“Influence of advertisement on customers based on AIDA model”

AUTHORS	Mithun S. Ullal https://orcid.org/0000-0002-0334-7283 Iqbal Thonse Hawaldar https://orcid.org/0000-0001-7181-2493 https://publons.com/researcher/1456475/iqbal-thonse-hawaldar/

ARTICLE INFO	Mithun S. Ullal and Iqbal Thonse Hawaldar (2018). Influence of advertisement on customers based on AIDA model. *Problems and Perspectives in Management*, *16*(4), 285-298. doi:10.21511/ppm.16(4).2018.24
DOI	http://dx.doi.org/10.21511/ppm.16(4).2018.24
RELEASED ON	Wednesday, 05 December 2018
RECEIVED ON	Thursday, 14 June 2018
ACCEPTED ON	Tuesday, 20 November 2018

LICENSE	This work is licensed under a Creative Commons Attribution 4.0 International License

JOURNAL	"Problems and Perspectives in Management"
ISSN PRINT	1727-7051
ISSN ONLINE	1810-5467
PUBLISHER	LLC “Consulting Publishing Company “Business Perspectives”
FOUNDER	LLC “Consulting Publishing Company “Business Perspectives”

NUMBER OF REFERENCES	NUMBER OF FIGURES	NUMBER OF TABLES
25	1	5

© The author(s) 2026. This publication is an open access article.

BUSINESS PERSPECTIVES

LLC "CPC "Business Perspectives"
Hryhorii Skovoroda lane, 10, Sumy, 40022, Ukraine

www.businessperspectives.org

Mithun S. Ullal (India), **Iqbal Thonse Hawaldar** (Bahrain)

INFLUENCE OF ADVERTISEMENT ON CUSTOMERS BASED ON AIDA MODEL

Abstract

The paper is based on information which is a combination of store advertisement and consumers' path inside the store along with product information. With this information, the authors find how advertisement affects the behavior of consumers when making the decision. The findings suggest that advertisement has a small impact on customers inside the stores. Null effect is determined, and one standard deviation in advertising has an impact on store traffic by 1.2%. But the impact at a lower end of the model is observed. One standard deviation in advertisement has impacted the store sales by 8.4%. Based on further data mining, the research has found that there is no significant improvement in the number of customers, but the increase in sales is because of the higher quantity of purchases by the existing consumers. However, the effect of advertisement on products placed in the same or nearby shelf is not found, the impact on product varieties in the same segment is also not found. Based on these research findings, the authors find the right approach towards advertisement.

The research is limited to consumers of retail industry in a Tier 3 Indian city of a developing geographic segment only.

Keywords advertising, AIDA model, path tracking

JEL Classification M31, M37

Received on: 14th of June, 2018
Accepted on: 20th of November, 2018

© Mithun S. Ullal, Iqbal Thonse Hawaldar, 2018

Mithun S. Ullal, Assistant Professor, Sahyadri College of Engineering and Management, India.

Iqbal Thonse Hawaldar, Professor, Department of Accounting and Finance, College of Business Administration, Kingdom University, Bahrain.

This is an Open Access article, distributed under the terms of the Creative Commons Attribution 4.0 International license, which permits unrestricted re-use, distribution, and reproduction in any medium, provided the original work is properly cited.

INTRODUCTION

Creativity without strategy is art, creativity with strategy is advertising. The advertisement does not just inform, it develops desires and dreams in the target consumer's mind. The retail advertisement has reached 14 billion dollars, which is roughly 1.6% of overall sales. However, the stores across the world using leaflets and fliers account for around 45% of total expenditure on advertisement. The amount of expenditure demands that the advertisers should identify the impact of feature advertising based on AIDA model.

1) Will advertisement increase the number of footfalls?

2) Is there the traffic towards specific parts of the store?

3) Most importantly, does advertisement have an impact on sales?

The decision makers should identify the level of AIDA model, which absorbs the maximum impact of advertisement. The advertisement of a product which attracts consumers to the store to buy that specific product also results in having high probability of purchasing other products as well.

The analysis of customer action through the AIDA model is applied in the practical world. Marketers believe that advertisements

increase the number of footfalls, but the proof of this is not available. This may also be due to lack of reliable data on this subject. The knowledge of the marketers is mainly limited to effects of advertisement on products sold, but not on multiple levels of the AIDA model.

The article involves the in-depth observation of consumer behavior in stores across Tier 3 Indian cities. Facts about the consumer behavior are obtained here due to manual tracking of consumers at the stores. The path of various consumers that are divided based on demography and location of each point of time, that is, over five minutes, 10 and 15 minutes, was tracked. Based on matching it with store locations, we track at what time a consumer visited certain products located at various locations inside the store. The consumers' purchase along with the feature advertising was also tracked. These observations help us to understand the effect of advertisements on various levels of purchase decisions of the consumers.

The paper answers on the level of maximum impact of advertising based on AIDA model. It also tries to find valid information on cross selling through advertisements.

The impact of advertisements on various levels of AIDA model could be answered by the number of customers who visit a particular product in the store. Next analysis of advertisement on purchase decision is found. The next question is answered by identifying and tracking the sales data of the products stored next to the category under feature advertising.

The findings are related to the impact on the number of customers by advertisements to particular products. Analysis is done by finding the number of customers for product category, keeping other aspects of product mix unaltered. The research finds that the number of customers does not increase because of feature advertising. The null effect is estimated and it is found that one standard deviation results in an increase by a mere 1.2%, which shows that sales are driven by advertisements only when a consumer visits the product category.

Also, the effect of advertisement on a purchase is identified. The number of products that are advertised has some impact on the outcome. SD increase in advertisement has 9.4% increase in purchase quantity. The research finds that sales here are driven by consumer purchasing different products under the same brand name that has advertised its products. However, the number of brands in the consumer's shopping cart along with the number of consumers remains unchanged. The quantity of a product, though, remains unchanged by advertisements. Thus, the impact of the advertisement is minimal at various levels of the AIDA model. The effect is mainly due to the same number of customers purchasing different varieties of the product, which is advertised.

