From Macro to Micro: The Dynamic Impacts of Discounts Depth and Discounts Breadth on Customer Deal Proneness

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Abstract:

The effects of discounts' features on retailer's performance metrics are substantially studied by academic researchers. However, there is relatively little research on impacts from the store and category discounts' depth and breadth on customers' dynamic behavior related to deal, which is a deal proneness. Using detailed scanner data from the membership database of a multichannel grocery retailer, the researcher can examine individual purchasing behavior and his exposure to the different discount characteristics from different store settings at a different visiting time. Autoregressive distributed lag model is employed to estimate the average dynamic impacts from these variables. This study found that: (1) The variety of discounts makes consumers more deal-prone than the depth of discounts (2) Customer's previous behavior play less important role compared to macro discounts' environments and (3) An online channel can moderate these impacts by making store depth and category breadth more significant to a customer's deal proneness than other variables.

Keywords: Promotional Discounts, Deal Proneness, Multichannel Grocery Shopping

Track: Pricing & Promotions

1. Introduction

A substantial number of marketing research papers studied the effect of the discount on retail sales with respect to (1) the store level, which is a product's sales, a brand sales, a category sales, a price elasticity; and (2) customer level, which is category incidence, brand choice, and purchase quantity (van Heerde & Neslin, 2017). However, there has been relatively little quantitative research on customer's dynamic behavior or characteristic which is a deal proneness or customer's susceptibility to purchase on deal.

The purpose of this study is to measure dynamic impacts of discount characteristics including depth (size of discounts) and breadth (number of unique items discounted) for both store level and category level on customers' deal pronenesses represented by constructed consumer deal proneness index, consumer's dealing activity and deal-oriented character. The moderating effects of online channel are also investigated. The detailed scanner data from 2014 to 2016 comes from a membership database of an established grocery retailer in The Nordics. It allows the researcher to examine individual purchasing behavior and exposure to the different discount characteristics from different store settings in each week. Autoregressive distributed lag model (ADL) is employed to estimate average dynamic impacts from variables of interest on the customer deal proneness, assuming that customer behaviors are habitual.

The findings from this study yield both theoretical and managerial contributions. First, the customers' deal proneness is not a static character and can be affected by both store and category discounts characteristics. Second, using point of sales data based on members from the loyalty program, the researcher could draw conclusions for general individual behavior using macro variables. Third, the retail managers could apply these findings to manage store settings and design discounts' characters to influence their customers' deal proneness.

2. Relevant literature

Deal proneness has been defined and formulated in various ways. Lichtenstein, Netemeyer, and Burton (1990) conceptually defined deal proneness as "an increased propensity to respond to a purchase offer because the form of the purchase offer positively affects purchase evaluations" (p.55). Webster (1965) developed the quantitative measure of deal proneness called "Deal Prone Index" which is "the propensity of the consumer family to buy the product class under consideration on a deal basis" (p.157). Deal proneness is also defined in regard to consumer purchasing behavior that most of the items purchased are on deal (Blattberg et al., 1978; Montgomery, 1971).

Prior academic literature treats deal proneness as a static characteristic that is correlated with consumers' demographic factors (Webster, 1965; Montgomery, 1971). However, promotional discounts could have dynamic effects on dealing activity (Kopalle et al., 1999). For example, the same consumer can be differently sensitive to promotional price over time due to the offering frequency (Mela et al., 1997) and his price perception from the previous discount offered (Kalyanaram & Winer, 1995). Moreover, Krishna (1994) developed a normative model suggesting that a purchasing on deal pattern could be affected by dealing distribution. Hence, it is reasonable to investigate dynamic impacts of discount characteristics on customer's deal proneness.

