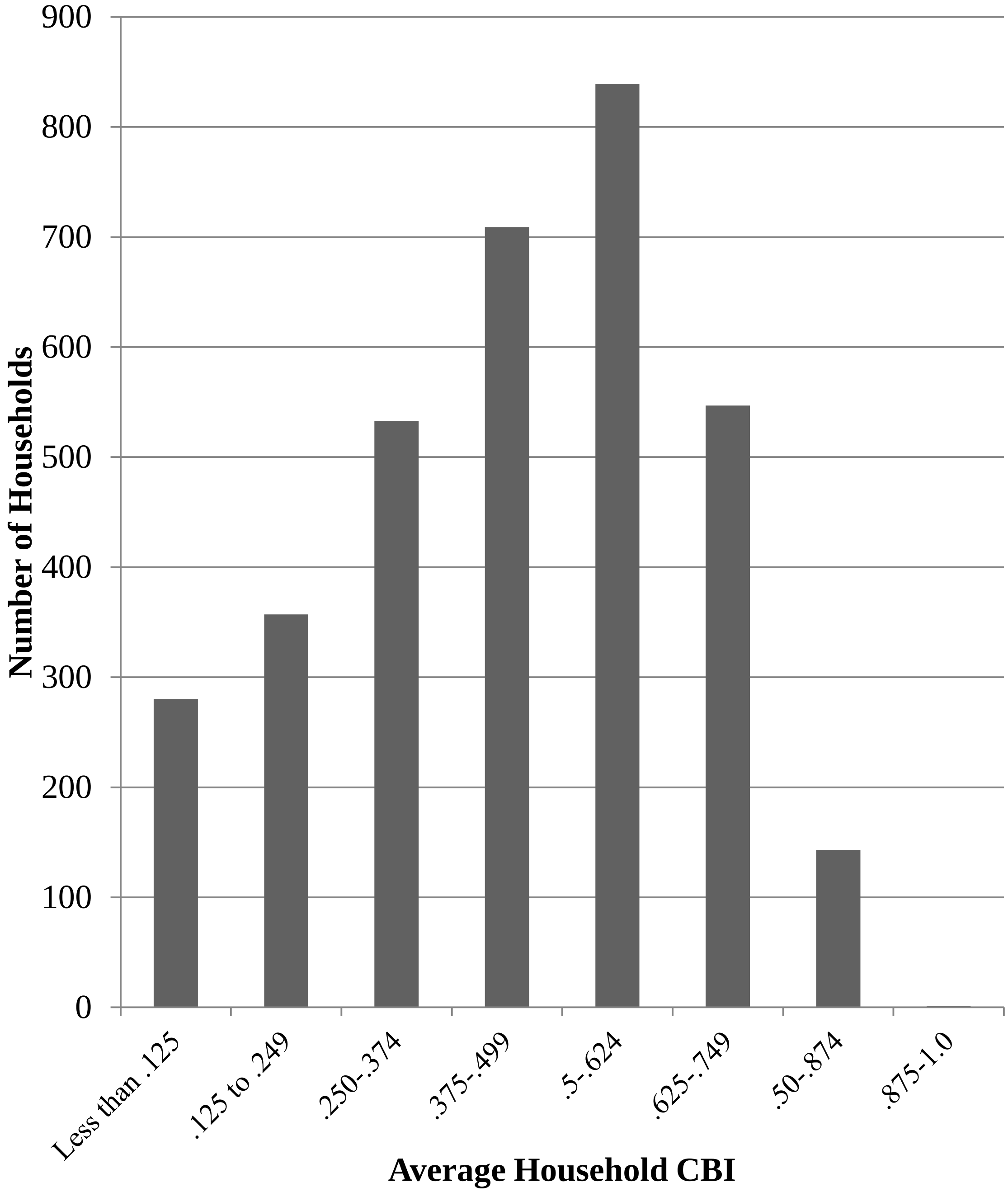


Figure 3
Market-Level CBI by Quarter (2004-2008)