Also, the research is done on the impact of advertisement on the products in store place in close vicinity. This is presented in the latter part of the paper by mapping the customer path with the store layout. There is no conclusive evidence that advertising of the particular category leads to sales of products placed next to it. Also, the impact on the rest of the related commodities remains unchanged.

Finally, consumer behavior is mapped to the data obtained to conclusively tell that the effect of advertisement is only on the last level, that is, active in the AIDA model. It may be because the consumer may observe an ad without Interest, Desire and Action. Its impact is limited to the recall of the product at the touch point with it. This is the lower end of the AIDA model and the effect of the ad is found only here. It could also mean that consumers who have taken the decision to purchase are only paying attention to the ads and not others. This behavior of the consumers minimizes the effects of ads on the first three stages of the AIDA model.

http://dx.doi.org/10.21511/ppm.16(4).2018.24

1. LITERATURE REVIEW

Advertising has an impact on quantity sold but at various stages is found to be ineffective (Seiler & Yao, 2017). Promotions and advertisements have long lasting impacts (Jedidi, Mela, & Gupta, 1999). Advertisements further become important because of the long-lasting impacts it has on brand evaluations (Keller, 1987) and it also has effects on consumer brand choices (Mela, Gupta, & Lehmann, 1997). Business is a voluntary exchange that creates value (Mackey, Sisodia, & George, 2014) and understanding the customer buying process is important in business (Nancy, Goodstein, Grewal, & Price, 2009). This buying process could be affected by advertisements and sales promotions by the marketers (Neslin & Blattberg, 1990) and visuals such as pricing also affect the customers minds (Raj, Suri, & Grewal, 2017). The visuals in the form of dynamic presentation affects the customers (Roggeveen, Grewal, Townsend, & Krishnan, 2015). Store ads also affects store choice as found by Srinivasan and Bodapati (2006). Digital displays also affect the sales (Roggevven & Grewal, 2016). Effects of customers satisfaction built through loyalty programs affect the business (Magi & Anne, 2003). Advertisements however convert high number of consumers to buy in a category (Seiler & Yao, 2017). Store atmosphere is also connected to the psychology of the customer (Spence, Nancy, Puccinelli, Grewal, & Roggeveen, 2014).

The article adds to the literature of Seiler and Pinna (2016) whose findings on price saving by searching in the store are published. The multitude of articles referred do not track the consumer's path inside the store and match it with the position of the advertisement. Finding the effect of the marketing of a product on consumers based on AIDA model at various levels is the objective of this paper.

There is a lot of literature on advertisement effects on the selling of the products in close vicinity. The online advertising spillovers are quantified by Sahni (2016) and also evidence of the same could be found in Lewis and Nguyen (2014) on the impact of ads on other products close by. Simester (2013) argues that the impact is limited to categories where customer has problems in changing to other brands. Also, Sahni, Zou, and Chintagunta (2016) have argued that the impact of ads on related products exists in coupons provided with discounts, as well as consumer purchase products without discounts. However, the impact in stores across Tier 3 cities of a developing country market like India is not found. This is due to intensive consumer tracking, ads placing and mapping the same with the store layout.

This article is different from the existing literatures, as it tracks the impact of ads on purchases and also on consumer's path inside the store. Also, the quantity purchased is the main issue along with brands and products. The impact of various levels of consumer decision making process are done by Honka, Hortacsu, and Vitorino (2016) and Johnson, Lewis, and Nubbemeyer (2016), which is limited to financial products and ads on the Internet. This paper further adds to the research of Hui, Fader, and Bradlow (2009), which has observed the consumer track and its inconsistencies and, analysis of impulse buying behavior has been researched here. Literature on monetary and non-monetary costs of search and its history has been researched by Bronnenberg, Kim, and Mela (2016) (2016). Shapiro (1984) has given spillover effects in healthcare segments. Honka, Hortacsu, and Vitorino (2016) have researched the advertisement impact on different stages of decision making process by consumers in financial business. Johnson, Lewis, and Nubbemeyer (2016) have given the effect of advertisement on Internet advertising on the consumer process of decision making. Measuring advertisement effects is important to marketers (Bagwell, 2007).

The information obtained along with the statistics is provided here along with the effects of ads for sales. The various tests follow and finally the effect of ads on other products in close proximity is checked. The paper ends with various available literature that agrees upon the findings.

2. METHODOLOGY

The information is obtained from stores across Mangalore and Udupi that are part of the supermarket chain. The stores selected have all the types of products and brands in any category. These stores and the consumer purchases along with the path the consumer takes were tracked for consec-

utive 60 days. Information of all consumers was obtained and the shopping cart was analyzed and the price was identified. The consumer's path was mapped on to the consumer's purchases. Table 1 gives the data on how these two are combined along with the position an item was stored. This is mapped on to advertising inside the store.

2.1. Consumer path tracking

The consumer inside the store is under observation and is tracked manually. Each consumer's location is tracked every 10 seconds. The location is mapped onto store layout divided into separate segments. Each segment is five square feet. Every consumer in this segment is tracked with the amount of time having spent in each segment. 10% of the consumers visiting the store during the day were being tracked to identify the variable of the number of consumers visiting a product. We note the visits of consumers by identifying the location of each products and the segments to which these products belong. The consumer if tracked in at least 4 particular segments leading to a product category is said to have visited the product category in that segment. Also, the time spent in category was being tracked. Figure 1 represents variables of a consumer visit to a product category. The diagram shows the shelf, which has an advertised category at the consumer eye level. A series of track points corresponding to this shelf are referred to track if consumer went to the concerned shelf. The time spent in the segment was manually calculated. The combination of these variables, product visits, timing of the visit and time spent in each segment was empirically analyzed. The timings were calculated by taking the total of the number of categories and the number of variables at the product category. In case the subject buys the product and the same is observed in the consumers bill, the product is noted as a purchase. The purchase is only counted if path data are available to the product. These product locations are matched with the track points. The arrow line shows the consumers' path inside the store. The sample used to track and purchase is the same set of consumers.