Discounts' characteristics can have substantial impacts on many retailers' metrics such as sales, profitability, etc. In the category level, the category discount's depth has a positive effect on the same category's sales in the same store and in other stores of the same retailer (Raju, 1992). Product assortment or the breadth (number of brands) in a retail store can increase overall category performance (Dhar et al., 2001). Moreover, customers tend to react more to promotions when there are fewer brands offered in a category (Narasimhan, Neslin, and Sen 1996). Besides the research stream in promotional effects on category and brand metrics, recent research by Gauri et al. (2017) showed that category discounts' depth and breadth in a store can impact store performance including traffic, sales per transaction and profit margin.

Even though a number of prior studies conclude that discounts depth and breadth have impacts on consumer behaviors (Baumol & Ide, 1956; Alba et al., 1999; Ashok & Kent, 2005; Briesch et al., 2009). Yet, it is unclear how customers' exposures to category and store discounts' depth and breadth together will influence his/her purchasing characteristic or deal proneness of that category.

In the context of grocery retailing, the effects of price promotions between the offline channel and the online channel are different because the promotions in one channel can have negative effects on the same category's level of purchase in another channel during the promotion period (Breugelmans & Campo, 2016). Moreover, Campo and Breugelmans (2015) found that online experience could moderate the effects of store factors, especially the store assortment to customer's allocation of category spending. Thus, it is interesting to explore how online channel moderates impacts of discount characteristics on consumer deal proneness.

3. Conceptual Framework

The literature reviewed in the previous section can be summarized in the framework illustrated in Figure 1. The customer deal proneness is constructed based on various definitions of deal proneness and assumed to be a dynamic variable changing over time and influenced by the store environments. The key independent variables influencing customer's deal proneness are discount depth and discount breadth at the store level and category level in which a consumer encounters at the current visiting time and the last visiting time. For simplicity and with the intention to maintain a higher degree of freedom and preserve the number of observations, the dynamic impact from previous visit is investigated. Whether a customer made purchases online at that time moderates these effects.

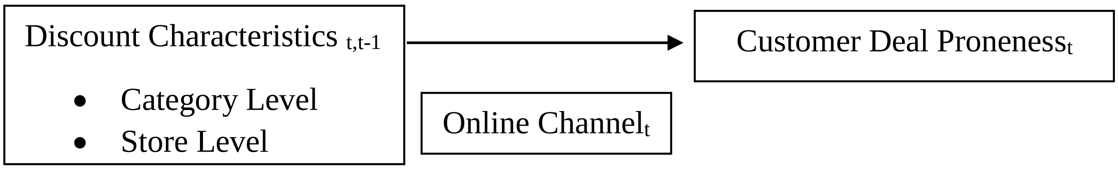

Figure 1. Conceptual Framework

4. Data Description

4.1 Scope of data

Data employed in this study is obtained from a leading grocery retailer in the Nordics. The dataset includes point of sales or detailed scanner data from 2014 to 2016, store locations and their settings, and a customer identity number from the loyalty program. Point of sales data allow the researcher to record every transaction on a daily basis and to infer what were sold and discounted in the store. The customer identity number enables the researcher to track a customer's purchasing behavior per visit and his/her exposure to the different discount characteristics in each visit.

The researcher uses dataset from eight multichannel stores to construct the daily store depth and breadth while studies the individual deal proneness from customers with more than 50 daily visits in the period of interest. This selection reduced the total number of customers in the whole dataset from 7,073 customers with total 1,466,737 transactions to 5,013 customers with total 577,634 transactions.

There is a total of 546 subcategories formally defined by the retailers. However, this study focuses on total top 15 categories. The average store's and category's depth and breadth a customer experienced each week is calculated accordingly. From these 15 categories, four categories are chosen including milk, packaged bread or pastry, coffee and carbonated drink as representatives for categories with different storability and impulsiveness. This is because the storability or stockpiling and impulsiveness of the category can impact consumers' purchasing decisions and promotional elasticities (Narasimhan, et al., 1996).

4.2 Operationalization of measures

The dependent measure of interest is the customer deal's proneness which is represented by Deal Prone Index (DPI), Dealing activity (DA) and Deal-Oriented character (DO). Table 1 describes the details of the variable operationalization.