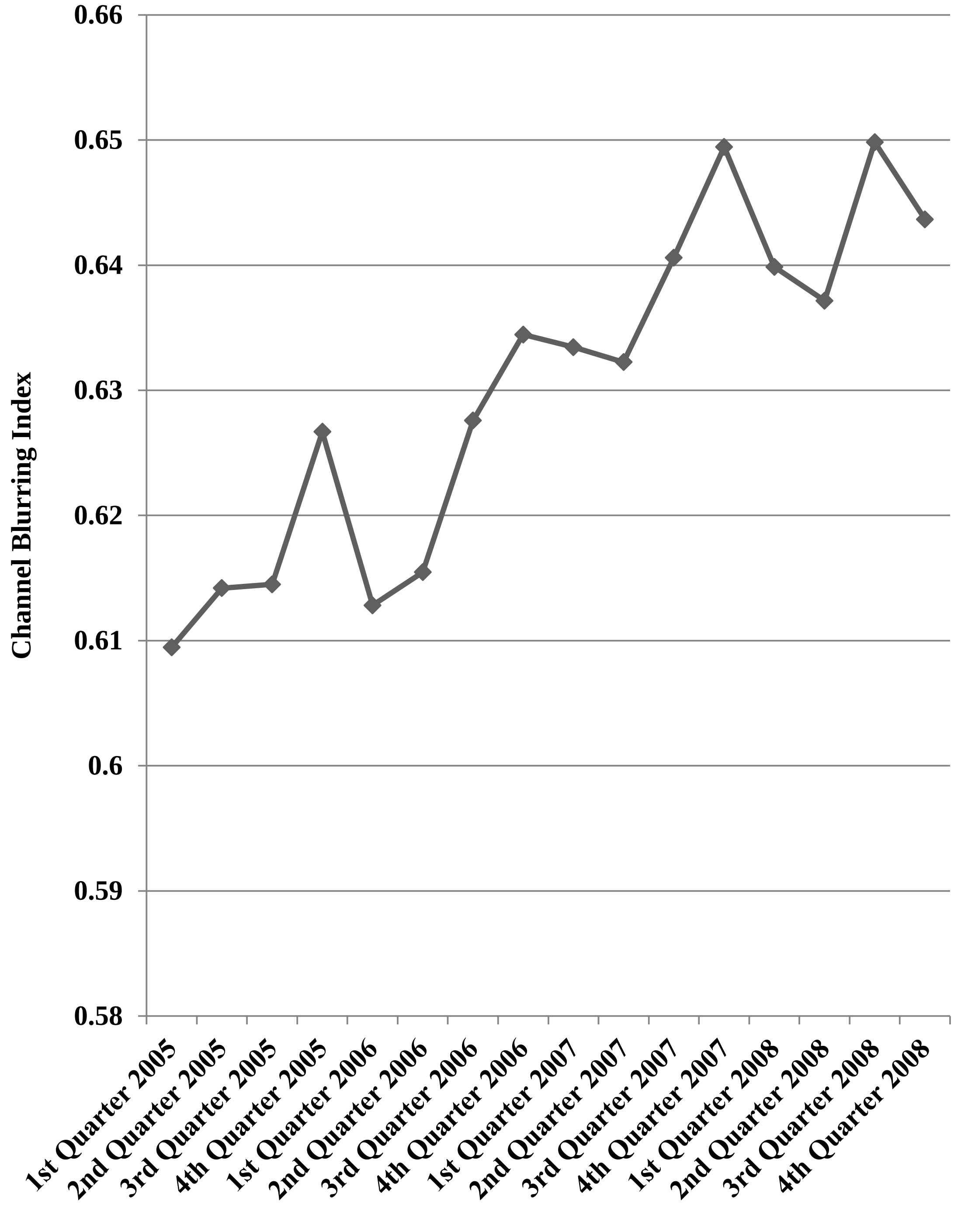
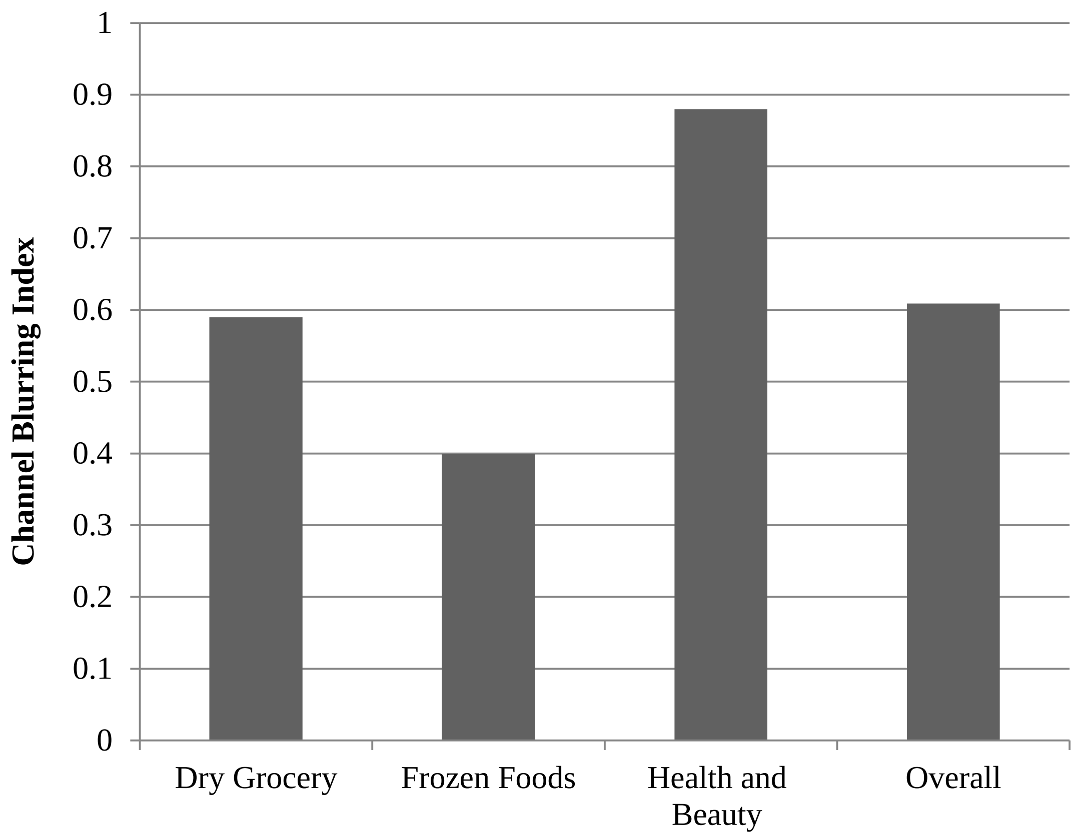