Location of the consumer inside the aisle is noted in the segment of traffic points. Product locations are fixed, which is shown as grids. Products are synchronized with traffic points. The blue line shows the consumers' path.

2.2. Data on advertisement

The purchase and path tracking data of consumers are further supplemented by advertising data, which are obtained by the study of the store layout. The information recorded includes advertising of the product, its price and displays. The product advertising is considered only if it is seen in the store weekly advertisements such as leaflets and in-store TV ads. Ads are usually in the stage of markets, which is the reason these stores can only give one pamphlet per store (Gupta & Lehmann, 1997). Then, we can identify concerned product data pertaining to the advertisement from all outlets of the similar brand of store situated at the same locality. The majority of our research is conducted on a daily basis, the odds of store change in weekly levels. The data cover 49 days and contain 8 sets of featured products in a category. The

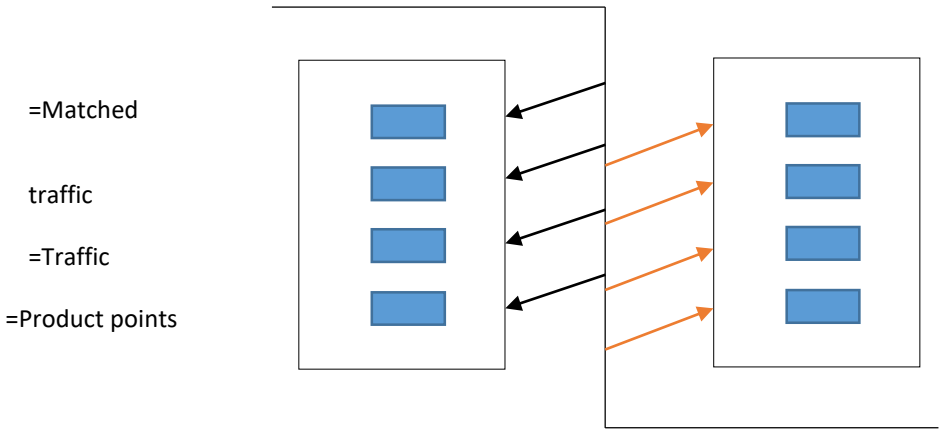

Figure 1. Customer path

http://dx.doi.org/10.21511/ppm.16(4).2018.24

number of products advertised is used as a primary method of advertising category for the regression analysis. All the regressions in this paper are using the number of products advertised as the regressor and the outcomes are similar in effect and direction.

The product displays vary across the stores in Mangalore and Udupi region, so the product displays cannot be ascertained across other stores. However, product displays are calculated by the fraction of outlets of the same owner showing a commodity per week, which is regarded as the chances of display for the product. Since all the stores have identical products, this calculation will help us know the chances for a commodity to be shown.

2.3. The data obtained

The data obtained include 1,000 products in 15 categories across 49 days. The path tracking data on the limitation imposed on the time and product advertisement is a limitation of the category. The number of categories is much larger than 15, but a lot of categories do not have ads placed on them and also are not frequently purchased by customers, thus, cannot provide relevant variations for this research. The types of products vary across locations and they include a varied set of categories from groceries to sports shoes, perishable and non-perishable goods, etc.

2.4. Statistics

At the beginning, we give an idea of the path and sales across the categories. The columns 1 and 2 of Table 1 show total daily product category tracks and also the percentage of consumers in each track. The finding varies in different categories in terms of the number of tracks they are exposed to.

The boxes show 15 categories of products. Table 1 shows category wise product locations.

A product is located at two places, one is the main location and the second the sub-location. Sub-location receives more consumers, because consumers going for other products need to pass this category. So only consumers going to the main location are being tracked over here. Also, the primary locations of the products have names of products clearly mentioned, so it can be confidently said that consumers going towards these categories seek that particular product. The sales of a particular category are also traced along with the number customers who buy it. Findings on the product quantity along with the featured products and the standard deviation of featured products are provided. 20% of product categories are advertised on a particular day. For empirical study, variations exist in the number of products that are advertised. The types of ads are not correlated and hence the effect of ads from the effect of other variables such as displays can be made out. The ads and display correlation is 0.4 after adjusting for product type effects that are non-variable. The commodities advertised are not the same as the commodities in the outlet.

3. FINDING THE IMPACT OF ADS

3.1. Product path

First, the effect of ads on product category tracks needs to be found. The effect of ads has not been found by researchers due to the absence of data on the consumer's track inside the store. These data on movement of consumers inside the store help us by identifying the effect of advertising on various levels of AIDA model. We follow the consumers' path on a daily basis to advertised products within a category and control other marketing activities. Around the category level, standard errors are clustered. The regression we found is as follows:

$$Category\ traffic = A \cdot Number\ of\ advertised\ products + XB + C + D + Ect. \quad (1)$$

where X is vector, D denotes day fixed effects, C denotes category effects, Ect provides regression error term.

The total of products advertised is included, the average price of the category is displaced and the number of items is displayed. Total advertisement and MRP are used as control variables in track regression for making it comparable with regression value of sales.