Variables	Formula	Description
DPI_{it}	ΣV_{mt} where $V_m = (c_{im}-E_m)(R_{im})$ and $-1 \leq DPI_{it} \leq 1$	The propensity of customer *i* to buy the product class under consideration on a deal basis (weighted by customer brand share) (Webster, 1965) at time *t*
c_{imt}	$d_{imt}/ \Sigma a_{imt}$	The percentage of family *i*th's purchases of the *m*th brand on a deal basis (*d* is the number of units purchases on deal basis and *a* is the total number of units purchases)
E_m	$(\Sigma d_{im}=D_m) / (\Sigma a_{im}=s_j)$	The percentage of deal sales to total sales for *m*th brand
R_{im}	$\Sigma a_{imt} / \Sigma a_{it}$	The family *i*th brand share to the *m*th brand
DA_{it}	$\Sigma d_{it}/ \Sigma a_{it}$ And $0 \leq DA_{it} \leq 1$	The percentage of the *i*th customer's purchases of product category on a weekly deal basis (Montgomery, 1971; Henderson, 1994)
DO_{it}	$= 1$ When $DA_{it} > 0.5$ $= 0$ When $DA_{it} \leq 0.5$	An indication variable equal to 1 if a customer is deal-oriented whose most of the items purchased in the category are on deal

Table 1. Dependent variable notation & description.

Independent variables are discount depth and discount breadth. In order to operationalize discounts' depth and breadth, this study assumes that all recorded transactions reflect total number of products presented in the store. First, daily discount depth and discount breadth of each store are constructed from observed transactions in the whole dataset. Table 2 describes the details of the independent variable operationalization. Then, these variables are matched with the date (d) when and the store (b) where customer i visited for each day in a week. Consequently, each individual is exposed to different average weekly $StoreDepth_{it}$, $StoreBreadth_{it}$, $CategoryDepth_{it}$, $CategoryBreadth_{it}$ in the period of interest. However, this study is interested in the visiting time in which it does not need to be consecutive weeks. This means that the latest week the customer visited a store (t-1) can be two or more weeks before the current visit.

Variables	Formula
$StoreDepth_{db}$	(1/The number of discounted products$_{bt}$)* Σ(Value$_{discount}$/Price$_{regular}$)
$StoreBreadth_{db}$	The number of discounted products$_{db}$/ The number of sold product$_{db}$
$CategoryDepth_{db}$	(1/The number of discounted products in the category$_{db}$)* Σ(Value$_{discount}$/Price$_{regular}$)
$CategoryBreadthj_{db}$	The number of discounted Products in the category$_{db}$/ The number of sold Products in the category$_{db}$

Table 2. Independent variable notation & description.

The moderating variable is $Online\ Channel_{it}$ which is an indication variable equal to 1 if a customer i purchased product online at least 1 time in the week t. The control variable is $Holiday_t$ which is an indication variable equal to 1 if there is a holiday in the week t.

5. Empirical Analysis and Results

This study proposes that a customer's deal proneness is dynamic influenced by his previous behavior, which could tentatively capture specific customer's heterogeneity, and store environments including discounts' characteristics. As each different customer has different t-1 point of time, and total time for analysis (T) in the dataset, it is reasonable to treat the dataset as a pooled cross-sectional data. Thus, the appropriate model is

$$Deal\ Proneness_{it} = \alpha_{it} + \beta_{1i}Deal\ Proneness_{t-1} + \beta_{2i}StoreDepth_t + \beta_{3i}Online{:}StoreDepth_t + \beta_{4i}StoreDepth_{t-1} + \beta_{5i}StoreBreadth_t + \beta_{6i}\ Online{:}StoreBreadth_t + \beta_{7i}StoreBreadth_{t-1} + \beta_{8i}CategoryDepth_t + \beta_{9i}Online{:}CategoryDepth_t + \beta_{10i}CategoryDepth_{t-1} + \beta_{11i}CategoryBreadth_{jt} + \beta_{12i}Online{:}CategoryBreadth_{jt} + \beta_{13i}CategoryBreadth_{t-1} + \beta_{14}Holiday_t$$

Where Deal Proneness$_{it}$ consists of DPI_{it}, DA_{it}, and DO_{it}.