Figure 4

CBI by Department



Appendix A

Appendix A contains three ancillary tables that support our main analysis, choice of variables, and variable operationalization.

Table A1
Model Estimation Results-CBI Annual Measure

	Parameter	Std. Error	P-Value
Intercept	-2.572	0.001	<0.001
CBI_{t-1}	4.571	0.003	<0.001
Retired HH	0.019	0.001	<0.001
Two Wage Earners	-0.024	0.002	<0.001
Households with Children	0.019	0.001	<0.001
Household Income	-0.001	0.000	<0.001
Trip Chaining	0.091	0.002	<0.001
Basket Size	-0.000	0.000	0.023
Private Label Share	-0.009	0.004	0.032
Price Index	-0.001	0.000	<0.001
Assortment Breadth	0.000	0.000	<0.001
Assortment Depth	0.034	0.002	<0.001
Retail Density	-0.000	0.000	0.442
Pittsburgh	-0.011	0.002	<0.001
Columbus	0.014	0.002	<0.001

Table A2
Model Estimation Results-10 Mile Retail Density

	Parameter	Std. Error	P-Value
Intercept	-1.464	0.018	<0.001
CBI_{t-1}	2.686	0.008	<0.001
Retired HH	-0.030	0.004	<0.001
Two Wage Earners	-0.044	0.007	<0.001
Households with Children	0.012	0.004	0.002
Household Income	-0.001	0.000	0.033
Trip Chaining	0.176	0.007	<0.001
Basket Size	-0.001	0.000	<0.001
Private Label Share	-0.064	0.015	<0.001
Price Index	-0.002	0.001	<0.001
Assortment Breadth	0.000	0.000	0.782
Assortment Depth	-0.072	0.008	<0.001
Retail Density	-0.0003	0.000	<0.001
Pittsburgh	0.073	0.006	<0.001
Columbus	0.006	0.007	0.396

Table A3
Model Estimation Results-Full Parameter List

	Parameter	Std. Error	P-Value
Intercept	-1.467	0.018	<0.001
CBI_{t-1}	2.687	0.008	<0.001
Retired HH	-0.030	0.004	<0.001
Two Wage Earners	-0.044	0.007	<0.001
Households with Children	0.012	0.004	0.002
Household Income	-0.001	0.000	0.010
Trip Chaining	0.177	0.007	<0.001
Basket Size	-0.001	0.000	<0.001
Private Label Share	-0.063	0.015	<0.001
Price Index	-0.002	0.001	0.001
Assortment Breadth	0.000	0.000	0.531
Assortment Depth	-0.074	0.008	<0.001
Retail Density	-0.001	0.000	<0.001
Pittsburgh	0.074	0.006	<0.001
Columbus	0.006	0.007	0.430
2nd Quarter 2005*	-0.001	0.010	0.901
3rd Quarter 2005	0.058	0.010	<0.001
4th Quarter 2005	0.101	0.010	<0.001
1st Quarter 2006	-0.040	0.010	<0.001
2nd Quarter 2006	-0.002	0.010	0.862
3rd Quarter 2006	0.035	0.010	<0.001
4th Quarter 2006	0.096	0.010	<0.001
1st Quarter 2007	-0.007	0.010	0.489
2nd Quarter 2007	0.045	0.010	<0.001
3rd Quarter 2007	0.036	0.010	<0.001
4th Quarter 2007	0.069	0.010	<0.001
1st Quarter 2008	-0.022	0.011	0.040
2nd Quarter 2008	-0.001	0.010	0.902
3rd Quarter 2008	0.025	0.010	0.017
Scale(ϕ)	6.329	0.050	

*There is no parameter for the 1st quarter of 2005 because it was used to generate the lag parameters. Also, the 4th quarter of 2008 parameter is not estimated because it is the base case.