Table 1. Traffic, sales and ads in various categories

Features	Traffic	Traffic share	Primary location traffic	Traffic share primary location	No. of consumers purchases	Quantity purchased	Different brands purchased	Advertised products	Features	S.D.
Apparels	3,122	97.56	780	24.37	242	311	102	106	15.9	2.7
Food	3,104	97	624	19.5	198	284	81	127	18.6	6.4
Farm	2,907	90.84	636	19.87	176	211	68	66	6.1	1.4
Washing	2,803	87.59	514	16.06	183	192	72	78	13.7	8.3
Personal	2,765	86.40	512	16	174	183	67	41	5.2	5.6
Home sol.	2,166	67.68	427	13.34	92	95	18	20	3.4	2.1
Child sec.	1,987	62.09	403	12.59	164	245	81	41	4.3	3.5
Home decor	1,863	58.21	512	16.75	142	223	18	14	0.6	0.8
Furniture	1,415	44.21	396	12.37	124	186	201	133	0.5	0.8
Wellness	983	30.70	291	9.09	116	172	253	142	32	10.1
Sports	814	25.43	198	6.18	101	182	31	26	26.2	23.7
Utensils	415	12.96	164	5.12	78	116	41	38	1.7	1.4
Footwear	326	10.18	126	3.93	65	67	27	24	2.5	2.3
Snacks	251	7.84	84	2.62	57	58	19	13	7.4	3.6
Leisure	197	6.15	56	1.75	32	35	34	17	0.8	1.4

Note: Daily average value for respective variable is provided.

A consumer has visited a category if he passes four track points, which is the same for all product locations of the category. Table 2 gives regression results, which prove that the effect on category tracks is from features, which is statistically small (p-value of 0.7). There is a small value to the coefficient for the features of the commodity. An excess in product display by 1 leads to an increase in traffic by 0.7%. An increase of a unit of SD in features variable increases the commodities featured by 9. This leads to six additional consumers. This effect of the ads is small when compared to the overall customers going to a shop. One standard deviation increase leads to 0.591% increase in category traffic. On average, 3,200 customers visit the store. The dependent variable is taken as sales in a given category in regression, we find an increase in purchases by 12%. Other methods have been used to find the capacity of the null result with respect to impact of features on consumers' path.

The paper has a list of regressions that put varied meanings of category tracks. Rather than assumptions on a visit to a category by consumer when they traverse at least 4 segments, the article takes into account more understandable meanings, which needs the consumers to multiple segments.

The next two columns of Table 2 show the outcomes of two regressions that show that a consumer has visited a category if he passes through at least five to seven segments. The outcomes are similar to our basic specification. The predictions are not positive and the SE are minimal when compared with first basic column. A bigger regression analysis is made from 1 to 20 segment track points on the basis of the category. In 20 segments, the impact is insignificant with p-value of 0.7.

In the second test, we define the category based only on the location of every category. Multiple locations are provided to categories. Primary is on the front part of the shelf and secondary location is other general areas of the store. The general areas experience higher segments. A consumer who gives importance to a displayed ad is looking out for the displayed category, there may be the effect on categories of primary locations, because they have sign post.

Method of recording is a comparison of day and category. The requirements here with respect to marketing is the quantity of products that are promoted, the commodity price level estimate and a substitute for quantity of promoted products. Category level clustering of SE is done.

http://dx.doi.org/10.21511/ppm.16(4).2018.24

Table 2. The effect of ads on traffic category

Dependent variable	Cat visits	Cat visits	Cat visits	Cat visits
Category visit	> 3	> 5	> 3	> 5
Mean	1,900	1,209	1,032	641
S.D.	1,300	1,196	511	445
Features	0.612	–0.426	–0.139	–0.101
Category	There	There	There	There
Fees	Yes	Yes	Yes	Yes
Ads control	Yes	Yes	Yes	Yes
Observation	441	441	441	441
Recordings	15	15	15	15
Days	60	60	60	60

Again, segment track measures are made for primary locations only for each category for five and eight track points. The outcomes of these are also reported in the column. These provide us the effect of the null hypothesis along with the estimates point and SE are the same as in the earlier columns of Table 2.

A group of alternative measures of category segments considers the time spent on each segment corresponding to a category. Throughout such metrics like the total time spent, we analyze minimal and insignificant coefficient estimates. Owing to the layout of the store, some locations have more segments to be crossed than others. All 100% of consumers walk through apparel, because it is placed at the entrance. The effect here on segments is minimal to maximum rate of baseline track. This requires to assess the baseline considerations in the first row and leave 6 categories with maximum consumer visits. On excluding categories with more than 75% average customers, estimated effect remains negligible. The standard error is 2 when using 75% cut off. Finally, track impact is hidden due to repeat of advertisements of feature of nearby categories. For example, if two products are displayed side by side, any visit to one product would count as a visit to other product as well. If ads are alternative to these two products in way that only one product ads are shown in a week, then, ads in any specific category will not impact the other tracks due to total ads for both products are the same. Based on testing the correlations on spaces, there is lack of proof of systematic repetition of space. Ads for products are kept on the aisle, which are the same and are not correlated, and space among the two types of commodities estimate advertisement is correlated. In varied details, the effect of ads on similar product tracks is minimal. It is found that ads are able to bring a large number of consumers to areas of advertised products.

3.2. Product category sales

Here one has to identify the impact on sales by ads. We have to find whether any effect of the ads on purchase is found and the magnitude of impact compared to the null effect on consumers' path. Also, we research the impact of ads on consumer purchase into different adjusting margins.

The regression is as follows:

$$Sales = A \cdot Feature\ number + \\ + XB + C + D + Ect. \quad (2)$$

Here *Sales* denote the amount of product in a category purchased in a particular day. *Feature number* denotes the quantity of advertising commodities among the similar on the same day. Variables of the vector are measured by X of marketing. C and D are category and day effects that are fixed, error term of regression is denoted by *Ect*. This is similar to analysis of the category track and *Sales* is the dependent variable.

The measure of observation day and product category combination. The controls used in marketing quantity of a particular category of advertised products, the average category price and level of advertised products. SE are centred at the category level.

Table 3. The effects of ads on sales

Dependent variable	Cons purchase	Cons brand	Cons diff	Quantity brands
Mean	71.4	79.9	93.6	112.1
S.D.	90.5	105.3	121	142.3
Features	0.129	0.236	1.15	1.38
Category FE's	Exist	Exist	Exist	Exist
Fes of day	Exist	Exist	Exist	Exist
Controls of ads	Exist	Exist	Exist	Exist
Observation	441	441	441	441
Categories	15	15	15	15
Days	60	60	60	60

To bifurcate the impact of ads on various parts of alteration, multiple measures of purchase outcome that go further with the AIDA model are used. The

number of consumers purchases in a category is recorded. This metric is furthering into purchases of other products and brands from the same category, as well as multiple purchases of the same product. To identify various features, one has to find the consumer quantity/brands and customer/types of UPC along with a total quantity purchased. Let's start with the example of a consumer who bought three products of A and 2 units of B product of similar category. Sales here is marked a consumer one, 3 consumers/couples of UPC and five of the sum. If both products come under the same brand, ex Patanjali, it is considered as one consumer/brand pairs.