The proposed model is an autoregressive distributed lag (ADL) that allows an estimation of dynamic relationships by adding lags of the independent and dependent variables. A linear regression is employed to estimate the coefficients for DPI and DA across customers while a binary logistic regression is employed to the coefficients for DO. The regression results are summarized and shown in the Table 3. It is important to note that the multicollinearity problem and heteroscedasticity problem were tested and not found in these regressions.

According to estimated empirical results, the store and category discounts' depths and breadths generally explain the variation in the DA and DO better than DPI with higher R-squared. The customer's previous behavior (Deal Proneness_{t-1}) has a relatively smaller size of impact on DPI ($\beta_1 \leq 0.29$), DA ($\beta_1 \leq 0.33$) and DO ($\beta_1 \leq 1.19$) compared to macro discounts' environment across these four categories. For example, the store discounts' breadths have statistically higher estimated coefficients for DPI ($\beta_5 \leq 0.71$), DA ($\beta_5 \leq 0.92$) and DO ($\beta_5 \leq 5.57$). The higher importance of discounts' characteristics emphasize the individual dynamic behavior based on the store discounts' features (Krishna, 1994; Kopalle et al., 1999).

The variety of discounts offered both at the store level and category level represented by the breadth variables (β_5, β_{11}) tend to have statistically significant positive effects on all consumers' deal proneness' measures and relatively higher level of influence compared to the depth of discounts (β_2, β_8) across four categories. This means that customers will be more deal-prone when they encounter a variety of discounted products offered more than the products on deep discount. Moreover, the store discounts' breadth seems to impact customer deal proneness more in milk and packaged bread while the category discounts' breadth seems to do more in coffee and carbonated drink. For example, the proportion of promoted products in the store influences DPI of milk for 0.71 while the proportion of promoted items in the coffee category influences DPI of coffee for 0.41. These findings imply that category characteristics may play moderating roles in the importance of the store and the category discounts' breadths. Moreover, these discounts' characteristics variables tend to have a significant carry-over effects as customers may consider discounts' conditions offered at the latest time they visited**.** Yet, the estimated magnitudes of these variables are relatively small compared to current discounts' characteristics.

An online channel significantly moderates the impacts of discounts' depth and breadth. First, customers are less susceptible to the store discounts' breadth when they purchased online as $\beta_6 < \beta_5$ for all consumers' deal proneness' measures across four categories. Second, unlike purchasing offline, store discounts' depth becomes statistically significant with relatively higher magnitude of coefficient (β_3) even though it is still less than the magnitude of store discounts' breadth coefficient (β_6). Third, the category discounts' breadth becomes the most influential variable to consumers' deal proneness' when they made purchase online since significant coefficients (β_{12}) have highest sizes compared to other online moderating variables ($\beta_3, \beta_6, \beta_9$).