Results of regression from number of consumers is the dependent variable in Table 3. The estimated impact is insignificant, which is similar to our earlier findings with respect to the effect of the null hypothesis features on track of category. There is no increase in the total consumers visiting a category because of ads and also consumers who pass through the segment do not purchase the product, which is advertised. In the next column, which analyzes the effect of ads on the quantity of consumer brand pairs, no impact at all is found. Impact of ads on consumer' UPC pairs is measured next. Here a significant rise in the number of consumers UPC pairs is found.

The beginning two columns show null result; this leads us to the finding that ads increase the basket size of the same number of consumers where they buy a variety of commodities of the similar company. Multiple buying of products on the variable of the outcome is found where dependent variable is the number of purchases. The coefficient is statistically significant and increases marginally in the co-efficient magnitude. To find the level of impact estimated on total number of products purchased, let's take an example of an increase of 8 units of products, a one standard deviation. This shows an increase of 11-12 products being sold extra. This has a large impact in comparison to the traffic to that category. Increase in eight products in a given category increases the traffic by a mere 0.2%. So collectively, ads increase the basket size (more products purchased by the same consumer) and not the number of consumers. Also, the basket size increase is because of consumers buying variety of the same brand products. The outcome is that ads increase the purchase quantity of a consumer who already wants to buy. There is no increase in sales of an advertised product due to category level regressions. Product stage regression gives conclusion that ads increase the sales of that product, but the product sales in the given category, which is not advertised, remain unaffected. So, ads help the consumer who already has made a purchase decision to buy a brand to add the advertised product of the same brand also to his cart.

3.3. Number of consumers

The research provides proof that ads do not increase the number of consumers coming to the store.

If we assume that effect of ads in a week increases throughout the levels of AIDA model, category traffic effect unavailability leads to no effect on the number of consumers. The effect of null hypothesis on category traffic leads to no effect on traffic at store. Ads may get consumers to the store who may not have the interest to buy a product advertised. This can happen if ads affect the price image of the outlet or develop the store brand. However, we do not look into these aspects, as it is not within the range of our research.

3.4. Consumer behavior prior to purchase

To support our study, we find the effect of ads on outcomes related to consumer behavior prior to the purchase. That is, the time of the category presence and the time spent in a particular category. These two have not been observed prior to this. Here we try to track it by using path data. The research on this can identify if ads lead to consumers planning to purchase the product of an advertised category and due to which the category presence may be in the beginning part of the trip because of ads. Dwell timing may change if ads impact the process of searching for a product. However, both these outcomes are unaffected by ads. Ads do not lead consumers to change the timing of the buying process. Its impact on the time taken to search for the product is also not found.

4. TESTS

Variation in ads cannot be found so the effect of feature ads on traffic, sales and others is based on fluctuation in ads in a category over a period

http://dx.doi.org/10.21511/ppm.16(4).2018.24

of time. Bias could come in the form of various forms of ads that could be correlated, and demand could go up independent of ads.

To overcome this, we control all other marketing activities and the research excludes holidays and major Indian festivals, thus, overcoming fluctuations in demand. Also, ads are pre-determined by the retailer and thus may be unchanged (Anderson, Malin, Nakamura, Simester, & Steinsson, 2016). The two statements may inflate sales due to ads may have a positive correlation to demand. Clarity is not gathered on how these two aspects can develop an effect on category tracks and an impact on product sales. Researching the both is herein done below.

4.1. Demand graph changes in time

To manage demand spikes smoothly, we take categories and time periods in regression. We take a category and day the basis of the research due to which controlling demand at large scale is not possible.

All major chain stores in Mangalore and Udupi are selected. The multiple stores help us manage marketing activity and also control category-specific time trends in all stores.

In the regression below:

$$Salesscw = A \cdot Feature\ Numscw + \\ + XscwB + Ecw + Lsc + Escw, \quad (3)$$

where *S* is stores, *c* is category, *w* is week, *Xscw* is products promoted category, average price and displayed quantity products, *Salesscw*, *Feature Numscw* and *Xscw* are now store-specific, *Ecw* is demand fluctuation per week.

Due to ads being changed every week, we have ads information pertaining to a week, store effect can be controlled. After calculating demand spikes, we take identified values in our regression.

The outcomes affected by demand spikes are shown as other control variables for both path and sales regression in Table 4, which is based on specifications of earlier tables. The effect of taking demand on feature ad co-efficient in both regression calculations is small, the result of the path, as well as impact on sales, is strong with the inclusion of additional variable. Impact of market level demand for sales is strong and statistically insignificant.

4.2. Marketing at store level

Other than products advertised in stores, there is other marketing, which is done on a larger scale. These ads are geographically independent and thus do not affect any store in particular. The demand spikes are thus included in a shift in demand curve due to this large-scale marketing activity. Imputed demand is used to control differences in marketing programs, which is affecting stores in the same area. Ads that run inside the store will also have an impact, but it is not going to affect all categories. The regression control for all time varying activities is the same for all categories through set of day fixed impact.

4.3. Correlation in marketing

The problem could come from feature ads correlation due to other activities related to marketing like price and products. Price and displays are controlled in the regression analysis. For the price, we take category, price level average and the total items in number. The display is controlled by weekly average of the local market.

To identify the effect of displays on the study, we first need to analyze the statistics on display usages.

Out of the marketing activities affecting our research, displays are less projected. Also, there is no correlation among marketing tools. Display mistakes due to this on sales are minimal.

Regressions, in addition to this, are used to identify impact due to mistakes in display control differences. The displays effect on the path and sales regression may vary. In sales regression, when managing mistakes in displays, the impact of feature ads might be inflated. In regression of paths, the position in difference appears minimal. Ads of products are put in any part of the store, and not in front of the category. The front part and the end part of the shelf ads are an example of this. Due to this, less number of customers might be reported, because they pick the product at a different loca-

tion. This method can take us to bias towards zero in path regression and a positive difference in the regression of sales. To solve this problem, we take the variable in sales of estimation as products picked. If the display sends consumers to a different category, as consumers pick the product at different places in the path and outcome of sales will be biased towards nil, the difference in path, sales impact is not due to this.

Testing the answers received as to display ads lead to sales from secondary positions to main positions. This test could be done by calculating for every category and day, the quantity of selling goods and also the number of products picked for a position. If the ads send consumers away from a category, then, pickups of products not displayed should reduce. This hypothesis is tested by regression of the ratio of product picked to sales based on feature ads and other control variables. Regression using both primary location and all location pickups is calculated. As the result, the displays do not have an effect on purchase, and feature ads have some small effect. These analyses prove that displays do not send consumers away from permanent locations. Impact on sales of ads feature is not because of effect of displays that are put up in main locations. The coefficient of the ads featured effects on total sales per day is 1.02.

4.4. Errors in measurement

The study identifies the error in measurement of difference in estimation. Category path numbers and total of ads variables can have errors in measurement. The product feature here is, however, measurement error free. Measurements are in displays and path regressions. The errors here are not very detrimental. Measurement error in path count can exist. This is due to separation of the consumer from their cart. The path is dependent variable, so all the errors in measurement in the path will decrease the accuracy of the regression, but won't give estimates that are biased. The coefficient on ads in path regression is identified and the effect is small.

A display variable could also be error prone, as it is included variable of control, effect in errors in calculation of interest coefficient. Calculation errors give biased estimates of the impact of feature ads. If managing displays is required to identify the impact of feature ads, the error prone display will not be able to manage variation in quantity of displays completely.

Such things will not cause problems for the path and sales results. Displays are positively correlated with feature ads and they will have a positive impact on the path and sales. So, lack of control for displays will show an upward bias in feature co-efficient. Error prone displays cannot give us impact of null on the path, it may inflate the effect of feature ads on a sale. This may rarely happen, as the effect of advertisement features on overall sales where ads are checked with no errors is same as the effect found in the information. Both the variables are not correlated and thus the effect of the display control in feature impact is less. Coefficient in feature in path and regression in sales remains

Table 4. Tests: the recording unit is day and category combination

Dependent variable	Baseline	Baseline	Demand spike category visit	Demand spike quantity purchased	Pickup sales category visit	Pickup sales quantity purchased
Visit to category	> 3 segments visited	N/a	> 3 segments visited	N/a	N/a	N/a
Ads	0.591	1.38	0.961	0.544	0.0021	–
Input demand	0.891	0.364	(0.481)	(0.0007)	0.645	0.432
Category effect	Yes	Yes	Yes	Yes	Yes	Yes
Day effect	Yes	Yes	Yes	Yes	Yes	Yes
Marketing	Yes	Yes	Yes	Yes	Yes	Yes
Recording	441	441	441	441	441	441
Categories	15	15	15	15	15	15
Days	60	60	60	60	60	60

Note: The rule here in marketing are total advertised commodities, price of category averages and a substitute for total of advertised products. SE are clustered at level of category.

http://dx.doi.org/10.21511/ppm.16(4).2018.24

the same when displays are taken as control variables rather than when displays are ignored as it is shown in Table 4.

5. CROSS SALES IMPACTS

While identifying the impact of ads based on AIDA model, we have to identify the effects of data mining in terms of cross sales. First, whether ads in a category affect the sale in the category of products stored next to it is identified. The analysis here takes into account the complete information on the locations of the products inside the store. Such cross sales within the stores are hardly studied due to the fact that store layouts and locations of products cannot be easily mapped in Tier 3 cities. We have found that ads do not have an impact on number of the consumers visiting a product category, so cross sales are also not going to occur. Also, category sales expansion, substitution, etc. are analyzed.

5.1. Cross sales across categories

Analysis of cross sales ad's impact is the same as investigation in sales of similar products. But we have replaced sales of products kept close by in a category as the dependent variable. The same regression is used along with the category of control, impacts of day and marketing measurements. The drawback here is that sales in adjacent categories are equated to feature ads of selected category, still cannot control for ads of adjacent categories. Since all the 15 products are not stored nearby, the ads information on all products placed adjacent to focal category is not available. However, we have found that no correlation exists for feature ads in the focal category. Due to this, regression which cannot control feature ad of categories.

To identify the adjacent product to the set of 15 products for which ads are tracked, we first identify spots where products of a particular category are stocked. Upon identifying these coordinates, we then research all product spots that are in close vicinity of the product belonging to the category. All category locations are used and here vicinity means 10 feet within each product location. Next, we identify all products in that location and calculate the sales per day across all products. The sale of all products in the vicinity of 15 products is obtained. The findings in the corresponding table show that cross sales effects are not very likely to happen. The identified impact corresponding to 1/100 reduction sales of a commodity at 5% error is between 0.4% and 2.4%. The path regression corresponding to this is bigger. Impact of magnitudes in the confidence interval is small in size.

Table 5. Cross sales within and outside the category

Factors considered	Cross sales		Within category cross sales
Dependent variable	Quantity	Quantity	Quantity
Recording unit	Category	Category	Product
Products in vicinity	< 10 feet All location	< 10 feet Primary location	N/a
Mean	646	201	1.96
S.D.	589	136	6.09
Features	–1.200	–0.453	0.724
Feature substitute	(1.831)	(0.594)	(0.246)
Different products	–		–0.376
Same brand	–		(0.294)
Different products	–		–0.345
Different brand	–		0.376
Category effect	Yes	Yes	Yes
Product effect	No	No	No
Day effect	Yes	Yes	Yes
Marketing	Yes	Yes	Yes
Recording	441	441	441
Product	N/a	N/a	N/a
Categories	15	15	15
Days	60	60	60

Note: Recording is day and category in columns 1 and 2 and day and product in column 3. The inspection in marketing of advertised products in given category, category level rates and a substitute of quantity advertised products in columns 1 and 2. The column 3 has the percentage of different types of every other different.