	Milk			Packaged Bread		
	DPI	*DA*	*DO*	*DPI*	*DA*	*DO*
Deal Proneness$_{t-1}$ (β_1)	**0.299**	**0.277**	**1.75**	**0.214**	**0.193**	**1.187**
StoreDepth (β_2)	-0.007	**-0.068**	**-2.495**	**0.049**	0.034	**-0.861**
Online: StoreDepth (β_3)	0.169	0.291	2.673	**0.321**	**0.377**	**2.159**
StoreDepth$_{t-1}$ (β_4)	**0.133**	**0.093**	**0.984**	**0.056**	**0.047**	0.363
StoreBreadth (β_5)	**0.712**	**0.912**	**5.565**	**0.420**	**0.565**	**4.495**
Online: StoreBreadth (β_6)	**0.421**	**0.525**	**5.584**	0.101	0.168	1.030
StoreBreadth$_{t-1}$ (β_7)	**0.039**	**-0.044**	-0.148	**0.167**	**0.127**	**1.190**
CategoryDepth (β_8)	**0.054**	**0.050**	**-1.90**	0.164	**0.396**	**3.682**
Online: CategoryDepth (β_9)	-0.070	-0.096	-9.035	**0.068**	**0.262**	**2.501**
CategoryDepth$_{t-1}$ (β_{10})	-0.022	-0.012	-0.286	-0.004	**-0.051**	**-0.318**
CategoryBreadth (β_{11})	**0.032**	0.014	**1.179**	**0.214**	**0.302**	**1.715**
Online: CategoryBreadth (β_{12})	0.177	0.137	0.960	**0.572**	**0.714**	**5.351**
CategoryBreadth$_{t-1}$ (β_{13})	-0.011	0.004	-0.090	**-0.077**	**-0.087**	**-0.805**
R-squared	0.2653	0.3165	0.645	0.166	0.209	0.471
	Coffee			Carbonated Drink		
	DPI	*DA*	*DO*	*DPI*	*DA*	*DO*
Deal Proneness$_{t-1}$ (β_1)	**0.188**	**0.333**	**1.58**	**0.224**	**0.242**	**1.12**
StoreDepth (β_2)	**0.123**	0.049	0.202	**0.084**	**0.063**	0.273
Online: StoreDepth (β_3)	-0.157	-0.098	-0.478	**0.309**	**0.437**	**2.402**
StoreDepth$_{t-1}$ (β_4)	**0.129**	0.034	0.187	0.047	**0.091**	**0.464**
StoreBreadth (β_5)	**0.182**	**0.079**	**0.224**	**0.110**	**0.239**	0.860
Online: StoreBreadth (β_6)	-0.046	-0.148	-1.443	0.063	0.226	**1.195**
StoreBreadth$_{t-1}$ (β_7)	**0.077**	0.024	0.145	**0.049**	0.013	0.074
CategoryDepth (β_8)	**-0.052**	**0.501**	**2.634**	**0.048**	**0.537**	**2.67**
Online: CategoryDepth (β_9)	0.147	**0.524**	**2.872**	-0.056	**0.325**	1.29
CategoryDepth$_{t-1}$ (β_{10})	**0.097**	**0.087**	**0.459**	**0.054**	**-0.048**	-0.166
CategoryBreadth (β_{11})	**0.416**	**0.790**	**4.366**	**0.491**	**0.615**	**3.511**
Online: CategoryBreadth (β_{12})	**0.473**	**0.968**	**5.380**	**0.440**	**0.485**	**2.559**
CategoryBreadth$_{t-1}$ (β_{13})	**0.049**	**-0.080**	**-0.385**	-0.011	-0.024	-0.108
R-squared	0.117	0.263	0.446	0.091	0.133	0.291

Table 3. Regression results showing unstandardized selected estimates of β for different deal proneness measures which are DPI, DA and DO

6. Conclusion and Implications

The results from using detailed data, matching and constructing macro and micro variables, and analyzing the dynamic relationship yield a number of implications to academic researchers and retailers.

The variety of discounts offered makes consumers more deal-prone than the depth of discounts. This gives the new insight to the research area related to promotional features and their effectiveness between offline and online channel. As customers behave differently in the online channel due to its moderating role, the retailers could influence them to be more or less deal-prone by adjusting the store discounts' dept and the category discounts' breadth.

Even though this study provides some insights for both academics and practitioners, there are some limitations that should be concerned. First, the study's assumptions that every customer in the dataset is exposed to the store environment and all recorded transactions reflect total number of products presented in the store may not be held. Second, data is needed to be more explored in terms of normality and stationary processes. Third, the role of category characteristics should be included. Hence, future research could investigate these issues further and develop dynamic models that could treat this dataset as a panel data for better insights and predictions.

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