Power of the outcomes to other sets of product nearby items is calculated. The diameter is reduced to 10 feet and definitions that are according to primary locations of categories than all product locations are used. The outcomes of these are reported in the corresponding tables and the effects are negligible. Also, 5, 10, 15 feet radius is used to define vicinity. No effect is found in regressions. The products in vicinity's relation with the main product are also taken into account. All the products are categorized as substitutes, compliments and none and regression analysis of each is done. All analysis shows insignificant effects.

So, the final statement is ads do not lead to cross sales and decisions of advertisements for products can be made independently of other products.

5.2. Cross sales within category

Impact of feature ads on individual products has to be now identified. The boundary of ads impact at commodity, company and product level is identified. *p*, *b* and *c* commodity company and product. *bp* refers to product brand that commodity *p* belongs to, *cb* refers to category that brand *b* belongs to.

The regression is as follows:

$$Salesp = A1\ Featurept + A2\frac{Feature - p_t}{Nb_j - 1} + \\ + A3\frac{Feature - b_t}{Ncb - Nb_j} + Z_{jt}B + C_j + D_t + e_{jt}. \quad (4)$$

Here *Featurept* substitutes the difference the same as to one if commodity *p* is displayed in day *t*. *pt* gives other product featured in the same brand except the product *j*. Nb_j is the commodities of company brand b_j. The fraction of other commodities of the same company is the variable. $Feature - p_t$ is the number of products in category cb that *b* belongs to, but excludes all products of brand *b*. Dividing the number of products of other brands, this variable gives the fraction of featured products of other brands in the same category. Z_{jt} denotes other controls of marketing. *C*, *D* gives the commodity and effects of day, and e_{jt} is the error. SE are there at level of product.

The following formula can be used to analyse product substitution effect, cross sales and category expansion effects. At level of product, the sales impact is given by

$$E\left(\frac{\Delta Sales_{jt}}{\Delta Feature_{jt}} = 1\right) = A1. \quad (5)$$

Same way, expected difference for different commodities of the given company can be calculated. Products of the similar company, $Feature_{jt}$ increase by 1, difference becomes $A2/(Nb_j - 1)$. As $Nb_j - 1$ other products are there within the brand, the estimated difference average in the brand level is given by

$$E\left(\frac{\sum \Delta Sales_{jt}}{Feauture_{jt} = 1} = 1\right) = A1 + \\ + \left(Nb_j - 1\right)\frac{A2}{\left(Nb_j - 1\right)} = A1 + A2. \quad (6)$$

The impact of total sales at category level is $A1 + A2 + A3$. This allows us to use substitution, as well as cross sales impact, at different levels.

The findings from the regression are presented in Table 5. Table 5 also gives estimates for other marketing variables. There is a significant impact at the product level and no effect on brand and category level. So, feature ads lead to increase in commodity sales is advertised and there is no impact on other commodities sales. There is proof of cross sales in products because of advertisements in the store.

6. RESULTS

The findings are as follows:

1. Ads have no effect on path being advertised.
2. Ads impact on quantity is because of the increase in purchases by the same consumer of the same brand.
3. Ads have no impact on products in the vicinity.
4. Impact of ads on other product in the same category is not found.

The findings show that ads help in increasing the basket size of consumers who have already taken the decision to purchase by making them add other products of the same brand to their purchase list. The article provides answers as to why the impact of ads is only at the Desire and Action stage of AIDA model.

Consumers who observe the ads do not take action immediately and recall the ad when exposed to the product. A consumer passing through the category is not possible to recall the ads. Ads may change the purchase decisions of consumers of the commodity, but not in brand level or cat-

http://dx.doi.org/10.21511/ppm.16(4).2018.24

egory. Those who don't have intentions to buy a product do not feel motivated by the ad. But the consumers who already want to buy a product may change their intentions and buy more of the same brand. The information contained in the ads brings this change in consumers and also raises the awareness levels of products. Consumers' attention is gained by feature ads for brands, which they have already taken the decision to purchase. Ads impact of buying of advertising products is based on buying the brand it belongs to.

CONCLUSION

The article uses a new kind of data, which are a combination of information about the ads and paths taken by consumers inside the stores. This information gives details of the various levels of AIDA model that have not been identified before. Ads have an effect on the number of products sold, it is not having a big impact on attention and interest stages. Ads do not change the tracks of the consumers. It also does not convert the consumer to buy a product. The null result of consumer path is calculated and it is found that ad impact on consumer path is small even at the upper level of confidence interval. The ads effects are mainly due to consumers buying more products within the category. The analysis of cross sales of ads shows that there are no cross sales because of ads. These analyses give the effect of ads based on AIDA model. Ads do not increase the category path so chances of cross sales in other categories are non-existent. There are no cross sales within individual product at the category level. Ads increases sales of the products that are advertised. The hike in sales are from consumers who have already made the decision to purchase the brand who join the commodity advertised to their cart. The findings say the advertisers need not pay attention to synchronize ads across categories or products. Also, the ads also do not reduce the increase in sale of other commodities of related products and outlets can increase sales of similar products by ads. Cross sales that are non-existing are good, but however ads slightly increase competitor's sales.

REFERENCES

1. Anderson, E., Malin, B., Nakamura, E., Simester, D., & Steinsson, J. (2016). Informational rigidities and the stickiness of temporary Sales. *Journal of Monetary Economics, 90*(2017), 64-83. Retrieved from https://www.nber.org/papers/w19350
2. Bagwell, K. (2007). *Handbook of industrial organisation, chapter 28* (3rd vol.). Elsevier.
3. Bronnenberg, B. J., Kim, J., & Mela, C. F. (2016). Zooming on choice: How do customers search for cameras online? *Marketing science, 35*(5), 695. http://dx.doi.org/10.1287/mksc.2016.0977
4. Gupta, S., & Lehmann, D. (1997). The long-term impact of promotion and advertising on consumer brand choice. *Journal of Marketing Research, 34*(2), 248-261. Retrieved from https://www.jstor.org/stable/3151862?seq=1#page_scan_tab_contents
5. Honka, Hortacsu, E. A., Vitorino, A. M. (2016). Advertising, customer awareness and choice: Evidence from U.S. Banking Industry. *The RAND Journal of Economics, 48*(3), 611-646. https://doi.org/10.1111/1756-2171.12188
6. Hui, S. K., Fader, P., & Bradlow, E. (2009). The travelling salesman goes shopping: The systematic deviations of grocery paths. *Marketing science, 28*(3), 566-567. https://dx.doi.org/10.2139/ssrn.942570
7. Jedidi, K., Mela, C. F., Gupta, S. (1999). *Managing advertising and promotion for long run portability* (Working Paper). Marketing science Institute. Retrieved from http://www.msi.org/reports/managing-advertising-and-promotion-for-long-run-profitability/
8. Johnson, G. A., Lewis, R., & Nubbemeyer, E. (2016). The Online Display Ad Effectiveness Funnel & Carryover: Lessons from 432 Field Experiments. *SSRN*. https://dx.doi.org/10.2139/ssrn.2701578
9. Keller, K. (1987). Memory factors in advertising: The effect of advertising retrieval cues on brand evaluations. *Journal of Consumer Research, 14*(3), 316-333. https://doi.org/10.1086/209116
10. Lewis, R., & Nguyen, D. (2014). A Samsung Ad for the iPad? Display Advertising's Competitive Spillovers to Search. *SSRN Electronic Journal.* http://dx.doi.org/10.2139/ssrn.2374414
11. Mackey, J., Sisodia, R. S., & George, B. (2013). *Conscious Capitalism: Liberating the Heroic Spirit of Business.* Cambridge, Harvard business review press (368 p.). Retrieved from https://hbr.org/product/conscious-capitalism-liberating-the-heroic-spirit-of-business/10845-HBK-ENG

12. Magi, Anne W. (2003). Share of wallet in retailing: the effects of customer satisfaction, loyalty cards and shopper characteristics. *Journal of Retailing, 79*(2), 97-106. https://doi.org/10.1016/S0022-4359(03)00008-3

13. Mela, C. F., Gupta, S. & Lehmann, D. R. (1997). The long term impact of promotion and advertising on consumer brand choice. *Journal of Marketing Research, 34*(2), 248-261. https://doi.org/10.2307/3151862

14. Nancy, M. P., Goodstein, R. C., Grewal, D., Price, R. (2009). Customer Experience Management in Retailing: Understanding the Buying Process. *Journal of Retailing, 85*(1), 15-30. https://doi.org/10.1016/j.jretai.2008.11.003

15. Neslin, S. A, & Blattberg, R. C. (1990). *Sales promotion: Concepts, Methods and strategies* (2nd ed.). Prentice Hall. Retrieved from https://books.google.com.ua/books/about/Sales_promotion.html?id=CjIPAQAAMAAJ&redir_esc=y

16. Raj, Suri, Grewal, D. (2017). *Should prices be placed in the left visual or right visual field* (Working paper).

17. Roggeveen, A. L., Grewal, D., Townsend, C., & Krishnan, R. (2015). The impact of dynamic presentation format on customer preference for hedonic products and services. *Journal of Marketing,* 34-49. Retrieved from https://www.ama.org/publications/JournalOfMarketing/Pages/dynamic-presentation-hedonic-products-services-willing-to-pay.aspx

18. Roggevven, A. L., Grewal, D. (2016). Do Digital Displays Enhance Sales? Role of Retail Format and Message Content. *Journal of Retailing, 92*(1), 122-131. https://doi.org/10.1016/j.jretai.2015.08.001

19. Sahni, N. S. (2016). Advertising Spillovers: Evidence from Online Field Experiments and Implications for Returns on Advertising. *Journal of Marketing Research, 53*(4), 459-478. https://doi.org/10.1509/jmr.14.0274

20. Sahni, N., Zou, D., & Chintagunta, P. K. (2016). Do Targeted Discount Offers Serve as Advertising? Evidence from 70 Field Experiments. *Management Science, 63*(8), 2397-2771. https://doi.org/10.1287/mnsc.2016.2450

21. Seiler & Pinna (2017). Estimating Search Benefits from Path-Tracking Data: Measurement and Determinants. *Marketing Science, 36*(4), 471-643. https://doi.org/10.1287/mksc.2017.1026

22. Seiler, S., & Yao, S. (2017, September). The Impact of Advertising Along the Conversion Funnel. *Quantitative Marketing & Economic, 15*(3), 241-278. Retrieved from https://www.gsb.stanford.edu/faculty-research/publications/impact-advertising-along-conversion-funnel

23. Simester, D., & Anderson, E. T. (2018, October). Advertising in a Competitive Market: The Role of Product Standards. *Journal of Marketing, 50*(4). https://doi.org/10.1509/jmr.11.0538

24. Spence, C., Nancy, M. P., Puccinelli, N. M., Grewal, D., & Rooggeveen, A. L. (2014). Store atmospherics: A multisensory perspective. *Psychology and marketing, 31*(7), 472-488. https://doi.org/10.1002/mar.20709

25. Srinivasan, V., & Bodapati, A. (2006). *The impact of store ads on store choice* (Working Paper No. 1935). Stanford Business. Retrieved from https://www.gsb.stanford.edu/faculty-research/working-papers/impact-feature-advertising-customer-store-choice

http://dx.doi.org/10.21511/ppm.16(4).2018.24